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Real Exchange Rate Movements and the Relative Price of Non-traded Goods*

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ABSTRACT

We study the quarterly bilateral real exchange rate and the relative price of non-traded to traded goods for 1225 country pairs over 1980–2005. We show that the two variables are positively correlated, but that movements in the relative price measure are smaller than those in the real exchange rate. The relation between the two variables is stronger when there is an intense trade relationship between two countries and when the variance of the real exchange rate between them is small. The relation does not change for rich/poor country bilateral pairs or for high inflation/low inflation country pairs. We identify an anomaly: The relation between the real exchange rate and relative price of non-traded goods for US/EU bilateral trade partners is unusually weak.

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1. Introduction

In a very influential paper, Engel (1999) shows that almost all of the variance in the bilateral real exchange rates between the United States and a number of OECD, especially European Union (EU), countries is attributable to fluctuations in the real exchange rates of traded goods, and almost none is attributable to fluctuations in the relative prices of non-traded to traded goods. This evidence stands in stark contrast to the implications of traditional real exchange rate theory. In that theory, whose origin dates to the work of Cassel (1918) and Pigou (1923), all movements in the bilateral real exchange rate between two countries are due to fluctuations in the bilateral relative price of non-traded to traded goods.

In light of Engel's evidence, many international business cycle researchers have abandoned the traditional view of real exchange rate movements. New Open Economy Macroeconomics (NOEM) favors models in which international markets for traded goods are, first, segmented, so that deviations from the law of one price for traded goods can arise, and, second, subject to nominal price rigidities, which sustain those deviations. These two features of NOEM models mean that purely monetary shocks to the nominal exchange rate cause persistent fluctuations in the relative common currency price of traded goods, and these fluctuations alone drive aggregate real exchange rate movements (see, for example, Betts and Devereux 2000). There is no role whatsoever for fluctuations in the relative price of non-traded to traded goods in real exchange rate determination. Chari, Kehoe, and McGrattan (2002), for example, cite Engel's evidence as the motivation for ignoring the distinction between traded and non-traded goods in their work.

In this paper, we extend Engel's analysis to a large set of bilateral real exchange rates. Based on our results, we argue that the abandonment of traditional real exchange rate theory — or at least a modified version of it — in the analysis of international business cycle fluctuations has been premature. Specifically, we find that the measured relation between the bilateral real exchange rate and the relative price of non-traded to traded goods is strong on average. In contrast to the traditional theory, and in accordance with Engel's results, we do find significant bilateral deviations from the law of one price for baskets of goods that are traded, and that these deviations play a large role in real exchange rate fluctuations. To the extent that these deviations in the relative prices of traded goods are systematically smaller than are those in aggregate price levels, however, the relative prices of non-traded to traded goods also play a significant role. We argue that traditional real exchange rate theory should be modified, but not abandoned, in international macro models.

We analyze the statistical relation between the bilateral real exchange rate and the relative price of non-traded to traded goods for a diverse set of 50 countries, and all possible 1225 ($= 50 \times 49/2$) pairs of countries, in quarterly data over the period 1980 through 2005. We examine three key dimensions of this relation. First, we quantify the similarity of directional movements in the two variables by the sample correlation between them; second, we quantify the similarity of the magnitude of fluctuations in the two variables by the ratio of their standard deviations; and third, we compute a variance decomposition of the real exchange rate, given by the fraction of the variance of the real exchange rate accounted for by movements in the relative price of non-traded to traded goods. We compute our three summary statistics for deviations from mean in levels, in yearly differences, and in four-year differences for each pair of measured bilateral real exchange rates and relative prices of non-traded goods.

We find three key results. First, in the full sample of 1225 bilateral pairs, we find that the measured relation between the bilateral real exchange rate and the relative price of non-traded to traded goods is strong on average. The trade weighted average correlation between the two variables is positive, between 0.50 and 0.65, depending on whether we analyze deviations in levels or differences, and, although the volatility of the relative price of non-traded goods is only 50 to 60 percent that of the real exchange rate, fluctuations in the relative price of non-traded goods account for as much as one-third of the variance of bilateral real exchange rates. Second, we find that the relation between the bilateral real exchange rate and the relative price of non-traded goods is much stronger, according to all three of our statistics, for pairs of countries that enjoy an intensive trade relationship and for pairs of countries that have a relatively stable real exchange rate. Third, we find that for US/EU trade partners, which trade relatively little compared to the size of the economies involved, the relation between the real exchange rate and the relative price of goods is dramatically weaker than it is for any other classification of trade partners or trade blocs in our data. This is true despite the fact that the subset of all 49 US bilateral real exchange rates and relative prices exhibit just as strong a statistical relation as we observe in the full sample. The overall strength of the statistical relation between the bilateral real exchange rate and relative price of non-traded goods does not, therefore, depend systematically on whether or not the United States is one of the countries in the trade pair being studied; but, conditional on the United States being one of the countries in the trade pair, it does depend systematically on whether an EU country, or a non-EU country, is paired with the United States.

Interestingly, we find little evidence that the presence of high income/low income bilateral trade pairs in our sample biases our results in favor of a larger role for the relative price of non-traded goods in real exchange rate fluctuations. Similarly, we find little evidence that the presence of high inflation/low inflation bilateral trade pairs in our sample raises the size of the measured relation between the real exchange rate and the relative price of non-traded goods.

These results suggest that one cannot draw general conclusions about the role for bilateral real exchange rates of changes in the relative price of non-traded goods based solely on US/EU exchange rate data. As demonstrated convincingly by Engel (1999), and reflected in our own results, the movements in these particular bilateral real exchange rates are completely dominated by deviations from the law of one price for traded goods. Evidently, however, this result does not generalize to bilateral real exchange rates for other country pairs. For example, when we analyze our data in four-year differences, only 7 percent of the variance of bilateral US/EU real exchange rates is accounted for by the relative price of non-traded goods. The relative price of non-traded goods accounts for 29 percent of the variance of US/non-EU real exchange rates, however, and 39 percent of the variance of the United States' real exchange rates with its two North American Free Trade Area (NAFTA) partners, Canada and Mexico. Because our results show that high trade intensity is associated with a much stronger relation between the bilateral real exchange rate and the relative price of non-traded goods, the exceptionally weak measured relation between US/EU bilateral real exchange rates and the relative price of non-traded goods might be accounted for simply by the relatively small fraction of US trade accounted for by US/EU bilateral trade: US/EU trade accounts for only 21.0 percent of all US trade on average over 1980–2005, compared to 28.6 percent that is accounted for by US/NAFTA trade, for example, even though the EU has a GDP more than six times larger than that of Canada and Mexico. Using multivariate regressions on our whole sample, however, we show that this is not the case: When we regress the statistics that measure the strength of the relation between the bilateral real exchange rate and the relative price of non-traded goods on a number of variables, the EU/NAFTA dummy variables consistently have coefficients that are negative and significant

— both in economic and in statistical terms — even when we control for the intensity of trade relationships and for the volatility of bilateral real exchange rates.

Similar results to those found here are documented for a much smaller sample of countries by Betts and Kehoe (2006), who examine the relation between the bilateral real exchange rate and the associated bilateral relative price of non-traded to traded goods for the United States with five of her largest trade partners — Canada, Germany, Japan, Korea, and Mexico — over the period 1980 through 2004. There, we show that the strongest measured relations between the two variables are associated with the two largest trade relationships — those between the United States and her two NAFTA partners, Canada and Mexico. Much weaker measured relations are associated with the trade relationships of the United States with the remaining three countries, and especially with Germany — the country in the sample with the smallest ratio of trade to GDP with the United States. Here, we demonstrate that the suggestion of this earlier finding — that the strength of the relation between the bilateral real exchange rate and the bilateral relative price of non-traded goods is greater the more important the trade relationship between two countries — is robust in a much larger and more diverse sample of countries. This result can be interpreted as saying that the more traded is an aggregate basket of goods between two countries, the smaller will be observed law of one price deviations for that basket because of arbitrage. Our results are also related, if tangentially, to those of Crucini, Telmer and Zachariadis (2005) who show, in a large disaggregated data set of bilateral relative prices among EU countries, the more traded is a particular good, the smaller is its cross-country price dispersion. Betts and Kehoe (2001) find a similar result for more aggregative, sectoral Mexico-US price data: the more traded is the gross output of a major sector, the smaller is its bilateral relative price deviation.

