Accounting for Real Exchange Rates using Micro-Data *

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Abstract

The classical dichotomy predicts that all of the time-series variance in the aggregate real exchange rate is accounted for by non-traded goods in the CPI basket because traded goods obey the Law of One Price. In stark contrast, Engel (1999) found that traded goods had comparable volatility to the aggregate real exchange rate. Our work reconciles these two views by successfully applying the classical dichotomy at the level of intermediate inputs into the production of final goods using highly disaggregated retail price data. Since the typical good found in the CPI basket is about equal parts traded and non-traded inputs, we conclude that the classical dichotomy applied to intermediate inputs restores its conceptual value.

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1 Introduction

One of the central puzzles in international economics is the high time-series variance of aggregate real exchange rates (RER). An enduring explanation for the aggregate RERs variance is the classical dichotomy theory of Balassa (1964), Salter (1959), Samuelson (1964) and Swan (1960). This is the notion that the consumption basket consists of goods that are mostly traded and services that are mostly non-traded. According to the classical dichotomy, traded goods satisfy the law of one price (LOP) such that all of the time-series variance in aggregate RERs must be accounted for by the RERs for non-traded services.

This paper re-examines the usefulness of distinguishing between goods and services in accounting for the time-series variance of the aggregate RER. The earliest systematic empirical investigation of this issue is Engel (1999), who worked with a two-sector representation of the aggregate RER using CPI data:

\[ q_{jkt} = \omega q_{jkt}^N + (1-\omega)q_{jkt}^T, \]

where \( q_{jkt}^N \) is the relative price of an aggregate of housing and other services and \( q_{jkt}^T \) is the relative price of an aggregate of goods across country pair \( j \) and \( k \) at date \( t \). The variance of the aggregate RER may be computed from equation (1) as follows:

\[ \text{var}(q_{jkt}) = \omega \text{cov}(q_{jkt}^N, q_{jkt}) + (1-\omega)\text{cov}(q_{jkt}^T, q_{jkt}), \]

where \( \omega \) is the consumption-expenditure share of services. Dividing through both sides by the variance of the aggregate gives the variance decomposition,

\[ 1 = \omega \beta_{jk}^N + (1-\omega)\beta_{jk}^T. \]

As noted by Engel, the classical dichotomy assumes that traded goods prices deviate from international price parity by a time invariant wedge, reflecting good-specific tariffs or quotas, shipping costs and destination-specific markups over marginal cost. As such, traded goods relative prices are assumed not to fluctuate over time and thus cannot contribute to time-series variation in the aggregate RER. This assumption places stark restrictions on the variance decomposition, namely: \( \beta_{jk}^T = 0 \), which implies \( \beta_{jk}^N = \omega^{-1} \). Engel found that
for bilateral US RERs with Canada, Germany and Japan, $\beta_{jk}^T \approx 1$, which also implies that $\beta_{jk}^N \approx 1$. Simply put, goods and services are basically indistinguishable with each component contributing to RER movements in proportion to its expenditure share. His results are widely viewed as a repudiation of the classical dichotomy.\(^1\)

Another possible interpretation of Engel’s finding is that the allocation of consumption expenditure to the non-traded and traded aggregates using the available published CPI sub-indices is infeasible and thus fails to do justice to the classical dichotomy theory. For example the price index for food includes both groceries and restaurant meals. Given the choice, it would be preferable to allocate groceries to the traded aggregate and restaurant meals to the non-traded aggregate.

To circumvent this problem we utilize a novel source of microeconomic price data, the Economist Intelligence Unit (EIU) global survey of retail prices. The survey spans 301 goods and services across 123 cities (mostly capitals) of the world. Using these line-item price data along with estimates of the share of non-traded and traded inputs into the production of each item (estimated by Crucini and Yilmazkuday (2013)), we allocate items to the non-traded category when the estimated non-traded inputs cost share exceeds 60%.\(^2\) The microeconomic RERs of individual items are then weighted using U.S. expenditure weights to construct the aggregate RER.

To compare our results with those of Engel, we average the $\beta$’s across location pairs within the OECD. The beta for the non-traded RER is 1.14 and the

\(^1\)Many other research papers have followed Engel’s lead and reach the same conclusion. In their review of the literature, Burstein and Gopinath (2013) emphasize that “Movements in RERs for tradable goods are roughly as large as those in the overall CPI-based RERs when tradable goods prices are measured using consumer or producer prices, but significantly smaller when measured using border prices.” Indeed, the baseline approach in Engel (1999) is to measure the price index of tradable goods for the CPI, which is based on retail or consumer prices. Alternatively, Engel (1999) and Betts and Kehoe (2006) measure the price of tradable goods using producer and other output price indices and reach the same conclusion. Burstein et al. (2006) find that the contribution of tradable goods prices to RER fluctuations is significantly smaller when measured using border prices.

\(^2\)Engel classified services and housing as non-traded and all other sub-indices of the CPI (referred to as commodities) as traded. We achieve basically the same classification when we label goods with a non-traded inputs cost share of 60% or higher as non-traded goods.
beta for the traded RER is $\beta^T = 0.82$. This is clearly a greater degree of separation between the two than Engel found. To gain some economic perspective, weighted by its expenditure share, the fraction of variance contributed by non-traded services is 64% ($0.56 \times 1.14 = 0.64$) with the remaining 36% accounted for by traded goods. This elevates the contribution of non-traded services by about 15% compared to Engel’s findings. While this represents progress for the classical dichotomy, the fact remains that the traded goods aggregate comes closer to contributing equally than it does to contributing nothing to aggregate RER volatility, as the classical dichotomy asserts.

Understandably, considerable research has been undertaken to develop models capable of generating a significant role for traded goods in accounting for the variability of the aggregate RERs. Before elaborating on these theories, it is useful to consider the level of heterogeneity in the contribution of LOP deviations to the variation in the aggregate RER. A trivial extension of the two-sector variance decomposition to $N$ goods yields the following expression:

$$1 = \sum_{i=1}^{N} \omega_i \beta_{ijk}.$$  \hspace{1cm} (4)

The advantage of starting with this decomposition is that it does not arbitrarily restrict the distribution of LOP deviations that comprise the aggregate RER. Figure 1 displays a kernel density estimate of the $\beta_{ijk}$. The distribution certainly does not lend itself to a two-category classification in which the betas for goods are all equal to zero and the betas for services are all equal to $\omega^{-1}$. Rather, there is a distribution that appears quite symmetric around unity. Thus, any theory that claims to explain aggregate RER volatility will need to incorporate quite vast heterogeneity in the contributions to variance across individual items. Three broad lines of research seem promising in achieving this goal.

The first line of research follows the classical dichotomy approach, but does so at the level of intermediate inputs into the production of final goods. This approach has its origins in the trade models developed by Sanyal and Jones (1982) and Ethier (1979), and more recent dynamic equilibrium models by Burstein, Eichenbaum and Rebelo (2005), Burstein, Neves and Rebelo (2003), Corsetti and Dedola (2005), Corsetti, Dedola and Leduc (2008) and Crucini
and Davis (2013). The second line of research focuses on the determination of prices at the border, what would be the traded inputs according to first line of research. According to this view, LOP deviations arise due to time-varying international markups that differ across destination markets. This approach recognizes that manufacturers of traded goods are often large multinational firms best viewed as operating in an imperfectly competitive market (see, for example, Alessandria and Kaboski (2011), Atkeson and Burstein (2008), Baxter and Landry (2012), Fitzgerald and Haller (2013), Gopinath et al. (2011) and the excellent review by Burstein and Gopinath (2013)). The third line of research recognizes that retail prices change infrequently while the nominal exchange rate varies continuously (see, for example, Carvalho and Nechio (2011), Kehoe and Midrigan (2007) and Obstfeld and Rogoff (2000)). Our approach is flexible enough to provide insights into how each of these perspectives helps us to understand both LOP deviations and the contributions of those deviations to variation in the aggregate RER.

The first two approaches are best discussed together. Continuing with the Cobb-Douglas form of the RER, taken down to the level of an individual final good, we have:

\[ q_{ijkt} = \alpha_i w_{jkt} + (1 - \alpha_i) \tau_{ijkt} . \] (5)

where \( \alpha_i \) is a good-specific cost-share of distribution (i.e., non-traded inputs), \( w_{jkt} \) is a distribution cost wedge and \( \tau_{ijkt} \) are time-varying deviations from the LOP. The distribution cost wedge is proxied by relative wages of unskilled labor to simplify the exposition. In general one would expect rental costs of retail space to play an important role as well. The trade cost wedge captures time-varying relative markups by exporting firms. If official and natural barriers to trade were not constant over time, they would appear here as well.

