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Working Paper 20-040



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Funding for this research was provided in part by Harvard Business School.

# Real Exchange Rate Behavior: New Evidence from Matched Retail Goods\*

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January 2019

## **Abstract**

We use a dataset containing daily prices for thousands of matched retail products in nine countries to study tradable-goods real exchange rates. Prices were collected from the websites of large multi-channel retailers and then carefully matched into narrowly-defined product categories, providing relative price *levels* data that collectively represent the bulk of expenditures on food, fuel, and consumer electronics in each country. Using bilateral results with the US, we show that relative prices in local currencies co-move closely with nominal exchange rates. Exchange-rate passthrough into *relative* prices is approximately 75%, compared to 30% with CPI data for the same countries and time periods. We decompose the difference and show that the majority of the difference – about 25 percentage points – comes from the use of closely-matched products. The rest of the gap owes about equally to the exclusion of non-tradable sub-categories and to our inclusion of entering and exiting goods. These results suggest that the retail prices for tradable goods can adjust quickly to nominal exchange rate movements and vice-versa, and have important implications for a vast literature that tries to characterize both the level and behavior of real exchange rates over time.

**JEL-Codes:** E3, F3, F4.

**Keywords:** Real Exchange Rate, Law of One Price, Purchasing Power Parity, Exchange Rate Passthrough, Online Prices.

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\*We thank Manuel Bertolotto, Augusto Ospital, and Belen Bazano, and the team at PriceStats for creating and sharing the matched-goods database. We thank the International Comparisons group at the World Bank for sharing results from the ICP 2011 round. Maria Fazzolari provided outstanding research assistance. We thank Javier Cravino, Gita Gopinath, Yuriy Gorodnichenko, Jesse Schreger, and seminar participants at the AEA, MIT Sloan, Boston University, Harvard Business School, ICIPP Princeton, and CEU for helpful comments and suggestions.

# 1 Introduction

The relative price of tradable goods across countries is at the core of many issues in international economics, from comparisons of output levels to the dynamics of the real exchange rate (RER) and the speed by which shocks are transmitted across borders. A well-established fact in the literature is that relative prices in local currencies are not strongly correlated with the nominal exchange rate (NER), particularly when prices are measured in retail markets.<sup>1</sup> This makes the RER both volatile and persistent, a fact labeled the “PPP puzzle” by Rogoff (1996). The traditional view that this was caused by the price of non-tradables was challenged by the seminal results in Engel (1999), who showed that tradable RERs constructed with Consumer Price Index (CPI) data can be just as volatile and persistent as non-tradable RERs.

When measured at the border, the adjustment of relative prices has been shown to be higher, so the focus in the literature has shifted to factors limiting the adjustment at the retail level. Many possible explanations have been proposed, including the ideas that retail markets are segmented by high transportation and distribution costs (Burstein et al. (2003)), that retail markups differ over time and space (Atkeson and Burstein (2008)), and that existing measures of retail relative prices may reflect biases stemming from sectoral aggregation (Imbs et al. (2005)), temporal aggregation (Taylor (2001)), or the disregard of entering and exiting goods (Nakamura and Steinsson (2012)).

While progress has been steady, the attempts to reach a consensus have been hampered by formidable empirical challenges. Most of the literature relies on CPIs which are not designed for international price comparisons. In particular, CPIs preclude any price *level* comparisons, they are constructed by separate national statistical offices (NSOs) using different methodologies and baskets of goods, and by construction they fail to capture the difference in prices between entering and exiting good varieties, which could be an important margin of price adjustment to nominal exchange rate fluctuations. An alternative is to use the price level database built by the World Bank’s International Comparisons Program (ICP), which collects and aggregates matched-product prices covering a broad set of goods to compare output across dozens of countries. Unfortunately, the coordination of multiple NSOs using traditional data collection methods requires more than five years to complete, severely limiting its uses for time-series applications.<sup>2</sup>

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<sup>1</sup>See Gopinath et al. (2011a) for a recent review of the literature.

<sup>2</sup>In addition to the low frequency, each round of ICP data collection uses different product lists and has a different methodology, leaving their panel dimension difficult to interpret. Similar issues arise with data collected for cost-of-living indices compiled by the Economist Intelligence Unit (EIU) and other consulting firms, which are designed for cross-section comparisons rather than time-series changes. At a more narrow level, the Economist magazine’s Big Mac index compares international prices of a single iconic product that is available in comparable form throughout most of the world. For the topics at hand, we can question the usefulness of a focus on any single product.

A more recent strand of the literature uses micro-price data obtained directly from retailers and scanner-data providers.<sup>3</sup> The evidence from these papers is mixed, with different pricing behaviors depending on the source of data, goods, retailers, and countries under study. Despite these efforts, it is still hard to find a large set of highly similar products that span the traded consumption bundle and are sold simultaneously in a large cross-section of countries, with prices that are sampled consistently and at relatively high frequency. Taylor (2001) nicely summarizes these challenges and the literature’s failure to meet them:

To meet the desired standard we would be hoping that hundreds of price inspectors would leave a hundred or more capital cities on the final day of each month, scour every market in all representative locations, for all products, and come back at the end of a very long day, with a synchronized set of observations from Seoul to Santiago, from Vancouver to Vanuatu. We cannot pretend that this happens.

This paper re-examines the behavior of retail relative prices and RERs using a new dataset constructed, in part, with web-scraping programs that try to substitute for Taylor’s “hundreds of price inspectors”. We combine the product-matching and price-level methodology of ICP, with the product details and high-frequency possibilities of micro-price data. The daily prices for over 50 thousand individual varieties were carefully matched into 350 narrow product categories that collectively represent the bulk of expenditures on food, fuel, and consumer electronics in nine countries: Argentina, Australia, Brazil, China, Germany, Japan, the United Kingdom, South Africa, and the United States. We use these data to build daily RERs for eight countries relative to the United States. Our main results are summarized as follows.

First, we show that online relative price levels are comparable to those collected physically by the World Bank’s ICP in 2011, and consistent with a large body of earlier work, we find that prices for individual goods differ meaningfully across countries when expressed in the same currency.<sup>4</sup>

Second, we find a stronger negative co-movement of relative prices in local currencies and the NER when calculated in our data than when calculated using data collected by national statistical agencies as part of their construction of CPIs. We quantify this long-run co-movement by estimating passthrough rates between the NER and *relative* price levels, due to the simplicity of this calculation and its ease of comparison across datasets. Our main specification, using price levels for all sectors and countries in our data, provides an estimated long-run relative passthrough close to 75 percent. As shown below, this notion of relative passthrough compares to the sum

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<sup>3</sup>For example, Crucini and Shintani (2008), Gopinath et al. (2011b), and Cavallo et al. (2014, 2015)).

<sup>4</sup>Further comparisons to ICP data can be found in Cavallo et al. (2018)

of passthrough rates in a two-country world where the good is produced in one country. By contrast, when we use CPI data obtained from NSOs for the same countries and time period, the passthrough falls to 30 percent.

Third, we decompose the difference with CPI data to show that approximately 8 percentage points are explained by sectoral and formula differences, 26 percentage points are caused by the use of matched relative prices, and 11 percentage points by accounting for the prices of new and disappearing varieties.

Among the sectoral and formula differences, we find that only 4 percentage points are caused by our focus on food, fuel, and electronics. This is consistent with Engel (1999) and other papers that use goods' CPIs to find persistent RERs. However, a better proxy for tradable goods can be obtained in some countries by using disaggregated CPIs that match the sub-categories in our own data. This implicitly excludes non-tradable services and raises passthrough by an additional 7 percentage points. This result, in turn, is partially compensated by a *reduction* of 3 percentage points when we use a bilateral Fisher index with expenditure weights from both countries at the lowest possible level of aggregation, which control for a potential measurement bias caused by proxying relative price levels with aggregate CPIs, a well-know result in the literature that uses ICP data.

The largest increase in passthrough rates occurs when we switch from CPIs to our matched-product data. One potential explanation is that the use of relative prices helps control for a variety of factors that affect local prices in both countries and are also correlated with NERs. For example, using goods that are not well matched in a relative price regression may introduce a bias if the goods are produced in different locations, are invoiced in different currencies (Gopinath et al. (2010) and Gopinath (2015)), or have different compositions of imported inputs (Goldberg and Hellerstein (2008)). The sign of the bias depends on the characteristics of the CPI data.

Another reason for higher passthrough may be that the product-matching process implicitly identifies goods at the retail level that are actually tradable. This could increase passthrough even without a *relative* price regression. Indeed, when we estimate passthrough into local retail prices alone (ignoring US prices), we still find a relatively high coefficient of 56%, similar to other long-run passthrough estimates for tradable goods at-the-dock (Burstein and Gopinath (2013))).

Finally, the price *level* data allows us decompose the relative price series into a continuing-goods component that ignores entry and exit of products (as CPIs tend to do), and an additional extensive margin term that captures whether entering and exiting products are more or less expensive. This margin is strongest in electronics, where much of the adjustment to NER shocks

seems to take place by replacing varieties of goods sold.

Overall, our results suggest that traded retail RERs shocks are less persistent than they appear to be when using CPI data. This makes them more consistent with the behavior of prices at-the-dock (Gopinath et al. (2011a)) and reduces the need for alternative explanations such as non-tradable distribution costs, heterogeneous retailer markups, and nominal rigidity at the retail level. At the same time, our findings are consistent with several results in the literature, such as the view that CPI data does not accurately reflect the price of pure-traded goods (Burstein et al. (2005)), the evidence linking tradability to PPP deviations in micro-price data (Crucini et al. (2005) and Crucini and Shintani (2008)), and the fact that passthrough tends to increase when goods are invoiced in foreign currency (Gopinath (2015))<sup>5</sup>.

The paper proceeds as follows. Section 2 discusses the literature in greater detail. Section 3 describes the data, the product matching process, and other measurement topics. Section 4 discusses the measurement of real exchange rates in levels, compares the results with 2011 ICP data, and provides a simple graphical analysis of relative prices and nominal exchange rates in each country. Section 5 provides the quantitative estimates of relative passthrough and decomposes the difference with results using CPI data. Section 6 concludes.

## 2 Related Literature

A large literature studies international price differences, absolute and relative law of one price (LOP) deviations, incomplete exchange rate passthrough, and real exchange rate behavior. These topics are intimately related, but data limitations have typically implied that they are studied in isolation.

Papers focusing on LOP deviations historically focused on a narrow set of goods, such as the analysis of prices of Big Macs and their ingredients in Parsley and Wei (2007), prices of *The Economist* magazine in Ghosh and Wolf (1994), or prices from a single retailer as in Haskel and Wolf (2001). Some more recent analyses span a much broader set of data but, typically, are only available at annual or lower frequency and with imperfect product matching. Important work, such as Crucini et al. (2005) and Crucini and Shintani (2008), use data from Eurostat and the Economist Intelligence Unit to highlight the role of non-tradables in generating cross-

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<sup>5</sup>Using import and export prices, Gopinath (2015) finds high passthrough outside the US and low passthrough in the US, results consistent with our measure that looks at the combined adjustment of two countries. We also find evidence of “product-replacement bias” in CPIs as highlighted by (Nakamura and Steinsson (2012)), though we find it’s quantitative significance to be more muted.

country price dispersion and to question the extent of persistence in good-level real exchange rates. Others assess international relative prices using retail scanner data, which offer a large set of well-measured relative prices but often constrain analyses to a single retailer and, typically, to comparisons of the United States and Canada. For example, Gopinath et al. (2011a) and Burstein and Jaimovich (2009) use data for a large retailer with presence throughout North America and provide evidence of a large border effect and extensive pricing to market at the wholesale level.

Closely related is the large set of papers documenting the extent of exchange rate passthrough. In recent years, this literature has been typically characterized by analyses of imports or exports of a particular country, using micro data which offer confidence that prices over time correspond to a fixed product or set of products, and which often allow the researcher to condition on price changes. Gopinath and Rigobon (2008), Gopinath et al. (2010), and Neiman (2010), among others, provide early estimates of incomplete passthrough using the micro data underlying the United States import price index constructed by the Bureau of Labor Statistics (BLS). Other work, including Berman et al. (2012), Fitzgerald and Haller (2014) and Amiti et al. (2014), document passthrough and pricing to market using micro-level export or transaction-level trade data for other countries. We measure passthrough taking account of product entry and exit, something that cannot be done in analyses of aggregated prices indices, as emphasized by Nakamura and Steinsson (2012).