We view our results as empirical regularities that models of exchange rate determination should try to capture. Most of the differences that we find across subsets of countries are statistically significant. This is only to be expected given the very large number of country pairs that we have in our data. It is interesting, therefore, to note that dividing our sample of country pairs along high inflation/low inflation lines or high income/low income lines often fails to produce statistically significant differences in the relations between the bilateral real exchange rate and the relative price of non-traded goods. We should be careful about inferring causation from our results, however. All of our criteria for sorting country pairs into subsets can be viewed as endogenous from the point of view of an economic model. This is perhaps most obvious in sorting trading pairs according to the variability of their bilateral real exchange rates, but it is true even in the case of sorting by trading blocs: We can view a country as choosing to form a trading bloc with other countries with which it has intense trading relationships and for which there is a large amount of arbitrage in the prices of traded goods.

Our findings suggest that neither the extreme approach to bilateral real exchange rate determination of the traditional theory nor that of the NOEM literature is appropriate. The traditional theory works best for pairs of countries that trade a lot with each other, and who share a relatively stable real exchange rate. The NOEM approach applies best to pairs of countries that trade little and share a relatively volatile real exchange rate. The role for real exchange rate fluctuations that is played by the relative price of non-traded goods depends crucially on how much trade two countries conduct with each other in the aggregate basket of goods, and this implies that a modified version of the traditional theory is appropriate: an approach in which goods — or aggregates of goods — can differ by the degree of their tradability between two countries. We explore such a modeling approach in Betts and Kehoe (2001) and find that it can account for several of the key empirical facts documented here. Drozd and Nosal (2008) explore a different approach to account for our results.

2. Methodology

2.1. Framework

The bilateral real exchange rate between two countries X and Y at date t is

$$RER_t = NER_t \frac{P_t^Y}{P_t^X}. \tag{1}$$

Here, NER_t is the nominal exchange rate of country X, or the number of units of X money per units of Y money, and P_t^i is a price index for country i at t, $i = X, Y$, which measures the units of country i currency required to buy one unit of country i goods at t.

Traditional real exchange rate theory assumes that traded goods are subject to arbitrage that eliminates international common-currency price differentials. Since the price indexes used to construct measured real exchange rates are functions of both traded and non-traded goods' prices, there is a natural decomposition of the real exchange rate in equation (1), which has been analyzed by Engel (1999) and Betts and Kehoe (2006). We denote by $P_t^{T,i}$ a price index for traded goods in country i:

$$RER_t = \left(NER_t \frac{P_t^{T,Y}}{P_t^{T,X}} \right) \left(\frac{P_t^Y}{P_t^X} \frac{P_t^{T,X}}{P_t^{T,Y}} \right) . \tag{2}$$

The first term denotes the bilateral real exchange rate of traded goods, which we denote by RER_t^T. It measures deviations from the law of one price for traded goods, and will also capture the effect for RER_t^T of any differences in the compositions of the baskets of traded goods across the two countries. The second term in (2) is a ratio of internal relative prices, which we denote as RER_t^N. We can write

$$RER_t^N = \frac{P_t^{T,X}}{P^X(P_t^{T,X}, P_t^{N,X})} \Bigg/ \frac{P_t^{T,Y}}{P^Y(P_t^{T,Y}, P_t^{N,Y})} \tag{3}$$

where $P_t^{N,i}$ is a price index for non-traded goods in country i, and we have made explicit the dependence of P_t^i on the indexes of both traded goods and non-traded goods, $P_t^{T,i}$ and $P_t^{N,i}$. It is this expression that we refer to as the bilateral relative price of non-traded to traded goods, or, more simply, as the relative price of non-traded goods.

The functional form of RER_t^N depends on how the aggregate price indexes are constructed in each country. In the case where $P_t^i = \left(P_t^{T,i}\right)^{\gamma_i} \left(P_t^{N,i}\right)^{1-\gamma_i}$, for example,

$$RER_t^N = \left(\frac{P_t^{N,Y}}{P_t^{T,Y}} \right)^{1-\gamma_y} \Bigg/ \left(\frac{P_t^{N,X}}{P_t^{T,X}} \right)^{1-\gamma_x} . \tag{4}$$

In general, however, to decompose the real exchange rate into the two components RER_t^T and RER_t^N, all we need are data on traded goods price indexes, and aggregate price indexes.

In what follows, we use equation (3), rather than equation (4), to calculate RER_t^N and so circumvent the need to assume a functional form for aggregate price measures, or to explicitly measure the prices of non-traded goods. We now rewrite (1) as

$$RER_t = RER_t^T \times RER_t^N , \tag{5}$$

which, in (natural) logarithms, is

$$rer_t = rer_t^T + rer_t^N . \tag{6}$$

Figure 1 graphs rer_t and rer_t^T for the bilateral pair Chile-United States.

According to the traditional theory, rer_t^T should be unrelated to the real exchange rate, and all real exchange rate fluctuations should be accounted for by rer_t^N. By contrast, NOEM assumes that rer_t^N accounts for almost none of the fluctuations in the real exchange rate and can be ignored. The remainder of this paper empirically assesses the relative merits of these two approaches to real exchange rate determination by measuring the strength of the statistical relation between bilateral real exchange rates, rer_t, and the bilateral relative price of non-traded goods, rer_t^N.

2.2. Summary statistics

To assess the strength of the relation between the bilateral real exchange rate rer_t and the associated relative price of non-traded to traded goods, rer_t^N, we use three summary statistics: the sample correlation coefficient between them, the ratio of the sample standard deviation of rer_t^N to the sample standard deviation of rer_t, and a sample decomposition of the variance of rer_t in terms of the fraction accounted for by rer_t^N.

We denote by $\mathrm{var}(rer)$ the sample variance of rer_t,

$$\mathrm{var}(rer) = \frac{1}{T_1 - T_0} \sum_{t=T_0}^{T_1} \left(rer_t - \overline{rer} \right)^2 , \tag{7}$$

and by $\mathrm{cov}\left(rer, rer^N\right)$ the sample covariance between rer_t and rer_t^N,

$$\mathrm{cov}(rer, rer^N) = \frac{1}{T_1 - T_0} \sum_{t=T_0}^{T_1} \left(rer_t - \overline{rer} \right) \left(rer_t^N - \overline{rer}^N \right). \tag{8}$$

In general in our data, $T_0 = 1980:1$ and $T_0 = 2005:4$, so that we have 104 observations and $T_1 - T_0 = 103$. The three summary statistics that we construct using these sample moments are

1. The sample correlation,

$$\text{corr}(rer, rer^N) = \frac{\text{cov}(rer, rer^N)}{(\text{var}(rer)\,\text{var}(rer^N))^{1/2}}. \tag{9}$$

2. The ratio of sample standard deviations,

$$\frac{\text{std}(rer^N)}{\text{std}(rer)} = \left(\frac{\text{var}(rer^N)}{\text{var}(rer)}\right)^{1/2}. \tag{10}$$

3. The variance decomposition in which the covariance between the two components of the real exchange rate, rer_t^T and rer_t^N , is allocated to fluctuations in rer_t^N in proportion to the relative size of its variance,

$$\text{vdec}(rer, rer^N) = \frac{\text{var}(rer^N)}{\text{var}(rer^N) + \text{var}(rer^T)}. \tag{11}$$

We also compute, but do not report results here, an alternative variance decomposition statistic in which half of the covariance is allocated to fluctuations in rer_t^N,

$$\text{vdec}(rer, rer^N) = \frac{\text{var}(rer^N) + \text{cov}(rer^N, rer^T)}{\text{var}(rer)}. \tag{12}$$

(Recall that $\text{var}\left(rer\right) = \text{var}\left(rer^N\right) + \text{var}\left(rer^T\right) + 2\,\text{cov}\left(rer^N, rer^T\right)$.) The results using this statistic are similar, but not identical, to those using statistic 3, and, for the sake of brevity, we omit them. For the Chile-US real exchange rate depicted in figure 1, for example, the variance decomposition (11) is 0.4896, while the alternative variance decomposition (12) is 0.4920. Notice that, rounding to two decimal places, both statistics are 0.49.