This formulation leads to a transparent mapping between the distribution and trade cost wedges in micro-prices, and the contribution of an individual LOP deviation to aggregate RER variability. Specifically, the contribution of good \( i \) to the variance of the aggregate RER is:

\[ \beta_{ijk} = \alpha_i \beta_{j}^w + (1 - \alpha_i) \beta_{ijk}^\tau , \] (6)

where \( \beta_{j}^w \) is the covariance of the aggregate RER with the relative unit cost of distribution and \( \beta_{ijk}^\tau \) is the covariance of the aggregate RER with the relative
price of the good at the dock.

Distribution cost models typically adhere to the classical dichotomy for traded inputs and thus impose the restriction $\beta_{ijk}^r = 0$. As such all LOP deviations at the retail stage arise from distribution costs and the variation of the contribution of individual goods and services to the variation in the aggregate RER depicted in Figure 1 would reflect heterogeneity in the cost shares, $\alpha_i$. As one might expect, we find an important quantitative role for both terms. Aggregating this equation across goods and parsing the variance into a distribution and a trade wedge, we find that the distribution component accounts for 81% of the variation and the trade component accounts for the remaining 19%. Simply put, while the strict version of the classical dichotomy is a straw man null, the conceptual idea that local inputs accounts for the lion’s share if aggregate RER variation turns out to be correct. Moreover, the role of traded inputs is substantial and consistent with a large body of literature documenting incomplete pass-through of exchange rates into prices at the dock.\(^3\)

Models in which prices are sticky in local currency units often treat the degree of price stickiness as common across all goods and services. These models impose a singularity on the cross-section of LOP deviations which results in a degenerate distribution for $\beta_{ijk}$ at 1. Recent extensions of time-dependent pricing models that allow for heterogeneity in the degree of price stickiness across goods are more promising. Consider the key equation from Kehoe and Midrigan (2007) where the LOP deviation for a particular good $i$ follows:

$$q_{ijkt} = \lambda_i q_{ijkt-1} + \lambda_i \Delta s_{jkt}$$

where $\lambda_i$ is the Calvo probability that the price does not change and $\Delta s_{jkt}$ is the change in the nominal exchange rate.

Applied to this model, the good-level beta in our variance decomposition

\(^3\)This is also consistent with the results suggested in Fitzgerald and Haller (2013) and Gopinath et al. (2011), in which significant LOP deviations remain even after controlling for non-traded inputs.
can be shown to equal\footnote{Recall, $\beta_{i,jk} = \frac{\lambda_i \cdot \text{cov}(\Delta s_{jkt}, q_{jkt})}{\text{var}(q_{jkt})}$}. 

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\beta_{i,jk} = \frac{\lambda_i \cdot \text{cov}(\Delta s_{jkt}, q_{jkt})}{1 - \lambda_i \cdot \text{var}(q_{jkt})}
$$

which equals zero in the flexible price case ($\lambda_i = 0$) and is increasing in the degree of price stickiness. The second term involves the \textit{level} of the aggregate RER and the \textit{change} in the nominal exchange rate. As the Calvo parameter is increased toward unity, the variance of the level of the RER goes to infinity while the change in the nominal exchange rate is taken to be a finite constant (i.e., the innovation to the nominal exchange rate change is finite). We find an important role of the nominal exchange rate in generating variations in LOP deviations across bilateral pairs for individual goods, suggestive of the notion that the exchange rate regime matters for relative prices volatility at the microeconomic level. However, due to the low frequency nature of the panel data used, we cannot explicitly assess the role of heterogeneous frequencies of price changes across goods (see, for example, Crucini, Shintani and Tsuruga (2013)).

The rest of the paper proceeds as follows. In Section 2, we present the data. In Section 3, we describe our methodology and compute individual contributions of LOP deviations to aggregate RER volatility. In Section 4, we document a striking positive relationship between the magnitude of the contribution of a LOP deviation to aggregate RER volatility and the cost-share of inputs used to produce that good. Then, we develop and estimate a two-factor model, and aggregate these factors to measure the contribution of intermediate inputs to aggregate RER volatility. In Section 5, we show that our microeconomic decompositions, when aggregated, look very similar to earlier studies using aggregate CPI data, but that the economic implications are very different. Section 6 concludes.
2 The Data

The source of retail price data is the Economist Intelligence Unit Worldwide Survey of Retail Prices. The EIU survey collects prices of 301 comparable goods and services across 123 cities of the world. The number of prices overstates the number of items because many items are priced in two different types of retail outlets. For example, all food items are priced in both supermarkets and mid-priced stores. Clothing items are priced in chain stores and mid-price/branded store. The prices are collected from the same physical outlet over time, thus the prices are not averages across outlets. The panel used in this study is annual and spans the years 1990 to 2005. The local currency prices are converted to common currency using the prevailing nominal exchange rates at the time the survey was conducted.

The data are supplemented with two additional sources from the U.S. Bureau of Economic Analysis: the National Income and Product Account and the Industry Economic Accounts Input-Output tables. The first supplementary data series are consumption-expenditure weights. These data are more aggregated than the EIU prices, leading us to allocate about 300 individual retail prices to 73 unique expenditure categories. We divide the sectorial expenditure weights by the number of prices surveyed in each sector so that each category of goods in the EIU panel has the same expenditure weight as in the U.S. CPI index. As some sectors are not represented in the EIU retail price surveys, the expenditure weights are adjusted upward to sum to unity.

The second supplementary source are the distribution wedges, the fraction of gross-output attributable to non-traded inputs. These include wholesale and retail services, marketing and advertisement, local transportation services and markups. For goods, we use 1992 sector-level NIPA data on expenditures by consumers and producers, and compute the difference between what consumers pay and what producers receive divided by that the consumers pay. For example, if final consumption expenditure on bread is $100 and producers receive $60, the distribution wedge is 0.40. For services, however, what consumers pay and what producers receive would be the same value by this accounting method. In reality, when a consumer (or that consumer’s health insurance provider) receives a medical bill, the charge includes wage compen-
sation for their doctor and the cost of any goods or other services included in the treatment, whether or not it is itemized on the invoice. In these circumstances, we use the 1990 U.S. input-output data to measure non-traded and traded inputs. Each retail item in the EIU panel is reconciled with one of these sectors and assigned that sector’s distribution wedge, leading to 30 unique sectorial shares. The median good has a distribution wedge of 0.41. The economy-wide average distribution wedge weighted by final expenditure is 0.48 for US cities, 0.49 for OECD cities and 0.53 for non-OECD cities. Overall, our distribution wedges are similar to those used in Burstein et al. (2003) and Campa and Goldberg (2010).

Instead of estimating the size of the distribution sector using aggregate data, Berger et al. (2012) measured the distribution wedges using U.S. retail and import prices of specific items from the U.S. CPI and PPI data. They find that the distribution wedges are distinctively larger than the estimates reported for U.S. consumption goods using aggregate data. Their median U.S. distribution wedge across all regular-prices CPI items is 0.57 for imports priced on a cif (cost, insurance, and freight) basis and 0.68 for imports priced on a freight-on-board basis. While their dataset allows for a disaggregated calculation of the distribution wedges, it does not include any services which constitute an important fraction of the surveyed prices in our dataset.\(^5\)

More importantly for our results, Burstein et al. (2003) and Berger et al. (2012) found that the distribution wedges are stable over time. Therefore, RERs variations are not coming from changes in distribution wedges, but from changes in traded and non-traded input prices consistent with the variance decompositions conducted below.

\(^5\)Since our story is about distribution shares, the ideal dataset for consumer goods would include border, or even better factory-gate prices. Although border and factory-gate prices have become increasingly available, they tend to be limited to a narrow set of product categories and countries. More importantly, they do not broadly represent consumer expenditure which is highly skewed toward services. In our study, we need fluctuations in the time-series over a set of goods that represents consumer expenditure over a large set of countries. From that point of view, we believe that the EIU data represent the best available dataset to work with.
3 Microeconomic Decomposition

The theoretical construction of the aggregate RER appeals to a utility function and the derivation of a corresponding price index. Let $C_{jt}$ denote consumption by individual $j$ at time $t$ consisting of a Cobb-Douglas aggregate of this individual’s consumption of various goods (and services), $C_{ijt}$, with weights $\omega_i$. We have:

$$U(C_{jt}) = \prod_i (C_{ijt})^{\omega_i}.$$  \hspace{1cm} (7)

Note that the $j$ index will also refer to the location where the individual purchases the goods, which given the nature of our data will be a city. Note also that the absence of an individual index on the $\omega_i$ means that all individuals have the same preferences.