Finally, empirical work on the persistence of real exchange rates per se more commonly abstract from micro data and work with sector or aggregate indices obtained from NSOs or similar institutions. Engel (1999) uses real exchange rates constructed from consumer and producer price indices to attribute the bulk of real exchange rate variation at both short and long horizons to the relative price of traded goods. Imbs et al. (2005) offers a view that standard estimates of real exchange rate persistence appear implausible because of aggregation bias. Chen and Engel (2004) argues that sectoral heterogeneity is insufficient for aggregation bias to quantitatively reconcile the real exchange rate's puzzling persistence and documents a number of problems with the sectoral Eurostat data used by Imbs et al.. Carvalho and Nechio (2011) clarifies the source of discrepancy in these results and theoretically demonstrates that a plausibly calibrated multi-sector model of sticky prices can replicate standard measures of the real exchange rate's behavior.

Our focus on scraped online prices as a datasource offers the ability to more easily jointly interact with all three of the above strands of the literature. Like the papers focusing on the cross section of LOP deviations, we can match a large number of products with high degrees of precision. Like the passthrough literature, we can interpret our results conditional on an



understanding of price stickiness in the data and can associate, at high frequency, exchange rate movements and relative price movements of the same goods. And like the real exchange rate literature, our data allow us to study multiple countries and with broad enough product coverage to reasonably approximate the behavior of traded goods price indices.

Given these helpful features of online pricing data, a number of recent papers have similarly focused on online prices to study LOP deviations and the behavior of the real exchange rate. Boivin et al. (2012) finds evidence consistent with low passthrough of exchange rates into prices of online book retailers in Canada and the United States. Cavallo et al. (2014) uses scraped data to demonstrate that LOP violations in prices from Apple, IKEA, H&M, and Zara are dramatically larger outside than inside common-currency areas such as the euro zone, and Cavallo et al. (2015) uses a subset of the same data to demonstrate that LOP violations with France, Germany, and Italy rapidly collapsed to zero when Latvia adopted the euro as its currency. In closely related work, Gorodnichenko and Talavera (2017) studies prices from online markets in Canada and the United States. The authors document high degrees of flexibility in online prices and passthrough rates that exceed typical estimates. Gorodnichenko et al. (2015), similarly, examines online prices in the United Kingdom and the United States from a large shopping platform and also emphasizes that online prices appear less sticky. Cavallo (2017) studies prices from large multinational retailers, rather than online markets or shopping platforms, and finds fewer differences when comparing online and offline prices. Bertolotto (2016) uses the same database of relative prices to estimate RER half-lives and, consistent with our findings, shows that RERs are far more persistent when CPI data are used.

International relative prices are also used in the large literature that focuses on the comparisons of national accounts and poverty levels across countries. From the work to create, improve, and maintain the Penn World Tables (e.g. Heston and Summers (88,96), Nuxoll (94), Feenstra, Inklaar and Timmer (13)) to the papers that study how to measure purchasing power parities across countries (e.g. Diewert (99), Hill(99), Deaton and Heston (10)), their implications for international comparison of poverty rates (e.g. Deaton (06, 10)), and the attempts to improve and expand the data collection of prices for similar goods across countries as part of the World Bank’s ICP (e.g. World Bank (14), Inklaar and Rao (16), and Deaton and Aten (16)). Our approach to measure real exchange rates relies, heavily, from the methods used by this international comparisons literature; in particular, for the way we classify and match the data across countries. Our analysis in section 5.1.2 is also closely related to the discussion on “interpolation bias” in that literature (See Inklaar and Rao (16), and Deaton and Aten (16)). Unlike that literature, for

simplicity, we focus on bilateral rather than multilateral real exchange rates.

### 3 Data Description

Our data were constructed in two steps. First, prices for individual goods were scraped off the websites of large retailers by an academic project at MIT called The Billion Prices Project (BPP) and a private firm called PriceStats.<sup>6</sup> Second, goods that could be matched across countries were organized and classified as varieties of a particular product. These product definitions are sufficiently narrow, in our view, as to be appropriately described as nearly the same product, with the exception that they are often available in different sized containers or bundles or with only minor variations in characteristics. This matching was performed by PriceStats using a machine-learning classifier combined with a manual verification of each good and its characteristics. Each product was also categorized into the appropriate 1-, 2-, and 3-digit (when possible) code using the United Nations Classification of Individual Consumption According to Purpose (COICOP). All products belong to three sectors: “Food and non-alcoholic beverages” (COICOP 100), “Fuels and lubricants” (COICOP 722), and “Recreation and Culture” (COICOP 900), which we subsequently refer to as “Electronics” because it predominantly includes consumer electronics. We refer to these three sectors below as “1-digit” sectors.

Daily prices for the varieties are translated into per-unit prices and aggregated to form a price for each product in each country on each day. For countries other than Japan and the United States, internet prices are quoted inclusive of taxes (in some cases this is required by law). For Japan, we increase the scraped food and electronics prices by 5 percent prior to April 2014 and by 8 percent subsequently, reflecting a change in their VAT rates. For the United States, we increase food prices by 1.0 percent and electronics prices by 5.1 percent as those are the unweighted average of state sales tax rates in 2014 (food is frequently an exempt category). Our data on fuel prices are always collected inclusive of local tax rates. These prices, together with daily information on the nominal exchange rate, allow us to measure international prices, daily, at product-specific or at aggregated levels.

#### 3.1 Scraping Online Prices

PriceStats scrapes millions of daily prices from hundreds of retailers’ sites in over 50 countries to use in high-frequency inflation indices. The focus is, exclusively, on prices from multi-channel

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<sup>6</sup>Cavallo and Rigobon are co-founders of both the BPP and PriceStats.

retailers, that sell both offline and online. Online-only stores, therefore, are excluded, as are brick and mortar stores that do not sell over the Internet. Other than fuel, as discussed below, the data are always collected directly from the retailer’s website, not from data aggregators, price comparison sites, or any other third party website, which may, potentially, alter the prices or the sample of products shown. This ensures that the data reflect the actual posted prices that an online buyer of these retailers would have seen when purchasing online on the date the price was collected.

Conceptually, web scraping is simple to understand. Every day, a software downloads the webpage where the product information is shown, scans the underlying code, uses a set of customized rules to identify the relevant information, and stores it in a database. More details on the web-scraping procedure and the BPP can be found in Cavallo and Rigobon (2016).

### **3.2 Choice of Countries, Stores, and Products**

From this large set of pricing data, a subset of countries, stores, and products are used. The scope of the matching of cross-border products, essential for this paper, was dictated by PriceStats and the countries of interest to its clients. Our data on matched products therefore include: Argentina, Australia, Brazil, China, Japan, South Africa, the United Kingdom, and the United States. These countries include five of the seven largest economies, two important “commodity currency” countries in Australia and South Africa, and Argentina, a high-inflation country which was also the first country studied as part of the BPP.

Within each of these countries, pricing data are obtained from large retailers that sell both online and offline. All countries include, at least, the largest three such retailers by sales, though most countries include many more. None of the retailers have exited our sample, so there is no extensive margin in terms of stores.

A distinction is made between “products” and “varieties” in our data. A “product” is actually a narrowly defined category, such as “Regular Heinz Ketchup, 1 gram”. Products are chosen based on their availability across multiple countries and, when combined, their representativeness of the bundle of consumption products. These products were chosen to ensure full coverage of all 3-digit COICOP subcategories in the three sectors (food, fuel, and electronics), for which online prices are available. Products are generally not available in all eight countries, but are always found in the United States and, typically, at least, several other countries. The median product is found in six of the eight countries in our data. “Varieties” are individual goods, such as a particular “Heinz Tomato Squeeze 20oz bottle” sold by a given retailer, whose prices are collected from

the web and make up the raw data. The varieties present in the raw data of each country are then linked to the products chosen for the cross-country comparison. The price for each of these products is then calculated in each day and in each applicable country by aggregating over the prices observed for a number of varieties of that product.

One difficulty in making cross-country price comparisons of what would, otherwise, be equivalent products is that they are often priced based on slightly varying units, particularly given heterogeneous standards for measurement of weight and volume. For example, apples are sometimes priced in kilograms and sometimes in pounds. Milk can be sold in liters and in half-gallons. Hot dogs arrive in six packs and in eight packs. We calculate the unit price for each variety of each product by dividing the raw price by the number of grams, items, or liters of the product. For each product, we then aggregate across all varieties by taking the geometric mean of these unit prices, though we’ve verified that alternate moments, such as the median or arithmetic mean, do not change our results.<sup>7</sup>

Types of products for which particular brands enjoy significant global market share are typically divided into products made by those brands and products lacking a global brand. For example, ketchup products are classified according to three types: (i) regular, (ii) low sodium (e.g. no salt), and (iii) other (including flavored). Further, ketchup products manufactured by Heinz are distinguished from those made by other manufacturers. In total, we therefore consider six different ketchup products, whose prices for each day in each country reflect an aggregation over prices of a number of varieties. For example, by the end of our data, the prices of 26 varieties of non-Heinz regular ketchup in the United States and 18 varieties in China were used to create the prices in those countries for the product “non-Heinz regular ketchup”. Some products, where branding can make an enormous difference, are only compared for a particular brand. For example, our data include prices for Logitech web cameras, which are separated into two products based on the definition of the cameras, but do not include web cameras of any other brands. Soy sauce products, by contrast, are not distinguished by brand. Table 1 lists a subset of the products that we scrape (the table shows 80 products, roughly one-quarter of the total number that we study).

Table 2 lists, for each of the eight countries in our data, the number of products and median number of varieties per product in each sector. We consider only those prices scraped during 2014 to better highlight meaningful cross-country differences rather than those emerging purely due to

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<sup>7</sup>This strategy reflects our view that the benefits of being able to study a broader set of the consumption bundle with prices averaged across outlets in each country outweighs the cost brought by ignoring price variation that may be due to quantity discounts.

different initial dates in our data. As can be seen in the bottom rows corresponding to the United States, our data in 2014 contain 172 different food products and 76 different electronics products. Most countries have more than 100 of the 172 food products and all countries have at least 53 of the 76 electronics products. All countries have at least two of the four total fuel products.

Most of the largest grocery retailers in these countries show the prices for all their products online. In some cases, the prices posted online serve merely to communicate what customers must pay to purchase items in the store. But more commonly, the prices are actually transaction prices. In particular, each of the top five grocery retailers in the United States and in the United Kingdom sell online, while four of the largest five in Australia, three of the largest five in Argentina, China, and Japan, and two of the largest five in Brazil and South Africa also do so.<sup>8</sup> Online sales of food take a variety of forms. Sometimes, the sales are made online but require the customer to pick up the items at the store. In other cases, online food orders can be delivered, either for a flat fee or for a fixed percentage delivery charge.

Fuel prices, unlike food and electronics prices, are typically obtained from government websites or other pages unaffiliated with any particular retailer. For example, the prices for fuel in Brazil are obtained from the “National Petroleum Agency,” which publishes weekly surveys of fuel prices that are then averaged based on reported fuel sales. Our source for Japan conducts similar weekly surveys. As such, these countries typically use only one variety to represent each fuel product’s price. Significantly more varieties are used in China and the United States, where we use data from private organizations which report provincial (for China) and state or city (for the United States) prices. Cross-country differences in our price collection methodology are clearly much larger for fuel than for food or electronics. The ability of fuel prices to alter our overall inference is quite limited though, as we report most of our results excluding fuel items.

The last column of Table 2 lists the median number of varieties used to obtain the daily unit price in each of these countries and categories. The typical food product’s price is obtained from aggregating over a large number of varieties, with the median exceeding 12 in five of our eight countries. The median number of varieties used to calculate unit prices of electronics products is always, at least, eight.

### 3.3 Comparing Online and Offline Prices

Online prices are interesting in their own right as Internet purchases constitute a rapidly growing share of consumption spending (Euromonitor, 2014). We claim, however, that the prices in our

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<sup>8</sup>We obtained market shares from Euromonitor International.

data, both in terms of their levels and their dynamic properties, are representative of offline prices for equivalent products. The evidence is presented in another paper, Cavallo (2017), where the results of a large-scale, simultaneous, online-offline data collection effort are shown. Online and offline prices for the same products were collected for more than 50 of the largest retailers in 10 countries, including most of those used for this paper. On average, over 70% of the prices were found to be identical. Online and offline price changes, while not simultaneous, have similar frequencies and average sizes. The remaining price differences are driven by location-specific sales, lack of synchronization, and measurement error.