We compute these three statistics for the log levels of the real exchange rate and its components, and for four-quarter (hence "year") log differences and sixteen-quarter (hence "four-year") log differences, we compute the correlation and the ratio of standard deviations as described above. For the Chile-US real exchange rate, the correlation is 0.94 in levels, 0.76 in yearly differences, and 0.92 in four-year differences, and the ratio of standard deviations is 0.53 in levels, 0.52 in yearly differences, and 0.50 in four-year differences. When dealing with the data in log differences, however, we modify the variance decomposition statistic to make our results comparable to those obtained by Rogers and Jenkins (1995) and Engel (1999):

3'. The mean squared error is the uncentered sample second moment; for the m th difference in rer_t , for example, it is

$$\text{mse}(rer) = \frac{1}{T_1 - T_0 - m} \sum_{t=T_0+m}^{T_1} \left(rer_t - rer_{t-m} \right)^2 . \tag{13}$$

The decomposition is

$$\text{msedec}(rer, rer^N) = \frac{\text{mse}(rer^N)}{\text{mse}(rer^N) + \text{mse}(rer^T)} . \tag{14}$$

To the extent to which there is a common trend in rer_t and rer_t^N, the mean square error decomposition assigns a larger role to rer_t^N than does the variance decomposition. For the sample of bilateral exchange rates that we consider here, however, such trends in the data are small compared to the other fluctuations, and our results do not depend much on our choice of decomposition statistic. For the Chile-US real exchange rate, for example, $\text{vdec}(rer, rer^N) = 0.36$ while $\text{msedec}(rer, rer^N) = 0.37$ in yearly differences and $\text{vdec}(rer, rer^N) = 0.43$ while $\text{msedec}(rer, rer^N) = 0.46$ in four-year differences.

3. Data

In this paper, we dramatically expand the scope of the empirical investigation into the relation between bilateral real exchange rates and the relative price of non-traded goods across countries in Betts and Kehoe (2006). We ask whether the tentative result that we obtain there for a small sample of bilateral pairs — that a modified version of the traditional real exchange rate theory works much better for pairs of countries which trade a lot with each other while the real exchange rate theory of NOEM works best for pairs of countries which do not — is robust in a much larger sample.

For the most part, the analysis of this paper is conducted for 50 countries, all the countries for which we have been able to collect quarterly real exchange rate and price data over the period 1980 through 2005, or a substantial sub-period thereof. The list of these 50 countries is presented in table 1, along with the percentage of world trade accounted for by each country on average over our sample period. In our data appendix, we describe the sources of our data in detail, and specific availability problems. These 50 countries account for 83.5 percent of all world trade on average over 1980–2005, and the 1225 bilateral trade relationships among them accounts for 71.0 percent. By far the largest trading country left out of the main part of our analysis is China (P.R.C.), which on average accounts for 2.7 percent of world trade; other countries left out include the countries of Eastern Europe and the former Soviet Union, and most of the countries in Africa. We do have shorter time series of annual data for China, however, which we analyze separately in section 8 below. When we add China to our data set, we have 51 countries that account for 86.2 percent of all world trade on average over 1980–2005, with the 1275 bilateral trade relationships among them accounting for 75.9 percent.

Our choice of price series reflects a desire to examine as large a sample of countries as possible, subject to the constraint that price measures are conceptually acceptable. For an aggregate price index, P^i, for each country i, we use consumer price indexes (CPIs). These are the (expenditure weighted) consumer prices for a basket of all goods and services consumed by a country. They are readily available for all of the countries in our sample at the quarterly frequency. They include the prices of many traded goods, including imported goods, and many domestic goods and services that are not traded. While they do not measure directly the price of a country's output, as do the gross output deflators used by Betts and Kehoe (2006), they do so indirectly by measuring the purchasing power of that output over the consumption basket.

In measuring the prices of traded goods, we must be more careful. On conceptual grounds alone, we prefer to use sectoral gross output deflators, on the basis of arguments presented in Betts and Kehoe (2006). These deflators measure the value of output at the production site, and are therefore exclusive of the prices of any non-traded marketing and other final consumption services that are included in CPI component data, or in disaggregated consumption expenditure data. In addition, by looking at sectoral detail on how much trade actually occurs in sectoral outputs, we can back up our choices of traded good sectors with data. We prefer to use sectoral gross output, rather than sectoral value added (gross domestic product — GDP) deflators, because value added deflators do not measure the price of sectoral outputs because they fail to reflect the value of intermediate goods. Furthermore, Betts and Kehoe (2006) show that the behavior of the measures of rer_t and rer_t^N constructed using GDP deflators differs substantially from that of the corresponding measures constructed using gross output deflators. Unfortunately, however, sectoral gross output data are readily available only for a small subset of countries and usually only at the annual frequency.

Our next conceptually preferred, and most broadly available, measure of a traded goods price index for a country is its producer price index (PPI) for all goods. While there are inevitably some producer goods that are not traded, PPI data are measured at the production site and hence exclude marketing and other non-traded consumer services. In addition, the prices of the items in the producer basket of goods are final output prices at the production site; in other words, they represent an improvement over value added data. Furthermore, PPI data are available for our entire set of 50 countries at the quarterly frequency. Finally, Betts and Kehoe (2006) show that the correlation between measures of rer^N that are based on sectoral gross output deflators and measures of rer^N that are based on PPIs is large and positive. While using PPI data has the benefits that we discuss, it also has costs, as discussed by Engel (1999). The fact that we did not uncover any systematic bias in using PPIs, as compared to sectoral gross output deflators in the small sample of bilateral country pairs in Betts and Kehoe (2006), does not conclusively rule out there being such a bias. Given the available data, we cannot determine if there is such a bias, however, because the CPI and PPI data that we have is all that are available for our large sample of bilateral pairs.

For the analysis in this paper, we neither detrend nor de-seasonalize the data. Betts and Kehoe (2006) conduct the same analysis as we do here for both detrended and non-detrended data. We find that detrending actually biases the results in favor of a stronger relation between rer_t^N and rer_t, quantitatively, while the general tenor of the results is unchanged. More importantly, we do not have an economic model of how trends and seasonal factors in prices and exchange rates are determined, nor of how they should impact the statistics we present here. We examine the data in quarterly levels, in four-quarter differences, and in sixteen-quarter differences, and we find that our results and conclusions are at least qualitatively, and sometimes quantitatively, invariant to the choice of frequency.

4. Empirical analysis

We first restrict ourselves to analyzing the subset of our data that is all 49 possible bilateral real exchange rates versus the United States. Table 2 presents the trade weighted means of our three statistics: the correlation, the relative standard deviation, and the variance decomposition statistic when the data are measured in levels or the mean squared error decomposition statistic when the data are measured in one-year or four-year differences.