Solving an expenditure minimization problem produces an ideal price index in the sense that it maps the prices of individual goods and services into a single consumption deflator with the property that aggregate consumption is consistent with the utility concept defined by the structure of preferences. For the case of Cobb-Douglas preferences, the price index $P_{jt}$ is a simple geometric average of good-level prices $P_{ijt}$ with the consumption-expenditure shares as weights in the average:

$$P_{jt} = \prod_i (P_{ijt})^{\omega_i}.$$  \hspace{1cm} (8)

This deflator satisfies $P_{jt}C_{jt} = \sum_i P_{ijt}C_{ijt}$, where the quantities of aggregate consumption and consumption of individual goods and services are the optimal levels chosen by consumers in city $j$, taking prices and income as given.

Converting prices to common currency at the spot nominal exchange rate, leads to the definition of the aggregate RER, $Q_{jkt}$, for bilateral city pair $j$ and $k$ as a function of microeconomic relative prices:

$$Q_{jkt} = \frac{S_{jkt}P_{jt}}{P_{kt}} = \prod_i \left( \frac{S_{jkt}P_{ijt}}{P_{ikt}} \right)^{\omega_i},$$  \hspace{1cm} (9)

where $S_{jkt}$ is the spot nominal exchange rate between city $j$ and $k$. Taking logarithms leads to a relationship in which the RER is a consumption-expenditure
weighted average of LOP deviations:

\[ q_{jkt} = \sum_{i} \omega_{i} q_{ijkt} \]  

(10)

Our microeconomic variance decomposition is achieved by taking the covariance of the variables on each side of this expression with respect to \( q_{jkt} \) and dividing all terms on each side of the equation by the variance of \( q_{jkt} \):

\[ 1 = \frac{\text{cov}(q_{jkt}, q_{jkt})}{\text{var}(q_{jkt})} = \sum_{i} \omega_{i} \frac{\text{cov}(q_{ijkt}, q_{jkt})}{\text{var}(q_{jkt})} = \sum_{i} \omega_{i} \beta_{ijk} \]  

\[ \text{where} \quad \beta_{ijk} = \frac{\text{cov}(q_{ijkt}, q_{jkt})}{\text{var}(q_{jkt})} = \frac{\text{std}(q_{ijkt})}{\text{std}(q_{jkt})} \times \text{corr}(q_{ijkt}, q_{jkt}) \]  

(11)

(12)

The contribution of good \( i \) to the variance of the aggregate RER is given by \( \omega_{i} \beta_{ijk} \). It is increasing in that good’s weight in expenditure, the relative standard deviation of its RER (relative to the aggregate) and its correlation with the aggregate RER. Quite apart from economizing on degrees of freedom in estimating a variance decomposition, the approach recognizes that we are interested in the covariance of the LOP deviations with the aggregate RER.

To fix ideas, suppose all prices are fixed in local currency units during the period and then adjusted to satisfy the LOP at the end of the period, with a nominal exchange rate change occurring during the period. Every single good in the distribution would contribute exactly the same amount to the variance of the aggregate RER, \( \beta_{ijk} = 1 \). Suppose instead that all traded goods adjusted instantaneously to the nominal exchange rate movement within the period while non-traded goods took one period to adjust. Now non-traded goods account for all of the variance and traded goods for none, \( \beta^{N} = \omega^{-1} \) and \( \beta^{T} = 0 \), where \( \omega \) is the share of expenditure on non-traded goods.

The first example characterizes the view that all goods markets are equally segmented, that goods are all alike, at least for the issue of understanding RERs. The second example characterizes thrust of the classical dichotomy, there are just two types of goods. The first view produces a degenerate distribution of the microeconomic \( \beta \)’s at 1, the second produces two degenerate

\[ \text{This is also the definition for the aggregate real exchange rate for common CES preferences, up to a first-order approximation.} \]
distributions, one for traded goods at $\beta^T = 0$ and one for non-traded goods at $\beta^N = \omega^{-1} = 1.7$ (using a non-traded expenditure share of 0.6, appropriate for our micro-data).

The obvious question to ask is: what does the distribution of $\beta_{ijk}$ look like? Figure 1 presents three kernel density estimates: one pools all goods (black line), one pools traded goods (red line) and one pools non-traded goods (blue line). The vertical lines display their averages. This distribution has little resemblance to either of the two views described above. There is far too much variation in the $\beta$’s to be consistent with the broad-brushed view that goods markets are equally segmented internationally, the support of the distribution extends from -2 to +4. At the same time, the distribution exhibits too much central tendency toward its mean of 0.81 to be consistent with a dichotomous classification of final goods.\footnote{If the classical dichotomy were to hold in the micro-data, the pooled density should be bimodal with a proportion of the data corresponding to traded goods centered at zero (no deviations) and the remaining proportion centered at 1.7. In fact, traded goods are centered at 0.76 and non-traded goods are centered at 1.03.}

Table 1 reports summary statistics for the microeconomic variance decomposition. The mean beta for non-traded goods does exceed the mean for traded goods in most cases, ranging from a difference of 0.27 (1.03-0.76) for all cities pooled together (Figure 1) to a low of 0.04 (0.87-0.83) for U.S.-Canada city pairs. The relative standard deviation of the LOP deviations average twice that of the aggregate RER, indicative of considerable idiosyncratic variation in LOP deviations. The mean correlation of LOP deviation and PPP deviation is 0.45 in the pooled sample. As Crucini and Telmer (2012) note, LOP deviations are not driven by a common factor such as the nominal exchange rate, much of the variation is idiosyncratic to the good.

In summary the contribution of individual goods to aggregate RER variability shows a central tendency, but with considerable variation across individual goods. Certainly the distribution is not the stark bimodality expected from the classical dichotomy applied to final goods. Our goal is to maintain the two-factor parsimony of the classical dichotomy, but with the tradability

\footnote{Note that although the product of the consumption weights and the betas need to sum to unity (11), the betas do not need to average 1.}
applied at the level of inputs. To accomplish this we first elaborate a simple
two factor model that stands in for the two types of inputs. Importantly, the
share of non-traded and traded inputs in the cost of the final good is assumed
to vary across individual final goods as measured by the distribution wedge.

4 The Intermediate Inputs Model

Many researchers have argued that the classical dichotomy is more appropriate
to apply at the level of inputs than at the level of final goods. Up until quite
recently the data has not been available to conduct a systematic investigation
of this hypothesis. We follow Engel and Rogers (1996) and Crucini, Telmer and
Zachariadis (2005), and assume that retail prices are Cobb-Douglas aggregates
of a non-traded input $W_{jt}$ and a traded input inclusive of a transportation cost
from the source to the destination, $T_{ijt}$:

$$P_{ijt} = W_{jt}^{\alpha_i} T_{ijt}^{1-\alpha_i} \tag{13}$$

The LOP deviation (in logs) becomes,

$$q_{ijkt} = \alpha_i w_{jkt} + (1 - \alpha_i) \tau_{ijkt}, \tag{14}$$

where each of the variables is now the logarithm of a relative price across a
bilateral pair of cities. Thus the LOP deviation for good $i$, across bilateral
city pair, $j$ and $k$, depends on the deviation of non-traded and traded input
costs across that pair of cities, weighted by their respective cost shares.

Elaborating on the cost structure of individual goods and services in this
way adds an additional layer to the original variance decomposition. The
betas for the individual retail prices of final goods may now be expressed as
a simple weighted average of the underlying betas for non-traded and traded
input prices:

$$\frac{\text{cov}(q_{jkt}, q_{ijkt})}{\text{var}(q_{jkt})} = \alpha_i \frac{\text{cov}(q_{jkt}, w_{jkt})}{\text{var}(q_{jkt})} + (1 - \alpha_i) \frac{\text{cov}(q_{jkt}, \tau_{ijkt})}{\text{var}(q_{jkt})} \tag{15}$$

$$\beta_{ijk} = \alpha_i \beta^w_{jk} + (1 - \alpha_i) \beta^\tau_{ijk} \tag{16}$$

$$= \beta^\tau_{ijk} + \alpha_i (\beta^w_{jk} - \beta^\tau_{ijk}) \tag{17}$$
This equation leads to two important insights. First, the $\beta_{ijk}$ for final goods are predicted to be increasing in the share of non-traded inputs $\alpha_i$, provided non-traded factor prices contribute more to RER volatility than do traded factor prices, $(\beta^w_{jk} - \beta^T_{jk}) > 0$. Note that this is a much weaker condition than the classical dichotomy where the relative prices of traded goods are assumed not vary at all across locations $(\beta^T_{jk} = 0)$, in which case the model would reduce to $\beta_{ijk} = \alpha_i \beta^w_{jk}$. Second, even if the classical dichotomy holds at the level of traded inputs, it will not hold at the level of final goods since, $\alpha_i \beta^w_{jk} > 0$.

