Markets and Markups:

A New Empirical Framework and Evidence on Exporters from China

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Preliminary: June 2018

Abstract

We develop a new empirical framework to analyse destination-specific markup and quantity adjustments to bilateral exchange rates by exporters. First, we develop an unbiased estimator of markup elasticity that isolates marginal costs in large unbalanced panels where the set of markets served by firms varies endogenously with currency movements. We use this estimator to quantify the relationship between quantity and markup adjustments across markets driven by relative exchange rate movements, which we refer to as cross-market supply elasticity. Second, we build a novel product classification distinguishing high- and low-differentiation goods. Exploiting information about Chinese "measure words" reported in customs declarations, we add value to existing systems including Rauch (1999) and the UN's Broad Economic Categories. Applying this framework to multi-destination exporters from China, we find that the average markup elasticity is higher for high-differentiation goods (20%) than for low-differentiation goods (6%). The cross market supply elasticities are correspondingly lower for high- than low-differentiation goods, 0.83 and 2.47 respectively. Finally, we discuss how these estimated elasticities can serve as diagnostics for the development of open economy macro models.

JEL classification: F31, F41

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

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We thank Andy Atkeson, Ariel Burstein, Natalie Chen, Thierry Mayer, our discussants Leonardo Melosi, Jakob Munch and Zhihong Yu, and participants at the Empirical Investigations in Trade and Investment Conference (Tokyo), March 2018; the Annual GEP/CEPR Postgraduate Conference, April 2018; the Rocky Mountain Empirical Trade Conference (Ottawa), May 2018; the China Finance Review International Conference (Shanghai), June 2018; the "New Issues in Macroeconomics" Conference (Ischia, Italy), June 2018; the Barcelona GSE Summer Forum, June 2018; the 2018 Tsinghua Workshop in International Finance; and participants in seminars at the University of Southern California, the Fed Board, and the University of Oregon, for comments. We are also grateful to those who offered feedback on preliminary versions presented at the Paris Trade Seminar, March 2017; the China Center for Economic Research at Peking University's Summer Institute (Yantai), June 2016; the Banque de France, December 2015; and the European Trade Study Group (Paris), September 2015.

We thank Cambridge INET, the Centre For Macroeconomics, and the Economic and Social Research Council (United Kingdom) for supporting our research. We thank the staff of the HMRC datalab, especially Yee-Wan Yau, for supporting us in our analysis of UK administrative data.

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.

While global and local shocks naturally lead firms to reconsider their pricing strategies, their choice sets are not unconstrained, but crucially reflect the extent to which firms have power in local markets and can keep the foreign markets for their products segmented to minimize arbitrage. For example, an exporting firm must consider not only the direct effect of changes in the value of its own currency on own competitiveness, but also the response of foreign rivals to swings in the bilateral exchange rates between destination markets and third countries—as this has key implications for the firm's residual demand and, hence, local pricing power. In this sense, an multilateral analysis of markup and quantity elasticities with respect to the exchange rate can provide fundamental insight on the effective degree of competition within and across markets, especially if this information is articulated by product and firm characteristics.

Trade globalization has heightened the importance of understanding the many factors that drive a global firm's pricing strategy. The availability of new, high-dimensional administrative customs databases has provided a wealth of new insights about the pricing behaviour of firms (Berman, Martin and Mayer (2012), Chatterjee, Dix-Carneiro and Vichyanond (2013), Amiti, Itskhoki and Konings (2014), Fitzgerald and Haller (2014), De Loecker et al. (2016), Fitzgerald and Haller (2018)). However, research has yet to exploit the data in ways that can inform our understanding of multilateral competition by exporters in local and global markets—and provide insights on the determinants of international trade elasticities. This is an important gap in the literature. Pricing-to-market has become a standard feature in open macro models, increasingly featuring firm dynamics and competition (see, e.g., Bergin and Feenstra (2001) and Atkeson and Burstein (2008)), vertical interactions of exporters with local producers and distributors (see, e.g., Corsetti and Dedola (2005)), and nominal rigidities in either local or a (third-country) vehicle currency (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

[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)).

of these gains vary with the market power of exporters.[2]

In this paper, we build an empirical framework suitable for analyzing the local or *destination-specific* markup and quantity adjustments of multi-destination exporters in firm and product-level administrative datasets.[3] On methodological grounds, our contribution is threefold. First, we construct an estimator of the markup elasticity to the exchange rate that exploits multiple destination-specific prices of individual products in order to net out changes in unobserved marginal costs—that we dub Trade Pattern Sequential Fixed Effects (henceforth TPSFE). The general approach builds on the seminal work by Knetter (1989). However, unlike Knetter's original method, our estimator is free of the bias introduced when firms endogenously discontinue or open destination markets in response to exchange rate fluctuations—implying that the panel of observations is endogenously unbalanced. We implement our TPSFE estimator conditional on price changes; our results are therefore fully comparable with recent estimates of exchange rate pass through derived using the approach of Gopinath, Itskhoki and Rigobon (2010) and estimates of markup elasticities by Fitzgerald and Haller (2014).

Second, following up on the TPSFE methodology, we show how to estimate market-specific responsiveness of *quantities* to currency fluctuations. 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.[4] 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 from differences in local factors). We refer to this measure as the

[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.

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

[4]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.

within-firm cross market supply elasticity (CMSE).[5]

Taken together, these two elasticities, the destination-specific markup elasticity (DSME) and the cross-market supply elasticity (CMSE) offer insights into the empirical relevance of local market structures for globally engaged firms. They further hold potential as a diagnostic for open economy macro models.

Clearly, the intensity of competition among firms varies not only with local market structure, but also systematically across different types of globally-traded products—producers of highly differentiated manufactured goods hold more pricing power than producers of undifferentiated commodities. Our third methodological contribution is a novel product classification of traded goods into categories of market power, or, equivalently, the degree of product differentiation. The core idea is a simple one: traded goods whose quantity is recorded in customs data by weight or volume are less differentiated than goods whose quantity is reported in countable units. Chinese customs data provide a unique opportunity to extend this simple idea into an exogenous classification system because the choice to record a product's quantity in units versus mass is predetermined by Chinese grammar and linguistics. We exploit linguistic information on "measure words" recorded in the Chinese Customs Database to construct a general product classification for the Harmonized System.

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.[6] This period includes both the last years of the dollar-peg regime (2000-2005) and the early years of the more relaxed managed

[5]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).

[6] 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.

float (2006-2014). The invoicing currency of Chinese exports is not recorded in our dataset, but the US dollar is widely-held to have been the principal invoicing currency for Chinese exports throughout this period.[7] Because exports to the US were subject to two different exchange rate regimes during our sample period, we exclude exports to the US in order to obtain a comparable sample of countries over the full sample period.[8] 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 foreign markets over 15 years.

Our main empirical findings are as follows. First, the destination-specific markup elasticity is moderate, especially for high-differentiation products—suggesting 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 show that destination-specific markup adjustments motivated by exchanges rate movements actually translate into differentiated quantity responses across markets. Applying our two stage diagnostic, the difference in cross-market elasticity between consumption goods and intermediates is substantial, 0.54 vs 2.92. 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. The CMSE for low differentiation intermediates, 3.27, suggests something much closer to an integrated world market.

From a theoretical perspective, our estimates of the destination-specific markup elasticity (DSME) and the cross-market supply elasticity (CMSE) provide a diagnostic tool to guide and discipline the development of open-economy models. In an ongoing work, we are developing a multi-country model with features drawn from leading contributions in the literature. At the end of the paper, we briefly summarize our results so far. They suggest that, while existing leading models of markup adjustment cannot match the evidence we produce in this paper, a model integrating their key elements can.

The rest of the paper is organized as follows. Section 2 presents our empirical framework.

[7] See appendix C.3 for evidence on dollar invoicing.

[8] 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)). Further, we treat the eurozone as a single economic entity and aggregate the trade flows (quantities and prices) to eurozone destinations at the firm-product-year level.

Section 3 summarizes the database. Section 4 presents our empirical results. In section 5, we describe our ongoing work to build a multi-country general equilibrium theoretical framework to understand markup and quantity adjustments across markets. We calibrate this model to match and interpret the estimated destination-specific markup elasticities and cross-market supply elasticities. A brief section discusses the implications of our analysis for open-economy modelling. Section 6 concludes.

2 Empirical Framework

In this section, we introduce an empirical framework designed to study adjustments to markups and quantities of products sold by firms across multiple foreign markets. Throughout our analysis, we will focus on (differences in) movements of bilateral exchange rates across destination markets as the main source of variation—without identifying the underlying shocks. It should be clear, nonetheless, that our framework can be applied to study markup and quantity adjustments more generally, i.e., to a variety of economic and policy disturbances, such as changes in trade costs and tariffs.

We will present, first, our Trade Pattern Sequential Fixed Effect Estimator (TPSFE), suitable for estimating markup elasticities to exchange rates while controlling for unobserved product-level marginal cost within a firm in an environment with endogenous market selection. Second, we show how to use the logic of the TPSFE to construct an estimator of cross-market quantity adjustments to exchange rate movements—shedding light on how exchange-rate-driven markup adjustments translate into quantity differences. This approach elucidates the within-firm-product relationship between quantity and markup adjustments across markets. Lastly, we describe a new classification for Harmonized System products which distinguishes between high and low differentiation goods and thus serves as a useful proxy for firms' market power.

2.1 Estimating a markup elasticity with a large customs database

A typical custom database records information on export values and quantities that varies along at least four dimensions: product, firm, foreign destination and time. Under the maintained assumption that unit values (obtained by dividing value by quantity recorded in the form) approximate prices (henceforth we will use the two terms interchangeably), let p_{ifdt} and q_{ifdt} denote, respectively, the (logarithm of the) price (unit value) and quantity of the good i, produced by the firm f and sold in destination d in the year t. Now, p_{ifdt} can always be decomposed into a markup component, μ_{ifdt}, and a marginal cost component mc_{ifdt}:[9]

[9]In appendix A.7.1, we show how the optimal price of a firm under any (static) pricing problem can always be decomposed into a markup component solely explained by the demand elasticity with respect to price and a

$$p_{ifdt} = \mu_{ifdt} + mc_{ifdt} \tag{1}$$

where all the terms above are denominated in the exporter's currency. The core question motivating our analysis is how to assess the response of the firm-product markup in a destination market to a change in the bilateral exchange rate e_{dt}, that is:

$$\frac{\partial \mu_{ifdt}}{\partial e_{dt}} = \frac{\partial p_{ifdt}}{\partial e_{dt}} - \frac{\partial mc_{ifdt}}{\partial e_{dt}} \tag{2}$$

As is well understood, the marginal cost is unobserved *and* is highly likely to be correlated with exchanges rates directly through imported inputs (see e.g., Amiti, Itskhoki and Konings (2014)) or indirectly, due to general equilibrium movements in the prices of factors of production (e.g., wages) and marginal costs.[10] This obviously creates a daunting challenge for empirical analyses.[11]

In principle, one could approach our question by constructing an estimate of marginal costs—a step that would require detailed firm-level information in conjunction with the customs dataset. Using balance sheet data, leading contributions have estimated productivity and marginal cost at the firm level [e.g., Berman, Martin and Mayer (2012) and Amiti, Itskhoki and Konings (2014)]. In relation to our question of interest, however, following this approach would confront us with a key issue. Even if we could obtain data on firms, information on production inputs would generally be available at the firm level—not at the firm-product level.[12] Without some assumptions on how inputs are allocated across products and destinations, it would not be possible to estimate marginal cost at the firm-product-destination level. By way of example, the seminal contribution by De Loecker et al. (2016) estimates firm-product level marginal costs and markups under the assumption that the production functions of single-product firms are representative of those of multi-product firms.

An alternative approach—with a much lower data requirement, i.e., relying exclusively on customs data—consists of exploiting price and exchange rate variation across destination markets, in the spirit of Knetter (1989).[13] Exploiting the fact that most firms sell their product to multiple

marginal cost component.

[10] For example, a positive home productivity shock that lowers the marginal cost of home producers may also appreciate the home currency against its trade partners.

[11] 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).

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

[13] Knetter (1989) studies responses of product level price indices to exchange rates. To control for product level marginal cost, this author adds destination fixed effects—a methodology that is suitable if the panel of observation

destinations, one can obtain an estimator that controls for changes in the unobservable product-level marginal cost within a firm over time by taking differences of prices and exchange rate changes across destination markets. Intuitively, for a firm selling in two destination markets d and d',

$$\frac{\partial \mu_{ifdt}}{\partial e_{dt}} - \frac{\partial \mu_{ifd't}}{\partial e_{d't}} = \frac{\partial p_{ifdt}}{\partial e_{dt}} - \frac{\partial p_{ifd't}}{\partial e_{d't}} - \left[\frac{\partial mc_{ifdt}}{\partial e_{dt}} - \frac{\partial mc_{ifd't}}{\partial e_{d't}} \right] \tag{3}$$

Our contribution to this identification strategy is twofold. First, we derive the identification condition for a multi-destination version of (3) and discuss assumptions under which identification strategies which exploit variation across destinations produce unbiased estimates. Our discussion clarifies what is required for identification in the presence of destination-specific costs, if any exist.[14] Second, we show how to construct an estimator that takes into account the fact that the choice of destination markets d and d' is endogenous and may change, grow, or shrink over time in response to many factors, including exchange rate swings.[15]

2.1.1 Identification condition

We start by writing an expression for marginal costs that allows for the possibility that variation depends not only on the firm and the product, but also on the destination:

$$mc_{ifdt} = \overline{mc}_{ift} + \psi_{ifdt} \tag{4}$$

where

$$\overline{mc}_{ift} \equiv \frac{1}{n^D_{ift}} \sum_{d \in D_{ift}} mc_{ifdt} \quad \text{and} \quad \psi_{ifdt} \equiv mc_{ifdt} - \overline{mc}_{ift}$$

The first term, $\overline{mc}_{ift}$, is the mean marginal cost, averaged across destinations for firm f's product i at time t (denominated in the exporter's currency). The second term, ψ_{ifdt} captures any destination-specific components of marginal cost, or, more generally, serves as a convenient way to handle possible changes in the composition of varieties shipped under a particular product code to specific destinations.

The general condition for an estimator of the markup elasticity that exploits cross-destination

is *balanced*, as is the case for *industry-level* price indices.

[14] We also provide a structural interpretation of the required assumptions in appendix B.4.

[15] In customs databases, a constant trade pattern of firm-product-destinations is highly unlikely to emerge, because bilateral exchange rate movements may cause a firm to be "priced out" of (or "priced into") some destinations. The endogenous selection of markets translates into a panel of observations that is endogenously unbalanced. We discuss this point in more detail in appendices B.2 and B.3.

variation to be unbiased is:[16]

$$\frac{1}{n^{DT}}\sum_{d}\sum_{t}(\overline{\psi}_{dt}-\overline{\psi}_{d})(e_{dt}-\overline{e}_{d})=0 \tag{5}$$

where $\overline{x}_j$ is the mean of variable x taken over all dimensions other than j. n^{DT} is the total number of destination-time periods. (For example, in a balanced panel, n^{DT} is the number of destinations n^D times the number of time periods n^T.) The first term, $(\overline{\psi}_{dt}-\overline{\psi}_{d})$, measures the deviations of the average destination-specific marginal cost component across firms and products within a destination over time. The second term, $(\overline{e}_{dt}-\overline{e}_{d})$, measures deviations of the bilateral exchange rate from its long-run mean over time.

The condition (5) is obviously satisfied if there is no destination-specific component to marginal costs. For example, if the goods sold to different destinations under the same product code are identical at the firm-product level, i.e., $\psi_{ifdt}=0$. More crucially, however, the condition clarifies that the presence of destination-specific marginal costs does not automatically lead to a violation of identification. An important instance in which condition (5) is satisfied occurs when the cross-destination distribution of the destination-specific component does not change over time, e.g., high quality varieties of a product are consistently sold to rich destinations.

It is worth stressing that the above identification condition is weaker than orthogonality of the destination-specific marginal cost component ψ_{ifdt} and the bilateral exchange rate e_{dt}, a condition which has been emphasized in the literature on exchange rate pass through (ERPT) (see, e.g., Corsetti, Dedola and Leduc (2008)). Note that only the mean of the destination-specific marginal cost component across all firms and products, $\overline{\psi}_{dt}$, enters the condition (5).

Finally, the identification condition requires no assumptions on firm and product idiosyncratic shocks. Indeed, this condition is implicit in studies aimed at estimating productivity (as these do not try to distinguish the marginal cost at the destination level)—see, e.g., Olley and Pakes (1996), Levinsohn and Petrin (2003), Wooldridge (2009) and De Loecker et al. (2016).[17]

[16] See appendix B for the derivation of (5) and a detailed extensive discussion.

[17] Olley and Pakes (1996), Levinsohn and Petrin (2003) and Wooldridge (2009) estimate firm-level productivity and thus can infer the average marginal cost over all products and destinations at the firm level. De Loecker et al. (2016) estimates the average marginal cost over destinations at the firm-product level. As an exercise, in appendix B.4, we explore an extension of De Loecker et al. (2016) in which we add a destination dimension to production costs. We discuss the assumptions that would be required in a structural framework for (5) to be satisfied. Specifically, we allow the functional form of the production function to be firm-product specific with a log-additive productivity term that is firm-product-destination specific. Note that De Loecker et al. (2016) would not be identifiable under these assumptions as their identification strategy requires some degree of separability in the functional form in which they have assumed the production function to be product-specific and the Hicks-neutral productivity to be firm-specific. In this extended framework, we show that our identification strategy recovers an unbiased estimate of the markup elasticity even when the marginal cost at the firm-product level varies across destinations, but only if the production function is constant return to scale. It is only when changes in relative demand across destinations lead to relative changes in quantities (which are associated with changes in destination-specific marginal cost) that condition (5) will

2.1.2 Trade Pattern Sequential Fixed Effects (TPSFE)

In this subsection, we introduce and discuss our estimator. We articulate the presentation in three steps—which also describe our estimation procedure. In the first step, we differentiate out the unobserved marginal costs by expressing all the observations on product i sold by firm f to multiple destinations at time t, in terms of deviations from their average. At each point in time, this average will be conditional on the set of destinations chosen by the firm. Hence, if we compare the observations obtained in our first step across time, the comparison will generally confound genuine cross-market changes in prices and (holding our identification condition) markups across destinations, with variations due to recalculating the mean conditional on different sets of destinations. To make sure that the results of the analysis are not contaminated by this problem, in a second step we identify trade patterns, defined as sets of destinations that may repeat identical over time for each firm. Using the trade-patterns so defined as a fixed effect in our empirical model, in a third and final step we regress product prices in deviations from means (first step) on exchange rates, controlling for a bunch of variables. By including the trade-pattern fixed-effect in the regression model, we effectively 'demean' observations one more time—to make sure that, when we compare observations over time, these are always calculated as deviations from a mean from an identical set of destination markets. In other words, the comparison is 'apples-to-apples' across sets of firm-product prices in different periods.

We dub this procedure "trade pattern sequential fixed effects" (TPSFE)—designed to address the bias associated with endogenous shift in trade destinations.[18] The following provides details in the three-step implementation procedure.

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

be violated. This is only the case if the production function is destination-specific. Under the standard assumptions of De Loecker et al. (2016) where the product function is not destination-specific, our estimator yields unbiased estimates with constant return to scale (CRS), increasing return to scale (IRS) and decreasing return to scale (DRS) production functions.

[18]The importance of bias in unbalanced panels with selection has long been discussed in labor economics, and is obviously a general econometric problem. After developing our estimator, we were made aware of the work of Correia (2017), who proposes a general high-dimensional fixed effects estimator (we thank Thierry Mayer for bringing this work to our attention). 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. The correct set of partitioning is essential to avoid introducing changes in the dimensions along which the unobserved marginal cost varies. Methods involving taking S-period time differences changes the dimensions along which unobserved variables vary—making it impossible to control for them in later stages. See appendices B.2 and B.3 for an extensive discussion. It is also important to stress that there is no unique way to correctly partition multidimensional data because it will depend on the context of the question being examined. For example, see Fitzgerald, Haller and Yedid-Levi (2016) who thoughtfully and appropriately partition high-dimensional Irish customs data in their analysis of firm-level export dynamics.

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:

$$\frac{1}{n^D_{ift}} \sum_{d \in D_{ift}} x_{ifdt} \quad \forall x \in \{p_{ifdt}, e_{dt}, X_{dt}\} \tag{6}$$

where n^D_{ift} 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:

$$\widetilde{x}_{ifdt,D_{ift}} = x_{ifdt} - \frac{1}{n^D_{ift}} \sum_{d \in D_{ift}} x_{ifdt} \quad \forall x \in \{p_{ifdt}, e_{dt}, X_{dt}\} \tag{7}$$

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:

$$\{d : p_{i'f'dt'} \text{ is observed} : i' = i, f' = f, t' = t\}. \tag{8}$$

(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.

$$\widetilde{p}_{ifdt,D_{ift}} = \kappa_0 + \kappa_1 \widetilde{e}_{dt,D_{ift}} + \widetilde{X}'_{dt,D_{ift}} \kappa_2 + TP_{d,D_{ift}} + \widetilde{u}_{ifdt,D_{ift}} \tag{9}$$

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 (9) 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 (9) identifiable.