To compute the trade weighted means, we weight each statistic for a particular US trade partner by the sample period average percentage of total US merchandise trade with the countries in our sample accounted for by the United States' bilateral trade with that particular partner. The trade weight for the statistic of country j, $j = 1,\ldots,49$, with respect to the United States is

$$weight_j = \frac{1}{26}\sum_{t=1980}^{2005}\left(\frac{exports_{US,j,t} + exports_{j,US,t}}{\sum_{i=1}^{49} exports_{US,i,t} + \sum_{i=1}^{49} exports_{i,US,t}}\right), \tag{15}$$

where $exports_{X,Y,t}$ is measured as free on board (f.o.b.) merchandise exports from country X to country Y at year t, measured in year t US dollars. The weight for Chile, for example, is 0.0043 because Chile accounts for 0.43 percent of the United States' trade with the 49 trade partners on average over 1980–2005. Trade between the United States and the total sample of 49 trade partners accounts for 87.2 percent of total US trade on average.

For all US bilateral real exchange rates, as shown in the first column of numbers in table 2, we find a trade weighted average correlation between rer_t and rer_t^N of 0.60 in levels, 0.60 in yearly differences, and 0.73 in four-year differences. These results are similar to those in Betts and Kehoe (2006) for a small sample of US bilateral trade partners. The high correlation between rer_t and rer_t^N suggests the presence of real shocks that drive both the relative internal price of goods and the real exchange rate. The magnitude of fluctuations in rer_t^N is less than one-half that of the real exchange rate, however, and rer_t^N accounts for between one-fifth and one-third of all bilateral US real exchange rate fluctuations.

In the first column of numbers of table 3, we show the same set of statistics for the 1225 bilateral real exchange rates in our data set. To compute trade-weighted averages of our statistics, for each bilateral pair in the sample, we compute total trade between the two countries at each year t, and divide this by the value of total trade between all 50 countries at that date. Total bilateral trade between any two countries, X and Y, is measured as the f.o.b. merchandise exports from X to Y plus (f.o.b.) exports from Y to X. The trade weight applied to the statistics that we compute for country X and country Y is, therefore,

$$weight_{X,Y} = \frac{1}{26}\sum_{t=1980}^{2005}\left(\frac{exports_{X,Y,t} + exports_{Y,X,t}}{\sum_{i=1}^{50}\sum_{j=1}^{49} exports_{i,j,t}}\right). \tag{16}$$

We find a trade weighted average correlation between rer_t and rer_t^N of 0.52 in levels, 0.51 in yearly differences, and 0.64 in four-year differences. The full sample correlation of rer_t and rer_t^N is somewhat smaller than we observe when we focus exclusively on the 49 bilateral US exchange rates, but the relative magnitude of fluctuations in rer_t^N is larger, at least 50 percent, and in the full sample rer_t^N accounts for between one-fifth and one-third of all bilateral real exchange rate fluctuations in the full sample as it does in the US bilateral exchange rate data.

The frequency distributions of our statistics in the whole sample are illustrated in figures 2 through 4. In these figures, we do not put any trade weights on bilateral pairs. Figure 2 plots the frequency distributions of $\text{corr}\left(rer, rer^N\right)$; figure 3 plots the frequency distributions of $\text{std}\left(rer^N\right)/\text{std}\left(rer\right)$; and figure 4 plots the frequency distribution of $\text{vdec}\left(rer, rer^N\right)$ for the data measured in levels and $\text{msedec}\left(rer, rer^N\right)$ for the data measured in one-year differences and in four-year differences. The value of 0.1033 for four-year differences in 0.9 to 1.0 in figure 2, for example, means that 114 of the 1225 bilateral pairs ($114/1225 = 0.1033$) have values of $\text{corr}\left(rer, rer^N\right)$ between 0.9 and 1.0.

Figure 2 shows that the sample distribution of $\text{corr}\left(rer, rer^N\right)$ for the data in levels is skewed towards high numbers, those in excess of 0.7. In contrast, the distributions of the correlation statistic for the data in differences are more concentrated around lower values, those in the range of 0.3–0.7. Interestingly, however, there are far fewer cases of negative correlations between rer and rer^N for the data in differences than there are for the data in levels. Figure 3 shows that the distribution of $\text{std}\left(rer^N\right)/\text{std}\left(rer\right)$ is clustered in the 0.3–0.7 range for the data in levels. For the data in differences, $\text{std}\left(rer^N\right)/\text{std}\left(rer\right)$ is more tightly clustered in the 0.2–0.5 range. Notice that this statistic tends to be smaller for one-year differences than it is for four-year differences. Figure 4 shows that the distribution of $\text{vdec}\left(rer, rer^N\right)$ for the data in levels is fairly uniform, although the largest cluster of values falls in the 0.1–0.4 range. The distribution of $\mathrm{msedec}\left(rer, rer^{N}\right)$ for the data in differences is more tightly clustered, but in the same range. For the data both in levels and in differences there is a significant fraction of bilateral pairs — between one-sixth and one-third, depending on the frequency of the data — for which the decomposition statistic is in the range 0.0–0.1.

We can conclude that, in a large set of bilateral pairs of countries, the real exchange rate shares similar directional movements with its non-traded goods component, and its fluctuations have a not too dissimilar magnitude measured by its standard deviation — about 1.5 to 2.0 times that of the non-traded goods component. Furthermore, fluctuations in the non-traded goods component of the real exchange rate account for roughly one-third of all fluctuations in the real exchange rate, leaving two-thirds of these fluctuations to be explained by the international relative price of traded goods.

5. Income levels and inflation rates

Are our results systematically biased by any particular features of our data? Two ideas prevalent in the literature on real exchange rates inform our choice of variables to examine.

First, it is widely believed that the behavior of bilateral real exchange rates is more strongly driven by the relative price of non-traded goods for pairs of countries whose income levels differ widely. Specifically, the relative price of non-traded goods is believed to play a more important role for real exchange rate fluctuations in trade relationships between rich countries and poor countries — such as the trade relationship between Mexico and the United States — than it is for real exchange rate fluctuations in trade relationships among rich countries, especially between the United States and Western Europe, the trade data most frequently examined by international business cycle analysts. This raises the question of whether the inclusion in our sample of both rich and poor countries is biasing our results in favor of a role in real exchange rate determination for non-traded goods prices.

Second, it is often argued that in high inflation countries, if the bilateral real exchange rate with a low or stable inflation country fluctuates, it is attributable to changes in the relative price of non-traded to traded goods across the two countries. The argument is that, in high inflation countries, there is little nominal rigidity that could contribute to deviations from the law of one price among traded goods in the face of rapid nominal exchange rate depreciation; nominal prices change as rapidly as the nominal exchange rate does. Hence, there is a very limited role for rer_t^T and a potentially larger relative role for rer_t^N in accounting for real exchange rate fluctuations in high inflation/low inflation country trade. This raises the question of whether, by including high inflation countries in our sample, we have biased our results in favor of finding a relatively high value of $\text{vdec}\left(rer, rer^N\right)$ and $\text{msedec}\left(rer, rer^N\right)$.

In the second and third columns of numbers in table 2, and in the second through fourth columns of numbers in table 3, we show that the inclusion of rich country/poor country trade pairs in our sample does not systematically bias upwards the measured relation between the relative price of non-traded goods and the real exchange rate. In this analysis, we classify a country as "high income" if its GDP per capita exceeds 10,000 USD in the year 2005 (taken from the World Bank's *World Development Report*), and we classify a country as "low income" otherwise. Chile, for example, is a low income country, with a GDP per capita of 7,300 USD in 2005, while the United States is a high income country, with a GDP per capita of 41,900 USD.