Ironically, the anecdotes that are often drawn into the debate are precisely the ones that elucidate the role of traded and non-traded inputs. Namely goods at the extremes of the distribution in terms of high and low values of $\alpha_i$. Of course anecdotes are misleading unless they help us explain the broader patterns in the data and aggregate RER variability, which is our focus.

Figure 2 presents a scatter-plot of the contribution of good $i$ to the variance of the bilateral RER averaged across international city pairs $(\beta_i)$ against the distribution wedge for that good (the non-traded input cost, $\alpha_i$). Two items toward the extremes of the distribution wedge are explicitly labelled: 1 liter of gasoline and a 2-bedroom apartment. Based on our reconciliation of the EIU micro-data with the U.S. NIPA data on the distribution wedge, the distribution wedge for gasoline is 0.19 while that of a 2-bedroom apartment is 0.93.

Three observations are immediate. First, there is a positive relationship between a final good’s contribution to RER variability and its distribution wedge, the correlation of $\beta_i$ and $\alpha_i$ is 0.69. Second, goods at the extremes such as fuel and shelter, which are often used to provide anecdotal evidence of traded and non-traded goods, fit the classical dichotomy more closely than goods toward the middle of the distribution, goods with an average distribution wedge. Third, averaging across goods obscures the role of tradability of intermediate inputs because the median good has a distribution wedge of 0.41, implying close to equal shares of traded and non-traded inputs in the cost of production. Put differently—through the lens of the intermediate input model—examining the median good is analogous to taking a simple average of fuel and shelter. Doing so averages away the differences in the underlying cost structure of the two goods. In the next section we develop a two-factor model to infer the role of traded and non-traded inputs across the entire distribution
of the micro-data.

4.1 Two-Factor Model

The objective of this section is to decompose the good-specific contributions to aggregate RER variation into the role of traded and non-traded inputs used in the production of each good. To accomplish this, we incorporate the fact that the cost of producing final goods involves different shares of non-traded and traded inputs, the $\alpha_i$ parameters measured along the horizontal axis of Figure 2. This answers the question: if the contribution of LOP variation in fuel to the aggregate RER is 5%, how much of this contribution to variance is coming from the traded inputs (gasoline) and how much is coming from the non-traded inputs (the other costs associated with operating a gas station). To achieve this, we estimate a two-factor model of the $\beta_{ijk}$ for each bilateral city pair. These two factors, one for the non-traded input and one for the traded input will later be aggregated back up to the level of the CPI to determine how much of the variation in the aggregate RER is due to variation in RER for non-traded and traded input costs.

To reduce the intermediate inputs model to a two-factor structure for each bilateral city pair, the traded factor is assumed to be the sum of a component common to all goods and an idiosyncratic component specific to the good:

$$\beta_{ijk}^T = \beta_{jk}^T + \nu_{ijk} .$$

(18)

The contribution of good $i$ to the variation of the bilateral RER across city pair $j$ and $k$ is now:

$$\beta_{ijk} = \alpha_i \beta_{jk}^w + (1 - \alpha_i) \beta_{jk}^\tau + \epsilon_{ijk} ,$$

(19)

where $\epsilon_{ijk} = (1 - \alpha_i) \nu_{ijk}$. In the language factor models, the $\beta_{jk}^w$ and $\beta_{jk}^\tau$ are the two factors and $\alpha_i$ and $(1 - \alpha_i)$, their respective factor-loadings.

4.2 Estimation

In the model of the previous section, the observables are the estimated betas, $\beta_{ijk}$, and the distribution wedges from the NIPA, $\alpha_i$; the unobservables are the two
factors of interest, $\beta_{jk}^w$ and $\beta_{jk}^T$. Consider the following linear regression model:

$$\beta_{ijk} = a_{jk} + b_{jk}x_i + \epsilon_{ijk}. \quad (20)$$

Comparing this equation to the theoretical model, it is apparent that the constant term and the slope parameter identify the two factors of interest:

$$\beta_{jk}^T = a_{jk} \quad (21)$$

$$\beta_{jk}^w = a_{jk} + b_{jk}. \quad (22)$$

We perform this regression separately for each city pair using the $\beta_{ijk}$ estimated from the expenditure-weighted version of the aggregate RER to conform with the existing macroeconomic literature. Note that since the distribution wedges are more aggregated than the betas, we take simple averages of the betas across $i$ for goods that fall into each sector for which we have distribution wedges. Following this aggregation, equation (20) is estimated by Ordinary Least Squares (OLS) to recover the non-traded and traded factors. We also report results obtained by Weighted Least Squares where each observation is weighted by the inverse of the number of goods falling into each distribution-share sector (not shown), they are almost identical to the OLS estimates.

Table 2 reports the estimated factors averaged across city pairs within different country groups. The standard deviations across city pairs are reported in brackets. The differences across groups of locations and individual city pairs is discussed in a subsequent section. The first column pools all city pairs. The traded-factor averages 0.54 while non-traded factor averages 1.03. This implies that, on average, non-traded inputs contribute twice as much as traded inputs to RER variations. Recall that the average traded and non-traded goods have betas of 0.76 and 1.03. Notice that the traded input factor is much lower than the average contribution of a traded good to aggregate RER.

---

8In Figure 2, the group of points with $\alpha = 0.93$ and $\beta > 1.2$ represent rents and shelters, a category with an important weight in the U.S. CPI. Excluding this group of points, the traded factor averages 0.58 and the non-traded factor averages 0.97.

9Figure 3 shows the traded-input factor betas in ascending order (red), alongside the corresponding non-traded factor betas (blue). The red and blue horizontal lines represent the factors’ mean of 0.5361 and 1.0330. The traded- and non-traded factors median (0.5421 and 1.0270) are nearly identical to the means.
variability while the non-traded factor is coincidentally equal to the average contribution of a non-traded good to aggregate RER variability. This reflects two interacting effects. First, the non-traded factor is the dominant source of variation. Second, the average traded good has far more non-traded factor input content than the average non-traded good. Thus, most of the bias in attributing non-traded factor content in the decomposition is found in traded goods. To see this more clearly, it is productive to examine the cross-sectional variance in the contribution of the non-traded and traded factor at the micro-economic level rather than average across goods as Table 2 does. We turn to this level of detail next.

4.3 The Role of distribution wedges

Recall that after averaging the estimated equation (20) across \( jk \) pairs, we arrive at a decomposition of our original good-level betas:

\[
\beta_i = 1.03\alpha_i + 0.54(1 - \alpha_i) + \epsilon_i \quad (23)
\]

\[
= 0.54 + 0.50\alpha_i + \epsilon_i \quad . (24)
\]

Simply put, a purely traded good is one which involves no non-traded inputs, \( \alpha_i = 0 \). If such a good existed in the retail basket, it would be predicted to contribute 0.54 times its expenditure share to aggregate RER variability. At the other end of the continuum, a purely non-traded good involves no traded inputs, \( \alpha_i = 1 \). If such a good existed, it would be expected to contribute 1.04 times its expenditure share to aggregate RER variability.

Table 3 shows the entire cross-sectional distribution of the good-specific contributions to RER variation, \( \beta_i \), decomposed in this manner. Goods are ordered from those with the lowest distribution wedge (0.17), an example of which is a ‘compact car,’ to goods with the highest distribution wedge (1.00), an example of which is the ‘hourly rate for domestic cleaning help.’ Note that each row is an average across goods sharing the same distribution wedge (the second column) and the first column is just an example of a good found in that sector.

Since the non-traded input beta, \( \beta_{jk}^{\text{w}_{j}} \), average 1.03, the contribution of the non-traded input is approximately equal to the distribution wedge, \( \alpha_i \). By our
metric a compact automobile looks a lot like 1 liter of unleaded gasoline, but very distinct from a two-bedroom apartment or the hourly rate for domestic cleaning help. The contribution of LOP variation in each of the former two cases are about 70% traded inputs and 30% non-traded inputs whereas the latter two are largely driven by the non-traded input factor. Another interesting comparison is fresh fish and a two-course meal at a restaurant. Both are treated as traded goods when CPI data are used because they fall into the same category, food. However, one is food at home (fresh fish) and the other is food away from home (two course meal at a restaurant). Should they be treated similarly, as food items, or differently as food at home and food away from home? Consistent with the two factor intermediate input model, Table 3 provides a definitive answer: treat them differently. Fresh fish is indistinguishable from unleaded gasoline both in terms of the dominate role of traded inputs and the relatively moderate contribution to aggregate RER variation (0.65). A restaurant meal is dominated by the non-traded factor (85 percent) and contributes 35% more to aggregate RER variability than does fresh fish.