To conclude, the reliability of our empirical framework rests on its capacity to address two fundamental issues, endogenous market selection and destination-specific marginal costs. Subsections B.2 and B.3 in the appendix carry out a series of assessments with the goal of exploring the bias that may arise from an endogenously unbalanced panel and destination-specific marginal costs under a range of reasonable parameters. Subsection B.4 gives a structural interpretation of the identification condition.

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

We now turn to the flip side of the cross-market markup adjustment, that is the adjustment of export quantities across destinations.[19] We are interested to gaining empirical insight in how relative price changes in response to relative exchange rate movements map into changes in relative quantities across markets. Towards this goal, we construct the following two-stage estimator. In the first stage, we rely on our TPSFE to obtain predicted prices, $\widehat{\widetilde{p}}_{ifdt,D_{ift}}$ using the specification (9):

$$\widehat{\widetilde{p}}_{ifdt,D_{ift}} = \widehat{\kappa}_0 + \widehat{\kappa}_1 \widetilde{e}_{dt,D_{ift}} + \widetilde{X}'_{dt,D_{ift}} \widehat{\kappa}_2 \tag{10}$$

In the second stage, we use the predicted prices as explanatory variables in the 'quantity' equation (11) specified below

$$\widetilde{q}_{ifdt,D_{ift}} = \gamma_0 + \gamma_1 \widehat{\widetilde{p}}_{dt,D_{ift}} + \widetilde{X}'_{dt,D_{ift}} \gamma_2 + TP_{d,D_{ift}} + \widetilde{v}_{ifdt,D_{ift}} \tag{11}$$

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

[19] The question can be addressed in different ways. One possibility is to regress quantities directly on exchange rates using the same specification as our TPSFE, (9), including the trade-pattern fixed effect. The possibility that we prefer, consists of regressing quantities on projection of prices on exchange rates. Both procedure yields very similar results.

of changes in relative quantities on changes in exchange-rate-driven relative prices.

As long as cost-side factors are perfectly controlled, $\widehat{\widetilde{p}}_{ifdt,D_{ift}}$ can be interpreted as the change in *relative markups denominated in the exporter's currency* in response to changes in relative *demand* conditions across destinations. Heuristically, it is well known that, 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—capturing the cross-market supply elasticity (CMSE) with respect to destination-specific bilateral currency appreciation.

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

$$\widetilde{q}_{ifdt,D_{ift}} = \lambda_0 + \lambda_1 \widetilde{p}_{dt,D_{ift}} + \widetilde{X}'_{dt,D_{ift}} \lambda_2 + TP_{d,D_{ift}} + \widetilde{v}_{ifdt,D_{ift}} \tag{12}$$

As shown in section 4, 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 (11) produces a significant, positive correlation: a positive coefficient γ_1 suggests that the relative supply curve is upward sloping within the firm. See appendix A.7.2 for an analytic discussion.

2.3 Refining Rauch (1999) on high- and low-differentiation products: A new product classification based on Chinese measure words

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. To this end, most studies adopt the industry classifications set forth by Rauch (1999), who identifies differentiated goods 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 construct a new, finer classification. The core idea is a simple one: traded goods whose quantity is recorded in customs data by weight or volume are less differentiated than goods whose quantity is reported in countable units. Chinese customs data provide a unique opportunity to extend this simple idea into an exogenous classification system because the choice to record a product's quantity in units versus mass is predetermined by Chinese grammar and linguistics. We exploit linguistic information on "measure words" recorded in the Chinese Customs Database to construct a general product classification for the Harmonized System.

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.[20] 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.[21] 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 almost all commodities traded on open exchanges are reported with mass classifiers—fully consistent with our view that mass classifiers identify low differentiation products.

For 2008, the dataset reports quantity using 36 different measure words. To illustrate the variety of measures used, table 1 reports a selection of measure words, the types of goods that use the measure word, and the percent of export value that is associated with products described by each measure word. In this table, qiān kè (千克) and mǐ, (米) are mass classifiers; the remaining measure words are count classifiers. The main point to be drawn from the table is that the nature of the Chinese language means that the reporting of differentiated goods, for example, automobiles, spark plugs and engines, takes place by reporting a number of items and the associated unique counter that is associated with that type of good. See appendix C.7 for additional examples of the Chinese quantity measures in our data.

Table 2 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 2 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

[20] 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.

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

Table 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

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

(a) Share of goods by classification: observation weighted

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

(b) Share of goods by classification: value weighted

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

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

Rauch as differentiated, 66.1 percent (47.1/71.3) uses count classifiers.[22] Second, every good that 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.

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]

3 Data

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]

Like other firm-level studies using customs databases, we use unit values as a proxy for prices.

[22] We have constructed a concordance for all HS06 products as high differentiation or low differentiation by 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 categories such collective enterprise, individual business and other enterprise into one category and refer to them as "other enterprises."

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 Empirical Results

In this and the next section, we present and discuss results obtained by applying our empirical framework to the Chinese Customs Database. In this section, we will first present our estimates on markup adjustment, and cross-market supply elasticities for the whole sample of Chinese exports. Then we will present estimates distinguishing between high- and low-differentiation goods. In the next section, we will refine our analysis by by grouping firms according to their registration type, distinguishing private and public, as well as domestic and foreign ownership.

As explained in section 2, we apply the TPSFE estimator conditional on a renminbi price changes. Specifically, we estimate all parameters *after* applying a data filter to the Chinese export data: for each product-firm-destination combination, we filter out absolute price changes 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

[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.

S-period. The S-period interval defining a price change can vary within a firm-product-destination triplet and across these triplets. That is, for a single firm-product-destination triplet, we might observe S-period differences of, say, 2, 3, 4 or more years, within the 15 years included in our panel. We provide an example on how the price change filter is constructed and how trade patterns are subsequently formulated based on the price-change-filtered database in appendix C.4.

Because we condition them on price changes, our pass through estimates can be compared to the evidence on *total* 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 this 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.

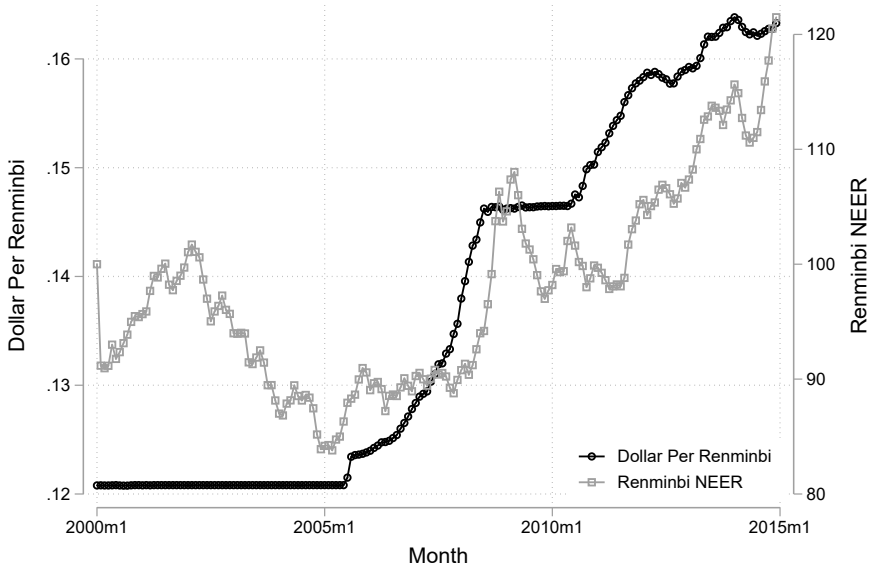


Figure 1: Reminbi Movements During Periods 2000 – 2014

We report results separately for the subsamples corresponding to the two exchange rate regimes pursued by China, the fixed exchange rate regime of 2000-2005 and the managed float regime of the latter period. Figure 1 plots the bilateral movement of the renminbi against the US dollar, as well as China's nominal effective exchange rate, over our entire sample period. As will be discussed in later sections, there is evidence that exporters' pricing behavior differs across the two environments.

In all our estimation, we treat eurozone countries as a single economic entity and integrate

their trade flows in a single economic region.[30] In addition, we exclude exports to the US and Hong Kong to ensure comparability of our estimates across regimes.

4.1 Markup adjustments and incomplete pass through

The evidence from our entire sample of exports (without distinguishing goods by their degree of differentiation) yields at least two important results. First, on average, destination-specific markup adjustments are moderate, 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 are shown in Table 3. 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.

As shown in the table, the elasticity of export prices (in renminbi) to bilateral 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 and 24% over 2006-2014 period. 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.

In interpreting these and the subsequent results, it is useful to decompose the price adjustment into three components: (a) a destination-specific markup adjustment, (b) a general markup adjustment that is the same across all markets and (c) any marginal cost change. When we estimate

[30] 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 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 3: Price and Markup Elasticities to Exchange Rates

	Price Elasticity (1-ERPT)		Markup Elasticity (Destination-specific)	
	(1) 2000-2005	(2) 2006-2014	(3) 2000-2005	(4) 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 based on the same estimation sample of filtered price changes following the procedure specified in appendix C.4. Note that constructing S-period time differenced variables will result in a smaller number of observations compared to fixed effect approaches as the starting year of each firm-product-destination triplet cannot take time differences and will create a missing value. 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 *.

the price elasticity to the exchange rate (columns 1 and 2), we capture the average of the price elasticity to bilateral exchange rates across all markets where the price adjustment is a mixture of movements in all three components mentioned above. In comparison, our TPSFE estimator captures the average of the relative price adjustments to relative exchange rate movements across all markets. Under our identification condition, the relative price adjustment is equivalent to the relative markup adjustment across destinations, i.e., the destination-specific adjustment of the markup.

In columns (3) and (4), we report our estimated destination-specific markup elasticities. Conditional on a price change in renminbi occurring at $t+s$, the average destination-specific 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 the exchange rate regime, as shown in column (4), the destination-specific 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.[31]

The differences in markup elasticities we detect across our subsamples are likely to reflect more than just 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 changes in the frequency and importance of cyclical (policy and technology) shocks at the national and global level that have occurred bwteen the two time periods.[32] We build a general multi-country framework for a more rigorous discussion and interpretation of our empirical estimates in Appendix A. We provide additional empirical estimates that relate to a firm's corporate structure in Appendix D.

4.2 High-differentiation versus low-differentiation goods

We now turn to our results from disaggregating the sample according to our product classification. To introduce and motivate our analysis, we find instructive to discuss two products as case studies, and 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

[31] 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.

[32] 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, Dedola and Leduc (2008). To wit: we would expect the price response to exchange rate movements to be quite different if the underlying shock is to productivity as opposed to monetary policy. Estimates of pass through conditional on a shock require methodologies, like VARs, suitable to identifying these shocks in isolation and tracing their effects on the exchange rate, export prices, and markups – see Forbes, Hjortsoe and Nenova (2017).

our CCHS classification, and wheeled tractors (measured with "liang"), as a high-differentiation good.

In figure 2, we plot data on the dispersion of markups across destinations for the top three 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.[33] 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.

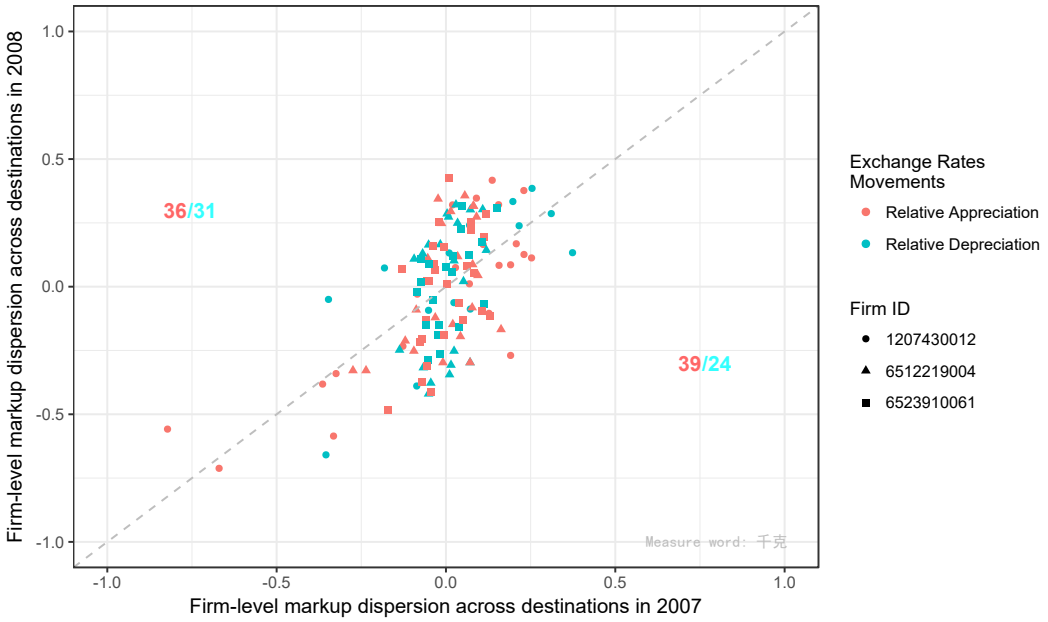
We color code each point representing a firm-destination pair according to whether the destination's currency appreciated or depreciated during 2007-2008 relative to the other destinations the firm was selling to. Red indicates relative appreciation, blue relative depreciation. Above and below the 45 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.

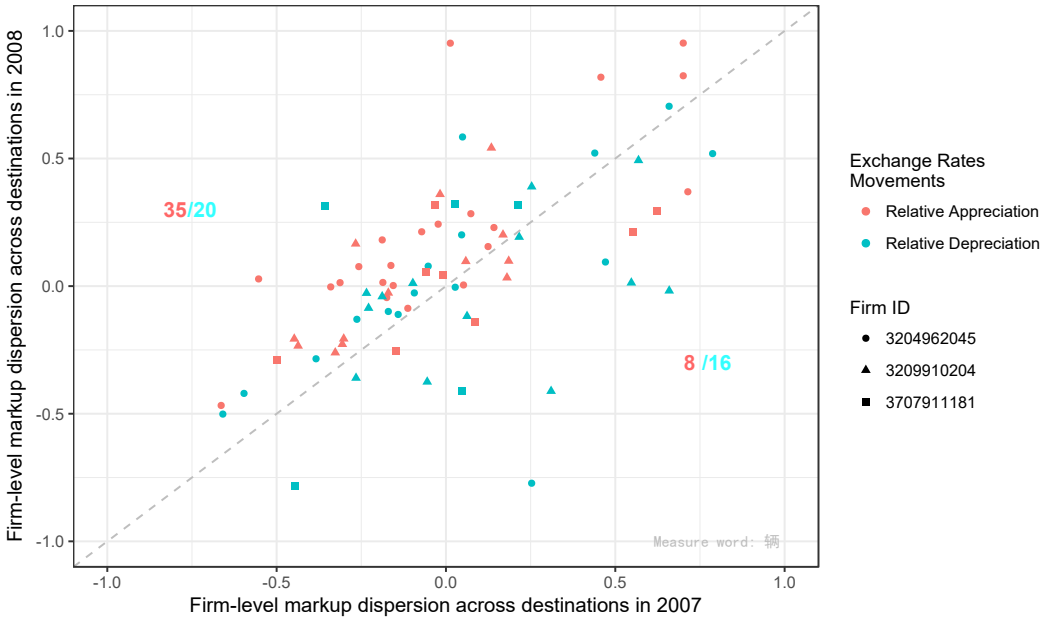
These two cases illustrate well the characteristic features of firm-level pricing that drive our econometric estimates presented below.

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

Figure 2: 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.

4.2.1 Markup elasticities using 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, product differentiation appears to be a good proxy for market power, validating the usefulness of our linguistics-inspired product classification.

Results are shown in table 4. For comparison, the first two columns of the table reproduce the key results from table 3, average export price and markup elasticities for the universe of Chinese exports. The remaining four columns report results for the subsamples of high- and low-differentiation goods. The first row refers to the dollar peg period, the second row to the more recent period in the sample. In both subperiods, the renminbi prices and 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.

Focusing on 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%.

4.2.2 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

Table 4: 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 based on the same estimation sample of filtered price changes following the procedure specified in appendix C.4. 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 *.

and intermediates according to the UN's Broad Economic Categories (BEC).[34] Results are shown in Table 5.

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 3, 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,

[34] 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.

column (4)).

During the dollar peg, a 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 producing 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.

As already pointed out, incomplete exchange rate pass through conditional on a price change can be decomposed into three components: a destination-specific markup adjustment, a common markup adjustment across markets and a change in production costs. Our estimates can provide insight into 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 for 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 destination-specific 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 a small destination-specific markup adjustment explaining only about one-quarter of the incomplete pass through.[35]

[35]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 5: 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 based on the same estimation sample of filtered price changes following the procedure specified in appendix C.4. 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 *.

4.2.3 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 6.

Table 6: 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 based on the same estimation sample of filtered price changes following the procedure specified in appendix C.4. 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 6, column (2)), our markup elasticity estimator reveals an increase in market power across the two currency regimes.

The most important takeaway from table 6 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.

4.3 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 7 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 7, 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 4). 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 7: 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 (12). The "CMSE" column is estimated based on equations (10) and (11). † 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 8 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 8: 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 (12). The "CMSE" column is estimated based on equations (10) and (11). † 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.

5 A Diagnostic for Open Macro Models

How can the destination-specific markup elasticity (DSME) and the cross-market supply elasticity (CMSE) inform our understanding of open economy macro modelling? In ongoing work, we use these estimated elasticities as a diagnostic tool to guide and discipline the development of a multi-country model with features drawn from leading contributions in the open macro literature.

This section briefly summarizes our results so far. Our theoretical contribution is to specify a multi-country model combining the main features of Atkeson and Burstein (2008) and Corsetti and Dedola (2005). The goal is to investigate which features are essential to match the markup and quantity elasticities we find in the data.

Our first diagnostic is informed by the patterns documented in section 4, showing how the magnitude of the DSME (CMSE) changes with the extent of product differentiation. In particular, the DSME (CMSE) is increasing (decreasing) as products become more differentiated, or equivalently, as the elasticity of substitution across varieties falls. These patterns, that the DSME is decreasing in the elasticity of substitution while the CMSE is increasing in the elasticity of substitution, are the first set of diagnostic targets for the model we build.

The second set of targets for our diagnostic is given by the magnitudes of the estimated elasticities, which differ across types of products (e.g., highly differentiated consumption goods, low differentiation intermediates, etc.). We assess our calibrated open economy macro model by examining its ability to match our evidence, for a standard and reasonable calibration of the fundamental

parameters (e.g., ρ, the elasticity of substitution within an industry, η, the elasticity of substitution across industries, etc.).

Our multi-country model has three building block. The first building block comes from Atkeson and Burstein (2008) (henceforth forth AB). These authors model competition among producers using a nested CES structure allowing for variable markups that are increasing in a firm's local market share. The second building block comes from Corsetti and Dedola (2005) (henceforth CD), which focuses on vertical interactions between international producers and local providers of non-traded distribution services. The CD structure, with its emphasis on the local distribution system, introduces a local cost component (in nontradable services) into final consumer prices. Thus, final consumer prices embody foreign production costs, a markup charged by the foreign producer, and a local distribution margin. Combining the features of these two models together integrates what we call, heuristically, an 'horizontal' and 'vertical' dimensions of the market structure relevant for markup-up adjustment. Multilateral competition between foreign exporters from different origins is the third, and final block of the model, which we specify with $H > 2$ countries. In light of our main results, the integration of the AB and CD models yields much more than the sum of the parts. A detailed presentation of the ($ABCD^H$) model and its success in matching the empirical results are provided in the appendix.

The key theoretical result is that the model can match our two diagnostics only if all the three building blocks are integrated in the specification—the $ABCD^H$ specification. If we shut down the CD feature of vertical interactions, the AB mechanism in isolation causes the DSME to be decreasing in the level of product differentiation, the opposite pattern relative to our empirical findings. Further, the CMSE is much too high. Conversely, if we shut down the AB features, the model with vertical interactions only (as specified in CD) can account for the qualitative pattern in the data—the DMSE is decreasing in the elasticity of substitution. However, the magnitude of the model-generated elasticities are still far from the empirical targets—the cross-market quantity elasticity is too high.

Combining features of the AB and CD models significantly improves the match. Specifically, we can show analytically how the relationship between the DSME (CMSE) and the degree of product differentiation depends on both the degree of 'horizontal' competition and the level of 'vertical' integration.

But a successful match crucially requires the modelling of multilateral competition. The point is that a changing economic environment in one destination country (country A) simultaneously affects exporters in the home country (in our case, China) and in the other trading partners of the destination country (from country B). To this end, when Chinese exporters perceive a change in economic conditions in destination A and decide to adjust their prices, competing exporters from other countries (B) are likely to perceive a similar shock and will adjust their prices accordingly.

The multilateral effect thus mitigates the pressure of horizontal competition and stabilizes quantity movements, bringing the theoretical CMSE close to the evidence.

In summary, for a model featuring horizontal competition and vertical interactions to match the qualitative pattern and quantitative magnitudes in our empirical results, multilateral competitive effects must be given appropriate weight in the analysis.