While the retailers in this paper and Cavallo (2017) are not always the same, these results provide strong evidence that large multi-channel retailers tend to have identical online and offline prices in most countries. Furthermore, we can measure the degree of nominal rigidity in our matched-product data and compare it to results in papers that use CPI data. We do this in Table 6 for the US by comparing the frequency of price changes in the three sectors with estimates in Nakamura and Steinsson (2008). Our prices tend to be *stickier*, particularly for food. This is consistent with the results in Cavallo (2016), which shows that measurement bias can lead to an increase the frequency of price changes in both scanner and CPI datasets.

### 3.4 Product Turnover, Quantities, and other Measurement Issues

The use of individual varieties to compute the daily average price of a given product in each country is affected by goods entering and exiting the sample. The scraping methodology ensures, subject to some errors, that the raw data contain the prices of varieties from the day they are first sold until the day they disappear from the store. However, whether each individual product variety is used to compute the average price for a given product on a specific date depends on whether that variety has been “matched” to the product. As varieties disappear and are replaced with new ones in the raw data, this requires a frequent “matching” of varieties to products to ensure that the average price is being measured with all varieties that fit the description over time.

The varieties in our data were first linked to products in 2013, and then continued to be updated every month since then. Only varieties being sold in 2013 were initially included, so, while historical data from those varieties are used in our price averages before that year, there are varieties in the raw data that disappeared before 2013 and are not impacting our average prices until that time. The number of varieties and products rises gradually from 2010 to 2013, and remains stable afterwards in all countries. To control for these compositional effects, we restrict

the sample to start only after a minimum number of products is available for sale in each category (food, fuel, and electronics).

Sale prices that affect all potential buyers are included in our data and statistics (though prices paid with coupons or other personalized discounts are not captured). Sales can greatly affect the prices per product on any given day, and, while they may introduce some high-frequency noise, they can also be an important margin of adjustment for real exchange rates.

Our data lack information about quantities, so we rely as much as possible on expenditure weights for subcategories provided by the national statistical agency in each country. In most cases, expenditure weights are publicly available at COICOP’s level 3. Below that level, our averages assign the same weight to every variety. Unfortunately, there is no way of knowing whether a particular variety is sold more than another one, or how this changes over time. This means, for example, that if people switch from an expensive variety to a cheaper one after a devaluation of the currency, we are not able to observe any change. This problem affects not only our data, but also the CPI datasets, which do not contain information for expenditure weights for highly-dissaggregated categories. However, an advantage of our data, in the context of this particular example, is that, if the expensive variety eventually disappears from the store or is replaced by a new cheaper version, this would immediately affect the average price measured for that product. Furthermore, if an adjustment via quantities also takes place, it would likely reinforce the high-passthrough results we discuss below.

## 4 Measuring Real Exchange Rates in Levels

### 4.1 Local Price Levels

We assume that all countries consume the same set of “products”  $i \in \Omega$ . In our empirical work, we will consider “Red Apples” and “Samsung 32 inch Basic LED Televisions” as examples of products  $i$ . Consumption of each product  $i$  is itself an aggregation of consumption of a number of “varieties”  $j \in \Omega_{i,t}$ . In our empirical work, we will consider varieties  $j$  of the product “Red Apples” to include Gala, Pink Lady, and Red Delicious. Varieties of the product “Samsung 32 inch Basic LED Televisions” would include variations in color or other minor differences (major differences, such as high definition or “smart TV” features, would constitute a different product).

Varieties  $j$  of product  $i$  might be packaged or measured in different units. In the case of “Red Apples”, for example, prices in the United States are generally quoted per pound while in most

other countries they are quoted per kilogram. Or sometimes product varieties include a package of six in one country, but a package of eight in another. For each product  $i$ , we define a consistent unit to be used across all countries to measure a unit price  $p_{ij,t}^y$ , so varieties  $j$  of product  $i$  can be appropriately compared across time and countries (and outlets therein).

We assume that all varieties  $j \in \Omega_{i,t}$  have equal steady-state expenditure shares and that the number of varieties is constant across countries and remains fixed over time,  $|\Omega_{i,t}| = |\Omega_i|$ . Further, we assume that our price scraping technology captures a subset  $N_{i,t}^y \in \Omega_{i,t}$  of the total varieties of product  $i$  in each country  $y$  at date  $t$ . We, therefore, approximate the log ideal price index of product  $i$  in country  $y$  at time  $t$  (up to a constant that is identical across time and countries) as the geometric mean of the unit prices of all scraped varieties. This gives:

$$\ln p_{i,t}^y = \frac{1}{N_{i,t}^y} \sum_{j \in N_{i,t}^y} \ln p_{ij,t}^y.$$

The number of true varieties is assumed equal across countries, even if the number of scraped varieties is not, so our measure does not allow for differences in the scale of  $N_{i,t}^y$  to influence the price level. We are also implicitly assuming that the selection of the subset  $N_{i,t}^y \in \Omega_{i,t}$  is orthogonal to price levels.

#### 4.1.1 Dispersion in Dollar Prices

The average product prices  $\ln p_{i,t}^y$  can be converted to US dollars to illustrate the failure of the law of one price across countries. This is done in Table 3, where we measure the cross-country dispersion in USD prices using the mean coefficient of variation for all products in different COICOP level 3 categories.

Electronics tend to have the lowest dispersion of dollar prices across countries, while food categories have the largest. In principle, this could be explained by higher tradability and opportunities for arbitrage in electronics. It can also be related to how narrow the product definitions tend to be within electronics and food, and how “similar” the goods really are across countries.

More generally, price dispersion in dollars is relatively high across countries. This is consistent with the results in the literature that show how the law of one price tends to fail for individual goods, particularly outside currency unions.<sup>9</sup>

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<sup>9</sup>See Cavallo et al. (2014, 2015) for evidence of the law of one price holding within currency unions.



## 4.2 Real Exchange Rate Levels

We now measure the bilateral real exchange rate with the United States for each country. We define  $e_t^{zy}$  to be the number of units of country  $z$ 's currency per unit of country  $y$ 's currency, so that an increase in  $e_t^{zy}$  is an appreciation of country  $y$ 's currency. The good-level real exchange rate  $q_{i,t}^{yz}$  is defined as the difference between prices in countries  $y$  and  $z$  after being translated into a common currency, so we have:

$$\begin{aligned}\ln(q_{i,t}^{yz}) &= \ln(p_{i,t}^y) - \ln(p_{i,t}^z) + \ln(e_t^{zy}) \\ &= \ln(rp_{i,t}^{yz}) + \ln(e_t^{zy}),\end{aligned}\tag{1}$$

where  $rp_{i,t}^{yz}$  stands for the relative price of product  $i$  at time  $t$ , though measured in different local currencies of countries  $y$  and  $z$ . The real exchange rate  $q_{i,t}^{yz}$  equals one when the LOP holds exactly.

To reach conclusions about pricing behavior at more general levels, we must aggregate across these product-level measures. We start by generating real exchange rate levels at the 3-digit COICOP level by taking the equally weighted geometric mean of product-level real exchange rates  $q_{i,t}^{yz}$  for all products  $i$  within that 3-digit category. Examples of 3-digit COICOPs include “Bread and cereals” (111), “Fuels and lubricants for personal transport equipment” (722), and “Equipment for the reception, recording, and reproduction of sound and picture” (911). We then use fixed weights derived from CPI expenditures shares at this 3-digit level in 2014 to aggregate up to our sectors “Food”, “Fuel”, and “Electronics”, or similarly for aggregations beyond that.

If the expenditure weights at level-3 were identical across countries, we could simply take the equally weighted average of product-level real exchange rates to reach more aggregated real exchange rate levels. But, in fact, the weights differ. To aggregate past the 3-digit level, therefore, we create Fisher (1922) indices, which equal the geometric mean of the Paasche and Laspeyres measures of the bilateral real exchange rate. The Paasche aggregates 3-digit real exchange rates using the weights of one of the countries in a bilateral pair, while the Laspeyres aggregates using the weights of the other country. All real exchange rate levels reported below for aggregated sectors use the Fisher measure. This ensures that the real exchange rate we measure is symmetric, meaning that the result is the same no matter which of the two countries is used as the base.

### 4.2.1 A comparison of 2011 Levels with ICP

The World Bank’s ICP is the only public source that generates international price comparisons for such a wide variety of goods and countries, and with a focus on matching goods which are highly similar. In order to compare our results with theirs, we obtained from them the product-level micro data underlying their most recent release, which was in 2011. The ICP covers all countries in our data other than Argentina, and, to align with the time period they cover, we generate an average of our daily real exchange rates during 2011, where available.

We cannot exactly match our products to those used by the ICP but start by generating unweighted geometric means of the real exchange rate levels for all products within each 3-digit COICOP. The ICP data typically include from 6-12 products per 3-digit COICOP, with each product price calculated from a sampling of 5-10 varieties, so the level of aggregation this implies in the ICP data is somewhat similar to that in our data.

Figure 1(b) plots along the x-axis the real exchange rate with respect to the United States for each country and 3-digit COICOP in the ICP data, while the y-axis gives the value for that category in our data. Each data point is labeled to show the country, and hollow circles are used to identify 3-digit categories within food, solid squares are used to identify the category within Fuel, and hollow triangles are used to identify the categories within Electronics. Starting with fuel, we see that our results align quite well with the ICP measures. One reason fuel relative prices lie closest to the 45 degree line may be that concerns over product mismatch are clearly least important in that sector. Food and electronics cluster more or less evenly on both sides of the 45 degree line, but, aside from the two large outliers for South Africa at the bottom-right of the plot, we characterize our data as broadly consistent with ICP’s in terms of relative price levels. A robust regression (which places less weight on outliers that it endogenously identifies) projecting the log real exchange rates in our data at the 3-digit level on those in ICP has a highly significant coefficient of 0.67 even after excluding the fuel categories.

Figure 1(a) similarly compares average 1-digit real exchange rates in our dataset with those from the ICP. Food and fuel look are closely related, particularly given that there are necessarily differences due to the time aggregation in the ICP’s annual survey. We note that our results differ more meaningfully with the ICP for electronics products, and these are, perhaps, the products where the relative quality of our matching procedure might be expected to be best.

While Figures 1(b) and 1(a) show the similarity of our results to those in the ICP, one might wonder if the same results could have been obtained without worrying about matching goods at such a disaggregated level. For instance, if we simply scraped thousands of prices for products

from supermarket web pages and compared their average prices, would this have been sufficient to generate useful data for real exchange rates analysis? To test this out, we repeat the exact analyses above but capture prices that are classified up to a 3-digit COICOP category, the lowest level of aggregation for which CPI expenditure shares exist in all our countries. For example, consider a supermarket web page listing dairy products. Our baseline methodology would use only those prices for our particular matched products, such as various types of unbranded milk (whole, skim, etc.) or various types of Philadelphia cream cheese (regular, low fat, etc.). In this alternate methodology, we simply record and take the average of a random set of prices in the dairy section of the web page, ignoring heterogeneity in product sizes or qualities, but making sure we end up with roughly the same number of varieties from each retailer and in each 3-digit category as in our baseline matched sample. We cannot do this for China and Japan before 2013 because the raw data contained non-latin characters that could not be processed by the machine learning algorithm that classifies the data.

Figure 1(c) plots the results. For any given ICP real exchange rate value on the x-axis, there are, at least, two y-axis values for any given country: one showing the results in our data with exact matches (the solid circles) and another one showing results that ignore product matching (the hollow squares). The exact-matched products track the ICP's values (and, therefore, cluster around the 45 degree line) dramatically more closely than do the unmatched items, which often have average values several orders of magnitude larger or smaller than what is found in ICP. To credibly study international relative prices of comparable goods, effort must be made to standardize on units and quality beyond simply averaging across a large number of goods.

#### 4.2.2 Relative Prices and Nominal Exchange Rates

The top row in Figures 2 to 4 show the daily bilateral real exchange rates with the United States over time for each country. The bottom row shows its components, the nominal exchange rate (a fall is a depreciation) and the relative price (a fall means local prices are falling relative to the United States). These figures only show the aggregate numbers for the three sectors (food, fuel, and electronics), but similar plots excluding fuel and for each individual sector can be found in the Appendix.