A good with a median distribution wedge (0.41) is toothpaste. Despite the fact that the cost of producing this good is skewed moderately toward traded inputs (59% traded inputs), non-traded inputs still dominate in accounting for the toothpaste beta, 0.40 versus 0.31 for traded inputs. This reflects the fact that our estimated non-traded factor is twice as important as our estimated traded factor in accounting for variation in the aggregate RER, 1.04 versus 0.54. Stated differently, for the traded input factor to dominate in contribution to variance requires a distribution wedge of less than 0.34 (i.e. a traded input share of more than 0.66).

4.4 The Role of Location

When focusing on the role of the distribution wedge, it was productive to average across bilateral pairs. Similarly, when focusing on the role of location, it is useful to average across goods. Recall, however, that the two estimated factors are location-specific and the group means of Table 2 suggested the presence of variation across location pairs in the two factors. To better visualize the full extent of the variation without presuming a source of the variation across city-
pairs, figure 4 presents kernel density estimates of the non-traded and traded factors.

The figure effectively convey three messages. The first, and central message, is that there is a strong central tendency toward the means initially reported in Table 2 (for both of the factors), supportive of the parsimony imposed by the two factor model. The second message is that the contributions of traded and non-traded inputs to aggregate RER variability are much more easily distinguished than was true of traded and non-traded goods. This is evident in comparing the two distributions in figure 4 with their counterparts in Figure 1. Third, the dispersion across locations in the estimated factors is significant and greater for the estimated traded factor (red line) than the estimated non-traded factor (blue line), consistent with the impression conveyed by the group-mean coefficients – reported in Table 2.\footnote{With regard to the classical dichotomy, we could not reject the hypothesis that the traded-inputs beta is 0 for 56\% of the sample. This statistics was computed using a two-tailed t-distribution with 95\% confidence intervals.}

What is responsible for the variation across location pairs in these distributions? figure 5 plots the non-traded and traded input betas for each bilateral city pair against the standard deviation of the nominal exchange rate for that bilateral city pair. Two features are notable. First, there is a positive and possibly concave relationship between the variability of the nominal exchange rate and both the non-traded and traded input betas in the variance decomposition. Second, the estimated non-traded input betas lie above the traded input betas.

The positive correlation between the estimated input betas and the volatility of the nominal exchange rate is more subtle. It is important to emphasize that this correlation is not simply a reflection of the positive covariance of nominal and RERs documented in the existing macroeconomics literature. Recall, the betas are components of a variance decomposition and thus have already been normalized by the level of the variance of the bilateral RER. What is happening as the nominal exchange rate variance increases is that the common source of LOP variation is rising relative to the idiosyncratic sources of variation. This occurs because movements in the nominal exchange rate
are almost by definition a common source of variability in LOP deviations. Since the non-traded factor is expected to exhibit less pass-through of nominal exchange rates to local currency prices, at least in the short run, it is also expected that the non-traded factor will lie uniformly above the traded factor. This is evident, the blue dots lie mostly above the red dots at each point along the x-axis (i.e. conditional on a value for the nominal exchange rate variance). This is not to say that changes in nominal exchange rates are causing RERs to vary, to identify the underlying causes of variation would require a richer model. For example, a monetary shock is likely to alter both the distribution of local currency prices and the nominal exchange rate whereas a crop failure in a particular country is unlikely to do either of these things. The thrust of the figure, however, is that real and nominal sources of business cycle variation are likely to play different roles in determining the traded and non-traded input betas we have estimated.

To summarize, we have demonstrated that the classical dichotomy is a very useful theory of the LOP when the theory is applied to inputs. What we do in the next section is show that this is also true at the aggregate level. Moreover, we also show that the EIU data are entirely consistent with the conclusions of the existing literature using aggregative CPI data when the theory is applied to final goods. Our interpretation, however, is very different.

5 Macroeconomic Decompositions

Macroeconomics is, of course, about aggregate variables. Our thesis is that if given the choice, macroeconomists would want to aggregate final goods based on their non-traded and traded factor content. Our methodology attempts to provide that choice. Here, we demonstrate the importance of this choice.

11Crucini and Telmer (2012) decompose the variance of the LOP deviations into time series variation and long-run price dispersion using the same data employed here. They find, as Engel did, that the time-series volatility of RERs of traded goods is comparable to that of non-traded goods whereas the long-run price dispersion goes in the direction of the classical dichotomy with more international price dispersion among non-traded goods. Thus, our paper seeks to resolve the more puzzling feature of the data, its time-series properties.
5.1 Aggregation Based on Intermediate Inputs

Recall that the microeconomic variance decomposition of the aggregate RER based on final goods is:

\[ 1 = \sum_i \omega_i \beta_{ijk} \]  \hspace{1cm} (25)

\[ \beta_{ijk} = \frac{\text{cov}(q_{ijkt}, q_{jkt})}{\text{var}(q_{jkt})} = \frac{\text{std}(q_{ijkt})}{\text{std}(q_{jkt})} \times \text{corr}(q_{ijkt}, q_{jkt}) . \] \hspace{1cm} (26)

Substituting our two-factor model for the LOP deviation, \( \beta_{ijk} = \alpha_i \beta_{jk}^w + (1 - \alpha_i) \beta_{jk}^r + \epsilon_{ijk} \), into this equation gives the theoretically appropriate method of aggregating the micro-data based on the model of intermediate inputs:

\[ 1 = \sum_i \omega_i \left[ \alpha_i \beta_{jk}^w + (1 - \alpha_i) \beta_{jk}^r + \epsilon_{ijk} \right] . \] \hspace{1cm} (27)

Notice that since the two intermediate factors are assumed to be location-specific, not good specific, the expression aggregates very simply to a two-factor macroeconomic decomposition:

\[ 1 = \pi \beta_{jk}^w + (1 - \pi) \beta_{jk}^r + \eta_{jk} , \] \hspace{1cm} (28)

where the weights on the traded and non-traded input factors, \( \pi \) and \( (1 - \pi) \) are consumption expenditure-weighted averages of the shares of non-traded and traded inputs into each individual good in the consumption basket. The residual term, \( \eta_{jk} \) is an expenditure-share weighted average of the \( \epsilon_{ijk} \).

In other words, the variance of the aggregate RER may be expressed as a weighted average of the two factors estimated from the micro-data. The weight on each factor depends on the relationship between taste parameters and relative prices that determine consumption-expenditure shares and production parameters, and relative factor prices that determine distribution wedges. Recall that the median distribution wedge in the micro-data is 0.41. The weight on the non-traded factor, \( \pi \), turns out to be much greater than this average because consumption tends to be skewed toward services which are intensive in distribution inputs. Using US NIPA data and the EIU micro-sample, \( \pi = 0.69 \). The dominant weight on the non-traded input factor, combined with the fact that \( \beta_{jk}^w \) is about twice the magnitude of \( \beta_{jk}^r \) is the reason that non-traded
inputs dominate the variance decomposition of the aggregate RER by a very large margin.

Table 4 shows just how large. The table reports the results using OLS estimates (WLS results are very similar). Beginning with the averages across the entire world sample, the non-traded factor accounts for about 81% (i.e.: 0.71/(0.71+0.17)) of the variance of the aggregate RER, while traded inputs account for the remaining 19%. The contribution of non-traded and traded inputs is moderately more balanced in the U.S.-Canada sub-sample, with non-traded inputs accounting for 73% and traded inputs accounting for the remaining 27%. Consistent with our earlier microeconomic decompositions, the OECD looks more like the U.S.-Canada sub-sample than does the non-OECD group.