6 Conclusions

The increasing availability of large, high-dimensional, administrative datasets of firms is enabling researchers to explore new questions into the operation of the global economy, as well as to re-examine classic questions in new ways. In this paper, we have proposed a new empirical strategy that exploits administrative data on exporters in order to examine both markup and quantity adjustments by firms. While our application is specifically to exporting firms, the methodology we developed can be applied to other contexts in which producers sell to multiple markets/buyers and may price discriminate across them.

Our first contribution in this paper is a framework to estimate the export price markup elasticity and the cross-market supply elasticity to bilateral exchange rate movements. We showed that the TPSFE estimator is capable of controlling for a firm's time-vary marginal cost at the product level, even when the panel of data is endogenously unbalanced. More importantly, we derive the identification condition for this estimator to show that we can recover an unbiased estimate of the markup elasticity even in the presence of destination-specific production costs, so long as the changes in any destination-specific component of production costs are not systematically correlated with changes in the exchange rate.

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

We find that firms exporting high differentiation goods from China make moderate but significant destination-specific adjustments to markups in response to movements of bilateral exchange rates—these adjustments account for up to three quarters of incomplete exchange rate pass through into import prices. In contrast, producers of commodities and low differentiation goods make mi-

nuscule or no adjustments. These different elasticities are mirrored (inversely) by cross market adjustments in quantities exported.

This empirical evidence provides an important diagnostic for the development of open economy models featuring a richer and more detailed account of firms' dynamics and strategies. We assess the extent to which leading models of export pricing and dynamics can account for the qualitative patterns and magnitudes of the elasticities we find in the data. Our results yield a sharp message: while leading models cannot match our evidence, a multi-country syncretic model—accounting for both multilateral competition among producers, and vertical interactions between exporters and local distributors—can.

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A Theoretical Framework

The world consists of H countries. In each country, there are two sectors, one selling goods that can be traded across countries and the other selling non-tradable goods such as services. There is a continuum of industry i within the tradable sector. Each industry processes goods with a natural degree of differentiation characterized by its within-industry elasticity of substitution ρ_i across varieties. The elasticity of substitution is strictly higher for varies within an industry, ρ_i, than across industries, $\eta < \rho_i$. There are M_i firms competing in each industry in an Atkeson and Burstein (2008) style. Further, we assume χ_i unit of non-tradable goods is needed to distribute a tradable product to the consumer as in Corsetti and Dedola (2005).[36] Firms in the non-tradable sector are assumed to be monopolistically competitive. As we exploit destination variations to control for unobserved marginal costs, our model abstracts away from imported inputs.[37]

Variables in this model have five dimensions with f, i, o, d, t standing for firm, industry, origin, destination, time respectively. Tradable and non-tradable sector are denoted with T and N respectively.

A.1 Consumer

There is a representative consumer in each destination d maximising its expected utility by choosing its optimal final consumption $C_{d,t}$ and labour supply $L_{d,t}$. As in Atkeson and Burstein (2008), we assume that the representative consumer can trade a complete set of international assets with its trade partners.

The representative consumer's profit maximization problem is given as follows,

$$\max_{C_{d,t}, L_{d,t}} E_0 \sum_{t=0}^{\infty} \beta^t U(C_{d,t}, L_{d,t})$$

subject to

$$U_{d,t} = log[C_{d,t}^{\varkappa}(1 - L_{d,t})^{1-\varkappa}]$$

$$P_{d,t}C_{d,t} + \sum_{o} \left[\sum_{\nu} p_{o,t}^{B}(\nu) B_{o,t}(\nu) - (1 + r_{o,t-1}) B_{o,t-1} \right] e_{o,d,t} = W_{d,t}L_{d,t} + \Pi_{d,t}$$

where holding $B_{o,t}(\nu)$ will earn $B_{o,t}$ unit of currency o at $t+1$ if state ν happens. $p_{o,t}^{B}(\nu)$ is the price of bond from origin o with state ν. $r_{o,t-1}$ represents the nominal interest rate paid in the unit

[36] 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.

[37] See recent discussions by e.g., Amiti, Itskhoki and Konings (2014) and Rodnyansky (2018).

of currency o from $t-1$ to t. $\Pi_{d,t}$ is the lump-sum profit from all domestic firms and exporters in country d.

The solution of the representative consumer's problem is given by

$$\frac{1-\varkappa}{\varkappa}\frac{C_{d,t}}{1-L_{d,t}} = \frac{W_{d,t}}{P_{d,t}} \tag{13}$$

$$\frac{C_{o,t}P_{o,t}}{e_{o,d,t}C_{d,t}P_{d,t}} = \frac{C_{o,t+1}(\nu)P_{o,t+1}(\nu)}{e_{o,d,t+1}(\nu)C_{d,t+1}(\nu)P_{d,t+1}(\nu)} \tag{14}$$

where (13) represents the optimal division of consumption and labor and (14) stands for the conventional international risk sharing condition.

A.2 Firms

The final consumption is CES aggregated from tradable and non-tradable goods.

$$\begin{aligned} C_{d,t} &= \left[(C_{T,d,t})^{\frac{\theta-1}{\theta}} + (C_{N,d,t})^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}} \\ P_{d,t} &= \left[(P_{T,d,t})^{1-\theta} + (P_{N,d,t})^{1-\theta}\right]^{\frac{1}{1-\theta}} \end{aligned} \tag{15}$$

where the elasticity of substitution between tradable and non-tradable goods is assumed to be θ.

A.2.1 Non-tradable sector

The non-tradable sector is assumed to be monopolistically competitive. The equilibrium price and direct consumption of non-tradable goods can be derived as follows:

$$P_{N,d,t} = \frac{\theta}{\theta-1} mc_{N,d,t} \tag{16}$$

$$C_{N,d,t} = \left(\frac{P_{N,d,t}}{P_{d,t}}\right)^{-\theta} C_{d,t} \tag{17}$$

Note that a part of non-tradable goods is used for distribution purposes. Therefore, the total demand for non-tradable goods equals the direct consumption $C_{N,d,t}$ plus the amount used for distribution as characterized in (50).

A.2.2 Tradable sector

The demand for tradable goods can be derived as

$$C_{T,d,t} = \left(\frac{P_{T,d,t}}{P_{d,t}}\right)^{-\theta} C_{d,t} \tag{18}$$

The tradable goods, $C_{T,d,t}$, are aggregated using a nested-CES function as in Atkeson and Burstein (2008). The consumption of tradable goods $C_{T,d,t}$ in destination d is aggregated across sectors with a constant elasticity of substitution across industries equal to η, i.e.,

$$C_{T,d,t} \equiv \left[\sum_i (C_{i,d,t})^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}, \quad P_{T,d,t} \equiv \left[\sum_i (P_{i,d,t})^{1-\eta}\right]^{\frac{1}{1-\eta}} \tag{19}$$

Within each industry, there are domestic and foreign firms producing different varies with a constant elasticity of substitution ρ_i. $f \in \mathbb{1}_{i,o} \cap \mathbb{1}_E$ denotes foreign exporters in industry i from origin o. $f \in \mathbb{1}_{i,d}$ denotes domestic firms in industry i. The industry-level consumption $C_{i,d,t}$ and price $P_{i,d,t}$ are given by:

$$\begin{aligned} C_{i,d,t} &\equiv \left[\sum_{o\neq d}\sum_{f\in\mathbb{1}_{i,o}\cap\mathbb{1}_E} (q_{f,i,o,d,t})^{\frac{\rho_i-1}{\rho_i}} + \sum_{f\in\mathbb{1}_{i,d}} (q_{f,i,d,d,t})^{\frac{\rho_i-1}{\rho_i}}\right]^{\frac{\rho_i}{\rho_i-1}}, \\ P_{i,d,t} &\equiv \left[\sum_{o\neq d}\sum_{f\in\mathbb{1}_{i,o}\cap\mathbb{1}_E} (p_{f,i,o,d,t})^{1-\rho_i} + \sum_{f\in\mathbb{1}_{i,d}} (p_{f,i,d,d,t})^{1-\rho_i}\right]^{\frac{1}{1-\rho_i}} \end{aligned} \tag{20}$$

Firms compete by choosing its price $p_{f,i,o,d,t}$ internalizing its impact on the industry level price index $P_{i,d,t}$[38]:

$$\max_{p_{f,i,o,d,t}} q_{f,i,o,d,t}\left[(p_{f,i,o,d,t} - \chi_i P_{N,d,t})e_{o,d,t} - mc_{f,i,o,t}\right]$$

subject to

$$q_{f,i,o,d,t} = \left(\frac{p_{f,i,o,d,t}}{P_{i,d,t}}\right)^{-\rho_i}\left(\frac{P_{i,d,t}}{P_{T,d,t}}\right)^{-\eta} C_{T,d,t} \tag{21}$$

where $mc_{f,i,o,t}$ is the marginal cost of firm f from sector s and origin o at time t; bilateral exchange rate $e_{o,d,t}$ is defined as units of currency o per unit of currency d at time t. We model vertical integration following Corsetti and Dedola (2005) and assume χ_i units of destination nontradable goods is need to distribute the product to the consumer, resulting an additional wedge, $\chi_i P_{N,d,t}$,

[38] In this nested CES structure, the main theoretical result is not sensitive to whether firms compete in prices or quantities. Atkeson and Burstein (2008) show that similar expressions can be derived if firms are competing in quantities.

in the profit maximisation problem.

A.2.3 Production Function

The production function is assumed to be linear in labour L and productivity Ω, i.e., $Y = F(\Omega, L) \equiv \Omega L$. We assume wages are identical across sectors and industries. The marginal cost of a firm is calculated by dividing the nominal wage of the original country by its productivity, i.e.,

$$mc_{f,i,o,t} = \frac{W_{o,t}}{\Omega_{f,i,o,t}} \tag{22}$$

$$mc_{N,d,t} = \frac{W_{d,t}}{\Omega_{N,d,t}} \tag{23}$$

A.3 Price, Market Share and Demand Elasticity

The optimal consumer price $p_{k,i,o,d,t}$ for exporter k from origin o to destination d denominated in the destination currency can be derived as

$$p_{k,i,o,d,t} = \frac{\varepsilon_{k,i,o,d,t}(ms_{k,i,o,d,t})}{\varepsilon_{k,i,o,d,t}(ms_{k,i,o,d,t}) - 1}\left(\frac{mc_{k,i,o,t}}{e_{o,d,t}} + \chi_i P_{N,d,t}\right) \tag{24}$$

where $-\varepsilon_{k,i,o,d,t}$ is the elasticity of demand with respect to consumer price; $mc_{k,i,o,t}$ is the marginal cost denominated in the exporter's currency; and $ms_{k,i,o,d,t}$ is the market share of the exporter k in industry i of destination market d defined as

$$ms_{k,i,o,d,t} \equiv \frac{p_{k,i,o,d,t}q_{k,i,o,d,t}}{\sum_f p_{f,i,o,d,t}q_{f,i,o,d,t}} = \frac{p_{k,i,o,d,t}^{1-\rho_i}}{\sum_f (p_{f,i,o,d,t})^{1-\rho_i}}.$$

Note that $\varepsilon_{k,i,o,d,t}$ is not a constant but varies with the exporter's market share. Specifically, under the assumption that the elasticity of substitution is higher within an industry than cross industries ($\rho_i > \eta$), $\varepsilon_{k,i,o,d,t}$ is a strictly decreasing function of market share, i.e., bigger firms face a less elastic demand and charge a higher markup.

$$\varepsilon_{k,i,o,d,t} = (1 - ms_{k,i,o,d,t})\rho_i + ms_{k,i,o,d,t}\eta$$

By log-linearizing equation (24), changes in price denominated in the exporter's currency can be decomposed into changes in markups and marginal costs, i.e.,

$$\widehat{p}_{k,i,o,d,t} + \widehat{e}_{o,d,t} = \underbrace{\kappa_{k,i,o,d,t}\widehat{ms}_{k,i,o,d,t} - \omega_{k,i,o,d,t}(\widehat{mc}_{k,i,o,t} - \widehat{e}_{o,d,t} - \widehat{P}_{N,d,t})}_{\text{changes in markup } \widehat{\mu}_{k,i,o,d,t}} + \widehat{mc}_{k,i,o,t} \tag{25}$$

where $\kappa_{k,i,o,d,t}$ is the price elasticity with respect to a firm's own market share, which strictly decreases in demand elasticity, $\varepsilon_{k,i,o,d,t}$, and strictly increases in the exporter's market share, $ms_{k,i,o,d,t}$, for a given set of within- and cross-industry elasticities, $\rho_i > \eta$,

$$\kappa_{k,i,o,d,t} \equiv \frac{\rho_i - \varepsilon_{k,i,o,d,t}}{(\varepsilon_{k,i,o,d,t})^2 - \varepsilon_{k,i,o,d,t}}$$

and $\omega_{k,i,o,d,t}$ represents the cost share of distribution,

$$\omega_{k,i,o,d,t} \equiv \frac{\chi_i P_{N,d,t} e_{o,d,t}}{mc_{k,i,o,t} + \chi_i P_{N,d,t} e_{o,d,t}}.$$

Changes in market share $\widehat{ms}_{k,i,o,d,t}$ is given by (55) discussed later on in the this text. Combining equations (55) and (25), we can obtain a general relationship for markup changes *expressed in the exporter's currency* as

$$\begin{aligned}\widehat{\mu}_{k,i,o,d,t} = &\left[1 - (1 - \lambda_{k,i,o,d,t})(1 - \omega_{k,i,o,d,t})\right](\widehat{e}_{o,d,t} - \widehat{mc}_{k,i,o,t}) \\ &+ (1 - \lambda_{k,i,o,d,t})\left[\omega_{k,i,o,d,t}\widehat{P}_{N,d,t} - \kappa_{k,i,o,d,t}\widehat{CE}_{k,i,o,d,t}\right]\end{aligned} \tag{26}$$

where $(1 - \lambda_{k,i,o,d,t})$ represents the incomplete pass through due to horizontal competitions,

$$\lambda_{k,i,o,d,t} \equiv 1 - \frac{1}{1 - (1 - ms_{k,i,o,d,t})(1 - \rho_i)\kappa_{k,i,o,d,t}};$$

$(1 - \omega_{k,i,o,d,t})$ represents incomplete pass through as a result of vertical integration due to the need to distribute products; and $\widehat{CE}_{k,i,o,d,t}$ is the total effect of competitors' reactions,

$$\widehat{CE}_{k,i,o,d,t} = \sum_{o'} \sum_{f \neq k} ms_{f,i,o',d,t}(1 - \rho_i) \left[\begin{array}{c} (1 - \omega_{f,i,o',d,t})(\widehat{mc}_{f,i,o',t} - \widehat{e}_{o',d,t}) + \\ \omega_{f,i,o',d,t}\widehat{P}_{N,d,t} + \kappa_{f,i,o',d,t}\widehat{ms}_{f,i,o',d,t} \end{array} \right]. \tag{27}$$

The last expression shows that, in a multi-country economy, the optimal price response of an exporter is a function not only of own (origin-specific) exchange rate shock, but also of bilateral exchange rate shocks affecting all other trade partners, weighted by a non-linear function of the competitor's market share. We should note here that this extra channel is neglected by open macro theory, as the vast majority of models assume a two-country framework, and is not discussed in the original analysis of Atkeson and Burstein (2008). As shown by de Blas and Russ (2015), the changing distribution of markups in respond to an aggregate shock could be quantitatively very different in a two-country versus three-country model with variable markups. In our later analysis, we will show adding this components helps us reconcile our empirical estimates with the theoretical predicted values.

The changes in the border price, equal to the consumer price minus the distribution cost, i.e., $p^b_{k,i,o,d,t} \equiv p_{k,i,o,d,t} - \chi_i p_{N,d,t}$, is given by

$$\widehat{p}^b_{k,i,o,d,t} = \frac{1}{1 - dm_{k,i,o,d,t}} \widehat{p}_{k,i,o,d,t} - \frac{dm_{k,i,o,d,t}}{1 - dm_{k,i,o,d,t}} \widehat{p}_{N,d,t} \tag{28}$$

where the distribution margin $dm_{k,i,o,d,t}$ is defined as

$$dm_{k,i,o,d,t} \equiv \frac{\chi_i p_{N,d,t}}{p_{k,i,o,d,t}} = \omega_{k,i,o,d,t} \frac{\varepsilon_{k,i,o,d,t} - 1}{\varepsilon_{k,i,o,d,t}} \tag{29}$$

Quantity responses can be derived from (21) as

$$\widehat{q}_{k,i,o,d,t} = -\varepsilon_{k,i,o,d,t} \widehat{p}_{k,i,o,d,t} + \frac{\rho_i - \eta}{1 - \rho_i} \widehat{CE}_{k,i,o,d,t} + \eta \widehat{P}_{T,d,t} + \widehat{C}_{T,d,t} \tag{30}$$

A.4 Relative price and quantity changes across destinations

In the following subsection, we discuss key properties of the model. In what follows, we refer to country 1 as the home economy and focus on the relative price and quantity responses of exporters in country 1 to destinations 2 and 3.

From (26), (28) and (30), we have

$$\widehat{p}_{k,i,1,2,t} + \widehat{e}_{1,2,t} - (\widehat{p}_{k,i,1,3,t} + \widehat{e}_{1,3,t}) = \widehat{\mu}_{k,i,1,2,t} - \widehat{\mu}_{k,i,1,3,t}$$
$$= \begin{bmatrix} \Gamma_{k,i,1,2,t}\widehat{e}_{1,2,t} - \Gamma_{k,i,1,3,t}\widehat{e}_{1,3,t} \\ -(\Gamma_{k,i,1,2,t} - \Gamma_{k,i,1,3,t})\widehat{mc}_{k,i,1,t} \\ +(1-\lambda_{k,i,1,2,t})\omega_{k,i,1,2,t}\widehat{P}_{N,2,t} - (1-\lambda_{k,i,1,3,t})\omega_{k,i,1,3,t}\widehat{P}_{N,3,t} \\ -(1-\lambda_{k,i,1,2,t})\kappa_{k,i,1,2,t}\widehat{CE}_{k,i,1,2,t} + (1-\lambda_{k,i,1,3,t})\kappa_{k,i,1,3,t}\widehat{CE}_{k,i,1,3,t} \end{bmatrix} \tag{31}$$

$$\widehat{p}^{b}_{k,i,1,2,t} + \widehat{e}_{1,2,t} - (\widehat{p}^{b}_{k,i,1,3,t} + \widehat{e}_{1,3,t}) = \frac{\widehat{\mu}_{k,i,1,2,t} - dm_{k,i,1,2,t}(\widehat{e}_{1,2,t} + \widehat{P}_{N,2,t})}{1 - dm_{k,i,1,2,t}} - \frac{\widehat{\mu}_{k,i,1,3,t} - dm_{k,i,1,3,t}(\widehat{e}_{1,2,t} + \widehat{P}_{N,3,t})}{1 - dm_{k,i,1,3,t}}$$
$$= \begin{bmatrix} \frac{\Gamma_{k,i,1,2,t} - dm_{k,i,1,2,t}}{1-dm_{k,i,1,2,t}}\widehat{e}_{1,2,t} - \frac{\Gamma_{k,i,1,3,t} - dm_{k,i,1,3,t}}{1-dm_{k,i,1,3,t}}\widehat{e}_{1,3,t} \\ -\left(\frac{\Gamma_{k,i,1,2,t}}{1-dm_{k,i,1,2,t}} - \frac{\Gamma_{k,i,1,3,t}}{1-dm_{k,i,1,3,t}}\right)\widehat{mc}_{k,i,1,t} \\ +\frac{(1-\lambda_{k,i,1,2,t})\omega_{k,i,1,2,t} - dm_{k,i,1,2,t}}{1-dm_{k,i,1,2,t}}\widehat{P}_{N,2,t} - \frac{(1-\lambda_{k,i,1,3,t})\omega_{k,i,1,3,t} - dm_{k,i,1,3,t}}{1-dm_{k,i,1,3,t}}\widehat{P}_{N,3,t} \\ -\frac{(1-\lambda_{k,i,1,2,t})\kappa_{k,i,1,2,t}}{1-dm_{k,i,1,2,t}}\widehat{CE}_{k,i,1,2,t} + \frac{(1-\lambda_{k,i,1,3,t})\kappa_{k,i,1,3,t}}{1-dm_{k,i,1,3,t}}\widehat{CE}_{k,i,1,3,t} \end{bmatrix} \tag{32}$$

$$\widehat{q}_{k,i,1,2,t} - \widehat{q}_{k,i,1,3,t} = \begin{bmatrix} -(\varepsilon_{k,i,1,2,t}\widehat{p}_{k,i,1,2,t} - \varepsilon_{k,i,1,3,t}\widehat{p}_{k,i,1,3,t}) \\ +\frac{\rho_i - \eta}{1-\rho_i}\left(\widehat{CE}_{k,i,1,2,t} - \widehat{CE}_{k,i,1,3,t}\right) \\ +\eta(\widehat{P}_{T,2,t} - \widehat{P}_{T,3,t}) + \widehat{C}_{T,2,t} - \widehat{C}_{T,3,t} \end{bmatrix} \tag{33}$$

where

$$\Gamma_{k,i,o,d,t} \equiv 1 - (1 - \lambda_{k,i,o,d,t})(1 - \omega_{k,i,o,d,t})$$

Equation (31) states that the change in relative *consumer prices* at two different destinations (converted into the exporter's currency) equals the change in relative markups across the two destinations. The latter in turn is decomposed in four terms, capturing, respectively, (i) the heterogeneous effect of changing marginal costs on markups, (ii) the relative movements in bilateral exchange rates, (iii) the relative change in non-tradable prices and (iv) the relative change in competition. Note that the relationship between these relative terms is governed by two key parameters, representing the degree of horizontal competition $\lambda_{k,i,1,2,t}$ and vertical integration $\omega_{k,i,1,2,t}$ respectively.

