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

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SM1 Data

SM1.1 Chinese customs data

China's export growth exploded over 2000-2014 (see table SM1-1). Statistics from customs data on firms, HS08 products, and firm-products highlight the growth at the extensive margin, including both net entry of firms, and net entry of firm-products. The total number of active exporters almost quintupled over our sample period, from 62,746 in 2000 to 295,309 in 2014. The number of annual transactions at the firm-HS08 product level increased at roughly the same pace as the number of exporters, from about 904 thousand in 2000 to 4.56 million in 2014. The value of total exports measured in dollars increased ten-fold from 2000 to 2014.

Table SM1-1: Chinese exports: firms, products and values, 2000-2014

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

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

In figure SM1-1, we lay out some basic facts about the evolution of different types of firms among Chinese exporters. In the Chinese Customs Database, firms report their registration type in one of the following eight categories: state-owned enterprise, Sino-foreign contractual joint venture,

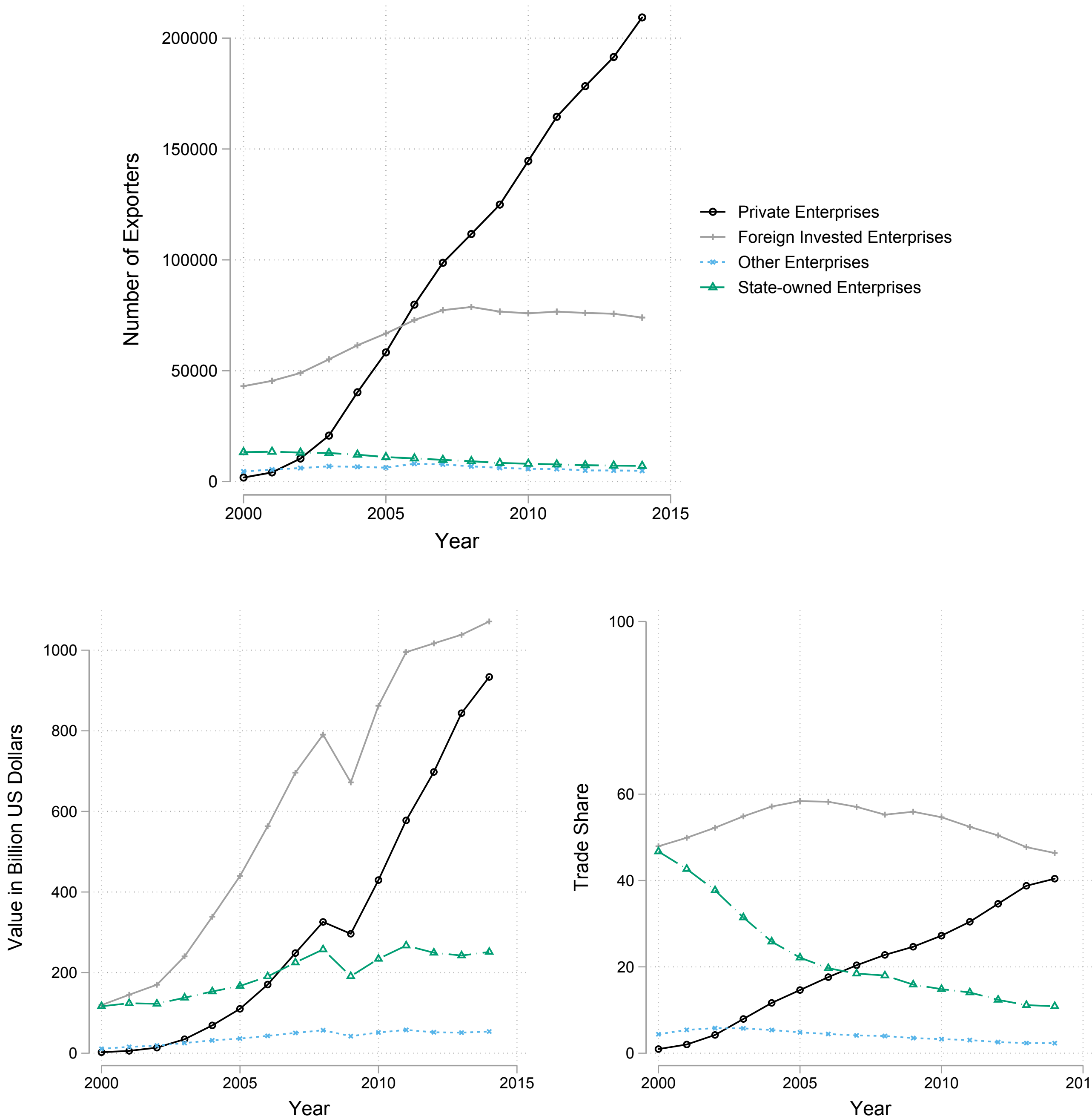


Figure SM1-1: The changing face of Chinese exporters, 2000-2014

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

Sino-foreign equity joint venture, wholly foreign owned enterprise, collective enterprise, private enterprise, individual business, and "other" enterprise. We combine Sino-foreign contractual joint ventures, Sino-foreign equity joint ventures, and wholly foreign owned enterprises into a single category - foreign invested enterprises (FIEs). Firms with other ownership structures, including collectives, individual businesses, and "other" enterprises, are lumped together under the descriptor "Other" enterprises.

A well-known fact is the extraordinary rate of entry into export activity by private enterprises. This is apparent in the top panel of the figure. From being a small and neglectable group in 2000, the number of private enterprises directly exporting goods from China to the rest of the world rose to over 200,000 by 2014.[1] Perhaps less known and understood, however, is the economic weight of a different category of exporters *from* China, the foreign-invested enterprises (FIEs). After a slow and steady rise between 2000 and 2006, their number stabilized at about 75,000 firms—dwarfing the presence of state-owned enterprises (SOEs). Indeed, in spite of the attention paid to them by the media, there were only 10,000 registered SOEs at the start of our sample period. This number gradually fell over time, as successive policy initiatives favored their privatization, or led some of them to exit from foreign markets (top panel, figure SM1-1).