Consider first the graphs on the left of Figure 2, which correspond to Australia. Between 2010 and late 2016, the real exchange rate fluctuates around a level of approximately 1.3, which means that this basket of goods is, on average, 30% more expensive than in the United States. While the real exchange rate is quite volatile, there is a tendency for it to mean-revert back to this level

over time. The reason for this can be seen in the bottom graph. When the nominal exchange rate was appreciating in 2010-2011, relative prices were falling, which kept the real exchange rate fluctuating around a stable level. Then, around the same time that the currency started to depreciate in mid-2013, relative prices started to rise.

The co-movement between relative prices (in local currencies) and the nominal exchange rate, appears to be even stronger in countries like Brazil and South Africa. Furthermore, in these cases, the level to which the real exchange rate seems to mean revert is closer to 1.

Argentina is a special case because it had both an official and black-market exchange rate during this time period. Figure 3(b) shows results using the official exchange rate, while Figure 3(c) shows the results with the black-market rate. In both cases, the nominal exchange rate tends to depreciate when prices rise, but they do so at different times and with different patterns. The official exchange rate lags behind relative price increases and tends to adjust via strong devaluations that take the relative exchange rate back to one (January 2014 and January 2016). The black-market exchange rate, on the other hand, depreciated faster than relative prices until 2015, which made these goods in Argentina about 40% cheaper than in the United States for a considerable amount of time. When the foreign exchange market was liberalized in december 2015, both the black-market and the official rate adjusted to take the real exchange rate close to one.

Similar patterns are visible in the other countries, although there is heterogeneity in these behaviors. In China, for example, the real exchange rate rose steadily until 2013. Since then, the nominal exchange rate depreciation has been compensating a steady increase in relative prices. In Japan, prices have been stable while the nominal exchange rate depreciated. In the United Kingdom, it was the nominal exchange rate that was stable until the 2016's Brexit.

While these plots provide suggestive evidence that relative prices in these sectors and nominal exchange rates are cointegrated, a more formal way to quantify these behaviors is needed to understand what drives them and be able to compare with results using CPI data.

There are many alternative ways to quantify these behaviors. We focus on measuring the rate of passthrough between nominal exchange rates and relative price level for two main reasons. First, it is a simple and transparent way to document the relationship between these two variables. Our data allow us to run a simple regression in levels. There are no complicated methodological assumptions or model specifications that can affect the results. We do not even have to impose a particular lag structure, as would be required for a passthrough regression in changes. Second, there are literally hundreds of papers with passthrough estimates, and surveys of the literature

such as Goldberg and Knetter (1997) and Gopinath et al. (2011a) that we can use to compare our results.<sup>10</sup>

## 5 Passthrough Estimates and Decomposition

We can characterize the joint behavior of relative prices and the nominal exchange rate econometrically. To do this, we estimate the cointegration relationship between log relative prices and the log nominal exchange rate as:

$$\ln(rp_t^{yz}) = \alpha^{yz} + \beta \ln(e_t^{zy}) + \epsilon_t^{yz}, \quad (2)$$

where  $t_0$  denotes the earliest observation for country pair  $yz$  in our data and where  $-\beta$  constitutes our estimate of long-run exchange rate passthrough. We always use the United States as a base country in each bilateral pair,  $z = USA$ . In our main results, we use the overall relative price term in our data, calculated using a Fisher index and including the price levels at product introduction and exit. Later on, we consider a number of different measures for the  $rp_{t+1}^{yz}$  term on the left hand side of equation (2), including a term that replicates standard continuing-model indices in our data, as well as versions of this relative price constructed using CPI data obtained from NSOs.

Our data are daily but, to be able to properly compare with monthly data on consumer prices collected by NSOs, we preserve only the observation corresponding to the last day of each month, effectively making our dataset monthly.

Our main results are presented in Table 4 for all countries and sectors, and are consistent with the qualitative analysis in the previous section. In each case, we report the  $\beta$  coefficient in equation 2 with the standard error below in parenthesis. Other than China and the United Kingdom, where the nominal exchange rates have barely moved, nearly all standard errors, presented in parentheses beneath the corresponding point estimates, are less than 5 percentage points.

The passthrough rate using all bilaterals and sectors is approximately 75%. Fuel has the highest passthrough rate of 96%, followed by food with 74% and electronics with 55%. Excluding fuel tends to decrease passthrough rates in all countries, with the only exception being Argentina, where fuel prices are strongly regulated by the government. These numbers are significantly higher than most estimates in the literature that uses CPI data. Why are our results so different?

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<sup>10</sup>In the Appendix, we show alternative results that compare simple correlations, granger causality, autoregressive models and stationarity tests, and vector error-correction models. Many of these methods, however, suffer from inherent limitations that are magnified by the relatively short time period covered by our data.

To answer this question, we created alternative indices using CPI data for the same categories, countries, and time periods available in our online dataset, and, starting with an all-items CPI, we gradually changed the sectors, formulas, and data used. This made it possible to decompose the difference into several stages, as shown numerically in Table 5 and graphically in Figures 5(a) to 6(d).

## 5.1 Decomposing the Difference

We start in column (1) in Table 5, which pools together all bilateral pairs with the United States and all sectors. Row (1) shows the passthrough estimate using an all-items CPI. At about 30%, this estimate is representative of the results in the literature. The difference with our benchmark estimate, now shown in row (6), is about 45 percentage points.

### 5.1.1 Sectors and Subsectors

One possible difference with other papers that use CPI data is that we are focusing on 3 highly-tradable sectors. To see the difference, in row (2) we show the passthrough rate when we limit the data to the same sectors. At this stage, we are using the 1-digit CPIs as provided by the NSOs and aggregating them using their respective official expenditure weights. Passthrough rises by only 4 percentage points. However, under COICOP these sectors are labeled “Food and Non-Alcoholic Beverages”, “Transport”, and “Recreation and Culture”. As the names suggest, these categories contain services and many non-tradable subcategories. So in row (3), we go deeper to try to match the exact same subcategories where we have online data. Fortunately, most of the countries in our sample provide CPIs and expenditure weights at the 3-digit COICOP level (eg. “Bread and Cereals”). The only exceptions are Argentina and China. Using these indices and aggregating them with expenditure weights and arithmetic means that replicate standard CPI methods, we are able to construct a 3-sector CPI that is more directly comparable to our data.

This approach implicitly excludes many services and non-tradable subcategories in “Transport” and “Recreation and Culture”, which are -by construction- not present in our online matched database. In these cases, passthrough rates rise 7 percentage points, to about 41%. This is the best proxy for a “tradable” CPI that we can be constructed for this set of sectors and countries.

### 5.1.2 Formula Effects and “Extrapolation Bias”

Another difference in our methods relative to other passthrough papers is that we use of a Fisher index to measure relative price across countries. This is a common method in the international comparisons literature, and it allows us to take into account expenditure weights from both countries and make our real exchange rate symmetric (independent of which country is chosen as the base).

This could, in principle, explain some of our differences in passthrough rates since using CPIs to measure relative price changes across countries can lead to an “extrapolation bias” in the measurement of relative price changes. This term comes from the international comparisons literature, where annual PPP exchange rates are usually calculated by relying on CPIs to extrapolate relative prices until a new ICP round of data collection takes place.<sup>11</sup>

An extrapolation bias occurs when we use CPIs to substitute for the relative price levels in each country. To compute CPIs, national statistical offices mainly use the weighted geometric average of the price relative of each good. Expenditure shares in each good are given by  $s_i^y$  and  $s_i^z$ , and they are independently used to construct the price index in each country.

$$\Delta \ln p_t^y = \sum_i^N s_i^y (\ln p_{i,t}^y - \ln p_{i,t-1}^y) \quad (3)$$

$$\Delta \ln p_t^z = \sum_i^N s_i^z (\ln p_{i,t}^z - \ln p_{i,t-1}^z) \quad (4)$$

The Fisher index of the relative price is given by

$$rp_t^{yz} = \left[ \frac{\sum_i^N p_{i,t}^y q_{i,t}^z}{\sum_i^N p_{i,t}^z q_{i,t}^z} * \frac{\sum_i^N p_{i,t}^y q_{i,t}^y}{\sum_i^N p_{i,t}^z q_{i,t}^y} \right]$$

where the first term is a Laspeyres index using the quantities of country  $y$ , and the second is a Paasche index using the quantities of country  $z$ .

This can be re-written in terms of expenditure shares  $s_i$  in the following way (see proof in the Appendix):

$$rp_t^{yz} = \left[ \sum_i^N \frac{p_{i,t}^y}{p_{i,t}^z} s_i^z * 1 / \sum_i^N \frac{p_{i,t}^z}{p_{i,t}^y} s_i^y \right]^{1/2}$$

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<sup>11</sup>See Deaton (2012) and Inklaar and Rao (2016).

By taking logs, we get:

$$\ln rp_t^{yz} = \frac{1}{2} \left[ \sum_i^N s_i^z (\ln p_{i,t}^y - \ln p_{i,t}^z) - \sum_i^N s_i^y (\ln p_{i,t}^z - \ln p_{i,t}^y) \right] \quad (5)$$

If we calculate the  $\Delta \ln rp_t^{yz}$  and use the CPI definitions above, we get that the change in relative prices is (see proof in the Appendix):

$$\Delta \ln rp_t^{yz} = \Delta \ln p_t^y - \Delta \ln p_t^z + \frac{1}{2} \left[ \sum_i^N (s_i^z - s_i^y) \left( \ln \frac{p_{i,t}^y}{p_{i,t-1}^y} + \ln \frac{p_{i,t}^z}{p_{i,t-1}^z} \right) \right] \quad (6)$$

The change in relative prices is, therefore, equal to the change in CPIs plus an additional term. This term disappears only if the expenditure shares or the inflation rates for all sectors are identical. If not, it can be positive or negative depending on the correlation between relative inflation rates and expenditure shares.

In row (4) of Table 5, we show the passthrough rate when we construct a relative price measure using CPIs and a Fisher index. Relative to a simple ratio of CPIs, the passthrough rate *falls* by about 4 percentage points on average.

To understand the sign of the bias, consider a depreciation of the currency in country  $y$ . Our result suggests that the increase in relative prices in  $y$  is *smaller* than what is measured with the simple ratio of CPIs. So the term in the equation above has to be negative, and the bias from using CPIs is positive. One way this could happen is that goods with higher share of expenditures (in relative terms) are also the ones with higher relative passthrough rates. That is, if  $(\ln \frac{p_{i,t}^y}{p_{i,t-1}^y} + \ln \frac{p_{i,t}^z}{p_{i,t-1}^z})$  is highest when  $s_i^y > s_i^z$ .

### 5.1.3 Matched Online Data and Relative Prices

Continuing with the decomposition, in Row (5) we show the passthrough rate when using our online data to construct a relative price measure that incorporates price changes of continuing goods. At this stage we are not yet incorporating the effect on the average price of a product caused by the price level differences of new and disappearing varieties. Nevertheless, the increase in the passthrough rate is the largest, at 26 percentage points.

One reason for this increase is that we are using *relative* prices for matched goods. That is, we care about not only about local prices, but also the price in the base country, which is also correlated with the nominal exchange rate. If the base country price is ignored, this amounts



to having a standard omitted variable bias. The outcome is the same if we use another good in the base country whose price is uncorrelated with the price of the good that we are trying to compare across countries. Intuitively, the better the quality of the matching of the products across countries, the smaller the bias.

To see this more formally, note that the model that we want to estimate is:

$$\ln(p_t^y) - \ln(p_t^z) = \alpha + \beta \ln(e_t^{zy}) + \mu_t \quad (7)$$

If products are not well matched across countries, the price that we observe in country  $z$  is a proxy for the true price of that good, which can be modeled as:

$$\ln(p_t^{proxy}) = \ln(p_t^z) + \epsilon_t \quad (8)$$

where  $\epsilon_t$  is an error term that may be correlated with the nominal exchange rate. In this case, the regression being estimated is:

$$\ln(p_t^y) - \ln(p_t^z) - \epsilon_t = \alpha + \beta \ln(e_t^{zy}) + \mu_t \quad (9)$$

and our estimate for the  $\beta$  is:

$$\begin{aligned} \hat{\beta} &= \frac{Cov(\ln(e_t^{zy}), \ln(p_t^y) - \ln(p_t^z) - \epsilon_t)}{Var(\ln(e_t^{zy}))} \\ &= \frac{Cov(\ln(e_t^{zy}), \alpha + \beta \ln(e_t^{zy}) + \mu_t - \epsilon_t)}{Var(\ln(e_t^{zy}))} \\ &= \beta - \frac{Cov(\ln(e_t^{zy}), \epsilon_t)}{Var(\ln(e_t^{zy}))} \end{aligned} \quad (10)$$

The sign of the bias depends on the type of mismatch of the goods and their reaction to NER fluctuations. Empirically, our results suggest that CPIs tend to cause a positive bias in the estimated  $\beta$ . Equation (10) implies that the way to minimize the bias in a relative passthrough regression it is to match products as closely as possible across countries.