Equation (32) states that the change in *relative border prices* is governed by the same set of variables also included in (31), but the parameters are scaled up by the distribution margin at different locations—as the need for distributing products creates a wedge between consumer and

border prices.

Equation (33) shows how quantities move across destinations. The change in relative quantities is a function of relative change in the consumer price, weighted by the demand elasticity $\varepsilon_{k,i,o,d,t}$, the relative change in the degree of competition, and the relative change in demand for tradable goods.

A.4.1 A three-country case study

To gain analytical insight on how prices and quantities respond to changes in local conditions, we start with a symmetric case where firms in each country have similar productivity and thus market share distributions. The symmetric assumption helps to simplify our analysis by ensuring that $\varepsilon_{k,i,1,2,t} = \varepsilon_{k,i,1,3,t}$, $\lambda_{k,i,1,2,t} = \lambda_{k,i,1,3,t}$, $\omega_{k,i,1,2,t} = \omega_{k,i,1,3,t}$. As above, we focus on country 1 as the country of origin. For clarity, we will focus on trade in a generic industry i, dropping all unnecessary subscripts.

The following three equations show the evolution of prices (at consumer level and at the border, respectively) and quantities.

$$\widehat{p}_2 + \widehat{e}_2 - (\widehat{p}_3 + \widehat{e}_3) = \Gamma(\widehat{e}_2 - \widehat{e}_3) + (1-\lambda)\omega(\widehat{P}_{N,2} - \widehat{P}_{N,3}) - (1-\lambda)\kappa(\widehat{CE}_2 - \widehat{CE}_3) \tag{34}$$

$$\widehat{p}^b_2 + \widehat{e}_2 - (\widehat{p}^b_3 + \widehat{e}_3) = \frac{\Gamma - dm}{1-dm}(\widehat{e}_2 - \widehat{e}_3) + \frac{(1-\lambda)\omega - dm}{1-dm}(\widehat{P}_{N,2} - \widehat{P}_{N,3}) - \frac{(1-\lambda)\kappa}{1-dm}(\widehat{CE}_2 - \widehat{CE}_3) \tag{35}$$

$$\widehat{q}_2 - \widehat{q}_3 = -\varepsilon(\widehat{p}_2 - \widehat{p}_3) + \frac{\rho - \eta}{1-\rho}(\widehat{CE}_2 - \widehat{CE}_3) + \eta(\widehat{P}_{T,2} - \widehat{P}_{T,3}) + \widehat{C}_{T,2} - \widehat{C}_{T,3} \tag{36}$$

From these three equations, we can see that the direct effect of relative changes in exchange rates on the consumer price is given by Γ, reflecting strategic complementaries due to horizontal competition and vertical interactions. The responsiveness of border prices, however, is dampened by the wedge induced by the need for distribution services, resulting in an overall elasticity given by $\frac{\Gamma - dm}{1-dm}$.

Rearranging (36), we get

$$\begin{aligned}\widehat{q}_2 - \widehat{q}_3 = &-\varepsilon(\Gamma - 1)(\widehat{e}_2 - \widehat{e}_3) - \varepsilon(1-\lambda)\omega(\widehat{P}_{N,2} - \widehat{P}_{N,3}) + \left[\frac{\rho - \eta}{1-\rho} + \varepsilon(1-\lambda)\kappa\right](\widehat{CE}_2 - \widehat{CE}_3) \\ &+ \eta(\widehat{P}_{T,2} - \widehat{P}_{T,3}) + \widehat{C}_{T,2} - \widehat{C}_{T,3}\end{aligned} \tag{37}$$

Since changes in relative quantities are a function of changes in relative prices, in turn a function of relative exchange rate movements, the coefficient on the latter is also a function of Γ—that is, $-\varepsilon(\Gamma - 1)$.

In order to relate these expressions to our estimators, we need to address the term capturing multilateral competitive effects ($\widehat{CE}_2 - \widehat{CE}_3$), which, as suggested by (27), is a complex function of bilateral exchange rates. Unfortunately, with firms competing in an Atkeson and Burstein (2008) style, there is no closed form solution for (27). We can however think of this competitive effect as an unknown function $\mathcal{G}$ of relative changes in exchange rates, $\widehat{e}_2 - \widehat{e}_3$, and other factors, uncorrelated with the relative change in bilateral exchange rates. This unknown function can then be approximated linearly with $a \cdot (\widehat{e}_2 - \widehat{e}_3)$, plus some function of other factors, as follows:

$$(1-\lambda)\kappa(\widehat{CE}_2 - \widehat{CE}_3) = \mathcal{G}(\widehat{e}_2 - \widehat{e}_3, \widehat{O}_2 - \widehat{O}_3) \approx a \cdot (\widehat{e}_2 - \widehat{e}_3) + \mathcal{O}(\widehat{O}_2 - \widehat{O}_3) \tag{38}$$

In general, a will reflect the multilateral effects of destination-specific changes in local conditions. Intuitively, altering the economic environment in country B would simultaneously affect exporters in country A and country C — exporters from both A and C receive shocks of a similar magnitude. In terms of exchange rates, the depreciation of country B's currency would simultaneously affect the bilateral exchange rates between A and B as well as between C and B.

By virtue of this approximation, equations (35) and (37) map into our estimators as follows:

$$\text{Destination Specific Markup Elasticity} \approx \frac{\Gamma - dm - a}{1 - dm} \tag{39}$$

$$\text{Cross Market Supply Elasticity} \approx \left[-\varepsilon(\Gamma - 1) + b \cdot a\right] / DSME \tag{40}$$

where b captures the quantity multiplier of the multilateral effect—which can be derived as

$$b \equiv \frac{1}{\kappa(1-\lambda)} \frac{\rho - \eta}{1 - \rho} + \varepsilon \tag{41}$$

Using the expressions for λ and ε, we can finally rewrite the equations (39) and (40) to get analytical solutions in terms of η, ρ, ω, the multilateral effect a and market shares ms.

$$\varepsilon = (1 - ms)\rho + ms \cdot \eta \tag{42}$$

$$\lambda = \frac{ms(1-ms)}{\frac{\rho}{\rho-\eta} - \frac{\rho}{\rho-1}ms + \frac{\eta-1}{\rho-1}ms^2} \tag{43}$$

$$b = \frac{\rho(2\rho - \eta - 1)}{\rho - 1} - \frac{\rho}{ms} - \frac{(\rho - \eta)^2}{\rho - 1}ms \tag{44}$$

$$DSME = 1 - \left[(1-\lambda)(1-\omega) + a\right] \cdot \frac{\varepsilon}{\varepsilon(1-\omega) + \omega} \tag{45}$$

$$CMSE = \left[\varepsilon(1-\lambda)(1-\omega) + b \cdot a\right] / DSME \tag{46}$$

We deal with the unobserved a using different methods. According to one method, we fix

the value of some analytical parameters, and search for possible values of a that fit our empirical estimates. For example, for given values of ρ, η and ms, we can find parameter values of ω and a that minimize the distance between the coefficients from empirical estimations and theoretically predicted values. Results are discussed in table (9).

As an alternative solution, we approximate a as

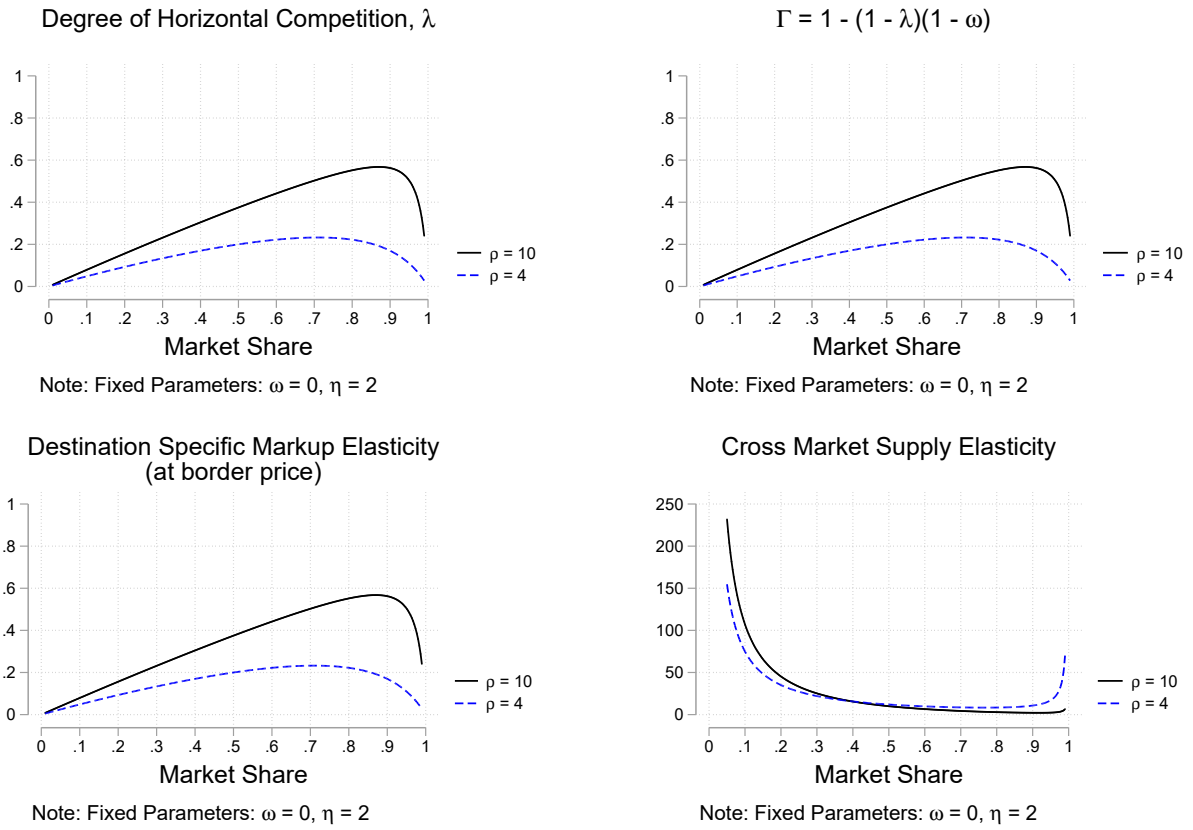
$$a \approx 0.99(1-\lambda)\kappa(1-ms)(\rho-1)(1-\omega) \tag{47}$$

Note that $(\rho-1)(1-\omega)$ is the coefficient in front of bilateral exchange rates in equation (27). $(1-\lambda)\kappa$ is the coefficient in front of the total effect of competitors' reactions as can be seen in (26). In general, parameters γ, κ and ω could be firm specific. In this approximation, we implicitly assumed that they are identical across firms. We discuss in greater detail how we construct our approximation in Section A.6.2.

A.4.2 Discussions on Analytical Solutions

In this subsection, we characterize the relationship between parameter values $\omega, \rho, \eta, ms, a$, and our DSME and CMSE estimates. To give a clear picture of how our model works, we conduct varies cases studies isolating each interacting channels separately. In each case, we fix a certain set of parameters and vary the others. In first four cases, we restrict the multilateral effect, a, to 0. To be consistent with our empirical analysis, we measure markups in the exporter's currency.

Case 1: Only Horizontal Competition, AB



In Case 1, we abstract from vertical interactions (by setting $\omega = 0$) and multilateral competition effects (by setting $a = 0$), so to focus on a specification close to the original model by Atkeson and Burstein (2008). With no vertical integration ($\omega = 0$), destination-specific markup adjustment is the same at the border and at the consumer price level. Both are driven by competition among producers of substitute goods—'horizontal competition' for short. Incomplete pass through is driven by the degree of horizontal competition, indexed by λ.

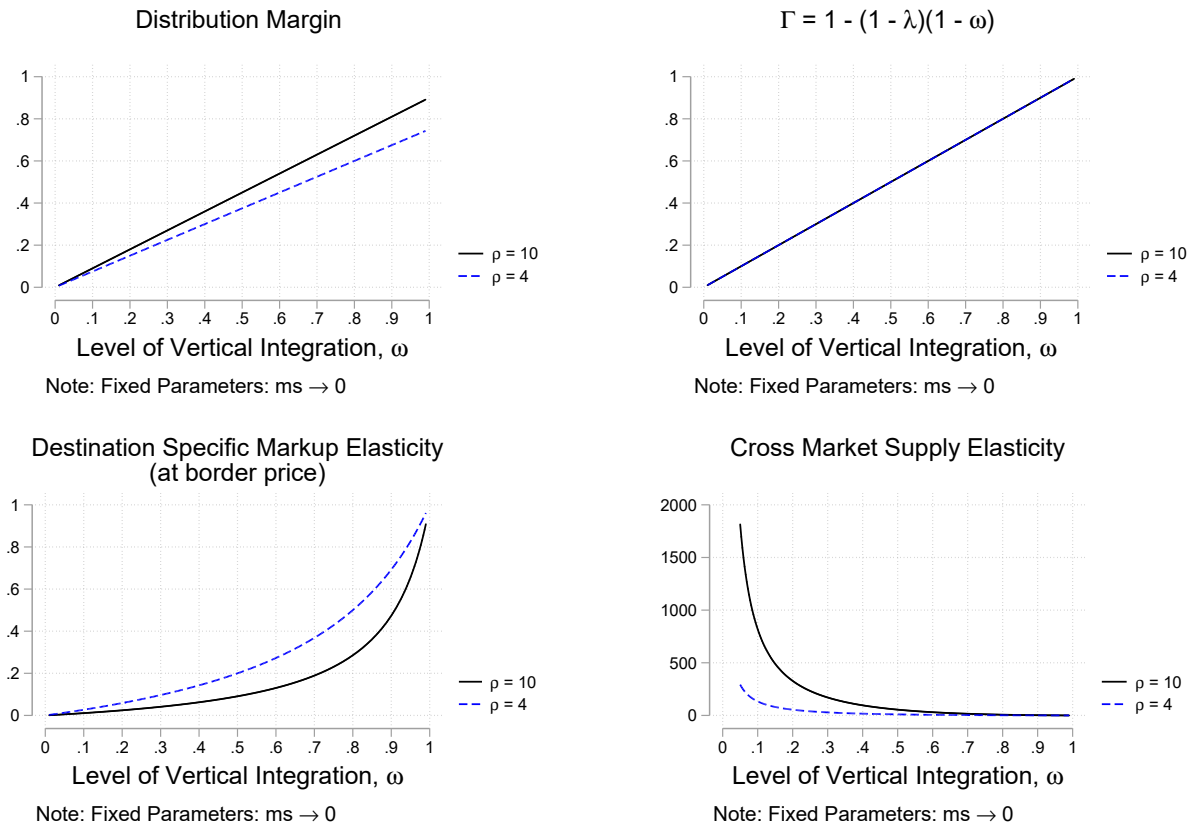
The four panels in Case 1 plots, respectively, λ, Γ, DSME and CMSE predicted by the model, against the market share—keeping the cross-industry elasticity of substitution, η, fixed at 2. Note that the lower panel on the left-hand-side column reproduces the well-known AB result, that markup adjustments is non linear in market share—hump-shaped when markups are measured in domestic currency, U-shaped if the markups are measured in the destination currency.

To explore the role of the elasticity of substitution, ρ, each panel plots two lines, one for a high value, one for a low value of ρ. A higher (lower) ρ represents a less (more) differentiated industry where the degree of substitution among varies is high (low). The results from this specification of the model are strikingly at odds with our empirical estimates of the DSME: as shown by the lower panel on the left-hand-side column, the model predicts a lower destination-specific markup

adjustment (measured in the exporter's currency) for more differentiated products. In our empirical section, we have seen that the DSME is always higher for more differentiated products. The picture is less clear-cut concerning the CMSE, whereas the two lines cross each other for values of ms around 0.5.

Looking at the magnitude of these elasticities, the range of theoretical DSME appear in line with our empirical estimates. However, the theoretical CMSE is too high relative to our empirical counterparts. In fact, as will be shown below, there is no numerical solution that can simultaneously match our empirically estimated DSMEs and CMSEs by varying ρ, η, ms while keeping $\omega = 0$ and $a = 0$ fixed.

Case 2: Only Vertical Integration, CD



In Case 2, we shut down that main mechanism highlighted by AB, by setting the market share of exporters to zero, i.e., $ms \to 0$. Instead, we focus on a specification close to the one originally studied by Corsetti and Dedola (2005). Here, vertical interactions between producers and distributors drive a wedge between prices at the border and at the consumer level—implying that, for a given within-sector elasticity of substitution ρ, the demand elasticity with respect to the border price is a strictly decreasing function of distribution margin, dm, in turn a linear function of the level of vertical integration, ω.

The four panels in the figure plot the predicted dm, Γ, DSME and CMSE against the degree of vertical interactions, indexed by ω, setting $ms \to 0$. By setting ms close to 0, we effectively shut down the horizontal competition channel, i.e., $\lambda \to 0$ and $a \to 0$, and simplify the model into a CES demand case where the elasticity of substitution among varieties is equal to ρ. In this case, the expression (45) can be simplified as follows:

$$DSME = \frac{1}{\rho(1/\omega - 1) + 1} \tag{48}$$

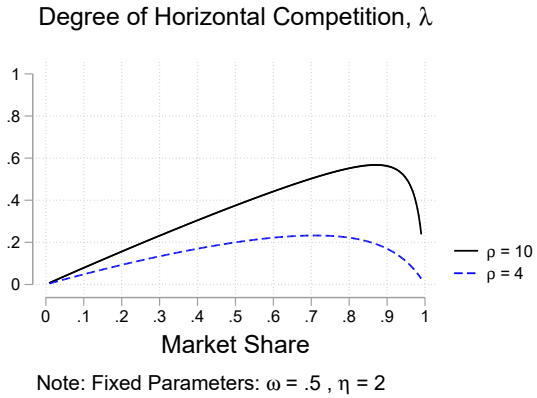
The markup elasticity with respect to the border price denominated in the exporters' currency, DSME, is strictly increasing function of the level of vertical interaction, ω. Intuitively, keeping the within-industry elasticity of substitution, ρ, fixed, a higher ω is associated with a larger distribution margin, causing the demand for the product to be less elastic with respect to the border price. Correspondingly, a higher level of vertical interaction, ω, monotonically decreases CMSE.

At the same time, however, DSME is a strictly decreasing function—and CMSE a strictly increasing function—of the within-industry elasticity of substitution, ρ. In line with the empirical evidence, the model predicts that the DSME is higher (markup adjustment is larger) for low elasticity (highly differentiated) goods—with quantity adjustments going in the opposite directions.

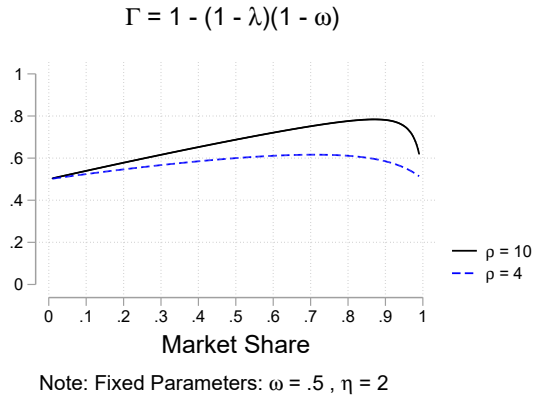
Qualitatively, the model with only vertical interactions appears consistent with our estimates of DSME and CMSE for products with different level of differentiation. However, the model does not square well quantitatively: the CMSE is too high.

In concluding the discussion of this case, note that the markup elasticity with respect to the consumer price, Γ, moves one-to-one with the level of vertical integration, ω, independent of ρ (see the panel on the upper right hand side).