The key message from the top panel of figure SM1-1 is reinforced by the evidence on export values and shares by different types of firms, shown in the bottom panel. By export value and share of total exports, the most important single group of exporters from China is that of foreign-invested enterprises. In 2014, the value of their exports was over US $1 trillion (bottom left panel of figure SM1-1). Over the period, exports from China that originated from firms that are wholly or partially owned by foreigners fluctuated between 45 and 58% of China's total exports.[2]

Conversely, the weight of SOEs, which were essentially at par with FIEs in 2000, declined dramatically from 2000 to 2007 and then settled into a slow and steady negative trend (bottom left panel, figure SM1-1). This is clear evidence that the role of SOEs in foreign trade has been far less dynamic than that of other types of firms. However, the diminishing weight of SOEs in foreign trade has been more than made up by private firms—reflecting both entry of new firms into export markets and privatization of SOEs. By the end of the sample, private firms account for a striking 40% of Chinese exports. We stress nonetheless that this large shift in export shares

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

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

between SOEs and private firms has not (so far at least) dented the share of exports by FIEs, which has remained quite stable over our sample.

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

SM1.3 Macroeconomic data

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

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

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

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

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

SM1.4 Additional information on the CCHS classification

SM1.4.1 The use of measure words in Chinese grammar

To illustrate how measure words encode meaning in Chinese, consider the problem of counting three small objects. Chinese grammar requires the use of a measure word between the number and the noun being counted. Thus, to say "three ballpoint pens," or "three kitchen knives," one would say the English equivalent of "three long-thin-cylindrical-objects [zhī, 支] ballpoint pens" and "three objects-with-a-handle [bǎ, 把] kitchen knives."[3] Both of these objects, ballpoint pens and kitchen knives, are measured with count/discrete classifiers (zhī and bǎ, respectively) and are, in our classification, high differentiation goods. In contrast, products reported with mass/continuous classifiers including kilograms (cereal grains, industrial chemicals), meters (cotton fabric, photographic film), and cubic meters (chemical gases, lumber) are low differentiation goods. Because measure words encode physical features of the object being counted, they allow us to identify when statistical reporting is for a high versus low differentiation good. According to Cheng and Sybesma (1999), "...the distinction between the two types of classifiers is made with explicit reference to two different types of nouns: nouns that come with a built-in semantic partitioning and nouns that do not – that is, count nouns and mass nouns."