A more general reason for why the matching matters might relate to our sampling procedure. By trying to find “matchable” products we are implicitly identifying goods that are more tradable and sensitive to movements in the nominal exchange rate. This effect should be present even if we do not use relative prices, so we can test for it using a local-price regression that ignores prices in the base country. That is, for every non-US country we simply regress local prices on the

US dollar NER. The results are shown in Column (6) in Table 5. The passthrough into these local-price regressions is still very high, at 56%. This is consistent with the estimates for long-run passthrough in papers that use prices at-the-dock, where goods are purely tradable by definition (see Burstein and Gopinath (2013)). In addition, consistent with the idea that they are more tradable, we find evidence that matched goods' prices are more flexible than other prices from the same data source. This can be seen in Table 7, where we compare the frequency of changes across samples in all countries. The matched products are between 19% and 82% more flexible than other goods found in the same online databases.

#### 5.1.4 Product Exit and Introductions

We now follow the argument presented in Nakamura and Steinsson (2012) and decompose our relative price series into a matched-model component that ignores entry and exit of products (discussed in the previous section) and an additional extensive margin term that captures whether entering and exiting products are more or less expensive than continuing goods and, therefore, alter the average level of prices.

We denote with  $N_{i,t}^{y,I}$  the set of varieties of product  $i$  which are first sold (or just introduced) at date  $t$ , and denote with  $N_{i,t}^{y,X}$  the set of varieties last sold (or about to exit) at date  $t$ . The number of sampled varieties in our data changes over time, but, since we model the magnitude of the true set of consumed varieties as stable, we do not allow for changes in the product's price index that are purely due to increases or decreases in the number of varieties, as in Feenstra (1994). Entry and exit only matters here through implications on the average per-variety price. We, therefore, write the time  $t + 1$  price of good  $i$  in  $y$  as:

$$\begin{aligned} \ln p_{i,t+1}^y &= \frac{1}{|N_{i,t+1}^y|} \left( \sum_{j \in N_{i,t+1}^{y,I}} \ln p_{ij,t+1}^y + \sum_{j \in N_{i,t+1}^y - N_{i,t+1}^{y,I}} \ln p_{ij,t+1}^y \right) \\ &= n_{i,t+1}^{y,I} \ln \left( \bar{p}_{i,t+1}^{y,I} \right) + (1 - n_{i,t+1}^{y,I}) \ln \left( \bar{p}_{i,t+1}^{y,I*} \right), \end{aligned} \quad (11)$$

where  $n_{i,t+1}^{y,I} = |N_{i,t+1}^{y,I}| / |N_{i,t+1}^y|$  is the number of new varieties at time  $t + 1$  as a share of the total scraped varieties, and where  $\bar{p}_{i,t+1}^{y,I}$  and  $\bar{p}_{i,t+1}^{y,I*}$  are the geometric means at time  $t + 1$  of prices in country  $y$  of newly entering and preexisting varieties of product  $i$ , respectively.

Instead of focusing on the divide between newly entering and preexisting varieties, one can also disaggregate the price level for product  $i$  at any time  $t$  between varieties that will exit and

varieties that will continue to the following period:

$$\begin{aligned}\ln p_{i,t}^y &= \frac{1}{|N_{i,t}^y|} \left( \sum_{j \in N_{i,t}^{y,X}} \ln p_{ij,t}^y + \sum_{j \in N_{i,t}^y - N_{i,t}^{y,X}} \ln p_{ij,t}^y \right) \\ &= n_{i,t}^{y,X} \ln \left( \bar{p}_{i,t}^{y,X} \right) + (1 - n_{i,t}^{y,X}) \ln \left( \bar{p}_{i,t}^{y,X*} \right),\end{aligned}\quad (12)$$

where  $n_{i,t}^{y,X} = |N_{i,t}^{y,X}|/|N_{i,t}^y|$  is the number of exiting varieties as a share of the total scraped varieties, and where  $\bar{p}_{i,t}^{y,X}$  and  $\bar{p}_{i,t}^{y,X*}$  are the geometric means at time  $t$  in country  $y$  of prices of varieties that will subsequently exit and varieties that will continue to the following period, respectively.

Combining equations (11) and (12), we can, therefore, write our measure for the change in the price index for product  $i$  as:

$$\begin{aligned}\Delta \ln p_{i,t+1}^y &= \ln p_{i,t+1}^y - \ln p_{i,t}^y \\ &= \Delta \ln p_{i,t+1}^{y,MM} + n_{i,t+1}^{y,I} \ln \left( \frac{\bar{p}_{i,t+1}^{y,I}}{\bar{p}_{i,t+1}^{y,I*}} \right) - n_{i,t}^{y,X} \ln \left( \frac{\bar{p}_{i,t}^{y,X}}{\bar{p}_{i,t}^{y,X*}} \right),\end{aligned}\quad (13)$$

where  $\Delta \ln p_{i,t+1}^{MM}$  is the change in a matched-model price index and simply equals the average log change in the price of all varieties that existed in both periods  $t$  and  $t + 1$ :

$$\Delta \ln p_{i,t+1}^{y,MM} = \frac{1}{|N_{i,t}^y \cap N_{i,t+1}^y|} \sum_{j \in N_{i,t}^y \cap N_{i,t+1}^y} \Delta \ln p_{ij,t+1}^y. \quad (14)$$

Equation (13) captures that the price of a product in a country can increase for three reasons. First, continuing varieties may cost more today than previously. Second, varieties that are newly available may cost more than varieties that are not new. Third, those varieties that became unavailable this period used to cost less, on average, than varieties which did not become unavailable in this period.

As with the real exchange rate levels, to reach conclusions about real exchange rate dynamics at more general levels, we use weights from CPI expenditure surveys and create Fisher indices. NSOs generally approximate changes in the log ideal price index as the sum of log changes in item-level prices, using a measure of expenditure shares for the fixed weights. We can combine the definition of the real exchange rate (1) and the decomposition (13) to better understand the

drivers of real exchange rate variation. We write:

$$\Delta \ln q_{i,t+1}^{yz} = \Delta \ln \left( rp_{i,t+1}^{yz,MM} \right) + \ln \left( rp_{i,t+1}^{yz,I} \right) - \ln \left( rp_{i,t+1}^{yz,X} \right) + \Delta \ln \left( e_{t+1}^{zy} \right), \quad (15)$$

where:

$$\Delta \ln \left( rp_{i,t+1}^{yz,MM} \right) = \Delta \ln \left( p_{i,t+1}^{y,MM} \right) - \Delta \ln \left( rp_{i,t+1}^{z,MM} \right),$$

and:

$$\ln \left( rp_{i,t+1}^{yz,k} \right) = \eta_{i,t+1}^{y,k} \ln \left( \frac{\bar{p}_{i,t+1}^{y,k}}{\bar{p}_{i,t+1}^{y,k*}} \right) - \eta_{i,t+1}^{z,k} \ln \left( \frac{\bar{p}_{i,t+1}^{z,k}}{\bar{p}_{i,t+1}^{z,k*}} \right),$$

for  $k = I, X$ . Finally, we can then write the change in the real exchange rate at some level of aggregation as:

$$\begin{aligned} \Delta \ln q_{t+1}^{yz} &= \Delta \ln \left( rp_{t+1}^{yz} \right) + \Delta \ln \left( e_{t+1}^{zy} \right) \\ &= \Delta \ln \left( rp_{t+1}^{yz,MM} \right) + \ln \left( rp_{t+1}^{yz,I} \right) - \ln \left( rp_{t+1}^{yz,X} \right) + \Delta \ln \left( e_{t+1}^{zy} \right), \end{aligned} \quad (16)$$

where  $\Delta \ln \left( rp_{t+1}^{yz,MM} \right)$ ,  $\ln \left( rp_{t+1}^{yz,I} \right)$ , and  $\ln \left( rp_{t+1}^{yz,X} \right)$  are Fisher indices of the equivalent objects at the product level (where they'd have an  $i$  subscript), and where  $\Delta \ln \left( rp_{t+1}^{yz} \right) = \Delta \ln \left( rp_{t+1}^{yz,MM} \right) + \ln \left( rp_{t+1}^{yz,I} \right) - \ln \left( rp_{t+1}^{yz,X} \right)$ . For now, we separate relative price terms from the nominal exchange rate – as opposed, for instance, to merging them to create a term  $\Delta \ln q_{t+1}^{yz,MM}$  – to be able to distinguish cases when real exchange rates are stable due to stable prices and nominal exchange rates, as opposed to the case where relative price adjustment offsets movement in the nominal exchange rate.

Row (6) shows that taking product entry and exit into account increases passthrough rates an additional 11 percentage points. Estimates uniformly increase in all sectors, although the increase is small for fuel (where varieties seldom enter or exit) and is large in electronics (where variety turnover is very common).

In drafts work, we aim to better understand what exactly drives this non-trivial contribution from product entry/exit margin. One possibility is that seasonal goods enter and exit our data in a way that is considered to be new goods, with a large price change occurring between seasons. Another possibility is that our lack of expenditure data implies we are overweighting “stale” goods until the point at which a new product enters.

## 6 Conclusions

We use a new dataset with carefully-matched products in nine countries to study the behavior of tradable real exchange rates from 2010 to 2016. Our data combines the broad coverage and price-level methodology of ICP, with the high-frequency and product-matching possibilities of micro-price data.

Our main contribution is to show that tradable good’s prices co-move strongly with the nominal exchange rate at the retail level. We quantify this phenomenon by estimating a rate of passthrough from nominal exchange rates to *relative* prices of 75%, over 45 percentage points higher our own results using CPIs for the same countries and time periods. We then decompose the difference and find that approximately 8 percentage points are explained by sectoral and formula differences, 26 percentage points are caused by the use of matched-goods’s prices across countries, and 11 percentage points by accounting for the prices of new and disappearing varieties.

There several caveats and limitations to the results presented in this paper. First, our time series are relatively short and cover only three tradable sectors and nine countries. While a significant improvement relative to other international micro-price datasets, we are still far away for the “desired standard” mentioned by Taylor (2001), and there is significant heterogeneity in pricing behaviors that still need to be addressed. Second, we have only looked at bilateral real exchange rates with the US, but it is possible that other bilaterals or multi-lateral series behave differently. Third, our data can have their own measurement biases. For example, if retailers change the barcodes of their existing products we may incorrectly interpret them as new goods, which would lead us to over-estimate the contribution of the extensive (intro/exit) margin in our decomposition. Something similar would happen with seasonal goods that have missing prices for a prolonged period of time. In addition, we use data from large retailers, which may have unique behaviors. For example, Goldberg and Hellerstein (2011) found that large firms adjust their prices more frequently in US Producer Price Index data, while Antoniadou and Zaniboni (2016) showed that exchange-rate passthrough increases with market share. More work is needed to understand the potential impact of these -and other- sampling characteristics in our data.

Overall, our results support the long-held view that existing measures of international prices based on CPIs are subject to a variety of measurement biases (Taylor (2001), Imbs et al. (2005), and Nakamura and Steinsson (2012)). Our findings may also reflect the growing importance of online transactions in retail markets. Papers such as Ellison and Ellison (2009) and Gorodnichenko and Talavera (2017) have found more flexibility and higher passthroughs in online marketplaces and price-comparison websites. While our data comes from retailers which sell the vast majority of

their goods offline, an increase in online competition could be prompting companies like Walmart to behave more like Amazon (see Cavallo (2017)). Understanding the impact of online transactions in retail markets, and how this might affect the way shocks are transmitted within and across borders, is an important topic for future research.