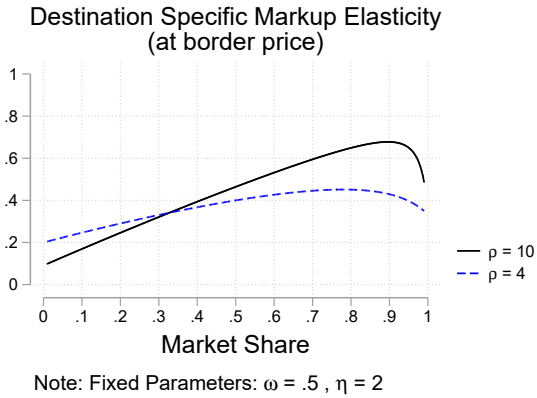
Case 3: Incorporating both Horizontal and Vertical Interactions, ABCD



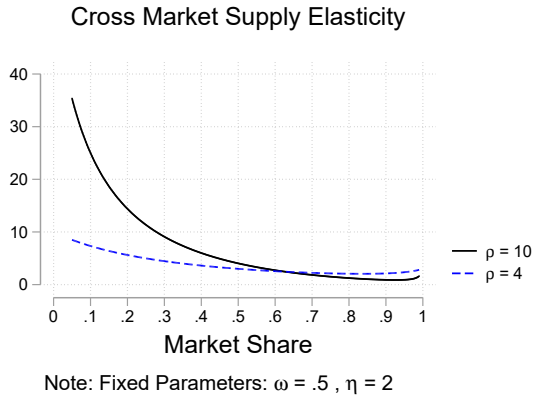
Note: Fixed Parameters: ω = .5 , η = 2



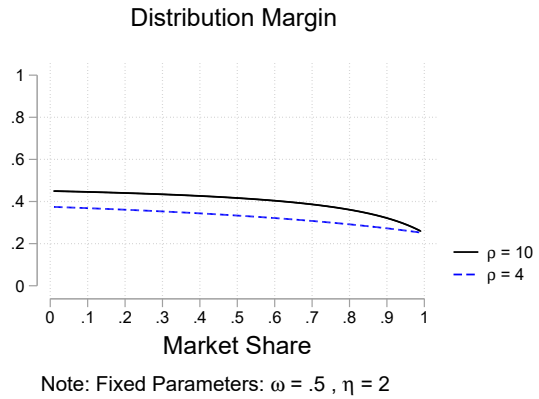
Note: Fixed Parameters: ω = .5 , η = 2



Note: Fixed Parameters: ω = .5 , η = 2



Note: Fixed Parameters: ω = .5 , η = 2



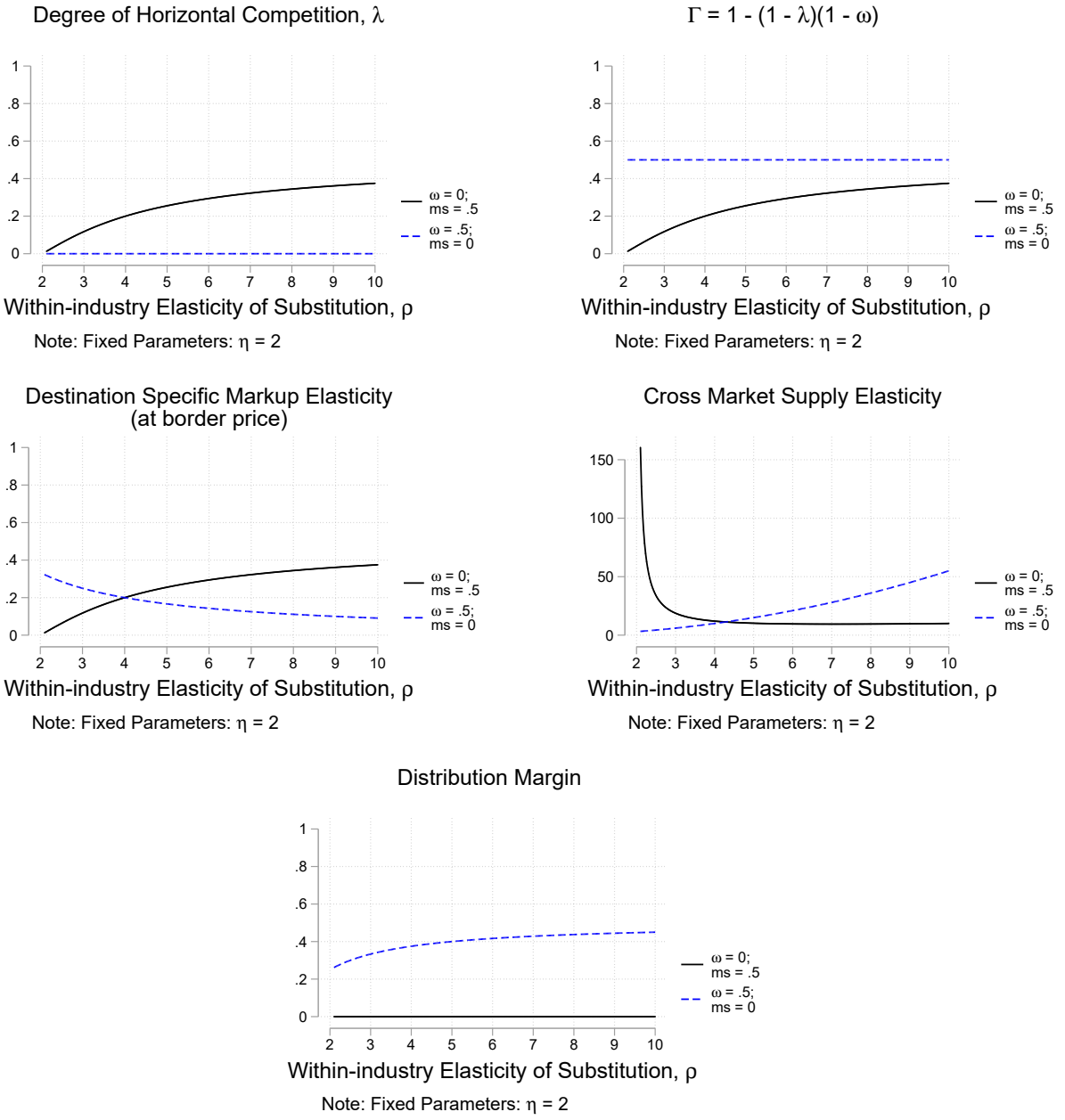
Note: Fixed Parameters: ω = .5 , η = 2

Case 3 shows that combining both horizontal and vertical interactions helps in lowering the magnitude of the theoretical CMSE closer to our empirical estimates. The panels are the same as in Case 1, but the figures are now plotted setting $\omega = .5$.

More importantly, the lower panel on the left-hand-side column shows that level of vertical and horizontal interactions impinges on the relationship between DSME and product differentiation (the value of ρ). With the cost share of the local component ω equals 0.5, DSME is increasing in the level of differentiation (a lower ρ) when the firm's market share is small and decreasing in the

level of differentiation when the market share is large. We characterize this relationship in further detail in the case to follow.

Case 4: Comparing the Effect of Horizontal and Vertical Components



Case 4 decomposes horizontal and vertical interactions. The panels plot the theoretically predicted λ, Γ, the $DSME$ at the border, the $CMSE$ and the distribution margin against the within-industry elasticity of substitution, ρ. Solid lines refer to the same model as in case 1, broken lines as in case 3.

With only horizontal competition (solid black line), the degree of horizontal competition, λ, is

strictly increasing in the within-industry elasticity of substitution, ρ. In this case,

$$DSME = \lambda \quad \text{and} \quad CMSE = \varepsilon(1/\lambda - 1) \tag{49}$$

When ρ approaches η (set equal to 2), the effect of horizontal is very small, the markup adjustments is close to zero. As the quantity differences across markets approaches the elasticity of substitution η, the CMSE goes to infinity. As ρ rises, the cross-market markup differences rise at a faster speed compared to cross-market quantity differences. As a result, CMSE is decreasing in ρ.

With only vertical interactions (dashed blue line), a higher ρ means a lower markup at the final consumer price[39]. Everything else equal, the cost of the local nontraded input makes up for a larger fraction of the final consumer price—which thus becomes more insulated from shocks like tariffs or exchange rates that hit the border price. Because of the insulating effect of a larger distribution margin, movements in the border price have less influence on the final demand: the border price/markup (denominated in the local currency) reacts more to changes in exchange rate and tariff changes—whereas the border price/markup denominated in the exporter's currency reacts less.

The implications for the CMSE can be understood as the result of two opposing forces from a rise in ρ. On the one hand, demand is more elastic because products are more substitutable (ρ is higher). On the other hand, demand becomes *less* elastic with respect to the border price due to a larger distribution margin. The panel suggests that the latter channel dominate and CMSE is larger for increasing values of ρ.

Intuitively, combining vertical and horizontal interactions, a firm that sells low differentiation products (high ρ) is more sensitive to competition from other firms in its industry. As it charges a lower optimal markup, the share of local components in its price is larger. Therefore, its marginal cost and price denominated in the local currency are more insulated from exchange rate movements. At the same time, a higher within-industry elasticity of substitution means that the demand for the firm's product is more sensitive to changes of the firm's own and competitors' prices—-making the firm more responsive to cost shocks and exchange rate movements.

[39]The markup at the consumer price is defined as the consumer price divided by the total cost denominated in the local currency, where the total cost includes the marginal cost of production of the exporter converted to the local currency plus the local cost of production and distribution.

Table 9: Incorporating Multilateral Effects, $ABCD^H$
Numerical Solutions: to target evidence, solving for parameters

Scenarios	Targets		Status	Residual	ms	η	ρ	ω	a
	DSME	CMSE							
Changing $\eta \in (1.01, 2)$, $\rho \in (2, 20)$, and $a \in (0, 1)$ with $ms = 0.2$ and $\omega = 0.5$	0.20	0.50	Solved	0.00	0.20	**1.18**	**3.02**	0.50	**0.11**
	0.10	2.00	Solved	0.00	0.20	**1.31**	**7.91**	0.50	**0.10**
	0.06	2.47	Solved	0.00	0.20	**1.46**	**12.85**	0.50	**0.10**
	0.04	4.72	Solved	0.00	0.20	**1.79**	**17.84**	0.50	**0.10**
Changing $\omega \in (0, 1)$ and $a \in (0, 1)$ with $ms = 0.2$, $\eta = 2$ and $\rho = 8$	0.20	0.50	Solved	0.00	0.20	2.00	8.00	**0.69**	**0.06**
	0.10	2.00	Solved	0.00	0.20	2.00	8.00	**0.55**	**0.09**
	0.06	2.47	Solved	0.00	0.20	2.00	8.00	**0.48**	**0.11**
	0.04	4.72	Solved	0.00	0.20	2.00	8.00	**0.43**	**0.12**
Changing $\eta \in (1.01, 2)$, $\rho \in (2, 20)$, $ms \in (0, 1)$, and $\omega \in (0, 1)$ with $a = 0$	0.20	0.50	Infeasible	-	-	-	-	-	-
	0.10	2.00	Infeasible	-	-	-	-	-	-
	0.06	2.47	Infeasible	-	-	-	-	-	-
	0.04	4.72	Infeasible	-	-	-	-	-	-

Table 9 reports our core results from using our evidence as diagnostic. In the table, the second and third columns reports the empirical estimates to be matched. The last five columns lists the parameters (or combinations of parameters) relevant to our exercise, the market share ms, the cross-industry elasticity of substitution η, the within-industry elasticity of substitution ρ, the degree of vertical integration ω, and the multi-lateral effect a. The range of values we allow these parameters to take is reported in the first column. The third column indicates whether we can solve the model.

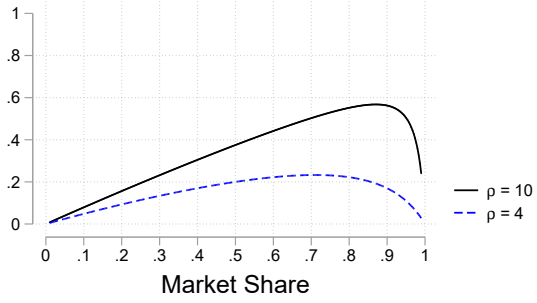
In what follows, we conduct three scenario analyses. In the first exercise, we fix ms and ω, and solve for η, ρ, and a to match our empirical estimates. As you can see, as the markup elasticity becomes smaller, the elasticity of substitutions get larger, meaning that products are more substitutable to each other.

In the second exercise, we fix the elasticity of substitutions (η, ρ) and let the level of vertical integration ω vary. As markup elasticity becomes smaller, the fitted value of ω gets smaller, suggesting a smaller proposition of local components.

The third exercise shows that, to match the magnitude and patterns of the empirical results, the multi-lateral effects cannot be shut down. In the third exercise, if we set the multilateral effect a to zero, the model is no longer able to match our empirical estimates.

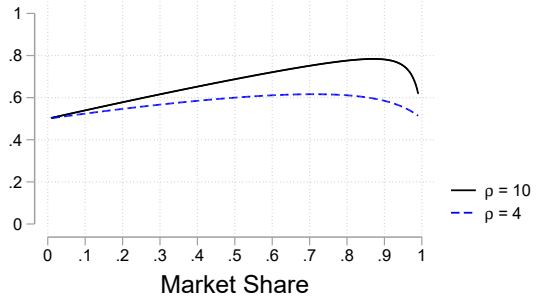
Incorporating Multilateral Effects: $ABCD^H$
Changing Market Share

Degree of Horizontal Competition, λ



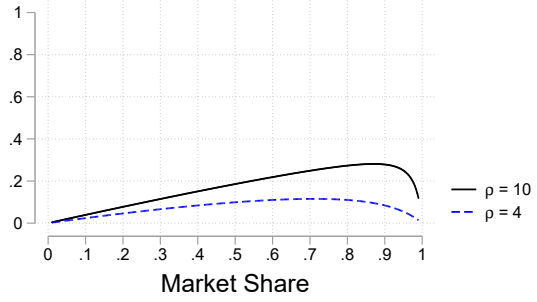
Note: Fixed Parameters: ω = .5 , η = 2

Γ = 1 - (1 - λ)(1 - ω)



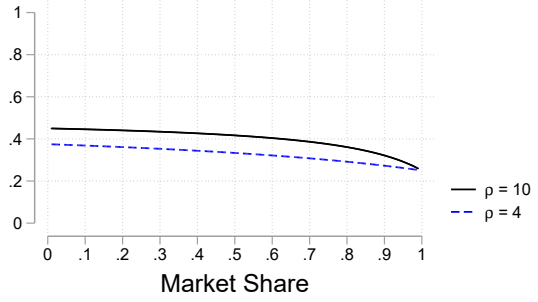
Note: Fixed Parameters: ω = .5 , η = 2

Multilateral Effect, a



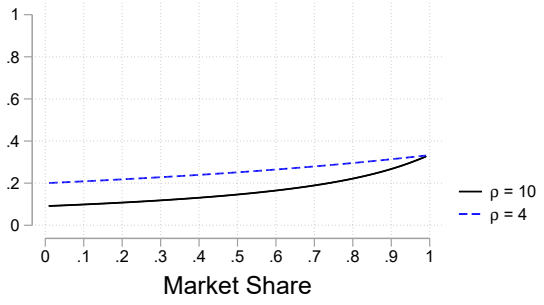
Note: Fixed Parameters: ω = .5 , η = 2

Distribution Margin



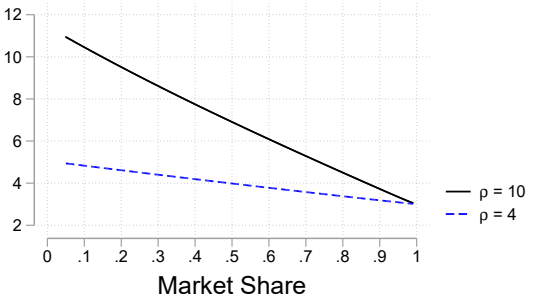
Note: Fixed Parameters: ω = .5 , η = 2

Destination Specific Markup Elasticity
(at border price)



Note: Fixed Parameters: ω = .5 , η = 2

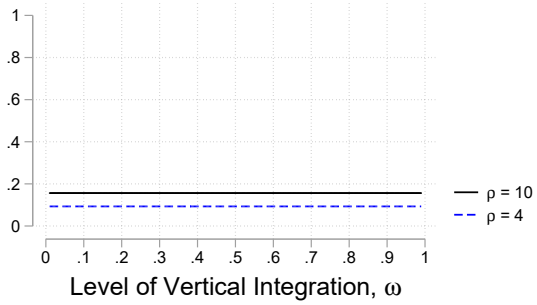
Cross Market Supply Elasticity



Note: Fixed Parameters: ω = .5 , η = 2

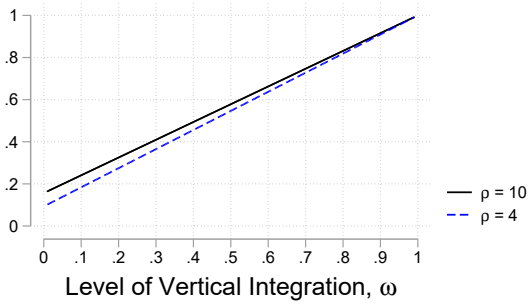
Incorporating Multilateral Effects: $ABCD^H$
Changing the Level of Vertical Integration

Degree of Horizontal Competition, λ



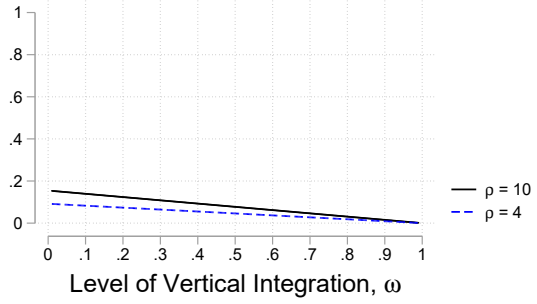
Note: Fixed Parameters: ms = .2, η = 2

Γ = 1 - (1 - λ)(1 - ω)



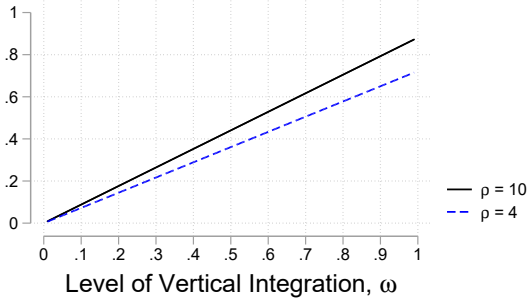
Note: Fixed Parameters: ms = .2, η = 2

Multilateral Effect, a



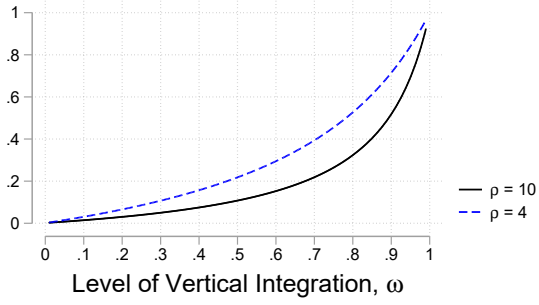
Note: Fixed Parameters: ms = .2, η = 2

Distribution Margin



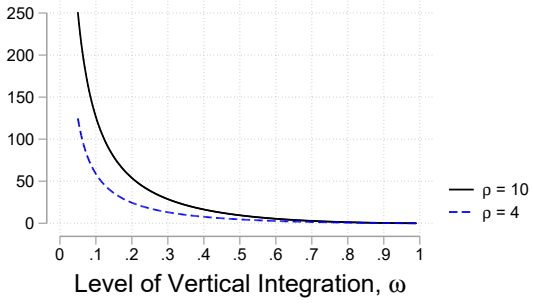
Note: Fixed Parameters: ms = .2, η = 2

Destination Specific Markup Elasticity
(at border price)



Note: Fixed Parameters: ms = .2, η = 2

Cross Market Supply Elasticity



Note: Fixed Parameters: ms = .2, η = 2

A.5 Equilibrium conditions

The competitive equilibrium is characterized as follows.

1. The representative consumer in each country chooses consumption, labour supply and optimal international bond holding to maximize its expected utility as in (13) and (14).

2. Firms in each country set prices to optimize their profits given its marginal cost as in (22) and (23). The optimal prices are given by (16) and (24).

3. Market clear. This involves the aggregation conditions (15), (19), (18), (20) and (21) together with other market clearing conditions listed below.

Total demand for non-tradable goods is given by

$$q_{N,d,t} = C_{N,d,t} + \sum_i \chi_i \left[\sum_{o \neq d} \sum_{f \in \mathbb{1}_{i,o} \cap \mathbb{1}_E} q_{f,i,o,d,t} + \sum_{f \in \mathbb{1}_{i,d}} q_{f,i,d,d,t} \right] \tag{50}$$

For each firm, the total quantity of products sold equals the quantity produced.

$$\Omega_{f,i,o,t} l_{f,i,o,t} = \sum_d q_{f,i,o,d,t} \tag{51}$$

$$\Omega_{N,o,t} L_{N,o,t} = q_{N,o,t} \tag{52}$$

The labor market is clear:

$$\sum_{f,i} l_{f,i,o,t} + L_{N,o,t} = L_{o,t} \tag{53}$$

Balance of trade (financial autarky case):

$$\sum_{f,i} (p_{f,i,d,o,t} - \chi_i P_{N,d,t}) q_{f,i,d,o,t} = \sum_{f,i} (p_{f,i,d,o,t} - \chi_i P_{N,o,t}) q_{f,i,o,d,t} * e_{o,d,t} \quad for\ o \neq d \tag{54}$$

I select the nominal wage $W_{o,t}$ in each origin as the numeraire and set it equal to one. In this model, the productivity distribution can be asymmetric across industries, sectors and countries. As a result, the bilateral nominal exchange rate is not necessarily equal to one. Under the financial autarky case, the steady state bilateral exchange rate is determined by the bilateral balance of trade condition.