SM1.4.2 Comparison to quantity-reporting in other customs systems

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

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

reporting systems.

Like Chinese, Japanese requires the use of measure words between a number word and a noun when counting. Documentation for Japanese trade declarations instructs that the WCO measurement unit “NO” (the English abbreviation for number of items) subsumes 11 indigenous Japanese measure words used with discrete nouns (個、本、枚、頭、羽、匹、台、両、機、隻、着). We interpret these instructions from Japanese customs declarations as a validation of our approach of using count classifiers in the Chinese Customs Database to identify discrete products in the Harmonized System. However, because the official measure of discrete items used in Japanese customs data is an English word, we cannot build a linguistics-based classification of discrete and continuous goods directly from measure words in Japanese data. This is one reason why we prefer to build the classification from Chinese rather than Japanese trade data.[4]

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

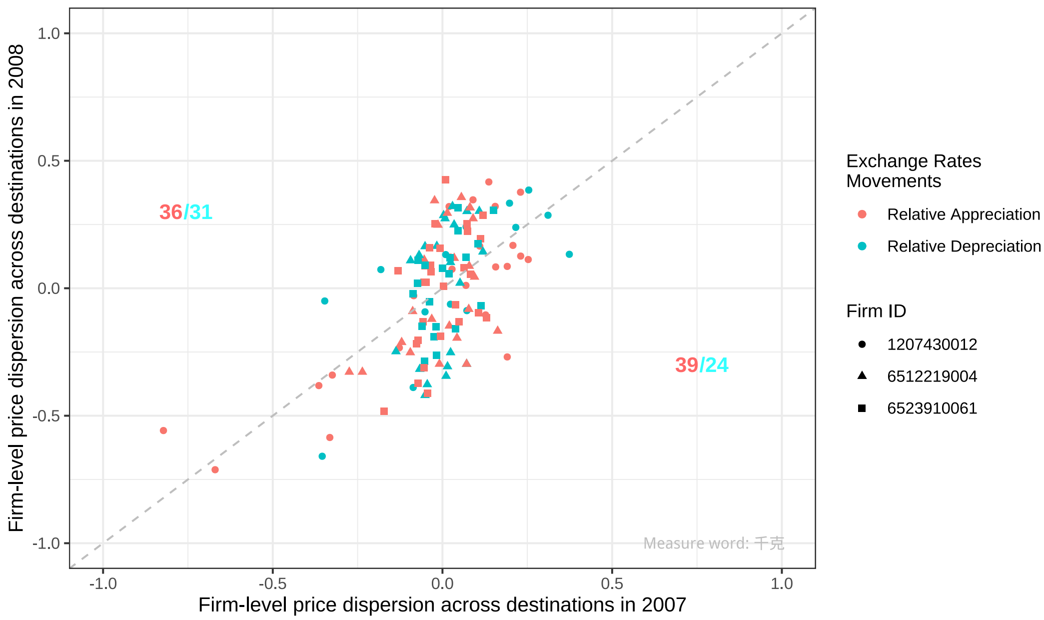
SM1.4.3 The dispersion of prices for high and low differentiation goods: A telling example