5.2 Aggregation Based on Final Goods

An alternative two-factor macroeconomic model of the RER is to apply the classical dichotomy at the level of final goods. To implement this using the micro-data we must first decide on a definition of a non-traded good. In theory, the micro-data provides an advantage because it allows us, for example, to assign fish to the traded category and restaurant meals to the non-traded category, rather than placing all food in the traded category. The rule we use to be consistent with the intermediate input concept of the classical dichotomy is to categorize a good as a ‘non-traded good’ if it has a distribution wedge exceeding 60 percent. This cutoff corresponds to a jump in the value of the distribution wedges across sectors from 0.59 to 0.75 (see Table 3 or Figure 2). Coincidentally, this categorization matches up very well with the categorical assignments used by Engel who used much more aggregated data. The traded-goods category includes: cars, gasoline, magazine and newspapers, and foods. The non-traded goods category includes: rents and utilities, household services (such as dry cleaning and housekeeping), haircuts and restaurant and hotel services.

With the assignments of individual goods and services to these two categories, the aggregate RER is:

$$q_{jkt} = \omega q_{jkt}^N + (1 - \omega)q_{jkt}^T .$$

where $q_{jkt}^N$ and $q_{jkt}^T$ are the bilateral RERs for non-traded final goods and
traded final goods built from the LOP deviations in the microeconomic data, weighted by their individual expenditure shares.\footnote{More precisely, the weights used earlier are renormalized to $\frac{\omega}{\omega} \left( \frac{\omega}{\omega + (1 - \omega)} \right)$ for non-traded (traded) goods so that the weights on the two sub-indices sum to unity.}

The variance decomposition of the aggregate RER is conducted using our beta method\footnote{The relationship between the microeconomic betas of our original decomposition and this two-factor decomposition is straightforward: $\omega_{jk} \beta_{jk}^N = \sum_{i \in N} \omega_{ijk} \beta_{ijk}$, and $(1 - \omega_{jk}) \beta_{jk}^T = \sum_{i \in T} \omega_{ijk} \beta_{ijk}$.}:

$$1 = \omega \beta_{jk}^N + (1 - \omega) \beta_{jk}^T .$$

Table 5 reports the outcome of the variance decomposition arising from this macroeconomic approach. It is instructive to compare Table 5 to Table 1 since they both use final goods as the working definition for traded and non-traded goods. What is the consequence of aggregating the data before conducting the variance decomposition? As it turns out, the betas are very similar across the two approaches. The average beta for non-traded (traded) goods pooling all location is 1.17 (0.78) using the two index construct (Table 5) compared to 1.03 (0.76) using the microeconomic decomposition. These are relatively small differences. The underlying sources of the contribution to variance, however, are different.

When using the macroeconomic approach, the non-traded RER contributes more to the variability of the aggregate RER for two reasons. First, the non-traded RER is more highly correlated with the aggregate RER than is the traded RER (0.96 versus 0.86). Reinforcing this effect is the fact that the non-traded sub-index of the CPI is more variable than the traded RER (1.22 versus 0.91). In contrast, when the microeconomic approach is used, non-traded and traded goods are not distinguished by the relative volatility of their LOP deviation (at least for the median good). Both types of goods have standard deviations twice that of the aggregate RER. Consistent with the macroeconomic approach, the LOP deviations of the median non-traded good has a higher correlation with the aggregate RER than does the median traded goods (0.55 versus 0.42). Thus traded goods have more idioynscratic sources of deviations from the LOP than do non-traded goods.
5.3 The Role of Location

Location also plays a role in determining the relative importance of traded and non-traded goods in accounting for RER variability. Figure 6 presents the entire distribution of the $\beta_{jk}$ for the case in which all locations are averaged (the first column of Table 5). The means for all goods, non-traded goods and traded goods from Table 5 are indicated with vertical lines at 0.97, 1.17 and 0.78, respectively. We see considerable variation in the relative importance of non-traded and traded sub-indices of the CPI across bilateral city-pairs, but the two distributions clearly have a different first moment, which was not at all obvious in the microeconomic distributions of Figure 1.

5.4 The Compositional Bias

To further clarify the difference between the implications of the classical dichotomy applied to intermediate inputs and final goods, this section estimates the compositional bias arising from using final goods to infer the factor content of trade at the level of the two sub-index deconstruction of the aggregate RER. Consider the traded and non-traded partition based on final goods and how the variance decompositions relate across the two methods.

The contribution of the non-traded aggregate RER to aggregate RER variability is:

$$\omega \beta_{jk}^N = \sum_{i \in N} \omega_i \left[ \alpha_i \beta_{jk}^w + (1 - \alpha_i) \beta_{jk}^T \right] ,$$

while the contribution of the traded aggregate RER to the aggregate RER variability is:

$$(1 - \omega) \beta_{jk}^T = \sum_{i \in T} \omega_i \left[ \alpha_i \beta_{jk}^w + (1 - \alpha_i) \beta_{jk}^T \right] .$$

Note that each contribution is written on the right-hand-side in terms of the intermediate input model.

Recall, the contribution of non-traded inputs to the variation in the aggregate RER variance according to the intermediate inputs model is actually:

$$\pi \beta_{jk}^w = \left( \sum_i \omega_i \alpha_i \right) \beta_{jk}^w ,$$
while the counterpart for the contribution of traded inputs is:

\[
(1 - \pi) \beta^T_{jk} = \left( \sum_i \omega_i (1 - \alpha_i) \right) \beta^T_{jk} . \tag{34}
\]

Using these four equations, the bias in the estimate of non-traded inputs to aggregate RER variance arising from using the final goods definition is

\[
\pi \beta^w_{jk} - \omega \beta^N_{jk} = \left( \sum_i \omega_i \alpha_i \right) \beta^w_{jk} - \sum_{i \in N} \omega_i \left[ \alpha_i \beta^w_{jk} + (1 - \alpha_i) \beta^T_{jk} \right] \tag{35}
\]

\[
= \left( \sum_{i \in T} \omega_i \alpha_i \right) \beta^w_{jk} - \left( \sum_{i \in N} \omega_i (1 - \alpha_i) \right) \beta^T_{jk} . \tag{36}
\]

and likewise, the bias for traded goods is

\[
(1 - \pi) \beta^T_{jk} - (1 - \omega_{jk}) \beta^T_{jk} = \left( \sum_{i \in N} \omega_{ijk} (1 - \alpha_i) \right) \beta^T_{jk} - \left( \sum_{i \in T} \omega_{ijk} \alpha_i \right) \beta^w_{jk} . \tag{37}
\]

Table 6 reports the average share of non-traded goods together with the traded and non-traded aggregate average contributions to RER volatility when all city pairs are used in the comparison. The aggregate contribution of traded goods using aggregation to final goods is about twice the their true underlying contribution based on the intermediate inputs model, 0.34 versus 0.17.

5.5 Relation with the Existing Literature

Engel and other researchers focus on whether RER fluctuations are primarily associated with movement in the relative price of traded goods across countries or with movements in the relative price of non-traded to traded goods. The equation Engel works with is

\[
q_t = q_t^T + \omega (q_t^N - q_t^T) , \tag{38}
\]

while we work with

\[
q_t = \omega q_t^N + (1 - \omega) q_t^T . \tag{39}
\]

Simple algebra allows us to express Engel’s variance decomposition in terms of betas for traded and non-traded aggregate s:

\[
1 = \beta^T + \omega (\beta^N - \beta^T) . \tag{40}
\]
Engel’s variance decomposition split the RER volatility into two components. The first component is the volatility in the traded RER. The second component is the variance between non-traded and traded aggregate prices. The approximate equality in the average betas for non-traded and traded aggregate shows explains why this decomposition attributes almost all of the variance in RER to traded goods: Since the aggregate $\beta^N - \beta^T$ is about 0.39 and $1 - \omega$ is less than one, $\beta^T$ must be close to 1 as Engel’s reports. This implies that the remaining volatility must be explained by the traded RER. Since $\beta^T$ is 0.78, 78 percent of RER fluctuations are attributable to movements in the relative price of traded goods.\textsuperscript{14}

As we saw in the previous sub-section, an important bias arise when one use traded and non-traded aggregate contributions. Using our two factor model, Engel’s decomposition becomes:

$$1 = \beta^T + \pi(\beta^N - \beta^T) + \varepsilon_{jk} .$$ (41)

Since $\beta^T$ is 0.54, this implies that 54 percent of RER fluctuations are attributable to movements in the relative price of traded intermediates.\textsuperscript{15} From this point of view, a considerable amount of volatility is coming from the relative price of non-traded to traded intermediates.