A.6 Solutions

A.6.1 Solution for market share

Note that both $\widehat{mc}_{k,i,o,d,t}$ and $\widehat{e}_{o,d,t}$ are state variables and exogenous to firms. After a shock, firms adjust their optimal prices and reach a new equilibrium. The deviation of market share $\widehat{ms}_{k,i,o,d,t}$ for firm k in the new equilibrium compared to the old one depends on the *ex ante* market structure, i.e., market share distributions $\{ms_{k,i,o',d,t}\}_{k\in\mathbb{1}_f,o'\in\mathbb{1}_o}$, marginal cost shocks to its competitors $\{\widehat{mc}_{k,i,o',t}\}_{k\in\mathbb{1}_f,o'\in\mathbb{1}_o}$, and the bilateral exchange rate movements of all trade partners of country d, $\{\widehat{e}_{o',d,t}\}_{o'\in\mathbb{1}_o}$.

$$
\begin{aligned}
&\widehat{ms}_{k,i,o,d,t}\left[1-(1-ms_{k,i,o,d,t})(1-\rho_i)\kappa_{k,i,o,d,t}\right]\\
&=(1-ms_{k,i,o,d,t})\left\{(1-\rho_i)\left[(1-\omega_{f,i,o,d,t})(\widehat{mc}_{k,i,o,t}-\widehat{e}_{o,d,t})+\omega_{f,i,o,d,t}\widehat{P}_{N,d,t}\right]\right\}\\
&-\sum_{o'}\sum_{f\neq k}ms_{f,i,o',d,t}\left\{(1-\rho_i)\left[(1-\omega_{f,i,o',d,t})(\widehat{mc}_{f,i,o',t}-\widehat{e}_{o',d,t})+\omega_{f,i,o',d,t}\widehat{P}_{N,d,t}+\kappa_{f,i,o',d,t}\widehat{ms}_{f,i,o',d,t}\right]\right\}
\end{aligned}
\tag{55}
$$

Equation (55) states that the importance of competitors reactions depend on the elasticity of substitution within industries, ρ_i, and the market share of its competitors, $\widehat{ms}_{k,i,o',d,t}$.

It is worth stressing that even under a firm specific shock, the equilibrium effect of changing market shares for other firms $\sum_{o'}\sum_{f\neq k}ms_{f,i,o',d,t}\kappa_{f,i,o',d,t}\widehat{ms}_{f,i,o',d,t}$ will not be zero in most cases. Note that the expression $\kappa_{f,i,o',d,t}$ is strictly increasing in market share $ms_{f,i,o',d,t}$. That is, the importance of changing market share of a competitor to firm f is strictly increasing in the market share of that competitor.

Under the presence of $\widehat{ms}_{f,i,o',d,t}$, there is no simple analytical solution for the change in market share after a shock even under first order approximation. Given a set of realised shocks and prior market structure distribution, market share conditions will formulate a system of M_i nonlinear equations that can be solved numerically.

A.6.2 Approximating for competitors' reaction, $\widehat{CE}$

To gain insights, we now solve equation (55) under the case where firms are *ex ante* identical after adjusting for exchange rate differences within industry i and destination d. That is, we analyse the case that

$$
\frac{mc_{k,i,o',t}}{e_{o',d,t}}=\frac{mc_{f,i,o,t}}{e_{o,d,t}}\quad\forall k\in\mathbb{1}_f,o'\in\mathbb{1}_o
$$

This condition implies the same market share $ms_{k,i,o,d,t}$, share of distribution cost $\omega_{f,i,o,d,t}$, price elasticity with respect to market share $\kappa_{k,i,o,d,t}$, and the degree of horizontal competition $\lambda_{k,i,o,d,t}$

across firms. We drop all unnecessary subscripts for clarity.

$$\begin{aligned}\widehat{ms}_{k,o}\left[1-(1-ms)(1-\rho)\kappa\right] =&(1-ms)(1-\rho)\left[(1-\omega)(\widehat{mc}_{k,o}-\widehat{e}_o)+\omega\widehat{P}_N\right]\\ &-ms(1-\rho)\sum_{o'}\sum_{f\neq k}\left[(1-\omega)(\widehat{mc}_{k,o'}-\widehat{e}_{o'})+\omega\widehat{P}_N+\kappa\widehat{ms}_{f,o'}\right]\end{aligned}$$

Note that $\sum_{o'}\sum_{f\neq k}\widehat{ms}_{f,o'}=-\widehat{ms}_{k,o}$. Rearrange and get

$$\begin{aligned}\widehat{ms}_{k,o} =&\frac{(1-\lambda)(1-\rho)(1-ms)}{1-\kappa(1-\lambda)(1-\rho)ms}\left[(1-\omega)(\widehat{mc}_{k,o}-\widehat{e}_o)+\omega\widehat{P}_N\right]\\ &-\frac{(1-\lambda)(1-\rho)ms}{1-\kappa(1-\lambda)(1-\rho)ms}\sum_{o'}\sum_{f\neq k}\left[(1-\omega)(\widehat{mc}_{f,o'}-\widehat{e}_{o'})+\omega\widehat{P}_N\right]\end{aligned}$$

Define $\Upsilon\equiv\kappa(1-\lambda)(1-\rho)ms$. We can write

$$\begin{aligned}\kappa\widehat{ms}_{k,o} =&\frac{1-ms}{ms}\left[(1-\omega)(\widehat{mc}_{k,o}-\widehat{e}_o)+\omega\widehat{P}_N\right]\Upsilon\left(1+\frac{\Upsilon}{1-\Upsilon}\right)\\ &-\sum_{o'}\sum_{f\neq k}\left[(1-\omega)(\widehat{mc}_{f,o'}-\widehat{e}_{o'})+\omega\widehat{P}_N\right]\Upsilon\left(1+\frac{\Upsilon}{1-\Upsilon}\right)\end{aligned}$$

The change in markup denominated in the exporter's currency can be written as

$$\begin{aligned}\widehat{\mu}_{k,o} =&\left[1-(1-\lambda)(1-\omega)\right](\widehat{e}_o-\widehat{mc}_{k,o})+(1-\lambda)\omega\widehat{P}_N\\ &-\Upsilon\sum_{o'}\sum_{f\neq k}\left[(1-\omega)(\widehat{mc}_{f,o'}-\widehat{e}_{o'})+\omega\widehat{P}_N\right]\\ &+\frac{1-ms}{ms}\frac{\Upsilon}{1-\Upsilon}\left[(1-\omega)(\widehat{mc}_{k,o}-\widehat{e}_o)+\omega\widehat{P}_N\right]\\ &-\frac{\Upsilon^2}{1-\Upsilon}\sum_{o'}\sum_{f\neq k}\left[(1-\omega)(\widehat{mc}_{f,o'}-\widehat{e}_{o'})+\omega\widehat{P}_N\right]\end{aligned}$$

The first line represents the direct effect of shocks. The second line reflects how the competitors reaction to these shocks would directly affect the optimal markup of exporter k. The third and fourth lines represent the indirect effects of changing competitors' market shares.

Consider the case where the destination country depreciates against all of its trade partners. That is, $\widehat{e}_{o'}=\widehat{e}_o\ \forall o\neq d$ and $\widehat{e}_d=0$. For clarity, we also keep the marginal cost of all firms fixed

and assume the price of non-tradable goods does not change in the destination.

$$\begin{aligned}\widehat{\mu}_{k,o} =& [1-(1-\lambda)(1-\omega)]\,\widehat{e}_o + \Theta\frac{1-ms}{ms}\Upsilon(1-\omega)\widehat{e}_o \\ &- \frac{1-ms}{ms}\frac{\Upsilon}{1-\Upsilon}(1-\omega)\widehat{e}_o + \Theta\frac{1-ms}{ms}\frac{\Upsilon^2}{1-\Upsilon}(1-\omega)\widehat{e}_o \\ =& [1-(1-\lambda)(1-\omega)]\,\widehat{e}_o - \kappa(1-\lambda)\widehat{CE}_{k,o}\end{aligned} \tag{56}$$

Where Θ is the proportion of domestic firms in the residual market of industry i at destination d. In a symmetric setup, Θ is the number of domestic firms divided by the total number of firms in industry i minus one, i.e., $M_d/(M-1)$. The last three terms of equation (56) represent the total effect of competitors' reactions, which can be written as

$$\begin{aligned}\kappa(1-\lambda)\widehat{CE}_{k,o} &= \frac{1-ms}{ms}\Upsilon(1-\omega)\widehat{e}_o\left(\frac{1-\Theta}{1-\Upsilon}\right) \\ &= (1-\omega)(1-\lambda)\kappa(\rho-1)(1-ms)\widehat{e}_o\left(\frac{1-\Theta}{1-\Upsilon}\right) \\ &\approx c\cdot(1-\omega)(1-\lambda)\kappa(\rho-1)(1-ms)\widehat{e}_o\end{aligned} \tag{57}$$

where c is a constant and expression (57) gives our approximation equation (47). Note that, in a general case without the symmetric assumption, Θ is likely to be an increasing function of market share of foreign firm k. For given size of domestic firms, a larger market share of foreign firm k implies a smaller residual market to be split with, indicating a greater market share of domestic firms in the residual market. This make it inappropriate to fix Θ as a parameter. However, note that Υ is also an increasing function of market share, i.e.,

$$\frac{\partial\Upsilon}{\partial ms} = \Upsilon^2\frac{\rho[\rho(1-ms)+\eta ms-1]}{ms^3(\rho-1)(\rho-\eta)} > 0 \tag{58}$$

In our approximation (47), we have assumed a simple proportional relationship between $1-\Theta$ and $1-\Upsilon$ and fixed c to 0.99.

A.6.3 Solution for a, b, κ and λ

Collect equations

$$\begin{aligned}
\lambda &= 1 - \frac{1}{1-(1-ms)(1-\rho)\kappa} \\
\kappa &= \frac{\rho-\varepsilon}{\varepsilon^2-\varepsilon} \\
\varepsilon &= (1-ms)\rho + ms\cdot\eta
\end{aligned}$$

Rearrange and get

$$\begin{aligned}
a &\approx (1-\omega)(1-\lambda)\kappa(\rho-1)(1-ms) \\
&= (1-\omega)\cdot\frac{1}{\frac{1}{\kappa(\rho-1)(1-ms)}+1} \\
&= (1-\omega)\cdot\frac{1}{\frac{\varepsilon(\varepsilon-1)}{(\rho-1)(\rho-\eta)ms(1-ms)}+1} \\
&= (1-\omega)\cdot\frac{1}{\frac{[\rho-(\rho-\eta)ms][\rho-(\rho-\eta)ms-1]}{(\rho-1)(\rho-\eta)ms(1-ms)}+1} \\
&= (1-\omega)\cdot\frac{(\rho-1)(\rho-\eta)ms(1-ms)}{\rho(\rho-1)-\rho(\rho-\eta)ms+(1-\eta)(\rho-\eta)ms^2} \\
&= (1-\omega)\cdot\frac{ms(1-ms)}{\frac{\rho}{\rho-\eta}-\frac{\rho}{\rho-1}ms-\frac{\eta-1}{\rho-1}ms^2}
\end{aligned}$$

$$\begin{aligned}
b &= \frac{1}{\kappa(1-\lambda)}\frac{\rho-\eta}{1-\rho}+\varepsilon \\
&= \left[\frac{1}{\kappa}-(1-ms)(1-\rho)\right]\frac{\rho-\eta}{1-\rho}+\varepsilon \\
&= \left[\frac{\varepsilon(\varepsilon-1)}{(\rho-\eta)ms}-(1-ms)(1-\rho)\right]\frac{\rho-\eta}{1-\rho}+\varepsilon \\
&= \frac{\varepsilon(\varepsilon-1)}{ms(1-\rho)}-(1-ms)(\rho-\eta)+\varepsilon \\
&= \frac{\varepsilon(\varepsilon-1)}{ms(1-\rho)}+\eta \\
&= -\left[\rho+(\eta-\rho)ms\right]\left[\frac{1}{ms}+\frac{\eta-\rho}{\rho-1}\right]+\eta \\
&= \frac{\rho(2\rho-\eta-1)}{\rho-1}-\frac{\rho}{ms}-\frac{(\rho-\eta)^2}{\rho-1}ms
\end{aligned}$$

$$\lambda = 1 - \frac{-ms(1-ms)(\rho-\eta) + (1-\rho-\eta)ms + \frac{\rho(\rho-1)}{\rho-\eta}}{-ms(1-ms)(1-\eta) + (1-\rho-\eta)ms + \frac{\rho(\rho-1)}{\rho-\eta}}$$
$$= \frac{ms(1-ms)}{\frac{\rho}{\rho-\eta} - \frac{\rho}{\rho-1}ms + \frac{\eta-1}{\rho-1}ms^2} \tag{59}$$

A.7 General Relationships (Model Free)

A.7.1 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.

$$\max_p q(p,\xi)p - c[q(p,\xi),\zeta] \tag{60}$$

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

$$\frac{\partial q(p,\xi)}{\partial p}p + q(p,\xi) = \frac{\partial c[q(p,\xi),\zeta]}{\partial q(p,\xi)}\frac{\partial q(p,\xi)}{\partial p} \tag{61}$$

From this equation, we can derive the optimal price as

$$p^* = \frac{\varepsilon(p^*,\xi)}{\varepsilon(p^*,\xi)-1}mc[q(p^*,\xi),\zeta] \tag{62}$$

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

A.7.2 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*

$$\frac{d\log(q^*)}{d\log(p^*)} = -\varepsilon(p^*,\xi) \tag{63}$$

Proof.

$$
\begin{aligned}
d\log(q(p^*(\xi,\zeta),\xi)) =& \frac{1}{q(p^*(\xi,\zeta),\xi)} dq(p^*(\xi,\zeta),\xi) \\
=& \frac{1}{q(p^*(\xi,\zeta),\xi)} \left(\frac{\partial q(p^*(\xi,\zeta),\xi)}{\partial p^*(\xi,\zeta)} dp^*(\xi,\zeta) + \frac{\partial q(p^*(\xi,\zeta),\xi)}{\partial \xi} d\xi \right) \qquad (64) \\
d\log(p^*(\xi,\zeta)) =& \frac{1}{p^*(\xi,\zeta)} dp^*(\xi,\zeta) \qquad (65)
\end{aligned}
$$

Substituting equation 65 into 64 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*

$$
\frac{d\log(q^*)}{d\log(p^*)} = \frac{\varphi_q(p^*,\xi)}{\varphi_p(\xi,\zeta)} - \varepsilon(p^*,\xi) \qquad (66)
$$

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.

$$
\begin{aligned}
d\log(q(p^*(\xi,\zeta),\xi)) =& \frac{1}{q(p^*(\xi,\zeta),\xi)} \left(\frac{\partial q(p^*(\xi,\zeta),\xi)}{\partial \xi} d\xi + \frac{\partial q(p^*(\xi,\zeta),\xi)}{\partial p^*(\xi,\zeta)} dp^*(\xi,\zeta) \right) \\
=& \left(\varphi_q(p^*,\xi) - \varepsilon(p^*,\xi)\varphi_p(\xi,\zeta) \right) \frac{d\xi}{\xi} \qquad (67) \\
d\log(p^*(\xi,\zeta)) =& \frac{1}{p^*(\xi,\zeta)} dp^*(\xi,\zeta) \\
=& \frac{1}{p^*(\xi,\zeta)} \left(\frac{\partial p^*(\xi,\zeta)}{\partial \xi} d\xi \right) \\
=& \varphi_p(\xi,\zeta) \frac{d\xi}{\xi} \qquad (68)
\end{aligned}
$$

□

B Estimator

In this section, we derive the identification condition in estimating markup elasticities using a four dimensional (firm-product-destination-time) customs database. Subsection B.1 derives the identification condition in a balanced panel. Subsection B.2 discussed a selection bias due to endogenously selection of markets and compare the identification condition of our proposed estimator with that of two commonly used alternatives. To fix ideas, we simulate a set of numerical examples in subsection B.3 to illustrate the bias that may arise from an endogenously unbalanced panel and discuss various cases where the marginal cost is destination-specific. Subsection B.4 gives a structural interpretation of the required identification condition.

B.1 Balance Panel

In a balanced panel, we can write the unbiasedness condition as

$$\frac{1}{n^I n^F n^D n^T}\sum_i\sum_f\sum_d\sum_t(\widetilde{mc}_{ifdt}-\frac{1}{n^I n^F n^T}\sum_i\sum_f\sum_t\widetilde{mc}_{ifdt})(\widetilde{e}_{dt}-\frac{1}{n^T}\sum_t\widetilde{e}_{dt})=0 \tag{69}$$

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; and

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

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

Therefore, we can rewrite equation (69) as

$$\frac{1}{n^I n^F n^D n^T} \sum_i \sum_f \sum_d \sum_t (\psi_{ifdt} - \overline{\psi}_d - \overline{\psi}_{ift} + \overline{\psi})(e_{dt} - \overline{e}_t - \overline{e}_d + \overline{e}) = 0 \tag{70}$$

Since exchange rates cannot vary at product and firm dimensions in a balanced panel, we can simplify equation (70) as:

$$\frac{1}{n^D n^T} \sum_d \sum_t (\overline{\psi}_{dt} - \overline{\psi}_t - \overline{\psi}_d + \overline{\psi})(e_{dt} - \overline{e}_t - \overline{e}_d + \overline{e}) = 0 \tag{71}$$

Note that, as a deviation term, the compositional error must satisfy

$$\frac{1}{n^D} \sum_d \psi_{ifdt} = 0 \quad \forall ift \tag{72}$$

With this relationship, we can write (71) as

$$\frac{1}{n^D n^T} \sum_d \sum_t (\overline{\psi}_{dt} - \overline{\psi}_d)(e_{dt} - \overline{e}_d) = 0 \tag{73}$$

B.2 Unbalanced panel

In this subsection, discuss a subtle yet worth noting difference in applying destination fixed effects to control unobserved marginal cost in an endogenously unbalanced panel.

B.2.1 Parsimonious Factor Decomposition to Illustrate the Endogenous Selection Problem

To illustrate this problem, we find it useful to decompose the markup and marginal cost components into collections 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 conciseness, and accounting for all possible combinations

among factors, we can write:

$$\begin{aligned}
\mu_{ifdt} &= \mathcal{F}_i + \mathcal{F}_f + \mathcal{F}_d + \mathcal{F}_t \\
&\quad + \mathcal{F}_{if} + \mathcal{F}_{id} + \mathcal{F}_{it} + \mathcal{F}_{fd} + \mathcal{F}_{ft} + black\mathcal{F}_{dt} \\
&\quad + \mathcal{F}_{fdt} + \mathcal{F}_{idt} + black\mathcal{F}_{ift} + \mathcal{F}_{ifd} \\
&\quad + black\mathcal{F}_{ifdt} \qquad (74) \\
\overline{mc}_{ift} &= \mathcal{C}_i + \mathcal{C}_f + \mathcal{C}_t \\
&\quad + \mathcal{C}_{if} + \mathcal{C}_{it} + \mathcal{C}_{ft} \\
&\quad + \mathcal{C}_{ift}
\end{aligned}$$

Equation (74) captures all possible factors driving the markup and the (common-across-destinations) cost components. 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 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 key problem 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 likely to be correlated with movements of the bilateral exchange rate $\mathcal{F}_{dt}$ and the unobserved marginal cost components.

To see the problem, consider a standard empirical model of nominal exchange rate pass through.[40] Usually, the first step in specifying these models consists of taking a time difference. 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 conditional

[40] 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 ratio.

on ifd:

$$\begin{aligned}\Delta_{s_{|ifd}} p_{ifdt} \;=\;& \Delta_{s_{|ifd}}\mathcal{F}_t + \Delta_{s_{|ifd}}\mathcal{C}_t \\ &+ \Delta_{s_{|ifd}}\mathcal{F}_{it} + \Delta_{s_{|ifd}}\mathcal{F}_{ft} + black\Delta_{s_{|ifd}}\mathcal{F}_{dt} + \Delta_{s_{|ifd}}\mathcal{C}_{it} + \Delta_{s_{|ifd}}\mathcal{C}_{ft} \\ &+ \Delta_{s_{|ifd}}\mathcal{F}_{fdt} + \Delta_{s_{|ifd}}\mathcal{F}_{idt} + \Delta_{s_{|ifd}}\mathcal{F}_{ift} + \Delta_{s_{|ifd}}\mathcal{C}_{ift} \\ &+ \Delta_{s_{|ifd}}\mathcal{F}_{ifdt}\end{aligned} \tag{75}$$

where $\Delta_{s_{|j}} x_{j,t} \equiv x_{j,t} - x_{j,t-s}\ \forall j \in \{f, i, f, d, fd, id, if, ifd\}$. Here is the problem: taking the S-period difference within a firm-product-destination changes the panel dimension along which components of the firm-product marginal cost ($\Delta_{s_{|ifd}}\mathcal{C}_t, \Delta_{s_{|ifd}}\mathcal{C}_{it}, \Delta_{s_{|ifd}}\mathcal{C}_{ft}, \Delta_{s_{|ifd}}\mathcal{C}_{ift}$) vary, which introduces possible biases due to a non-zero correlation between changes in cost components, and factors that are destination and time specific $\Delta_{s_{|ifd}}\mathcal{F}_{dt}$, e.g., destination-specific bilateral exchange rates. This is because selection of observations into the unbalanced, time-differenced panel depends on changes in bilateral exchange rates $\mathcal{F}_{dt}$ and the unobserved marginal cost, $\overline{mc}_{ift}$. 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. We provide a simulated example in B.3.1.