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

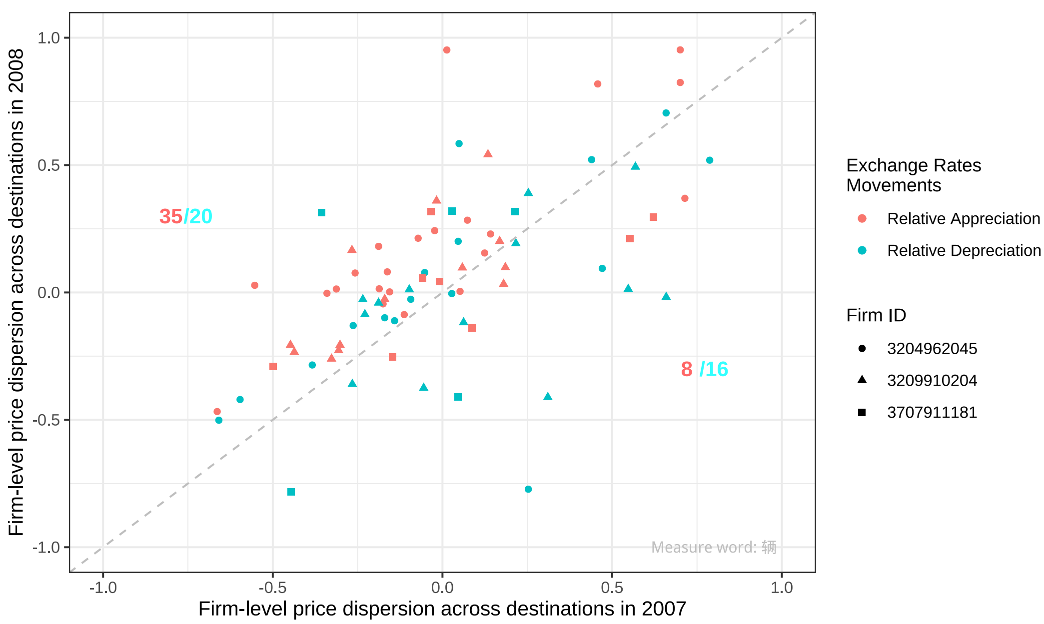
In figure SM1-2, we plot the dispersion of price residuals across destinations for the top three exporters of tomato paste (upper panel) and wheeled tractors (lower panel) in 2007 and 2008. For

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

Figure SM1-2: Price dispersion across destinations for top three firms in 2007 and 2008



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



Example 2: Wheeled Tractors (a high differentiation product)

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

each annual observation of a sale to a destination, we calculate the deviation of the sales price from its mean across all destinations within the firm-product-year triplet (where sales price is the log unit value in renminbi), i.e. $uv_{fidt} - \overline{uv}_{fit}$, and plot these deviations using different shapes (i.e., triangle, square, and circle) for each firm. The x-axis measures positive and negative deviations of the sales price from the mean value in 2007; the y-axis measures the deviations from the mean in 2008.[5] Any observation on the 45 degree line is a product whose relative premium or discount in its destination d did not change between 2007 and 2008. Thus, a point lying on the 45 degree line at 0.2 represents a product that was sold in some destination d at a 20% premium over the firm's mean price in both 2007 and 2008. An observation plotted *above* the 45 degree line depicts a product-destination whose price residual increased between 2007 and 2008 *relative* to the firm's sales of the good in other destinations. Conversely, an observation plotted below the 45 degree line represents a product-destination that saw its relative price fall.

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

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

SM1.4.4 An example of the fine detail in Chinese measure words

To illustrate the variety of count classifiers used for similar objects, note that "Women's or girls' suits of synthetic fibres, knitted or crocheted" (HS61042300) and "Women's or girls' jackets & blazers, of synthetic fibres, knitted or crocheted" (HS61043300) are measured with two distinct Chinese count classifiers, "tào, 套" and "jiàn, 件," respectively. Further, table SM1-2 documents

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

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

Two further points can be drawn from this table. First, this table illustrates that while Chinese customs statistics are reported for eight digits, in many cases, the final two digits of Chinese customs codes are 00, indicating that the eight digit code is identical to the corresponding six-digit code in the universal Harmonized System. This exemplifies a wider observation that only a single Chinese measure word is used to report quantity for all products in most six-digit HS code. By extension, Chinese measure words can be used to develop a universal classification for the Harmonized System at the six-digit product level. Second, the discrete noun "knife" or 'dao' (刀) appears in the description of every product reported below. This suggest that it would be theoretically possible to develop a binary classification system of Harmonized System products as discrete versus continuous through the use of natural-language processing software that is trained to recognize discrete nouns in any language. In this light, the use of Chinese measure words to identify discrete nouns can be seen as a shortcut in which the linguistic classification of Chinese measure words replaces the data training step.