In table 2, the second and third columns of numbers show that whether the United States trades with a rich or with a poor country does not have large or systematic effects on the values of the correlation statistic. The correlation between the real exchange rate and relative price of non-traded goods is somewhat higher for US trade relationships with poor countries when we measure the data in quarterly levels, but actually lower for US trade relationships with poor countries when we consider the data in yearly differences, or in four-year differences. There is a systematic difference both in the relative standard deviation statistic, however, and in the variance decomposition statistic, depending on whether the United States trades with rich countries or poor countries. Both the relative standard deviation of the non-traded goods component of the real exchange rate, and the fraction of real exchange rate variance it accounts for, are in fact lower when we analyze the data for US trade relationships with poor countries than for US trade relationships with other rich countries. This is true whether we consider the data in quarterly levels, in yearly differences, or in four-year differences. The non-traded goods component of the real exchange rate systematically accounts for less, not more, of the total variance of the real exchange rate, for rich/poor country trade pairs than it does for rich/rich country trade pairs.

In table 4, where we examine the data for all bilateral country pairs classified by the relative incomes of trade pairs, we see exactly the same pattern of results. While there is no systematic impact for the measured correlation of rer_t and rer_t^N of the relative incomes of two countries, both the relative standard deviation of rer_t^N and the fraction of variance of the real exchange rate accounted for by fluctuations in rer_t^N are systematically lower for rich/poor country pairs than the statistics for rich/rich country pairs and for poor/poor country pairs. That is, the inclusion of rich/poor country trade pairs in our sample actually tends to reduce, rather than increase, the role for the non-traded goods component in accounting for the variance of bilateral real exchange rate variance.

The fourth and fifth columns of table 2 show that the presence of relatively high inflation rate trade partners of the US in the sample biases our results in favor of a larger role for fluctuations in the relative price of non-traded goods. Here we define a "high inflation" country as one that has an annual geometric average CPI inflation rate over our sample period that is greater than or equal to 10 percent, and a "low inflation" country otherwise. The 49 bilateral trade partners of the United States are cut into two groups on the basis of this criterion. Chile, for example, is a high inflation country because it has an annual geometric average CPI inflation rate of 12.4 percent over 1980–2005, while the United States itself, with an average annual inflation rate of 3.6 percent, is a low inflation country. The fourth and fifth columns of numbers show that whether the United States trades with a high inflation or with a low inflation country does not have large or systematic effects on the value of the correlation statistic. The correlation between the real exchange rate and relative price of non-traded goods is somewhat higher for US trade relationships with high inflation countries when we measure the data in quarterly levels, but actually lower for US trade relationships with high inflation countries when we consider the data in differences. There is a systematic difference in both the relative standard deviation statistic and in the variance decomposition statistic, however, depending on whether we analyze US trade relationships with high inflation or with low inflation countries. Both the relative standard deviation of the non-traded goods component of the real exchange rate and the fraction of real exchange rate variance it accounts for are lower when we analyze the data for US trade relationships with high inflation countries than for US trade relationships with other low inflation countries. This is true whether we consider the data in levels or in differences. In particular, the non-traded goods component of the real exchange rate systematically accounts for less, not more, of the total variance of the real exchange rate for low inflation/high inflation country trade pairs, than it does for low inflation/low inflation country trade pairs.

The second through fourth columns of table 4 cut the sample of all possible bilateral pairs according to whether a particular pair of countries exhibits high/high, high/low, or low/low inflation rates over our sample, using the 10 percent average CPI inflation rate criterion. These results show that the value of the correlation statistic for high inflation/low inflation pairs lies between that for high inflation/high inflation country pairs and that for low inflation/low inflation country pairs, while both the relative standard deviation and the variance decomposition statistics are lowest, not highest, for the high inflation/low inflation pairs of countries.

In short, the inclusion of high inflation country/low inflation country trade pairs in our sample serves to reduce, rather than increase, the average percentage of bilateral real exchange rate variance accounted for by fluctuations in the relative price of goods. It does not systematically bias upwards the role of the non-traded goods component in accounting for real exchange rate fluctuations.

6. Trade intensity

How does the strength of the trade relationship between two countries affect the strength of the relation between the relative price of non-traded goods and the bilateral real exchange rate?

The sixth and seventh columns of numbers in table 2 show how the degree of trade intensity between the United States and its trade partners influences our results. We define the trade intensity of country X with respect to the United States as

$$tradeint_{X,US} = \frac{1}{26}\sum_{t=1980}^{2005}\left(\frac{exports_{X,US,t} + exports_{US,X,t}}{\sum_{world} exports_{X,i,t} + \sum_{world} exports_{i,X,t}}\right), \qquad (17)$$

the average fraction of the merchandise trade of country X that is trade with the United States. A bilateral trade relationship with the United States is defined as "high intensity" if $tradeint_{X,US}$ is greater than or equal to 15 percent and "low intensity" otherwise. Chile, for example, has a high intensity trade relationship with the United States, because trade with the United States accounts for 20.5 percent of Chile's total trade over 1980–2005 on average.

Table 2 shows that the relation between the real exchange rate and its non-traded goods component is substantially stronger when trade intensity is high than when trade intensity is low.

This is true when the data are measured in levels, in yearly differences, and in four-year differences. The differences are large and striking for all three statistics. The statistical relation between the US bilateral real exchange rate and the relative price of non-traded goods is much stronger when US trade is very important for a trade partner.

Turning to the whole sample, we now write the definition of trade intensity between any two countries, X and Y, as

$$tradeint_{X,Y} = \max \begin{bmatrix} \frac{1}{26}\sum_{t=1980}^{2005}\left(\frac{exports_{X,Y,t} + exports_{Y,X,t}}{\sum_{world} exports_{X,i,t} + \sum_{world} exports_{i,X,t}}\right), \\ \frac{1}{26}\sum_{t=1980}^{2005}\left(\frac{exports_{X,Y,t} + exports_{Y,X,t}}{\sum_{world} exports_{Y,i,t} + \sum_{world} exports_{i,Y,t}}\right) \end{bmatrix}. \qquad (18)$$

In this, we are implicitly assuming that trade intensity need only be high for one of the two countries in any bilateral trade relationship for the same strong relation between the relative price of goods and the real exchange rate to be observed. The Chile-US relationship is a high intensity relationship, even though Chile accounts for only 0.4 percent of US trade, because the United States accounts for 20.5 percent of Chilean trade.

The data in the second and third columns of numbers in table 5 confirm the results found in table 2 for US pairs. When we consider all possible bilateral country pairs, and sort them by the average sample value of $tradeint_{X,Y}$ into high trade intensity (where $tradeint_{X,Y}$ is greater than or equal to 15 percent) and low trade intensity groups, we find that high trade intensity is associated with a substantially closer relation of rer and rer^N in general and a much larger role for fluctuations in rer^N in real exchange rate fluctuations. This result is invariant to whether the data are measured in levels, yearly differences, or four-year differences.

7. Real exchange rate variability

In this section, we ask whether the variability of the bilateral real exchange rate between two countries, as measured by the standard deviation of that real exchange rate, influences the strength of the statistical relation between the relative price of goods and the real exchange rate. To address this question, we classify all bilateral real exchange rates according to whether they have “high” rer_t variability, where $\text{std}(rer)$ is greater than or equal to 15 percent, and “low”

rer_t variability otherwise. The Chile-US real exchange rate has high variability because $\text{std}(rer) = 0.240$, that is, 24.0 percent.

Our results for US bilateral real exchange rates, and for the full sample of all possible bilateral real exchange rates, are found in the last two columns of numbers in tables 2 and 5, respectively.

The answer to our question is that low variability bilateral real exchange rates are much more strongly associated with the relative price of non-traded goods than are high variability real exchange rates. Whether we analyze the data in levels, in yearly differences, or in four-year differences, all three statistics are much larger for bilateral US trade pairs that experience low variability in their bilateral real exchange rates, as shown in table 2. This result is broadly reflected in the full sample statistics, which are shown in table 5. Here, although the correlation statistics are higher for pairs of countries with high variability bilateral real exchange rates, both the relative standard deviation of rer_t^N and the portion of real exchange rate variance accounted for by rer_t^N are larger for low variability real exchange rate pairs.