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## Food Products

Basmati White Rice  
Jasmine White Rice  
Wheat All-Purpose Flour  
Barilla Spagueti (including whole grain)  
Non-Barilla Spagueti (including whole grain)  
Kellogg's Breakfast Cereal (excluding gluten free)  
Kellogg's Granola Breakfast Cereal  
Non-Kellogg's Breakfast Cereal (excluding gluten free)  
Non-Kellogg's Granola Breakfast Cereal  
Ground Beef  
Chicken Breast (whole)  
Honey-Baked Ham Cold Cut  
Smoked Ham Cold Cut  
Low-Sodium Ham Cold Cut  
Low Fat Hot Dogs  
Regular Hot Dogs  
Canned Tuna in Oil  
Canned Tuna in Water  
Philadelphia Regular Cream Cheese  
Philadelphia Fat Free or Low Fat Cream Cheese  
Brown Eggs  
White Eggs  
Nutella Chocolate Spread  
Extra Virgin Olive Oil  
Illy Coffee Beans (excluding decaf)  
Illy Decaf Coffee Beans  
Non-Illy Coffee Beans (excluding decaf)  
Non-Illy Decaf Coffee Beans  
Nesquik Chocolate Milk Mix  
Twinings Earl Grey Tea Bags  
Twinings Green Tea Bags  
Non-Twinings Earl Grey Tea Bags  
Non-Twinings Green Tea Bags  
Nestle Mineral Water  
Dasani Mineral Water  
Tropicana Pulp Free Orange Juice  
Tropicana Orange Juice With Pulp  
Non-Tropicana Pulp Free Orange Juice  
Non-Tropicana Orange Juice With Pulp

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## Electronics Products

LG Basic Blu-Ray Player  
LG Specialized Blu-Ray Player  
Samsung Blu-Ray Player  
Samsung Specialized Blu-Ray Player  
Sony Blu-Ray Player  
Sony Specialized Blu-Ray Player  
Samsung 32 Inch LED TV (excluding HD, Smart, 3D)  
Philips 32 Inch LED TV (excluding HD, Smart, 3D)  
Panasonic 32 Inch LED TV (excluding HD, Smart, 3D)  
Sony 44-47 Inch LED TV (Full HD, Smart, or 3D)  
Toshiba 44-47 Inch LED TV (Full HD, Smart, or 3D)  
Samsung 61-65 Inch LED TV  
LG 61-65 Inch LED TV  
Apple Ipod Shuffle 2GB  
Apple Touch 32GB  
Sony In-Ear Earphones  
Beats In-Ear Earphones  
Sennheiser Over-Ear Headphones  
Skullcandy Over-Ear Headphones  
Logitech Basic Webcam  
Non-Logitech Basic Webcam  
Apple 13 Inch Macbook  
Sony VAIO 14-16 inch Laptop (No Touchscreen)  
Apple Ipad Air 32GB (excludes 3G)  
Apple Ipad Air 64GB  
Apple Ipad 4 16GB with 3G  
Samsung 7inch Tablet  
HP Color Laser Printer  
Xerox Color Laser Printer  
Sandisk 4GB Memory Card  
Sandisk 32GB Memory Card  
Sony 4GB Memory Card  
Sony 32GB Memory Card  
Sony Playstation 3 500GB  
Sony Playstation 3 500GB Super Slim  
Sony Playstation 4  
Microsoft Xbox 360  
GoPro Full HD Camcorder  
Nikon 20-24mpx Digital SLR Camera

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Table 1: Sample Product Definitions

Notes: Sample of product definitions in Food and Electronics. These products were chosen to provide full coverage of all the COICOP Level 3 classification structure in these sectors.

Country	Sector	Products	Median Varieties per Product
Argentina (ARG)	Food and non-alcoholic beverages	100	24
Argentina (ARG)	Fuels and lubricants	2	1
Argentina (ARG)	Electronics	58	9
Australia (AUS)	Food and non-alcoholic beverages	119	12
Australia (AUS)	Fuels and lubricants	4	1
Australia (AUS)	Electronics	64	10
Brazil (BRA)	Food and non-alcoholic beverages	120	14
Brazil (BRA)	Fuels and lubricants	2	1
Brazil (BRA)	Electronics	70	14
China (CHN)	Food and non-alcoholic beverages	105	7
China (CHN)	Fuels and lubricants	4	32
China (CHN)	Electronics	70	17
Japan (JPN)	Food and non-alcoholic beverages	58	4
Japan (JPN)	Fuels and lubricants	2	1
Japan (JPN)	Electronics	53	11
South Africa (ZAF)	Food and non-alcoholic beverages	89	5
South Africa (ZAF)	Fuels and lubricants	3	1
South Africa (ZAF)	Electronics	54	8
United Kingdom (GBR)	Food and non-alcoholic beverages	134	17
United Kingdom (GBR)	Fuels and lubricants	3	2
United Kingdom (GBR)	Electronics	69	22
United States (USA)	Food and non-alcoholic beverages	172	28
United States (USA)	Fuels and lubricants	4	51
United States (USA)	Electronics	76	50

Table 2: Summary Statistics

L3 COICOP Category	Mean CV USD Price (1)	Countries (2)
Fish and seafood	0.23	9
Games, toys and hobbies	0.26	8
Information processing equipment	0.27	8
Photographic and cinematographic equipment and optical instruments	0.28	8
Equipment for the reception, recording and reproduction of sound and picture	0.30	8
Fuels and lubricants for personal transport equipment	0.30	7
Recording media	0.34	8
Sugar, jam, honey, chocolate and confectionery	0.36	9
Milk, cheese and eggs	0.36	8
Coffee, tea and cocoa	0.37	7
Mineral waters, soft drinks, fruit and vegetable juices	0.39	5
Food products n.e.c.	0.39	8
Meat	0.41	8
Bread and cereals	0.41	8
Vegetables	0.44	7
Oils and fats	0.49	8
Fruits	0.53	7

Table 3: Which Categories have Greatest Dispersion in US Dollar Prices?

Notes: We first calculate the price in USD in each country. We then get the coefficient of variation across countries (by product and month). We then average for all months, and, finally, for all products.

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<b>Relative Price</b>	<b>3 Sectors</b>	<b>Ex-Fuel</b>	<b>Food</b>	<b>Fuel</b>	<b>Electronics</b>
	(1)	(2)	(3)	(4)	(5)
(1) All Countries	-0.749 (0.013)	-0.721 (0.025)	-0.738 (0.027)	-0.955 (0.016)	-0.553 (0.031)
(2) Argentina	-0.790 (0.029)	-0.987 (0.055)	-1.010 (0.058)	-0.914 (0.041)	-0.988 (0.105)
(3) Australia	-0.655 (0.027)	-0.508 (0.044)	-0.577 (0.052)	-0.855 (0.031)	-0.164 (0.065)
(4) Brazil	-0.852 (0.042)	-0.575 (0.052)	-0.592 (0.053)	-1.383 (0.057)	-0.392 (0.062)
(5) China	-1.122 (0.154)	-0.921 (0.143)	-1.062 (0.169)	-1.690 (0.367)	-0.369 (0.115)
(6) Germany	-0.776 (0.061)	-0.593 (0.096)	-0.580 (0.100)	-0.920 (0.058)	-0.435 (0.095)
(7) Japan	-0.208 (0.037)	-0.170 (0.066)	-0.266 (0.075)	-0.660 (0.046)	0.106 (0.090)
(8) South Africa	-0.780 (0.020)	-0.591 (0.058)	-0.508 (0.065)	-0.956 (0.020)	-0.843 (0.060)
(9) UK	-0.582 (0.097)	-0.113 (0.113)	-0.069 (0.149)	-1.330 (0.108)	-0.219 (0.055)

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Table 4: Passthrough Estimates

Notes: All bilaterals calculated with respect to the United States. Results for benchmark series labelled ‘PPP Overall’ in other tables.

Price Measure	Relative Price Regressions					Price Regressions
	3 Sectors (1)	Ex-Fuel (2)	Food (3)	Fuel (4)	Electronics (5)	3 Sectors (6)
(1) CPI All items	-0.296 (0.007)					-0.374 (0.007)
(2) CPI 1-Digit	-0.344 (0.008)	-0.269 (0.013)	-0.251 (0.014)	-0.452 (0.010)	-0.183 (0.023)	-0.361 (0.008)
(3) CPI 3-Digit	-0.414 (0.011)	-0.299 (0.015)	-0.278 (0.015)	-0.743 (0.021)	-0.219 (0.031)	-0.357 (0.010)
(4) CPI 3-Digit Fisher	-0.376 (0.010)	-0.268 (0.015)	-0.268 (0.014)	-0.701 (0.019)	-0.194 (0.028)	-0.344 (0.010)
(5) PPP Matched Model	-0.638 (0.013)	-0.475 (0.024)	-0.513 (0.022)	-0.948 (0.016)	-0.117 (0.040)	-0.557 (0.019)
(6) PPP Overall	-0.749 (0.013)	-0.721 (0.025)	-0.738 (0.027)	-0.955 (0.016)	-0.553 (0.031)	
(7) PPP Overall Branded		-0.662 (0.026)	-0.661 (0.028)		-0.586 (0.033)	
(8) PPP Overall Unbranded		-0.69 (0.026)	-0.736 (0.028)	-0.955 (0.016)	-0.348 (0.047)	

Table 5: Passthrough Decomposition - All countries

Notes: All bilaterals calculated with respect to the United States.

Category	Monthly Frequency		Ratio PPP/CPI
	US PPP Online Data	US CPI Data Nakamura & Steinsson (08)	
Panel A: Weighed Means by Sector			
3- Sectors (matched)	46.7	48.5	0.96
Food	25.0	32.3	0.77
Fuel	96.1	87.4	1.10
Electronics	20.8	17.9	1.17
Panel B: Weighted Means by Sub-sector			
Cereals	17.2	23.7	0.73
Flour	29.6	15.4	1.92
Bread	10.7	27.1	0.39
Beef and Veal	29.1	45.6	0.64
Poultry	29.6	34.2	0.87
Whole Milk	24.0	32.3	0.74
Butter	23.2	38.3	0.60
Vegetable Oils	33.5	24.7	1.35
Fruits	20.5	45.1	0.45
Vegetables	23.1	46.7	0.49
Sugar	24.2	18.1	1.34
Sauces & Condiments	23.1	20.3	1.14
Tea	24.3	26.4	0.92
Cocoa and chocolate	17.2	16.5	1.04
Mineral water	13.6	29.4	0.46
Soft Drinks	31.7	29.7	1.07
Fuel	96.1	87.4	1.10
Cameras	29.6	17.9	1.66
Computers	26.1	32.9	0.79
Games and Toys	14.9	11.5	1.30

Table 6: Stickiness - Comparison with CPI data from US

Notes: Coicop Level 4 and US ELI classification matched using coding from Berardi et al (2015). Weights from Nakamura and Steinsson (08) ELI table. Not all categories could be matched.



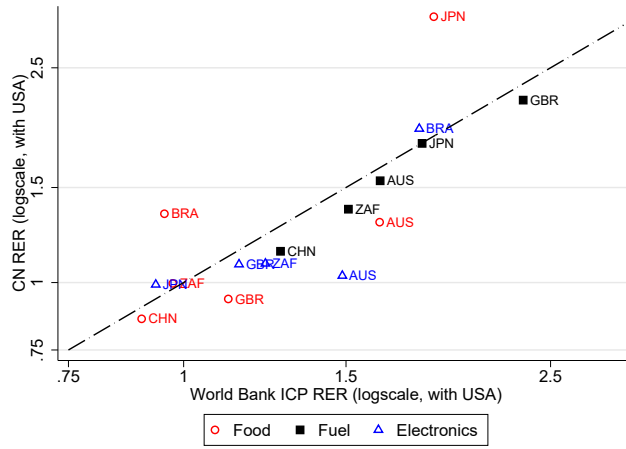
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Category	Country	Monthly Frequency		
		PPP Online Data	BPP Online Data	Ratio PPP/BPP
3 Sectors	Argentina	38.4	32.2	1.19
	Australia	41.1	33.9	1.21
	Brazil	52.4	38.5	1.36
	China	30.2	16.7	1.82
	Germany	30.8	22.3	1.38
	Japan	25.8	19.5	1.33
	South Africa	37.3	23.8	1.57
	UK	43.2	35.1	1.23
	USA	48.7	30.5	1.60

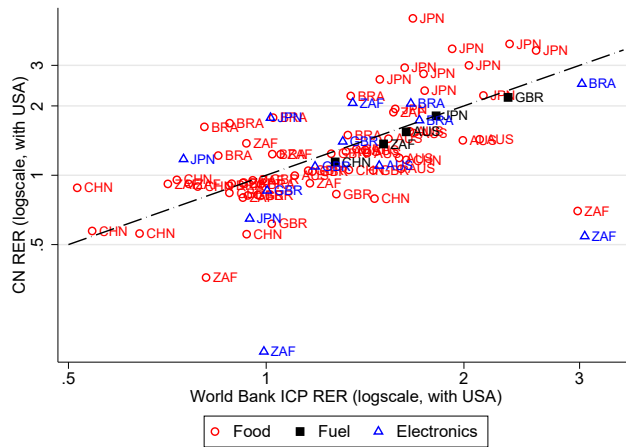
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Table 7: Stickiness - PPP Online Data vs BPP Online Data

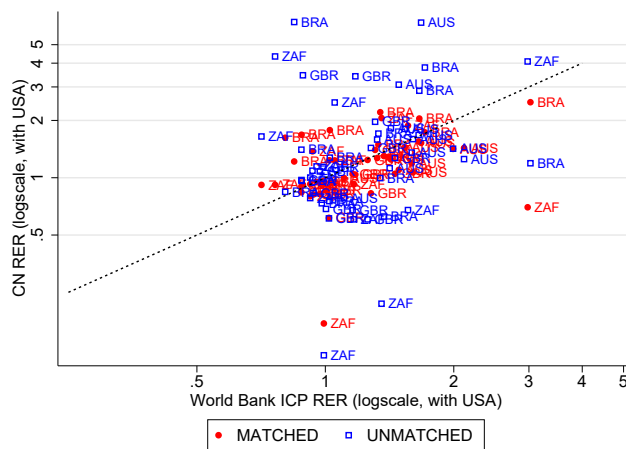
Notes: The PPP online data is a subset of the BPP online data. It includes only the goods that are matched across countries and used for computing the bilateral RERs.