A number of researchers modify Engel’s decomposition, but largely reinforce his conclusions about traded good prices. Out of concern about the functional form of the Cobb-Douglas aggregates, Betts and Kehoe (2006) work with:

$$q_t = q^T_t + (q_t - q^T_t) ,$$ (42)

where $q^T_t$ is a producer price index which is not contaminated by non-traded distribution services. This decomposition preserves the identity on the left and right-hand-side of the equality as necessary for a variance decomposition and has the desired attributes of using the producer price index, which is arguably a better proxy for traded goods prices than is an aggregate of consumer prices across highly traded goods. As is also apparent, there is no need

\textsuperscript{14}Using US-CA pairs, 88 percent of RER fluctuations are attributable to movements in the relative price of traded goods compared to 95 percent as reported in Engel’s work.

\textsuperscript{15}For US-CA pairs, this number rises to 67 percent.
to assign expenditure weights in the decomposition. Again, using our variance decomposition the beta-representation of the decomposition is:

$$1 = \beta^r + (1 - \beta^r) + \varepsilon_{jk}.$$  \hspace{1cm} (43)

The variance to be explained is the same as in Engel’s original contribution, namely the variance of the aggregate CPI-based RER. However, the variance of the traded goods prices is different, since producer prices replace the traded-CPI component on the right-hand-side. As one might expect, the variance of producer prices is higher than consumer prices, but the covariance of producer prices with the aggregate CPI may be lower. Since the beta is rising in relative variability and covariance, the implication of replacing a consumer price index for traded goods with a producer price index is expected to be ambiguous. These nuances notwithstanding, Betts and Kehoe find a modest reduction in the contribution of traded goods relative to Engel.

Parsley and Popper (2009) take a microeconomic approach using two independent retail surveys in the United States and Japan. The U.S. survey is conducted by the American Chamber of Commerce Researchers Association (ACCRA) and the Japanese survey is from the Japanese national statistical agency publication: Annual Report on the Retail Price Survey. Both contain average prices across outlets, at the city level. The Japanese survey is vastly more extensive in coverage of items than the ACCRA survey since it represents the core micro-data that goes into the Japanese CPI construction. Both data panels are at the city level and thus is quite comparable in many ways to the EIU data. Parsley and Popper restrict their sample to items that are as comparable as possible across the two countries. This selection criteria leaves them with a sample of highly traded goods.

To elaborate our method when micro-data are employed, rather than two sub-indices, consider applying item-specific weights, $\omega_i$ to LOP deviations. The aggregate RER becomes:

$$q_t = \sum_i \omega_i q_{i,t},$$  \hspace{1cm} (44)

Parsley and Popper follow Engel’s approach by placing an individual good in the lead position with a unit coefficient as its weight. That is, for each good
i, they work with:

\[ q_t = q_{i,t} + \left( \sum_{g}^{M} \omega_g q_{g,t} - q_{i,t} \right) . \]  \hfill (45)

Parsley and Popper then compute the variance of the lead term, the LOP variance and divide it by the total variance of the RER and define this ratio as the contribution of good \( i \) to the variance of the aggregate RER.

In terms of betas, their variance decomposition is:

\[ 1 = \beta_i + (1 - \beta_i) . \]  \hfill (46)

This is because the expenditure weighted average of the betas must equal unity by construction. However, the variance decomposition following our method is:

\[ 1 = \omega_i \beta_i + \sum_{g \neq i} \omega_g \beta_g , \]  \hfill (47)

As is evident, the good-specific variance contributions of Parsley and Popper’s are actually equal to our betas. However in following Engel’s approach they give each good a unit weight. As our decomposition shows, these good-specific betas need to be multiplied by expenditure shares in order to conduct a legitimate variance decomposition.

Parsley and Popper end up reconciling 28 items across the U.S. and Japan, 2 of which are services. They compute the contribution to variance at different horizons, including 5 quarters. At this horizon the good-specific contributions range from just under 0.5 to about 0.86. Interpreted as betas, these estimates certainly fall within the range we find, which spans negative values to values exceeding 1. However, they are not contributions to aggregate RER variance, to arrive at a legitimate variance decomposition each beta must be multiplied by its consumption-expenditure weight.

6 Conclusions

Using retail price data at the level of individual goods and services across many countries of the world, we have shown the classical dichotomy is a useful theory of international price determination when applied to intermediate inputs. Specifically, by parsing the role of non-traded and traded inputs at the retail
level, a significant source of compositional bias is removed from the micro-data and differences in the role of the two inputs is evident. Aggregate price indices are not useful in uncovering this source of heterogeneity in LOP deviations for two reasons. First, the dividing line between traded and non-traded goods at the final goods stage is arbitrary and more under the control of officials at statistical agencies whose goal is not to contrast the role of trade across CPI categories of expenditure. Second, even at the lowest level of aggregate possible, most goods and services embody costs of both local inputs and traded inputs. Consequently, the contribution of each LOP deviation to PPP deviations is a linear combination of the two components with the weights on the two components differing substantially in the cross-section.

Our results point to the usefulness of microeconomic theories that distinguish traded and local inputs and their composition in final goods as well as an important role of LOP deviations at the level of trade. This points to the need for a hybrid model with a distribution sector and segmentation at the level of traded inputs. In arguing for one stripped down model or another, macro-economists may unwittingly reject virtually all useful theories of international price determination.
References


### Table 1: Variance decomposition of real exchange rates, microeconomic approach

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<th>Non-OECD</th>
<th>US-Canada</th>
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<td>0.13</td>
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#### All goods
- Beta: 0.81, 0.84, 0.74, 0.83
- Correlation: 0.45, 0.43, 0.42, 0.38
- Rel. std. dev. LOP: 2.00, 2.18, 1.98, 2.19

#### Non-traded goods
- Beta: 1.03, 0.95, 1.11, 0.87
- Correlation: 0.55, 0.50, 0.57, 0.46
- Rel. std. dev. LOP: 2.00, 2.10, 2.07, 1.89

#### Traded goods
- Beta: 0.76, 0.81, 0.63, 0.83
- Correlation: 0.42, 0.42, 0.37, 0.36
- Rel. std. dev. LOP: 2.00, 2.20, 1.95, 2.26
### Table 2: Traded and non-traded inputs regressions, international pairs

<table>
<thead>
<tr>
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<td>(.52)</td>
<td>(.52)</td>
</tr>
<tr>
<td>beta (non-traded)</td>
<td>1.03</td>
<td>0.96</td>
<td>1.12</td>
<td>0.82</td>
</tr>
<tr>
<td></td>
<td>(.34)</td>
<td>(.32)</td>
<td>(.37)</td>
<td>(.26)</td>
</tr>
<tr>
<td>slope</td>
<td>0.50</td>
<td>0.30</td>
<td>0.78</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td>(.72)</td>
<td>(.64)</td>
<td>(.79)</td>
<td>(.64)</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.08</td>
<td>0.05</td>
<td>0.12</td>
<td>0.04</td>
</tr>
<tr>
<td>Number of pairs</td>
<td>4835</td>
<td>1543</td>
<td>856</td>
<td>52</td>
</tr>
</tbody>
</table>