In comparison, the first stage of our TPSFE estimator yields:

$$\widetilde{p}_{ifdt} = \widetilde{\mathcal{F}}_d + \widetilde{\mathcal{F}}_{id} + \widetilde{\mathcal{F}}_{fd} + \widetilde{\mathcal{F}}_{dt} + \widetilde{\mathcal{F}}_{fdt} + \widetilde{\mathcal{F}}_{idt} + \widetilde{\mathcal{F}}_{ifd} + \widetilde{\mathcal{F}}_{ifdt} + \psi_{ifdt} \tag{76}$$

where $\widetilde{x}_{ifdt} \equiv x_{ifdt} - \frac{1}{n^D}\sum_d x_{ifdt} \quad \forall x \in \{p_{ifdt}, \mu_{ifdt}, mc_{ift}, \psi_{ifdt}\}$. Clearly, the demeaning process differences out all the factors that are not destination-specific, including the firm-product time-varying marginal cost. If any destination-specific marginal cost components are present, destination demeaning will subtract out the average marginal cost across all destinations at the firm-product-time level and yield a term ψ_{ifdt}, reflecting any production cost differences across sets of varieties (e.g., compositional differences) sold in different destination markets under the same product code for the same firm in a particular time period.

B.2.2 Identification condition of our proposed estimator under endogenously unbalanced panel

We now prove our proposed estimator require the same identification condition of the balanced panel case. For our proposed estimator, the identification condition can be written as

$$\frac{1}{n^{IFDT}}\sum_i\sum_f\sum_d\sum_t(\widetilde{mc}_{ifdt,D_{ift}}-\frac{1}{n_t^{IFD}}\sum_i\sum_f\sum_d\widetilde{mc}_{ifdt,D_{ift}})(\widetilde{e}_{dt,D_{ift}}-\frac{1}{n_t^{IFD}}\sum_i\sum_f\sum_d\widetilde{e}_{dt,D_{ift}})=0 \tag{77}$$

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

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 $n_{ift}^D\equiv|D_{ift}|$.

Note that

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

Therefore, we can derive a condition similar to (70) as

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

Note that the destination average of exchange rate is now firm, product and time specific, depending on the set of destinations D_{ift}, i.e.,

$$\left(\overline{e}_{t,D_{ift}}\equiv\frac{1}{n_{ift}^D}\sum_{d\in D_{ift}}e_{dt}\right)\neq\left(\overline{e}_t\equiv\frac{1}{n_t^{IFD}}\sum_i\sum_f\sum_d e_{dt}\right)$$

However, it is straightforward to see that

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

In an unbalanced panel, our estimator requires the same condition as specified in equation (73).

$$\frac{1}{n^{DT}}\sum_{d}\sum_{t}(\overline{\psi}_{dt}-\overline{\psi}_{d})(e_{dt}-\overline{e}_{d})=0 \tag{78}$$

B.2.3 Alternative partitions require a more demanding condition to mitigate potential endogenous selection of markets

We derive the condition for unbiasedness for two alternative and closed related partition methods that are commonly used in the exchange rate pass through literature. We show these methods can produce biased estimates due to endogenous selection of markets even in the case where the marginal cost component is not destination-specific. In general, the condition of alternative partitions can be simplified to into two terms, the covariance between the compositional error and exchange rates as in equation (78) and an additional term captures the endogenous selection of markets.

We start with an alternative partition of firm-product-destination and time fixed effects (ifd,t). We ignore the naive wrong applications of (ifd,t) in an unbalanced panel and discuss the correct implementation only. 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 decomposed into two terms using (4), i.e.,

$$\begin{aligned}&\frac{1}{n^{IFDT}}\sum_{i}\sum_{f}\sum_{d}\sum_{t}(\widetilde{\psi}_{ifdt,T_{ifd}}-\frac{1}{n^{IFD}_{t}}\sum_{i}\sum_{f}\sum_{d}\widetilde{\psi}_{ifdt,T_{ifd}})(\widetilde{e}_{dt,T_{ifd}}-\frac{1}{n^{IFD}_{t}}\sum_{i}\sum_{f}\sum_{d}\widetilde{e}_{dt,T_{ifd}})+\\&\frac{1}{n^{IFDT}}\sum_{i}\sum_{f}\sum_{d}\sum_{t}(\widetilde{\overline{mc}}_{ift,T_{ifd}}-\frac{1}{n^{IFD}_{t}}\sum_{i}\sum_{f}\sum_{d}\widetilde{\overline{mc}}_{ift,T_{ifd}})(\widetilde{e}_{dt,T_{ifd}}-\frac{1}{n^{IFD}_{t}}\sum_{i}\sum_{f}\sum_{d}\widetilde{e}_{dt,T_{ifd}})=0\end{aligned} \tag{79}$$

where

$$\begin{aligned}\widetilde{\psi}_{ifdt,T_{ifd}}&\equiv\psi_{ifdt}-\frac{1}{n^{T}_{ifd}}\sum_{d\in T_{ifd}}\psi_{ifdt}\\\widetilde{\overline{mc}}_{ift,T_{ifd}}&\equiv\overline{mc}_{ift}-\frac{1}{n^{T}_{ifd}}\sum_{t\in T_{ifd}}\overline{mc}_{ift}\\\widetilde{e}_{dt,T_{ifd}}&\equiv e_{dt}-\frac{1}{n^{T}_{ifd}}\sum_{t\in T_{ifd}}e_{dt}\end{aligned}$$

Note that, even if the compositional term ψ_{ifdt} is always zero, the second line of expression (79) may not necessarily be zero due to endogenous selections. The time demeaning operation at the firm-product-time level changes the dimensions along which the unobserved marginal cost $\overline{mc}_{ift}$

vary, making $\widetilde{\overline{mc}}_{ift,T_{ifd}}$ destination-specific and moving along all four dimensions.

We now simply equation (79) to get a more clearer expression. Note that

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

Thus, the second line of expression (79) can be rewritten as

$$\frac{1}{n^{IFDT}}\sum_i\sum_f\sum_d\sum_t(\overline{mc}_{ift} - \overline{mc}_{if,T_{ifd}} - \overline{mc}_t + \overline{mc})(e_{dt} - \overline{e}_{d,T_{ifd}} - \overline{e}_t + \overline{e}) \tag{80}$$

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

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

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 (81) may or may not be zero depending on the nature of the unbalancedness.

$$\frac{1}{n^{IFDT}}\sum_i\sum_f\sum_d\sum_t(\overline{mc}_{if} - \overline{mc}_{if,T_{ifd}})(\overline{e}_d - \overline{e}_{d,T_{ifd}}) \tag{81}$$

If the unbalanced panel arises from endogenous selection related to marginal cost shocks and exchange rate movements, expression (81) will in general not equal zero.

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

$$\frac{1}{n^{DT}} \sum_{d} \sum_{t} (\overline{\psi}_{dt} - \overline{\psi}_{d})(e_{dt} - \overline{e}_{d}) + \\ \frac{1}{n^{IFDT}} \sum_{i} \sum_{f} \sum_{d} \sum_{t} (\overline{mc}_{if} - \overline{mc}_{if,T_{ifd}})(\overline{e}_{d} - \overline{e}_{d,T_{ifd}}) = 0 \tag{82}$$

Similarly, the condition for taking time differences conditional on firm-product-destination triplets can be written as

$$\frac{1}{n^{IFDT}} \sum_{i} \sum_{f} \sum_{d} \sum_{t} (\Delta_{s_{|ifd}} \psi_{ifdt} - \frac{1}{n_t^{IFD}} \sum_{i} \sum_{f} \sum_{d} \Delta_{s_{|ifd}} \psi_{ifdt})(\Delta_{s_{|ifd}} e_{dt} - \frac{1}{n_t^{IFD}} \sum_{i} \sum_{f} \sum_{d} \Delta_{s_{|ifd}} e_{dt}) + \\ \frac{1}{n^{IFDT}} \sum_{i} \sum_{f} \sum_{d} \sum_{t} (\Delta_{s_{|ifd}} \overline{mc}_{ift} - \frac{1}{n_t^{IFD}} \sum_{i} \sum_{f} \sum_{d} \Delta_{s_{|ifd}} \overline{mc}_{ift})(\Delta_{s_{|ifd}} e_{dt} - \frac{1}{n_t^{IFD}} \sum_{i} \sum_{f} \sum_{d} \Delta_{s_{|ifd}} e_{dt}) = 0 \tag{83}$$

where

$$\Delta_{s_{|ifd}} \psi_{ifdt} \equiv \psi_{ifdt} - \psi_{ifd,t-s_{|ifd}} \\ \Delta_{s_{|ifd}} \overline{mc}_{ift} \equiv \overline{mc}_{ift} - \overline{mc}_{if,t-s_{|ifd}} \\ \Delta_{s_{|ifd}} e_{dt} \equiv e_{dt} - e_{d,t-s_{|ifd}}$$

Even if marginal cost is not destination-specific and the first line is always zero, estimates can still be biased as the second line of (83) can be very different from zero due to endogenous selection of markets. We find further decomposing (83) does not provide more intuition. We turn to illustrate the property of our estimator and compare to alternative methods with the following simulated examples.

B.3 Simulated Examples on Endogenous Market Selections and Destination Specific Marginal Costs

B.3.1 Simulated Example: The Bias from Endogenously Unbalanced Panels

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:

$$\begin{aligned} p_{fdt} &= \beta_1 e_{dt} + \beta_2 mc_{ft} + u_{fdt} \\ e_{dt} &= \mathcal{F}_d + \mathcal{F}_t + \mathcal{F}_d * \mathcal{F}_t \\ mc_{ft} &= \mathcal{C}_f + \mathcal{C}_t + \mathcal{C}_f * \mathcal{C}_t \end{aligned} \tag{84}$$

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 (85).

$$\begin{gathered} u_{fdt} = \mathcal{I}_1 \mathcal{C}_f + \mathcal{I}_2 \mathcal{F}_d + \mathcal{I}_3 \mathcal{F}_t + \epsilon_{fdt} \\ \mathcal{F}_d \sim N(0,1) \quad \mathcal{C}_f \sim N(0,1) \quad \mathcal{F}_t = \mathcal{C}_t \sim N(0,1) \quad \epsilon_{fdt} \sim N(0,1) \end{gathered} \tag{85}$$

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,

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

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.[41]

Table 10 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

[41] 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.

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 10: 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.

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.

$$\Delta_{s|fd} p_{fdt} = \beta_1 \Delta_{s|fd} e_{dt} + \beta_2 \Delta_{s|fd} mc_{ft} + \Delta_{s|fd} u_{fdt} \tag{86}$$

where

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

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 (87), the unobserved marginal cost term is controlled by the destination demeaning

process.

$$\widetilde{p}_{fdt,D_{ft}} = \beta_1 \widetilde{e}_{dt,D_{ft}} + \widetilde{u}_{fdt} \tag{87}$$
$$\widetilde{e}_{dt,D_{ft}} = e_{dt} - \frac{\sum_{d \in D_{ft}} e_{dt}}{n^D_{ft}} = \widetilde{\mathcal{F}}_{t,D_{ft}}(1 + \mathcal{F}_d)$$

B.3.2 Simulated Examples: Various Cases of Destination-Specific Cost Components

In what follows, we expand our numerical example in B.3.1 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.

In this exercise, it is important to note that condition (72) provides additional information helps to pin down the functional form of the compositional term. In general, we could have set $\psi_{fdt} = \mathcal{A}_d + \mathcal{B}_{ft} + \mathcal{A}_d * \mathcal{B}_{ft}$. However, as a deviation term, the compositional error must satisfy (72) suggests a multiplicative relationship between factors varying at the destination dimension, $\mathcal{A}_d$, and factors varying at other dimensions, $\mathcal{B}_{ft}$, i.e.,

$$\psi_{fdt} = \mathcal{A}_d * \mathcal{B}_{ft} \tag{88}$$

with the restriction that $\frac{1}{n^D_{ft}} \sum_{d \in D_{ft}} \mathcal{A}_d = 0 \; \forall ft$. In what follows, we will consider various formulations of $\mathcal{A}_d$ and $\mathcal{B}_{ft}$, and compare the performance of estimators.

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.,

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

Parameters are set to 1 in the simulation for simplicity, i.e., $\beta_1 = \beta_2 = 1$.

Table 11: 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 11 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 10, 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 12 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 12: Performance of Estimators in the Presence of Compositional Errors – Setup B

	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	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 13. 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 13: 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 14: 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 14 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 $\beta_1 = 1$.[42] 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 14, 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 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.

[42] 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 $\beta_1 + \mu_3 * \mu_2$.

B.4 A Structural Interpretation of Assumptions Required by Our Estimator

In this subsection, we extend the framework of De Loecker et al. (2016) to add the destination dimension and discuss the structural assumptions that would be required for our main identification condition (5) to be satisfied.

B.4.1 Assumptions

In this extension, we incorporate destination-specific inputs $\{\boldsymbol{V}_{fidt}, \boldsymbol{K}_{fidt}\}$ and productivity differences, Ψ_{fid} at the firm and product level. In addition, we allow for the production function and Hicks-neutral productivity to be firm-product specific.

$$Q_{fidt} = F_{fi}(\boldsymbol{V}_{fidt}, \boldsymbol{K}_{fidt})\Omega_{fit}\Psi_{fid} \tag{89}$$

where Q_{fidt} represents the quantity of exports for product i from firm f to destinations d at time t; $\boldsymbol{V}_{fidt}$ denotes a vector of variable inputs, $\{V^1_{fidt}, V^2_{fidt}, ..., V^v_{fidt}\}$; $\boldsymbol{K}_{fit}$ denotes a vector of dynamic inputs; a firm-product pair make decisions on allocating its dynamic inputs across destinations D_{fit} in each time period, $\{K^1_{fidt}, K^2_{fidt}, ..., K^k_{fidt}\}$.

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

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

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

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

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

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

7. The state variables of the firm are

$$\boldsymbol{s}_{fit} = \{D_{fit}, \boldsymbol{K}_{fit}, \Omega_{fit}, \Psi_{fid}, \boldsymbol{G}_{fi}, \boldsymbol{r}_{fidt}\} \tag{90}$$

where $\boldsymbol{G}_{fi}$ includes variables indicating firm and product properties, e.g., firm registration types, product differentiation indicators. $\boldsymbol{r}_{fidt}$ collects other observables including variables

that track the destination market conditions, such as the bilateral exchange rate and destination CPI.

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

Note that the assumptions 1, 2, 4, 8 are standard in the literature. We inherit them from De Loecker et al. (2016) but allow the production function to be firm specific and the Hicks-neutral productivity to depend on the product. Assumption 5 is a relaxation rather than a restriction compared to the existing literature as it allows the additive productivity to be destination-specific.

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

The assumption that is crucial to our identification is 3. This condition implies the marginal cost at the firm-product-destination level does not depend on the quantity produced. If changes in relative demand across destinations, which will lead to quantity differences as long as the price is not fully sticky in the destination market, is also associated changes in relative marginal costs, condition 5 will be violated. As described in the next subsection, at the solution of the cost minimization problem, this condition ensures that the difference in the marginal costs across destinations is proportional to technology differences $\frac{\Psi_{fid'}}{\Psi_{fid}}$.

B.4.2 The cost minimization problem of a firm-product pair

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

Where K_{fit}^{k} is the accumulated capital input k in the previous period; K_{fidt}^{k} stands for the corresponding allocation for destination d; R_{fit}^{k} is the implied cost of capital.[43]

F.O.C.

$$\frac{\partial \mathcal{L}_{fit}}{\partial V_{fidt}^{v}} = W_{fit}^{v} - \lambda_{fidt} \Omega_{fit} \Psi_{fid} \frac{\partial F_{fi}(.)}{\partial V_{fidt}^{v}} = 0 \tag{91}$$

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

$$\frac{\partial \mathcal{L}_{fit}}{\partial K^k_{fidt}} = R^k_{fit} - \lambda_{fidt}\Omega_{fit}\Psi_{fid}\frac{\partial F_{fi}(.)}{\partial K^k_{fidt}} = 0 \tag{92}$$

Conditions (91) and (92) need to hold across inputs and across destinations, which implies

$$\frac{W^1_{fit}}{W^v_{fit}} = \frac{\frac{\partial F_{fi}(.)}{\partial V^1_{f,i,1,t}}}{\frac{\partial F_{fi}(.)}{\partial V^v_{f,i,1,t}}} = \frac{\frac{\partial F_{fi}(.)}{\partial V^1_{f,i,2,t}}}{\frac{\partial F_{fi}(.)}{\partial V^v_{f,i,2,t}}} = ... = \frac{\frac{\partial F_{fi}(.)}{\partial V^1_{f,i,D_{fit},t}}}{\frac{\partial F_{fi}(.)}{\partial V^v_{f,i,D_{fit},t}}} \qquad \forall v = 1, ..., V \tag{93}$$

$$\frac{W^v_{fit}}{R^k_{fit}} = \frac{\frac{\partial F_{fi}(.)}{\partial V^v_{f,i,1,t}}}{\frac{\partial F_{fi}(.)}{\partial K^k_{f,i,1,t}}} = \frac{\frac{\partial F_{fi}(.)}{\partial V^v_{f,i,2,t}}}{\frac{\partial F_{fi}(.)}{\partial K^k_{f,i,2,t}}} = ... = \frac{\frac{\partial F_{fi}(.)}{\partial V^v_{f,i,D_{fit},t}}}{\frac{\partial F_{fi}(.)}{\partial K^k_{f,i,D_{fit},t}}} \qquad \forall v, k \tag{94}$$

Note that the production function is assumed to be firm-product specific and constant return to scale. Together with equations (93) and (94), these assumptions imply the allocation of variable inputs is proportional to the ratio of the productivity deflated outputs across destinations. That is,

$$\frac{Q_{fidt}}{\Omega_{fit}\Psi_{fid}} = c \cdot \frac{Q_{fid't}}{\Omega_{fit}\Psi_{fid'}} \quad \rightarrow \quad c\boldsymbol{V}^*_{fidt} = \boldsymbol{V}^*_{fid't} \quad \text{and} \quad c\boldsymbol{K}^*_{fidt} = \boldsymbol{K}^*_{fid't} \tag{95}$$

Utilizing the relationship of (95) and the assumption that $F_{fi}(.)$ is constant return to scale, we can show

$$c_{fidt}\cdot\frac{\partial F_{fi}(\boldsymbol{V}^*_{fidt}, \boldsymbol{K}^*_{fidt})}{\partial V^v_{fidt}} = \frac{\partial [c_{fidt}F_{fi}(\boldsymbol{V}^*_{fidt}, \boldsymbol{K}^*_{fidt})]}{\partial V^v_{fidt}} = \frac{\partial F_{fi}(c_{fidt}\boldsymbol{V}^*_{fidt}, c_{fidt}\boldsymbol{K}^*_{fidt})}{\partial V^v_{fidt}} = \frac{\partial F_{fi}(\boldsymbol{V}^*_{fid't}, \boldsymbol{K}^*_{fid't})}{\partial V^v_{fid't}} \tag{96}$$

where $c_{fidt} \equiv \frac{Q_{fidt}\Psi_{fid'}}{Q_{fid't}\Psi_{fid}}$.

Rearrange (93) and get

$$\lambda_{fidt} = \left(\frac{\Omega_{fit}\Psi_{fid}}{W^v_{fit}}\frac{\partial F_{fi}(\boldsymbol{V}_{fidt}, \boldsymbol{K}_{fidt})}{\partial V^v_{fidt}}\right)^{-1} \tag{97}$$

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

$$\frac{\lambda_{fidt}/Q_{ifdt}}{\lambda_{fid't}/Q_{ifd't}} = \frac{\Psi_{fid'}}{\Psi_{fid}} \tag{98}$$

Although the marginal cost is firm-product-destination specific and time varying, the relative marginal cost is not. Therefore, condition (5) is satisfied.

B.4.3 A alternative extension

An alternative and more direct extension of De Loecker et al. (2016) is to simply redefine the product variety in their model. Notably, if we redefine product + destination as a variety, i.e., $j = \{i, d\}$, then the original setting and assumptions will go through.

We argue that this extension is less favorable for two reasons. The first one is practical. De Loecker et al. (2016) define a product variety as a two-digit industry. The need to define a product at industry level is mainly due to data restrictions. Had they used a more refined product definition, their estimator would suffer from a small sample problem and they would not have enough power to estimate. The small sample problem will be much more serve if one defines product + destination as a variety. This is not only due to the smaller number of observations by splitting the estimation sample into a smaller cell but also because of the frequent changes in the set of destinations a firm-product pair exports to.

The second one is related to the correct conceptual assumptions regarding production functions. De Loecker et al. (2016) relies on the assumption that the functional form of the production function is the same for single- and multi-product firms. In the context of this extension, the identification condition would require the functional form of the production function to be product-destination specific and invariant along the firm dimension. In the context of our problem in which controlling for firm-product level marginal cost is the primary concern, we think that keeping the flexibility of the production function at the product level is extremely valuable.

C Data

C.1 Descriptive Statistics of Chinese Customs Data

China's dramatic increase in export value over 2000-2014 includes extensive margin net entry on both the firm and firm-product dimensions. See Table 15.

Table 15: Chinese exports: firms, products and values, 2000-2014

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

C.2 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 16 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

Table 16: Multi-product, multi-destination exporters (2007)

		Number of Countries				
	No. of Products	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.