(a) 1-Digit



(b) 3-Digit



(c) 3-Digit - Matched vs Unmatched

Figure 1: Real Exchange Rate Levels Relative to the United States, ICP vs. CN in 2011

Notes: 2011 is the only year with ICP data in our 2010-2016 sample. ICP prices are collected by NSOs at some unpublished date during that year. We calculate the ICP real exchange rate using the average nominal exchange rate for that year. The CN real exchange rate is the average daily real exchange rate for the year 2011.

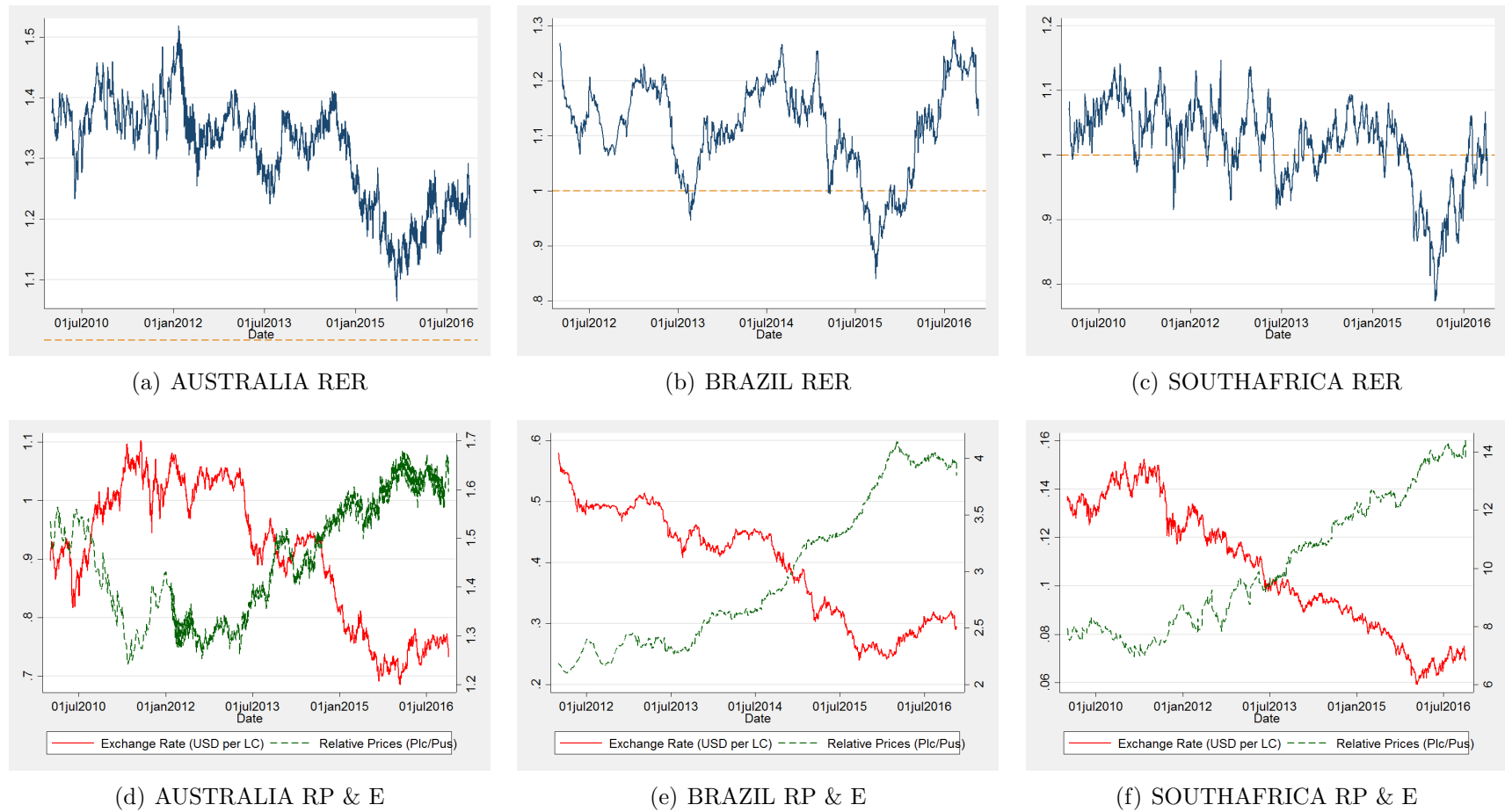
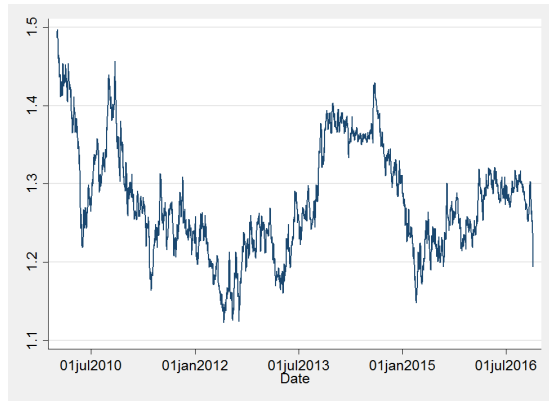
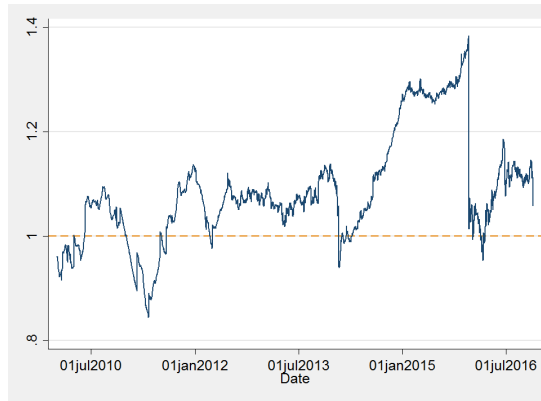


Figure 2: Real Exchange Rates, Relative Prices, and Nominal Exchange Rates - All Sectors

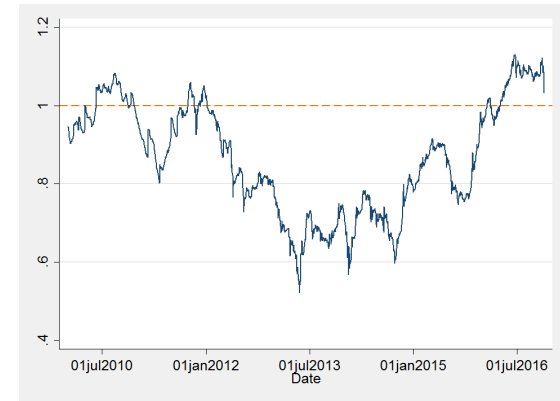
Notes: The solid (blue) line is the bilateral real exchange rate relative to the US in all sectors. It is computed as the relative price ( $P_{lc}/P_{us}$ ) multiplied by the nominal exchange rate (USD per local currency). The dashed (orange) line is drawn at the level where the RER is equal to one (the value predicted by absolute PPP). The solid (red) line is the nominal exchange rate expressed as local currency per unit of US dollars (an increase means the local currency depreciates). The dashed (green) line is the relative price expressed as the price in local currency over the price in the US. Relative prices are first calculated at the level of the product, and then aggregated with a geometric weighted average and a Fisher price index that uses the official CPI expenditure weights in both countries.



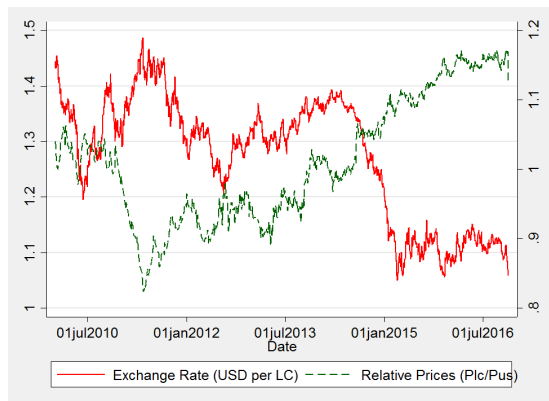
(a) GERMANY RER



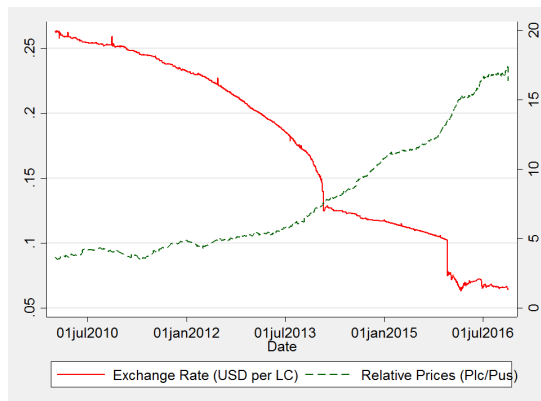
(b) ARGENTINA RER



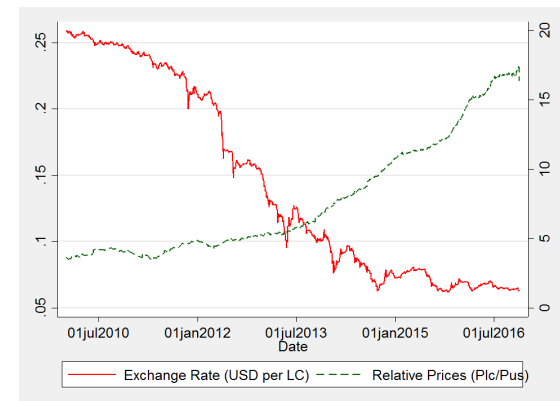
(c) ARGENTINA BLACK MARKET RER



(d) GERMANY RP &amp; E



(e) ARGENTINA RP &amp; E



(f) ARGENTINA BLACK MARKET RP &amp; E

Figure 3: Real Exchange Rates, Relative Prices, and Nominal Exchange Rates - All Sectors

Notes: The solid (blue) line is the bilateral real exchange rate relative to the US in all sectors. It is computed as the relative price ( $P_{LC}/P_{US}$ ) multiplied by the nominal exchange rate (USD per local currency). The dashed (orange) line is drawn at the level where the RER is equal to one (the value predicted by absolute PPP). The solid (red) line is the nominal exchange rate expressed as local currency per unit of US dollars (an increase means the local currency depreciates). The dashed (green) line is the relative price expressed as the price in local currency over the price in the US. Relative prices are first calculated at the level of the product, and then aggregated with a geometric weighted average and a Fisher price index that uses the official CPI expenditure weights in both countries.