Our results so far suggest that the relation between the real exchange rate and the relative price of non-traded goods for Chile-US is strong, not because Chile is poor and the United States rich nor because Chile has experienced high inflation and the United States has not, but because Chile and the United States have an intense trade relationship. Furthermore, the relation is strong in spite of the fact that the Chile-US real exchange rate is highly variable.

8. China

We have excluded China from our main analysis because we have only annual data on the CPI and PPI. In addition, the Chinese CPI data — and hence the analysis of this section — are available only for the period 1985 through 2005. In table 6, we present the results that we obtain from an analysis of the available Chinese data.

The price and exchange rate data for China's 50 trade partners in our sample that are used in this analysis are measured at the annual frequency. We compute trade weighted statistics as usual, applying the trade weight to statistics for country X with respect to China as in equation (16). The total bilateral trade between China and all 50 countries in our sample, measured in the denominator of this trade weight, accounts for 89.4 percent of total Chinese trade.

The first column of table 6 shows that there is a strong measured relation between the bilateral real exchange rate and the bilateral relative price of non-traded goods when the data are measured in levels or in four-year differences. The bilateral real exchange rate and relative price of non-traded goods are highly positively correlated, with a correlation coefficient of roughly 0.8, and non-traded goods prices account for almost 50 percent of all real exchange rate fluctuations. The relation is, anomalously, much weaker when the data are measured in annual differences, however. Nonetheless, no matter how we measure the data, the relation between bilateral China real exchange rates and bilateral China non-traded goods prices is much stronger when we analyze the data for trade partners with whom China shares a high trade intensity relationship, and when we analyze the data for trade partners with whom China shares a low variability real exchange rate.

The table also shows that there is no systematic bias in favor of a strong relation between bilateral China real exchange rates and non-traded goods prices arising from the presence of high inflation trade partners in the sample. Oddly — in light of our other results — there does seem to be some evidence that the inclusion of high income trade partners may somewhat raise the measured size of this relation, at least when the data are measured in levels and four-year differences. This second anomaly of the Chinese data warrants further investigation.

We have also recalculated the statistics for all 1275 ($=51\times 50/2$) bilateral trade relationships using annual data and including China, but do not report the results here. These results change very little from those in tables 3, 4, and 5 because, as Betts and Kehoe (2006) show, using annual, rather than quarterly, data has very little effect on our statistics. Including China tends to increase the statistics a little because China's bilateral real exchange rate has a stronger relation with the relative price of non-traded goods than the average in our sample. To come up with a close approximation of the results for all 1275 bilateral real exchange rates, we can average the results from table 6 with those from tables 3, 4, and 5, using the fact that China's trade with the other 50 countries in our sample accounts for 4.9 percent of world trade on average. To approximate $\text{corr}(rer, rer^N)$ in levels for all 1275 bilateral trade relationships, for example, we calculate

$$0.54=\left(\frac{4.9}{75.9}\right)0.79+\left(\frac{71.0}{75.9}\right)0.52\,. \tag{19}$$

The actual statistic is, in fact, 0.54. We need to keep in mind that China is a low income, low inflation country. Rather than averaging the results of table 6 with those of tables 3, 4, and 5, however, the interested reader can simply download our data from http://www.econ.umn.edu/~tkehoe and calculate the statistics directly.

9. Trade blocs

The results in the preceding sections show that there is a much larger measured relation between bilateral real exchange rates and the relative price of non-traded goods for pairs of countries that enjoy a large trade relationship than for pairs of countries that do not. In tables 7 and 8, we re-cut our sample of countries according to whether or not they are members of the two largest trade blocs in the world — the EU and NAFTA — and explore the implications of country membership of these blocs for real exchange rate behavior.

In table 7, we explore in more detail the relation between the bilateral real exchange rate and the relative price of non-traded goods for US bilateral trade relationships. We cut the sample of 49 bilateral trade partnerships with the United States that we first studied in table 2 according to whether a trade partner is a member of the EU or not, a member of NAFTA or not, or is neither a member of EU or NAFTA, which we refer to as "other." The final two rows of table 7 show that bilateral trade between the United States and the fourteen of the EU15 countries in our sample accounts for 21.0 percent of all US trade on average over the sample period. (The missing country is Portugal, for which we do not have quarterly PPI data.) This contrasts with 66.2 percent of US trade that is accounted for by bilateral trade with the non-EU countries in our sample, and 28.6 percent of US trade that is accounted for by bilateral trade with her two NAFTA partners, Canada and Mexico.

The numbers in table 7 are the weighted averages of the statistics for each grouping of countries vis-à-vis the United States, where the statistic of each country is weighted by its average sample share of all US trade in our sample. The measured relation between the bilateral real exchange rate and the relative price of non-traded goods is, as we would expect, noticeably stronger for US/NAFTA countries than it is for US/non-NAFTA countries, as shown by a comparison of the numbers in the fourth and fifth columns of the table. It is much weaker for US/EU country pairs, however, than it is for any other bilateral US/trade pairing group: US/non-EU pairs, US/NAFTA pairs, US/non-NAFTA pairs, and for US/other pairs.

The table shows that — as we would anticipate — there is a strong relation between the bilateral US real exchange rate and relative price of non-traded goods for the NAFTA trade partners compared to that for non-NAFTA trade partners. It also shows that the measured relation for the NAFTA trade partners is not very different from that for all non-EU countries. By far the most striking set of numbers in the table are those in the second column of data; the numbers that describe the statistical relation between the US bilateral real exchange rate and the relative price of non-traded goods with respect to EU countries are extraordinarily small.

In table 8, we explore this feature of our data a little more, examining the relation between the real exchange rate and the relative price of non-traded goods for all possible bilateral pairings of our 50 countries, where countries are grouped according to their EU or NAFTA membership status. Here, "within" trade bloc real exchange rate movements — those between the NAFTA/NAFTA and EU/EU pairs of countries — are most strongly associated with movements in the relative price of non-traded goods according to our statistical criteria. Again, however, the most striking are in the third column, which shows that there is an extraordinarily weak measured relation between the real exchange rate and relative price of non-traded goods for EU/NAFTA trade partners compared to any other set of bilateral trade relationships.

10. Economic and statistical significance

How significant are our results about the differences in the relations of real exchange rates and the relative price of nontraded goods prices? In this section, we provide some measures of the economic and the statistical significance.

Table 9 shows the results of Student's T tests on the differences in weighted means. For the weighted means in every column of tables 1–8, except for the first column, we test the hypothesis that the statistics for the bilateral pairs in that sub-sample are drawn from a distribution with the same weighted mean as the statistics for the rest of the sample. For example, for the $\mathrm{corr}(rer, rer^N)$ in levels for the column low/low in table 3, we are testing the hypothesis that the $\mathrm{corr}(rer, rer^N)$ statistics for the 231 low/low bilateral pairs, whose weighted mean is 0.63, are drawn from the same normal distribution as the statistics for the 994 bilateral pairs in the rest of the sample, whose weighted means is 0.51. In fact, a T test shows that we cannot reject this hypothesis at a 0.05 significance level. Notice, however, that most of the weighted means in tables 3, 4, 5, and 8, which report results for the entire sample, are statistically significantly different from the corresponding weighted mean for the rest of the sample. The major exceptions are the low/low income bilateral pairs in table 3, the high/high inflation bilateral pairs in table 4, and the subsets of bilateral pairs involving other countries, the countries in the intersection of non-EU and non-NAFTA. For the bilateral exchange rates for the United States in tables 2 and 7 and for China in table 6, fewer of the cuts into sub-samples produce statistically significant differences because there are so fewer observations. Notice, however, that the division of bilateral country pairs into partners with intense trade relationships and those without and into partners with a low variability of the real exchange rate and those with a high variability produces statistically significant differences. Furthermore, the bilateral exchange rates between the United States and its NAFTA partners are statistically significantly different from bilateral exchange rates with EU countries.