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 16, 33.1+14.7+25.0) and are responsible for 94.6% of export value (row 5 of the bottom panel of table 16).[44] 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.

[44]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 16, 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.

C.3 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, 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.[45]

Figure 3 presents the shares of import transactions and import value into the UK from China by invoicing currency.[46] Results are reported for three currencies, the euro (EUR), pound sterling (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."[47] 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.[48]

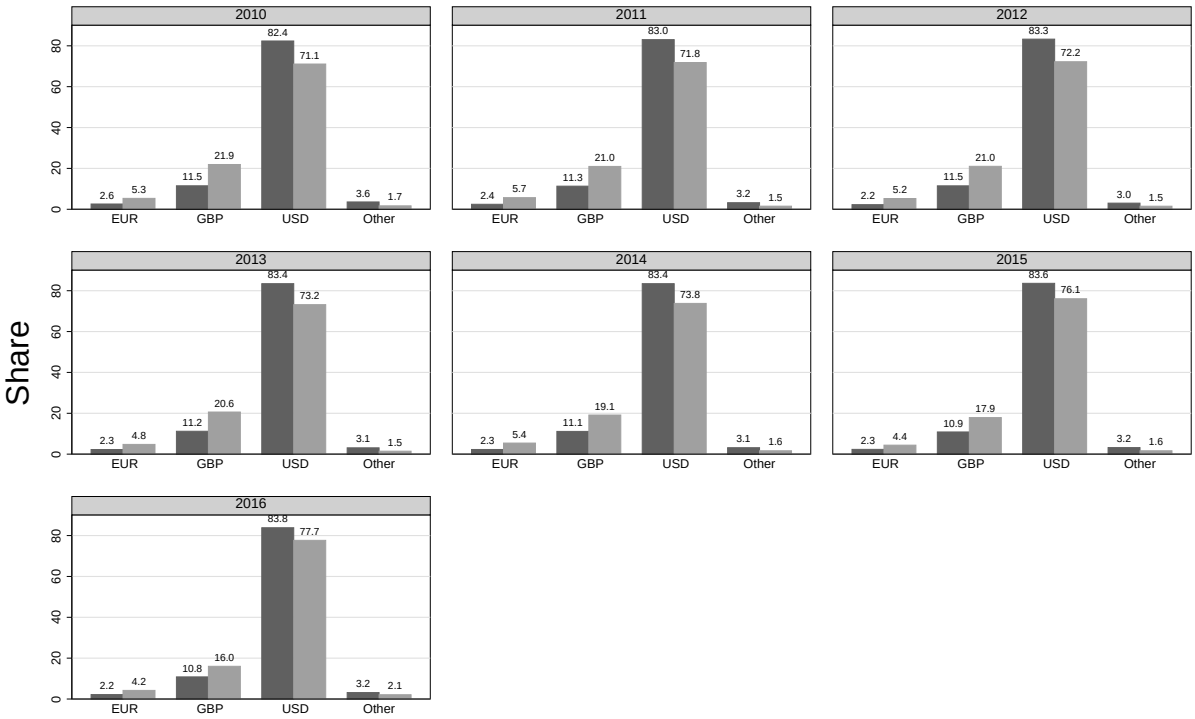
[45] The reporting requirements for invoice currency are described in *UK Non-EU Trade by declared currency of Invoice (2016)*, published 25 April 2017. See page 7: "Only data received through the administrative Customs data collection has a currency of invoice declared... For Non-EU import trade, businesses 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."

[46] To construct this figure, we begin with the universe of UK import transactions for goods originating from China over 2010-2016. Then, we aggregate all transactions within a year that are reported for a firm-CN08product-quantity measure-currency quadruplet to an annual observation for that quadruplet. The variable "quantity measure" records whether a transaction for a CN08 product is reported in kilograms or a supplementary quantity unit like "items" or "pairs." This leaves us with 2.004 million annual transactions which we use to construct figure 3.

[47] 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.

[48] See also Goldberg and Tille (2008) and Goldberg and Tille (2016) who document relatively large shares of

Figure 3: Invoicing currencies for UK imports from China



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

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 4 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 sizeable. In figure 4, these are indicated by "NR." [49]

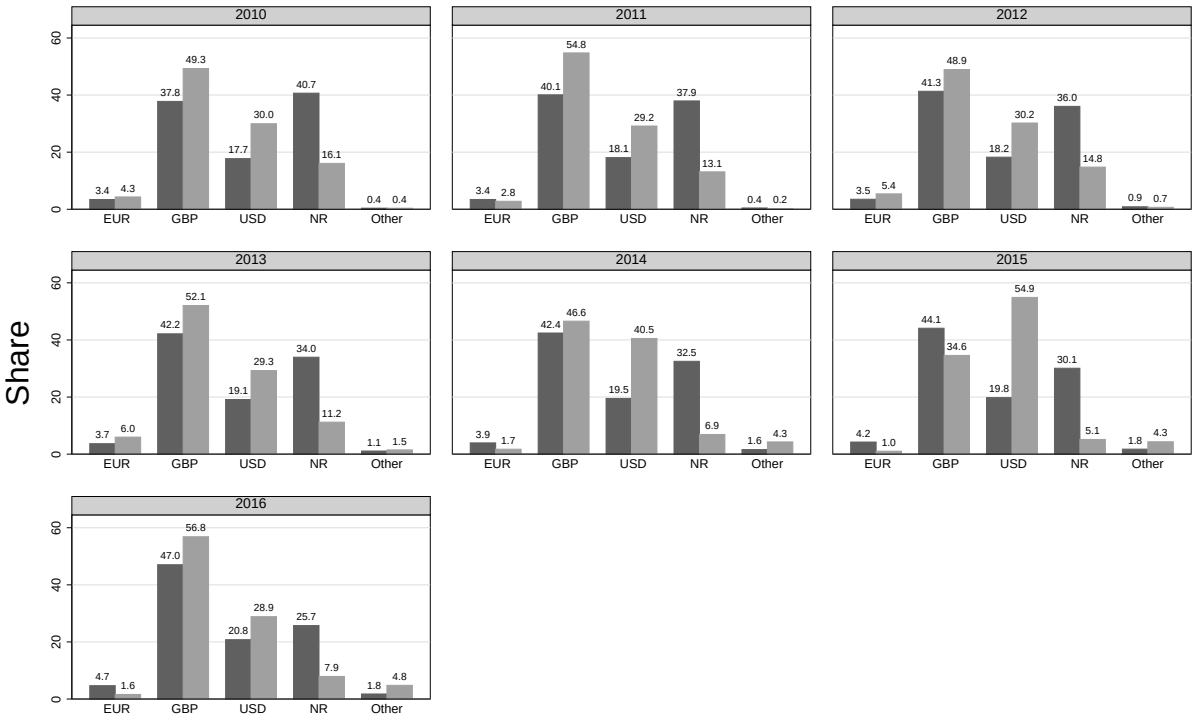
In almost all years the British pound sterling is the most important currency of invoicing for exports to China, both in transaction and value terms. Interestingly, the sterling does not dominate invoicing of exports entirely; substantial shares of exports are invoiced in US dollars. The euro appears 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. Pre-

exports invoiced in dollars for many countries.

[49]To construct figure 4 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 4: Invoicing currencies for UK exports to China



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

sumably 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 one single price for its product in dollars: this practice (arguably maximizing the markup relative to global demand) would rule out destination specific adjustment in markups. In this case, our TPSFE estimation should yield insignificant results. The same would be true if firms set different dollar prices across markets (in line with evidence of deviations from the law of one price), but do not adjust them in response to fluctuations in the exchange rate.

This suggests that our TPSFE estimator of markup elasticities can provide evidence on a relevant implication of what Gopinath has dubbed the 'International Price System.' Specifically, our empirical findings can inform us about the possibility of dollar invoicing translating into a 'reference price system' in which firms do not exploit market-specific demand elasticities, but price in relation to global demand. If a reference price system dominates, we would expect to observe firms setting one prevailing price in the global market for manufactured goods as they do for commodities.

C.4 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.

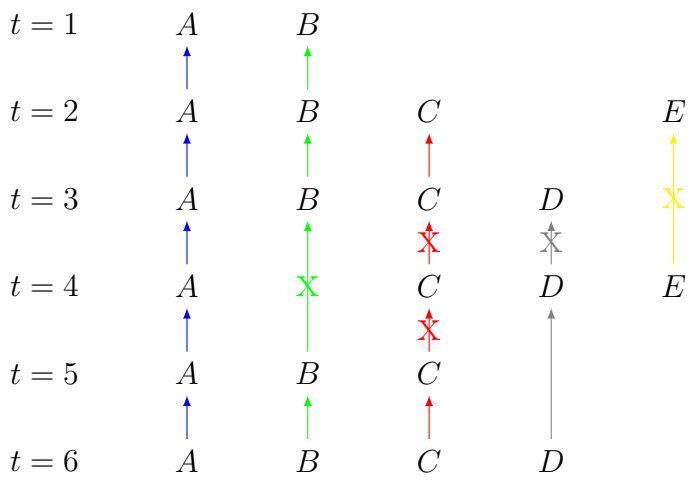
Consider a firm exporting a product to five countries, A through E, over 6 time periods. In the following matrix, rows are time periods and columns are destination countries. Empty elements in the matrix indicate that there was no trade.

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

The following matrix records prices by destination country and time:

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

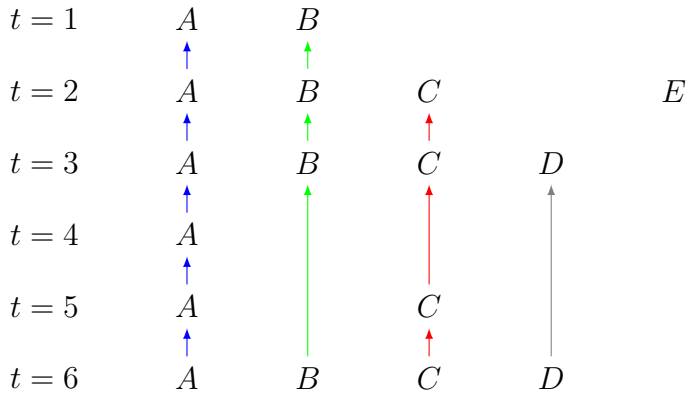
Suppose the pricing currency is the dollar and we want to identify price changes in dollars. First, we compare prices denominated in dollars (vertically) at the firm-product-destination level as illustrated in the following figure. Price changes less than 5% are marked with "x".



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 $|p_{C,5} - p_{C,4}| < 5\%$.[50] Rather, we repeat the above step using the remaining observations as illustrated below.



[50] 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.[51] Note that as no price changes can be formulated for the single trade record $p_{E,2}$, this observation is dropped from our sample.

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

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

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

In this example, we find 5 trade patterns, i.e., $A - B$, $A - B - C$, $A - B - C - D$, A, $A - C$, but only one pattern, $A - B - C - D$, which appears at least two times. To compare the change in relative prices across destinations, we require the same trade pattern be observed at least two times in the price-change-filtered dataset.[52] 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[53] (i.e., this is the second step of the TPSFE estimator).

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

[52] 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.

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

Table 17: A real data example of changing trade patterns: Exports of tomato paste (HS 20029010) by the firm with identifier 6512910023

C.5 Data cleaning process and the number of observations

Table 18: Stage 0 - Raw

	Observations	Destinations	8-digit HS Codes	Firms	Years
Number of unique values	108,465,375	246	10,002	581,141	15

Table 19: Stage 1 - Drop exports to the U.S. and Hong Kong

	Observations	Destinations	8-digit HS Codes	Firms	Years
Number of unique values	92,308,538	244	9,959	545,175	15

Table 20: Stage 2 - Drop if the destination identifier, product identifier or value of exports is missing; Drop duplicated company names

	Observations	Destinations	8-digit HS Codes	Firms	Years
Number of unique values	92,177,750	243	9,954	545,133	15

Table 21: Stage 3 - Collapse at firm-product-destionation-year level; integrating 17 eurozone countries into a single economic entity

	Observations	Destinations	8-digit HS Codes	Firms	Years
Number of unique values	83,439,048	243	9,954	545,133	15

Table 22: Stage 4 - Drop observations if bilateral exchange rates or destination CPI is missing

	Observations	Destinations	8-digit HS	6-digit HS	Firms	Years
Number of unique values	77,511,443	157	9,929	5,867	532,530	15

Table 23: Stage 5 - Drop if no price change (in RMB) at the firm-destination-product level

	Observations	Destinations	Products	6-digit HS	Firms	Years
Number of unique values	72,792,147	157	20,347	5,867	532,530	15

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

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

Table 24: Stage 6 - Drop single-destination firm-product-year triplets

	Observations	Destinations	Products	6-digit HS	Firms	Years
Number of unique values	50,355,418	157	17,258	5,446	356,541	15

Table 25: Stage 7 - Drop single-year firm-product-destination triplets

	Observations	Destinations	Products	6-digit HS	Firms	Years
Number of unique values	23,750,519	154	14,611	5,051	238,610	15

Finally, we drop "single-year firm-product-trade_pattern triplets." Including these observations will not change estimates of our proposed estimators[54] but over-report the number of observations in the estimation sample.

Table 26: Stage 8 - Formulating trade pattern; Drop single-year firm-product-trade_pattern triplets

	Observations	Destinations	Products	6-digit HS	Firms	Years
Number of unique values	5,940,011	154	14,172	5,007	209,499	15

C.6 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.

[54] These observations are entirely absorbed by our fixed effects and do not provide additional variation for identification. After applying destination demean at the firm-product-time level and trade pattern fixed effects, the residual variation is zero for all dependent and independent variables.

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.

C.7 Additional Information on the CCHS Classification

To illustrate how measure words encode meaning in Chinese, consider the problem of counting three small objects. Chinese grammar requires the use of a measure word between the number and the noun being counted. Thus, to say "three ballpoint pens," or "three kitchen knives," one would say the English equivalent of "three long-thin-cylindrical-objects [zhī, 支] ballpoint pens" and "three objects-with-a-handle [bǎ, 把] kitchen knives."[55] 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

[55]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.[56]

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 27 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.

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

Table 27: 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 28, 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 28: 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.

For twenty industrial sectors, Table 29 reports the share of products in each sector that are classified as high differentiation according to the Corsetti, Crowley, Han, and Song (CCHS) classification. For the 36 measure words in our estimation dataset, we categorize goods measured with the 24 count classifiers as high differentiation, while goods measured with 12 mass classifiers are treated as low differentiation.[57] 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

[57]We thank Prof. Lisa Lai-Shen Cheng for her feedback on our classification of measure words from the Chinese Customs Database into count and mass classifiers.

Table 29: 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.

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.

C.7.1 Rauch classification for China exports

In order to provide a Rauch classification for each product in the Chinese Customs Database, it was necessary to concord the SITC Rev. 2 product codes from Rauch's classification to HS06 product codes used in the Chinese Customs Database.

Table 30: 6-digit HS code matching rate with Rauch classification using HS2002toSITC2 concordance table and the conservative version of Rauch classification

	Number of 6-digit HS codes	Percent
Matched (Unique Rauch Classification for Each HS Code)	4,589	78.30
Unmatched (Multiple Rauch Classifications for Each HS Code)	1,272	21.70
Total	5,861	100.00

Table 31: 6-digit HS code matching rate with Rauch classification using HS2007toSITC2 concordance table and the liberal version of Rauch classification

	Number of 6-digit HS codes	Percent
Matched (Unique Rauch Classification for Each HS Code)	4,438	80.93
Unmatched (Multiple Rauch Classifications for Each HS Code)	1,046	19.07
Total	5,484	100.00

D Further Analysis: Firms, Markups and Market Power

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 4.2, we provided evidence that strategic pricing to market and markup adjustments are more prominent in the markets for high differentiation goods, especially consumption goods, while quantitatively less pronounced in the markets for low differentiation manufactured goods with higher degrees of competition. We now dig deeper into the Chinese Customs Database, and examine how to square our results 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).[58] 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 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.

D.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.

[58] 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.

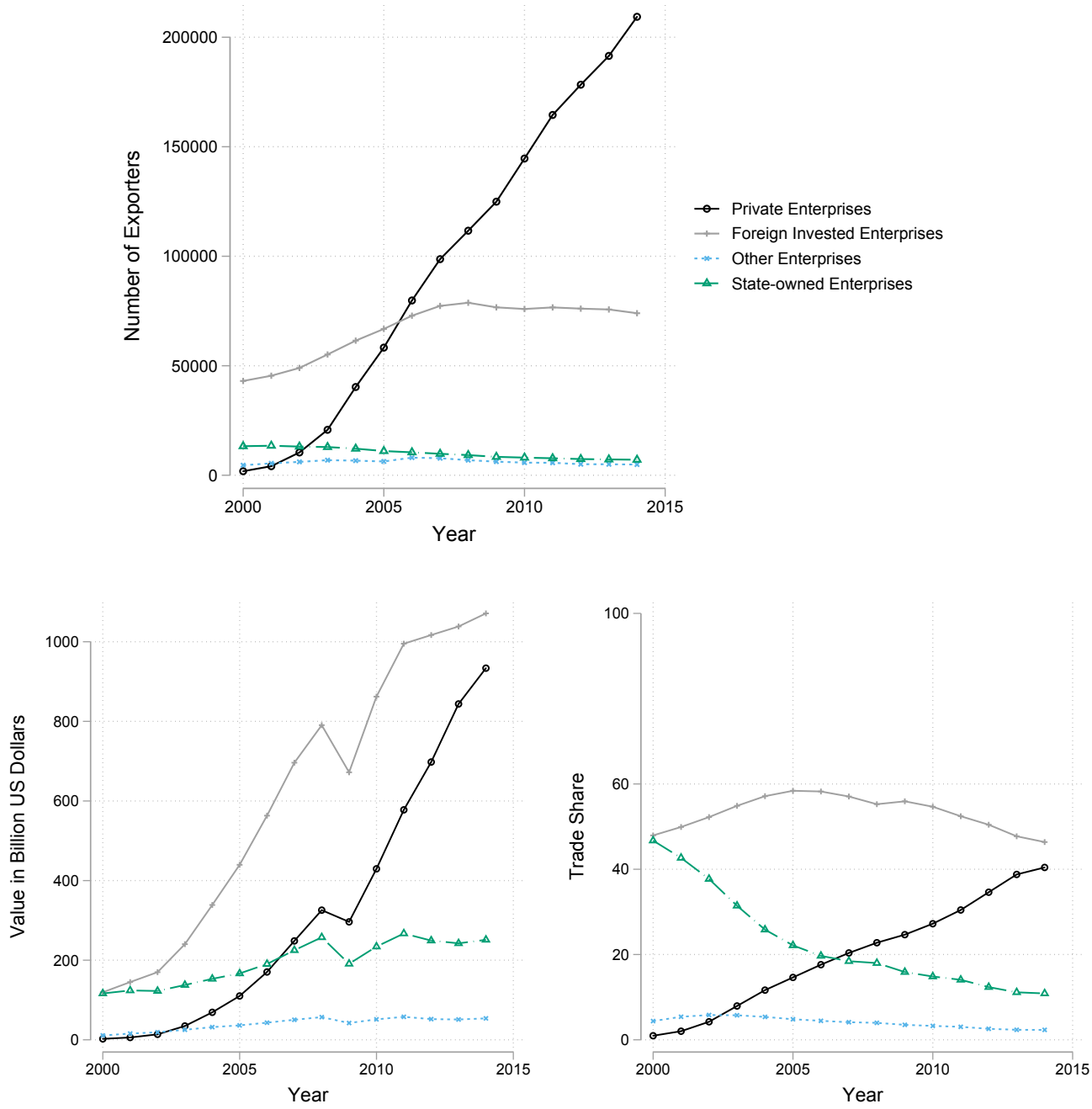


Figure 5: The changing face of Chinese exporters, 2000-2014

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.

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.[59] 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 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.[60]

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.

[59] 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.

[60] 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.

D.2 The market power of Chinese and foreign firms

Evidence on price, markup and supply elasticities by firm type is presented in table 32. 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 32, 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,

Relative to FIEs, the export price response to exchange rates by SOEs is smaller, 0.32 (see row 1, column (1) of table 32), 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 32). 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.[61]

The second and third panels of table 32 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

[61] 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 32: 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 (12). 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 (12). The "CMSE" column is estimated based on equations (10) and (11). † 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 *.

panel of table 32 cannot be attributed to a different typology of goods produced and exported across groups. Second, for each type of firm, results are consistent with our findings in section 4. Markup elasticities are higher for high-differentiation goods than for low-differentiation goods. Cross market supply elasticities are correspondingly lower for the former and higher for the latter group of goods.

To better appreciate the meaning and potential implications of our results for theory and policy, consider the response of different types of firms and products to an idiosyncratic appreciation of a foreign currency, say, the Mexican peso, relative to the renminbi. For private firms exporting goods with low differentiation, the depreciation of the renminbi leads to relatively high yet not complete pass through into the peso-denominated prices (1-.07 =93 percent, from row 9, column

(1) of table 32), and a small (2%) increase in the markup. This small increase in the markup 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 32). 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 32). 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.[62]

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

D.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 (33). 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)).

Table 33: 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 (12). 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 (12). The "CMSE" column is estimated based on equations (10) and (11). † 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 *.

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

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)).