Table SM1-2: Examples of count classifiers in the Chinese Customs Database

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

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

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

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

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

(a) Share of goods by classification: observation weighted

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

(b) Share of goods by classification: value weighted

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

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

SM1.4.6 Variation in the CCHS classification across industrial sectors

For twenty industrial sectors, Table SM1-4 reports the share of products in each sector that are classified as high differentiation according to the Corsetti, Crowley, Han, and Song (CCHS) classification. For the 36 measure words in our estimation dataset, we categorize goods measured with the 24 count classifiers as high differentiation, while goods measured with 12 mass classifiers

Table SM1-4: CCHS product classification across sectors

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

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

are treated as low differentiation.[6] Column one lists the HS chapters that define the sector. The second column provides the sector's share in China's total exports over 2000-2014. Quantitatively, important export sectors with large shares of high differentiation goods include optical and photographic equipment (79.7 percent), machinery and mechanical appliances (73.1 percent), textiles and apparel (68.4 percent), vehicles and aircraft (66.1 percent), stone and plaster articles (65.0 percent), leather goods (58.6 percent), and plastics and rubber articles (15.0 percent). The share of high differentiation products across sectors varies widely, but lines up with our prior Machinery and mechanical appliances and vehicles and aircraft are dominated by CCHS high differentiation goods while virtually all chemicals and base metal products are low differentiation.

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

SM1.4.7 Applying Rauch's classification to Chinese exports

In order to provide a Rauch classification for HS08 products in the Chinese Customs Database, it was first necessary to concord the SITC Rev. 2 product codes from Rauch's classification to universal HS06 product codes. At the HS06 level, 80% of products map into a unique category – differentiated, reference priced or organized exchange – but 20% of products have no unique mapping and are left unclassified. As noted in table 3, when applied to the universe of Chinese exports at the HS08 level, the 1-to-many and many-to-many concordance issue means approximately 12% of firm-product observations cannot be classified into Rauch categories.

Table SM1-5: Mapping HS06 (2007) products to Rauch categories (Rauch's liberal classification)

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

SM1.4.8 Integrating the CCHS and Rauch classification systems

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

To highlight the contribution of our product-feature-based classification system relative to Rauch (1999)'s market-structure based classification, we now integrate the two in our empirical analysis. Results are shown in table SM1-6.

Table SM1-6: Markup Elasticity by Rauch Classification

Category	All	HD Goods	LD Goods	n. of obs
2000 – 2005				
Differentiated Products	0.06***	0.10***	0.03	3,339,574
	(0.02)	(0.03)	(0.03)	[812,719]
Organized Exchange	0.05	-	0.05	36,656
	(0.07)		(0.07)	[11,945]
Reference Priced	0.06	0.14	0.05	332,678
	(0.06)	(0.16)	(0.07)	[88,809]
2006 – 2014				
Differentiated Products	0.08***	0.14***	0.04***	15,722,023
	(0.01)	(0.01)	(0.01)	[3,927,425]
Organized Exchange	-0.06	-	-0.05	99,373
	(0.06)		(0.06)	[28,086]
Reference Priced	0.05**	0.07	0.05**	1,537,937
	(0.02)	(0.11)	(0.02)	[364,723]

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

The most important takeaway from table SM1-6 is that the estimated markup elasticity of "differentiated" goods according to the Rauch classification, 8% in the later period, is an average of very different elasticities for high and low differentiation goods, 14% and 4% respectively. Unsurprisingly, our estimates of markup elasticities are zero for goods traded in organized exchanges, which in our classification are treated as low differentiation goods. Note that for organized exchange-traded goods we can expect prices in renminbi to change with their international market prices, whose movements may be correlated with bilateral exchange rates. For reference-priced goods, consistent with our hypothesis, we find no markup adjustment for the subset of high differentiation goods in this set. Results are less straightforward however for the low-differentiation goods—we find some degree of markup adjustment, although only in the later period.