We have consistently followed a tradition in the literature on real exchange rates in weighting statistics by trade weights. How different would our conclusions be if we did not use trade weights? Table 10 shows that the means of our statistics would change, but not by so much as to change our conclusions. In particular, we would still conclude that country pairs with intense trade relationships have bilateral real exchange rates that have stronger relations with the relative prices of non-traded goods than do country pairs with intense trade relationships, at least in terms of the relative standard deviation statistics and the variance and mean squared error decomposition statistics. So do country pairs with a low variability of their bilateral real exchange rate. Furthermore, the EU/NAFTA bilateral real exchange rates have relationships with the relative prices of non-traded goods that are statistically significantly weaker than those of the other bilateral real exchange rates in our sample.

For the T tests summarized in table 9, we have treated each of our nine statistics independently. It is probably preferable to view each of the three statistics for levels as the means of a three-dimensional vector that characterizes each bilateral real exchange rate in levels. We could do the same for the three statistics for yearly differences and for the three statistics for four-year differences. We could even view all nine statistics as the means of a nine-dimensional vector that characterizes each bilateral real exchange rate. Hotelling's (1947) generalized T^2 test — sometimes referred to as Hotelling's multinomial difference of means test — allows us to test whether subsets of vector-valued random variables come from the same population. (See, for example, Rencher 2002, page 118, for a textbook exposition.) For all bilateral pairs, the only subsets of three statistics that do not differ significantly from the others are the low/low income pairs in levels, yearly differences, and four-year differences, the high/high inflation pairs in levels, yearly differences, and four-year differences, and the EU/other bilateral pairs in levels. The only subsets of all nine statistics that do not differ significantly from the others are the low/low income pairs and the high/high inflation pairs. We can often reject the hypothesis that vectors of random variables are drawn from the same population with extraordinarily high confidence. The probability that vectors of nine statistics for the 49 bilateral pairs with intense trade relationships are drawn from the same population as the 1176 bilateral pairs without intense trade relationships, for example, is 2.4×10^{-66}.

To quantify the economic significance of our findings, it is useful to run regressions that allow us to control for a number of factors at the same time. Each row in table 11 reports the results of a regression of the statistic in the first column on the variables in the other columns, where all observations are weighted by the trade shares (16). The numbers in parentheses are standard errors, and asterisks indicate coefficients that are significantly different from 0 at the 0.05 confidence level according to a T test. In these regressions, *sum income* is the sum of the logs of income per capita for each bilateral pair in 2005, which, for Chile-US, is 19.538 ($=\log 7300+\log 41900$); *diff income* is the absolute value of the differences in the logs of income per capita, which, for Chile-US, is 1.748 ($=|\log 7300-\log 41900|$); *sum inflation* is the sum of the logs of the annual inflation factor for each country over 1980–2005, the log approximation to the sum of annual inflation rates, which, for Chile-US, is 0.152 ($=\log 1.124+\log 1.036$); *diff inflation* is the absolute difference in inflation rates, which, for Chile-US, is 0.081 ($=|\log 1.124-\log 1.036|$); $std(rer)$ is the standard deviation of the bilateral real exchange rate in levels, which, for Chile-US, is 0.240; and the remaining variables are dummy variables for trade bloc membership, and, for Chile-US, *NAFTA/other* is 1 and the others are 0. Notice that since other/other is the excluded dummy variable, the coefficients of the other dummy variables need to be interpreted in relation to it. The coefficient of −0.208 in the $\text{msedec}(rer, rer^N)$ row of the EU/NAFTA column, for example, means that, everything else being equal, having a bilateral pair made up of a member of NAFTA and a member of the EU, rather than both being members of neither, is associated with a mean squared error that is 0.208 lower.

As we interpret the results of the regressions in table 10, we keep in mind two things: First, as we have explained, every regressor can be interpreted as an endogenous variable in the context of a sensible economic model, which implies that we cannot make statements about causation. Second, the low values of the R^2 coefficients imply that, although the regressions produce many statistically significant coefficients, they do not provide for uniformly accurate decompositions of the variation in the statistics. Nonetheless, many of the results are economically, as well as statistically, significant. Notice that all of the coefficients of the trade intensity variable are statistically significant except that in the regression of $\text{corr}(rer, rer^N)$ in yearly levels. To understand the economic significance of the coefficient value 0.407 in the regression of $\text{msedec}(rer, rer^N)$ in four-year differences, we can increase trade intensity from 0.073, the level for Germany-US to, 0.205, the level of Chile-US, and calculate that we would expect the $\text{msedec}(rer, rer^N)$ statistic to increase by 0.054 ($= (0.205 - 0.073) \times 0.407$). Increasing it from 0.073 to 0.754, the level for Canada-US, should increase this fraction by 0.277. Notice that coefficients of $\text{std}(rer)$, although all significant, vary in sign. When we control for other factors, we find that volatile real exchange rates tend to be associated with high correlation statistics at all three frequencies, but with low relative standard deviations and variance decompositions. Increasing $\text{std}(rer)$ from 0.111, the level for Canada-US to 0.166, the level for Germany-US, we would expect $\text{msedec}(rer, rer^N)$ in four-year differences to decrease by 0.061. Increasing it from 0.111 to 0.463, the level for Peru-US, we would expect this statistic to decrease by 0.391. Notice that the differences in the dummy variables for EU/NAFTA and NAFTA/NAFTA are large in many of the regressions. The one for $\text{msedec}(rer, rer^N)$ in four-year differences is not one of them, however, and we expect a NAFTA/NAFTA pair like Canada-US to have a higher $\text{msedec}(rer, rer^N)$ than Germany-US from this difference for only 0.049 ($= -0.159 - 0.208$). Nonetheless, we have succeeded in accounting for most of the difference between Canada-US and Germany-US for $\text{msedec}(rer, rer^N)$ in four-year differences. Adding the difference because of trade intensity, 0.277, to the difference because of real exchange rate volatility, 0.061, to the difference because of trade bloc affiliations, 0.049, we obtain a difference of 0.386. In fact, $\text{msedec}(rer, rer^N)$ in four-year differences for Canada-US is 0.499 and that for Germany-US is 0.046, which differ by 0.454. Given the low R^2

coefficients, we could find other examples where the regressions do not account as well for differences across bilateral pairs, but this particular example is an important one. The low msedec(rer, rer^N) statistic for bilateral pairs like Germany-US has led many economists to totally abandon any sort of theory that distinguishes between traded and non-traded goods in modeling real exchange rate fluctuations. The high msedec(rer, rer^N) statistic for bilateral pairs like Canada-US prompts us to try to modify, rather than reject, the traditional theory. Furthermore, we would consider a model to be successful if it could generate the same sorts of co-movements in the real exchange rate and the relative price of nontraded goods that we have identified in this paper.

11. Conclusion

We have documented that there is a strong and robust statistical relation between the real exchange rate and the relative price of non-traded to traded goods. Specifically, we find in a large sample of 50 countries and 1225 associated bilateral real exchange rates over the sample period 1980 through 2005:

Fact 1. Directional movements of the relative price of non-traded goods and the real exchange rate tend to be similar, as measured by the simple correlation between the two variables, which is about one-half in levels and yearly differences, and two-thirds in four-year differences.

Fact 2. The volatility of the relative price of non-traded goods, as measured by its relative standard deviation, is about two-thirds that of the real exchange rate in levels and one-half in yearly differences and four-year differences.

Fact 3. The relative price of non-traded goods accounts for about one-third of real exchange rate variance in levels, one-fifth in yearly differences, and one-quarter in four-year differences.