Note: Minimum of 4 observations per city pair.
<table>
<thead>
<tr>
<th>Example</th>
<th>$\alpha_i$</th>
<th>Non-Traded</th>
<th>Traded</th>
<th>Residual</th>
<th>Cont. (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Compact car (1300-1799 cc)</td>
<td>0.17</td>
<td>0.17</td>
<td>0.44</td>
<td>0.07</td>
<td>28%</td>
</tr>
<tr>
<td>Unleaded gasoline (1 liter)</td>
<td>0.19</td>
<td>0.19</td>
<td>0.43</td>
<td>-0.02</td>
<td>30%</td>
</tr>
<tr>
<td>Fresh fish (1 kg)</td>
<td>0.22</td>
<td>0.21</td>
<td>0.44</td>
<td>0.07</td>
<td>32%</td>
</tr>
<tr>
<td>Time (news magazine)</td>
<td>0.32</td>
<td>0.32</td>
<td>0.36</td>
<td>0.05</td>
<td>47%</td>
</tr>
<tr>
<td>Toilet tissue (two rolls)</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.00</td>
<td>50%</td>
</tr>
<tr>
<td>Butter (500 g)</td>
<td>0.36</td>
<td>0.36</td>
<td>0.33</td>
<td>-0.01</td>
<td>52%</td>
</tr>
<tr>
<td>Aspirin (100 tablets)</td>
<td>0.37</td>
<td>0.36</td>
<td>0.34</td>
<td>0.01</td>
<td>51%</td>
</tr>
<tr>
<td>Marlboro cigarettes (pack of 20)</td>
<td>0.37</td>
<td>0.37</td>
<td>0.33</td>
<td>0.06</td>
<td>53%</td>
</tr>
<tr>
<td>Electric toaster</td>
<td>0.39</td>
<td>0.38</td>
<td>0.33</td>
<td>0.02</td>
<td>54%</td>
</tr>
<tr>
<td>Toothpaste with fluoride (120 g)</td>
<td>0.41</td>
<td>0.40</td>
<td>0.31</td>
<td>-0.05</td>
<td>57%</td>
</tr>
<tr>
<td>Compact disc album</td>
<td>0.41</td>
<td>0.41</td>
<td>0.30</td>
<td>-0.05</td>
<td>57%</td>
</tr>
<tr>
<td>Insect-killer spray (330g)</td>
<td>0.45</td>
<td>0.45</td>
<td>0.27</td>
<td>-0.03</td>
<td>62%</td>
</tr>
<tr>
<td>Paperback novel</td>
<td>0.49</td>
<td>0.47</td>
<td>0.27</td>
<td>-0.03</td>
<td>63%</td>
</tr>
<tr>
<td>Razor blades (5 pieces)</td>
<td>0.49</td>
<td>0.49</td>
<td>0.27</td>
<td>-0.01</td>
<td>64%</td>
</tr>
<tr>
<td>Batteries (two, size D/LR20)</td>
<td>0.50</td>
<td>0.49</td>
<td>0.27</td>
<td>-0.04</td>
<td>65%</td>
</tr>
<tr>
<td>Socks, wool mixture</td>
<td>0.52</td>
<td>0.52</td>
<td>0.25</td>
<td>0.05</td>
<td>68%</td>
</tr>
<tr>
<td>Men’s shoes, business wear</td>
<td>0.52</td>
<td>0.52</td>
<td>0.25</td>
<td>0.03</td>
<td>67%</td>
</tr>
<tr>
<td>Lettuce (one)</td>
<td>0.52</td>
<td>0.52</td>
<td>0.25</td>
<td>0.05</td>
<td>68%</td>
</tr>
<tr>
<td>Frying pan (Teflon)</td>
<td>0.53</td>
<td>0.53</td>
<td>0.25</td>
<td>-0.01</td>
<td>68%</td>
</tr>
<tr>
<td>Light bulbs (two, 60 watts)</td>
<td>0.57</td>
<td>0.57</td>
<td>0.22</td>
<td>-0.18</td>
<td>72%</td>
</tr>
<tr>
<td>Child shoes, sportwear</td>
<td>0.59</td>
<td>0.58</td>
<td>0.21</td>
<td>-0.03</td>
<td>73%</td>
</tr>
<tr>
<td>Tennis balls (Dunlop, Wilson or equivalent)</td>
<td>0.59</td>
<td>0.59</td>
<td>0.21</td>
<td>-0.11</td>
<td>74%</td>
</tr>
<tr>
<td>Two-course meal at a restaurant (average)</td>
<td>0.75</td>
<td>0.75</td>
<td>0.13</td>
<td>0.00</td>
<td>85%</td>
</tr>
<tr>
<td>Electricity, monthly bill (average)</td>
<td>0.76</td>
<td>0.75</td>
<td>0.13</td>
<td>0.04</td>
<td>86%</td>
</tr>
<tr>
<td>Man’s haircut (tips included)</td>
<td>0.85</td>
<td>0.85</td>
<td>0.08</td>
<td>-0.04</td>
<td>91%</td>
</tr>
<tr>
<td>Taxi, airport to city center (average)</td>
<td>0.86</td>
<td>0.85</td>
<td>0.07</td>
<td>-0.01</td>
<td>92%</td>
</tr>
<tr>
<td>Telephone line, monthly bill (average)</td>
<td>0.92</td>
<td>0.90</td>
<td>0.04</td>
<td>0.03</td>
<td>96%</td>
</tr>
<tr>
<td>2-bedroom apartment</td>
<td>0.93</td>
<td>0.91</td>
<td>0.04</td>
<td>0.24</td>
<td>96%</td>
</tr>
<tr>
<td>Annual premium for car insurance</td>
<td>0.94</td>
<td>0.93</td>
<td>0.03</td>
<td>0.01</td>
<td>97%</td>
</tr>
<tr>
<td>Hourly rate for domestic cleaning help</td>
<td>1.00</td>
<td>1.00</td>
<td>0.00</td>
<td>-0.08</td>
<td>100%</td>
</tr>
</tbody>
</table>
**Table 4: Macroeconomic variance decomposition, intermediate input approach**

<table>
<thead>
<tr>
<th>Contribution of</th>
<th>All pairs</th>
<th>OECD</th>
<th>Non OECD</th>
<th>US-CA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-traded share ($\pi$)</td>
<td>0.69</td>
<td>0.69</td>
<td>0.69</td>
<td>0.68</td>
</tr>
<tr>
<td></td>
<td>(.02)</td>
<td>(.20)</td>
<td>(.02)</td>
<td>(.02)</td>
</tr>
<tr>
<td>Contribution of</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Traded inputs</td>
<td>0.17</td>
<td>0.20</td>
<td>0.10</td>
<td>0.21</td>
</tr>
<tr>
<td></td>
<td>(.15)</td>
<td>(.14)</td>
<td>(.16)</td>
<td>(.17)</td>
</tr>
<tr>
<td>Non-traded inputs</td>
<td>0.71</td>
<td>0.66</td>
<td>0.78</td>
<td>0.56</td>
</tr>
<tr>
<td></td>
<td>(.23)</td>
<td>(.22)</td>
<td>(.25)</td>
<td>(.18)</td>
</tr>
<tr>
<td>Error term</td>
<td>0.12</td>
<td>0.14</td>
<td>0.12</td>
<td>0.23</td>
</tr>
<tr>
<td></td>
<td>(.20)</td>
<td>(.22)</td>
<td>(.21)</td>
<td>(.21)</td>
</tr>
<tr>
<td>Number of city pairs</td>
<td>4835</td>
<td>1543</td>
<td>856</td>
<td>52</td>
</tr>
</tbody>
</table>
Table 5: Variance decomposition of real exchange rates, macroeconomic approach

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>OECD</th>
<th>Non-OECD</th>
<th>US-Canada</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std. dev. RER</td>
<td>0.14</td>
<td>0.13</td>
<td>0.13</td>
<td>0.10</td>
</tr>
<tr>
<td>Number of city pairs</td>
<td>4835</td>
<td>1543</td>
<td>856</td>
<td>52</td>
</tr>
<tr>
<td>Non-traded weight</td>
<td>0.57</td>
<td>0.56</td>
<td>0.58</td>
<td>0.55</td>
</tr>
<tr>
<td>Traded weight</td>
<td>0.43</td>
<td>0.44</td>
<td>0.42</td>
<td>0.45</td>
</tr>
</tbody>
</table>

All goods

Beta                        | 0.97 | 0.98 | 0.96     | 0.99      |
Correlation                  | 0.91 | 0.92 | 0.89     | 0.94      |
Rel. std. dev. LOP           | 1.06 | 1.06 | 1.08     | 1.05      |

Non-traded goods

Beta                        | 1.17 | 1.14 | 1.23     | 1.10      |
Correlation                  | 0.96 | 0.96 | 0.96     | 0.96      |
Rel. std. dev. LOP           | 1.22 | 1.18 | 1.29     | 1.15      |

Traded goods

Beta                        | 0.78 | 0.82 | 0.69     | 0.88      |
Correlation                  | 0.86 | 0.88 | 0.82     | 0.92      |
Rel. std. dev. LOP           | 0.91 | 0.94 | 0.86     | 0.96      |
Table 6: Compositional bias

<table>
<thead>
<tr>
<th></th>
<th>Aggregate using final goods</th>
<th>Aggregation using Intermediate inputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-traded share</td>
<td>0.57</td>
<td>0.69</td>
</tr>
<tr>
<td>Contribution</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Traded</td>
<td>0.34 (34%)</td>
<td>0.17 (19%)</td>
</tr>
<tr>
<td>Non-Traded</td>
<td>0.66 (66%)</td>
<td>0.71 (81%)</td>
</tr>
</tbody>
</table>
Figure 1: Density Distributions of Betas, Microeconomic Decomposition

![Graph showing density distributions of betas for different categories: All goods, Traded goods, Non-traded goods. The graph includes lines for each category with density on the y-axis and beta on the x-axis.]
Figure 2: Sectoral Betas and Distribution Shares
Figure 3: Traded and non-traded inputs factor betas
Figure 4: Density Distributions of Factor Betas
Figure 5: Factor Betas and Nominal Exchange Rate Volatility
Figure 6: Density Distributions of Betas, Macroeconomic Decomposition