SM1.5 Trade pattern statistics by product differentiation

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

Table SM1-7: Number of Unique Trade Patterns - High Differentiation Goods

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

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

Table SM1-8: Number of Unique Trade Patterns - Low Differentiation Goods

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

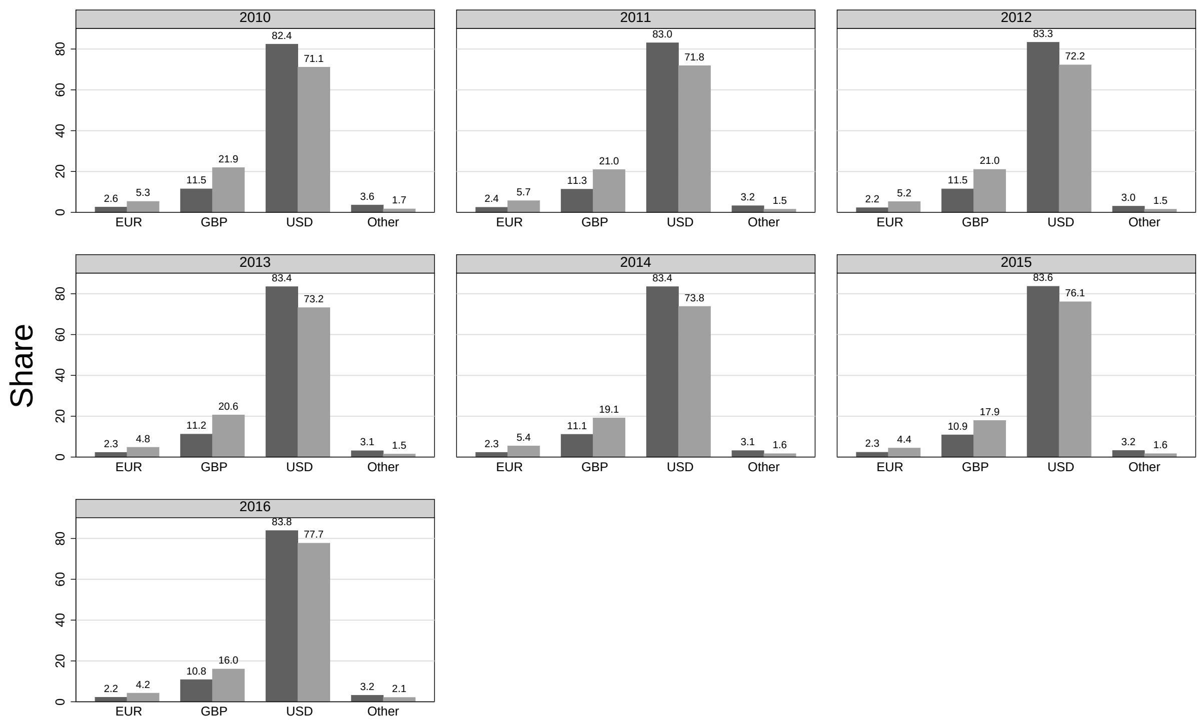
Note: We start from the whole sample of all firms selling *low differentiation* goods and drop firm-product pairs that only exported once in their lifetime. For each firm-product pair, we calculate its total number of exporting years and the number of unique trade patterns in its lifetime and then put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

SM1.6 In which currency do exporters from China invoice?

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

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

Figure SM1-3: Invoicing currencies for UK imports from China



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

Since 2010, HMRC has recorded the invoicing currency for the vast majority of import and export transactions between the UK and non-EU trading partners.[7] Figure SM1-3 presents the

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

shares of import transactions and import value into the UK from China by invoicing currency.[8] Results are reported for three currencies, the euro (EUR), pound sterling (GBP), and the US dollar (USD). All transactions that use other currencies of invoice, for example, the Swiss franc, Japanese yen or Chinese renminbi, are aggregated into the category "Other."[9] In each graph, the dark bar refers to the share of transactions and the light grey bar refers to the share of import value reported in the relevant currency.

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

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

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

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

[8] To construct this figure, we begin with the universe of UK import transactions for goods originating from China over 2010-2016. Then, we aggregate all transactions within a year that are reported for a firm-CN08product-quantity measure-currency quadruplet to an annual observation for that quadruplet. The variable "quantity measure" records whether a transaction for a CN08 product is reported in kilograms or a supplementary quantity unit like "items" or "pairs." This leaves us with 2.004 million annual transactions which we use to construct figure SM1-3.