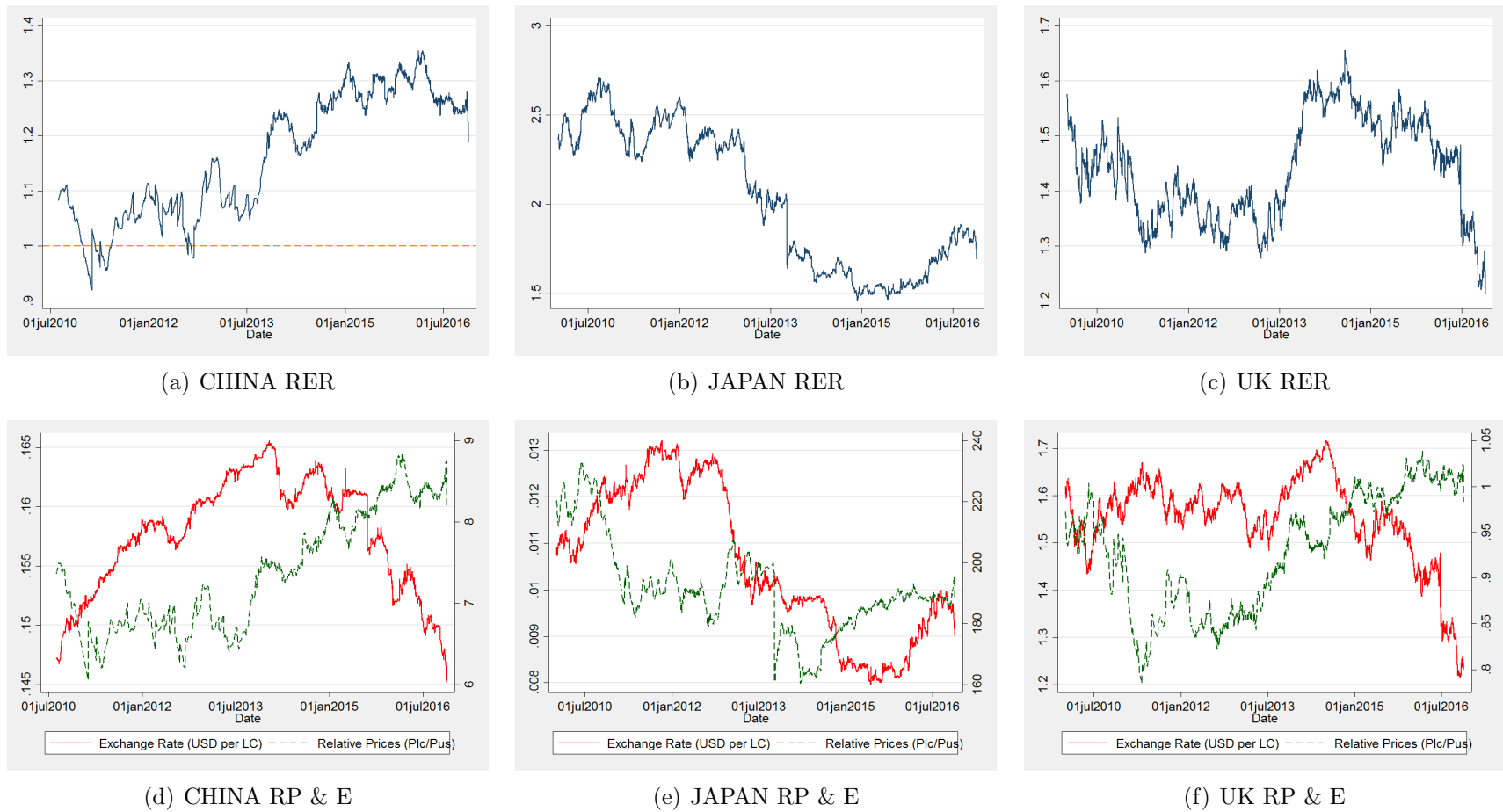


Figure 4: Real Exchange Rates, Relative Prices, and Nominal Exchange Rates - All Sectors

Notes: The solid (blue) line is the bilateral real exchange rate relative to the US in all sectors. It is computed as the relative price ( $P_{lc}/P_{us}$ ) multiplied by the nominal exchange rate (USD per local currency). The dashed (orange) line is drawn at the level where the RER is equal to one (the value predicted by absolute PPP). The solid (red) line is the nominal exchange rate expressed as local currency per unit of US dollars (an increase means the local currency depreciates). The dashed (green) line is the relative price expressed as the price in local currency over the price in the US. Relative prices are first calculated at the level of the product, and then aggregated with a geometric weighted average and a Fisher price index that uses the official CPI expenditure weights in both countries.

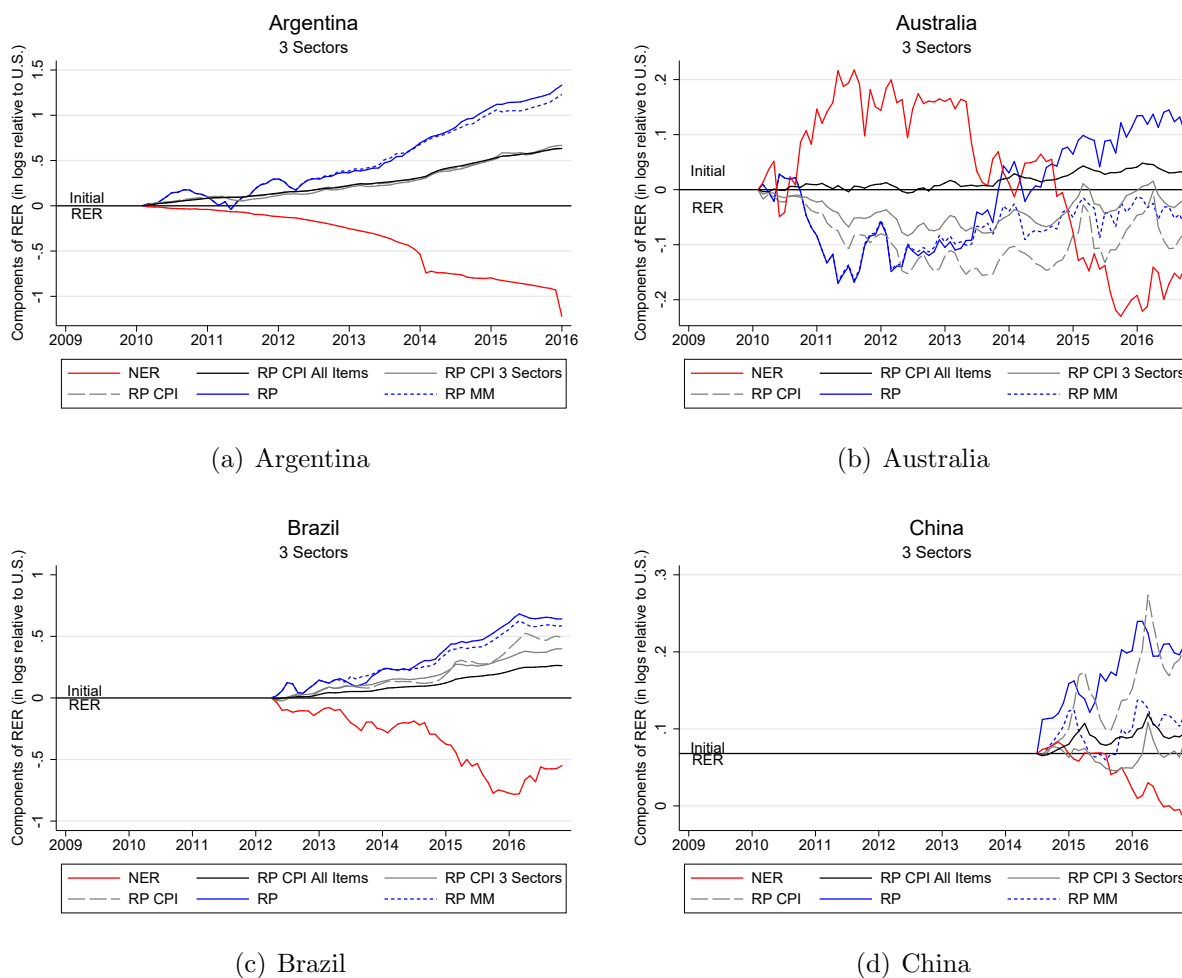
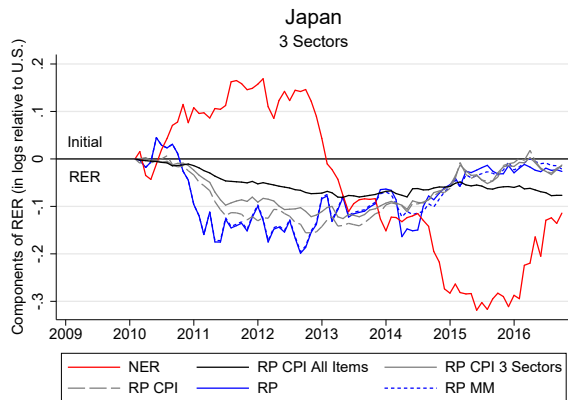
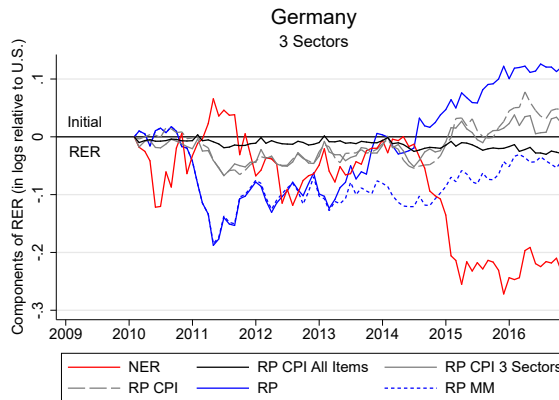


Figure 5: Decomposing the Difference With CPIs - All Sectors

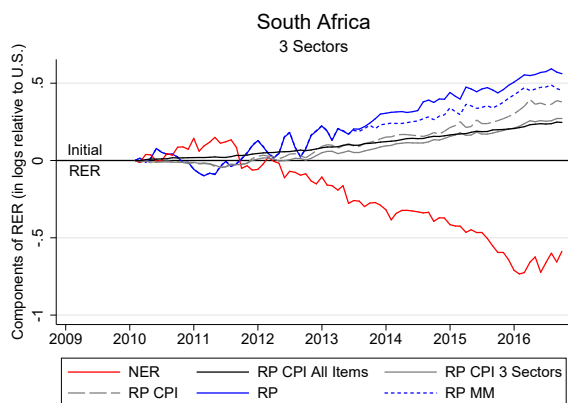
Notes: This figure shows the time series used to estimate the passthrough decomposition in the first column of Table 5. All series are normalized to the first date with data for that country. The solid red line is the nominal exchange rate expressed as units of US dollars per unit of the local currency. The black/gray lines are the relative price series constructed with CPI data. The blue lines are relative price series constructed with online matched data. In terms of the notation used in Table 5, the black line is the “CPI All Items”, the solid gray is “CPI 3-digit”, and the dashed gray is “CPI-Fisher”, the dashed blue is “PPP Matched Model”, and the solid blue line is “PPP Overall”. Similar graphs for individual sectors are shown in the Appendix.



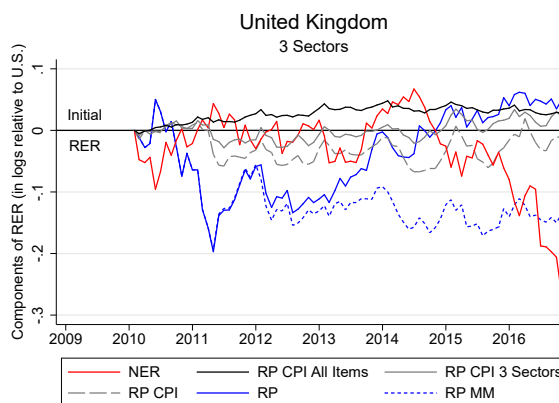
(a) Japan



(b) Germany



(c) South Africa



(d) United Kingdom

Figure 6: Decomposing the Difference With CPIs - All Sectors

Notes: This figure shows the time series used to estimate the passthrough decomposition in the first column of Table 5. All series are normalized to the first date with data for that country. The solid red line is the nominal exchange rate expressed as units of US dollars per unit of the local currency. The black/gray lines are the relative price series constructed with CPI data. The blue lines are relative price series constructed with online matched data. In terms of the notation used in Table 5, the black line is the “CPI All Items”, the solid gray is “CPI 3-digit”, and the dashed gray is “CPI-Fisher”, the dashed blue is “PPP Matched Model”, and the solid blue line is “PPP Overall”. Similar graphs for individual sectors are shown in the Appendix.