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

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

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

SM1.7 Price changes and trade patterns

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

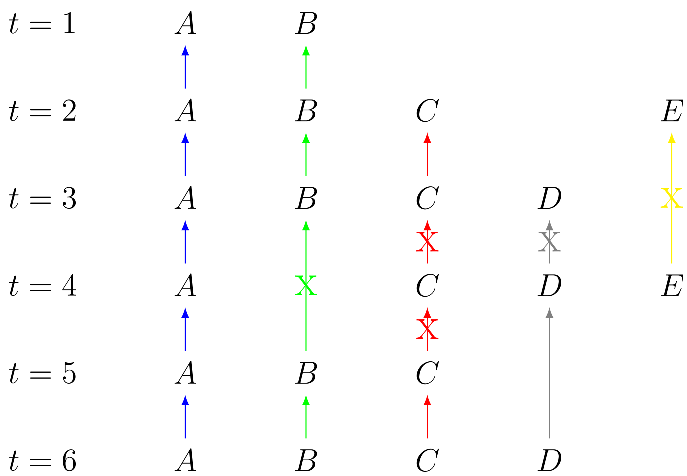
Consider a firm exporting a product to five countries, A through E, over 6 time periods. In the following matrix, $t = 1, 2, 3, ...$ indicates the time period and A, B, C, D, E indicates the country. Empty elements in the matrix indicate that there was no trade.

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

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

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

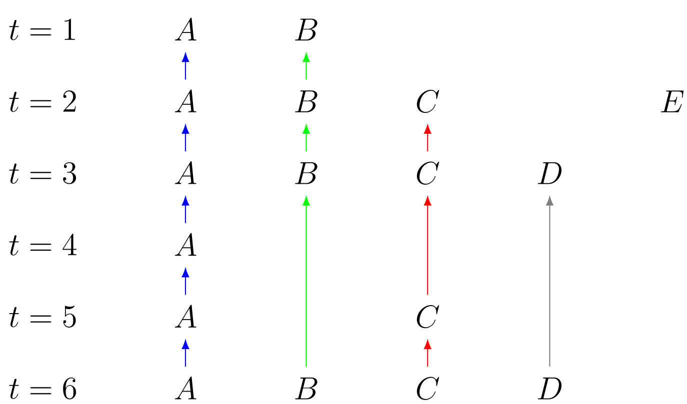
Suppose the pricing currency is the dollar and we want to identify price changes in dollars. First, we compare export prices denominated in dollars over time and at the firm-product-destination level as illustrated in the following figure. Price changes less than 5% are marked with “x”.



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

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

Note that we did not treat $p_{C,5}$ as missing at this stage. This is because $|p_{C,5} - p_{C,3}|$ could be $> 5\%$ even if both $|p_{C,4} - p_{C,3}| < 5\%$ and $|p_{C,5} - p_{C,4}| < 5\%$.[11] Rather, we repeat the above step using the remaining observations as illustrated below.



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

[11] Variables are in logs.

As no prices are sticky, we can stop the iteration.[12] Note that as no price changes can be formulated for the single trade record $p_{E,2}$, this observation is dropped from our sample.

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

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

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

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

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

SM1.8 Data cleaning process and the number of observations

Table SM1-9: Key Statistics for Our Data Cleaning Process

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

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

Stage 0: Raw data
Stage 1: Drop exports to the U.S. and Hong Kong
Stage 2: Drop if the destination identifier, product identifier or value of exports is missing; drop duplicated company names
Stage 3: Collapse at the firm-product-destination-year level; integrating 17 eurozone countries into a single economic entity
Stage 4: Drop observations if bilateral exchange rates or destination CPI is missing
Stage 5: Filtering price changes (in logs, denominated in dollar) < 0.05 at the firm-product-destination level following the method described by SM1.7
Stage 6: Drop single-destination firm-product-year triplets
Stage 7: Drop single-year firm-product-destination triplets
Stage 8: Formulating trade pattern; Drop single-year firm-product-trade-pattern triplets
(Finally, we drop "single-year firm-product-trade-pattern triplets." Including these observations will not change the estimates obtained from the TPSFE estimator because they do not provide the within firm, product and destination *intertemporal variation* upon which the estimator relies.)

SM2 General Model-Free Relationships

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

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

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

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

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

The first order condition of the firm is given by

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

From this equation, we can derive the optimal price as

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

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

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

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

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

Proof.

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

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

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

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

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

Proof.

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

□

SM3 Estimating markup elasticities with heterogeneous responses

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

SM3.1 The implicit weight of observations

To introduce this issue, consider the following simple specification:

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

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

The OLS estimate of β is given by

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

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

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

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

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

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

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

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

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

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

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

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

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

SM3.2 Approximation bias

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

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

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

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

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

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

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

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