The strength of the relation between real exchange rates and the relative price of non-traded goods is not biased upwards by the presence of rich/poor country pairs in our sample nor by the presence of high inflation/low inflation country pairs. Furthermore, the strength of the statistical relation between the bilateral real exchange rate and relative price of non-traded goods does not depend in any systematic way on whether or not the United States is one of the countries in the trade pair being studied.

Nonetheless, we identify two features of the data that do systematically and significantly increase the strength of the statistical relation between the relative price of non-traded goods and the real exchange rate in our large sample of countries.

Fact 4. The relation between the bilateral real exchange rate and relative price of non-traded goods is stronger when the intensity of the trade relationship between two countries is high.

Fact 5. The relation between the bilateral real exchange rate and the relative price of non-traded goods is stronger, as measured by the relative standard deviation and variance decomposition, when the variability of the bilateral real exchange rate between two countries is low. The correlation between the real exchange rate and the relative price of non-traded goods is lower, however, when the variability of the real exchange rate is low.

In addition, we find the following anomaly.

Anomaly. The statistical relation between the bilateral real exchange rate and the relative price of non-traded goods for US/EU country pairs, and for EU/NAFTA country pairs, is extraordinarily weak compared to the same relation measured between the countries in any other two trade blocs.

We leave to future research a more thorough investigation of this anomaly, and the development of models that can account for the regularities that we have documented.

Another topic worth investigating is the effect of different exchange rate regimes on the relationship between the real exchange rate and the relative price of non-trade goods. (See, for example, Mendoza 2000.) Using our data set, we could divide our data for different bilateral pairs into different sub-periods according to the prevailing exchange rate regimes. Of course, as Reinhard and Rogoff (2004) argue, the exact classification of an exchange rate regime is no easy matter. This too we leave to future research.

Data Appendix

The data on the consumer price index (CPI), producer price index (PPI), and nominal exchange rates are taken from the International Monetary Fund's November 2007 *International Financial Statistics* CD-ROM. We use OECD PPI series from their *Main Economic Indicators* database instead of the IFS data for all available countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Korea, Luxembourg, Mexico, Netherlands, New Zealand, Spain, Switzerland, and the United States. We also use OECD data for Netherlands CPI because the IFS data have a jump upwards between 1980Q4 and 1981Q1 followed by smooth data and then a jump downwards between 1984Q1 and 1984Q2, and we use OECD data for Germany CPI because they span both sides of reunification. In the cases of El Salvador, Greece, Jordan, and Turkey, either wholesale price indexes are the only series available or they offer greater coverage from the IFS CD-ROM. For Greece and Turkey, we splice their PPI series onto their WPI series for 2005Q1–Q4 because the WPI series ends in 2004. The maximum coverage of the data series is 1980Q1–2005Q4, though some series are shorter. All series are contiguous, except those of Jordan, Turkey, and Trinidad and Tobago. These missing values are interpolated, except for Greece, for which annual data are constructed by averaging quarterly data. In the case of Trinidad and Tobago, the available PPI data for 2000Q2–Q3 appear to be errors and are treated like missing data. All missing data are listed in table 12.

The data on bilateral and total trade volumes are taken from the International Monetary Fund's November 2007 *Direction of Trade Statistics* CD-ROM. To compute yearly bilateral trade between two countries, the sum of exports from the home country and exports from the partner country are divided by the sum of total exports from the home country to the world and total exports from the world to the home country. These yearly values are averaged over 1980–2005. All export data are taken free-on-board (f.o.b.). The *Direction of Trade Statistics* does not have data for Belgium and Luxembourg separately 1980–1996. Nor does it have export data for South Africa 1980–1997. For these three countries, and for all bilateral trade relationships involving them, the weights (15) and (16) and the trade intensity statistics (17) and (18) use average fractions of trade over the available years. We assume that the trade shares for these three countries are the same in the years for which we do not have data as they are on average in the years for which we have data.

Chinese annual CPI and PPI data are taken from the 2001 and 2006 *China Statistical Yearbook* and have been downloaded from the web site of the National Bureau of Statistics of China, http://www.stats.gov.cn/english/statisticaldata/yearlydata.

GDP and population data are from the World Bank's *World Development Indicators*.

All the data and more precise documentation can be found at http://www.econ.umn.edu/~tkehoe.

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Table 1

COUNTRIES IN THE SAMPLE

Average percent world trade 1980–2005

Argentina	0.36	Hong Kong (P.R.C.)	2.52	Peru	0.12
Australia	1.12	India	0.66	Philippines	0.43
Austria	1.14	Indonesia	0.75	Saudi Arabia	1.31
Belgium	2.75	Ireland	0.73	South Africa	1.73
Brazil	0.94	Israel	0.41	Singapore	0.47
Canada	3.67	Italy	4.19	Spain	1.88
Chile	0.25	Japan	6.87	Sri Lanka	0.08
Colombia	0.20	Jordan	0.08	Sweden	1.37
Costa Rica	0.07	Korea	1.95	Switzerland	1.68
Cyprus	0.06	Luxembourg	0.17	Thailand	0.80
Denmark	0.83	Malaysia	1.04	Trinidad and Tobago	0.07
Egypt	0.26	Mexico	1.49	Turkey	0.54
El Salvador	0.04	Netherlands	3.84	United Kingdom	5.19
Finland	0.67	New Zealand	0.25	United States	13.60
France	5.64	Norway	0.79	Uruguay	0.05
Germany	9.24	Pakistan	0.20	Venezuela	0.42
Greece	0.39	Panama	0.15	Total	83.47

Table 2

US BILATERAL REAL EXCHANGE RATES

Means weighted by trade

		income level		**inflation**		**trade intensity**		**std(rer)**	
	all	**high**	**low**	**high**	**low**	**high**	**low**	**high**	**low**
levels									
corr(rer, rer^N)	0.60	0.58	0.69	0.63	0.59	0.72	0.34	0.58	0.63
std(rer^N)/std(rer)	0.46	0.48	0.41	0.41	0.47	0.52	0.33	0.32	0.64
vdec(rer, rer^N)	0.30	0.31	0.24	0.22	0.31	0.37	0.12	0.15	0.48
4-quarter differences									
corr(rer, rer^N)	0.60	0.61	0.56	0.57	0.60	0.68	0.42	0.56	0.64
std(rer^N)/std(rer)	0.41	0.41	0.39	0.37	0.42	0.47	0.27	0.27	0.58
msedec(rer, rer^N)	0.20	0.21	0.17	0.17	0.21	0.26	0.08	0.10	0.34
16-quarter differences									
corr(rer, rer^N)	0.73	0.75	0.66	0.71	0.74	0.82	0.55	0.70	0.78
std(rer^N)/std(rer)	0.39	0.39	0.39	0.37	0.39	0.45	0.26	0.26	0.55
msedec(rer, rer^N)	0.24	0.24	0.22	0.22	0.24	0.31	0.09	0.11	0.40
countries	49	27	22	17	32	20	29	34	15
percent US trade	87.2	68.3	18.9	16.0	71.2	59.9	27.3	48.5	38.7

Table 3

INCOME LEVELS
ALL BILATERAL REAL EXCHANGE RATES

Means weighted by trade

	all	**high/ high**	**high/ low**	**low/ low**
levels				
corr(rer, rer^N)	0.52	0.46	0.72	0.63
std(rer^N)/std(rer)	0.64	0.67	0.49	0.55
vdec(rer, rer^N)	0.33	0.33	0.32	0.33
4-quarter differences				
corr(rer, rer^N)	0.51	0.50	0.57	0.61
std(rer^N)/std(rer)	0.50	0.53	0.39	0.43
msedec(rer, rer^N)	0.22	0.22	0.18	0.22
16-quarter differences				
corr(rer, rer^N)	0.64	0.63	0.66	0.71
std(rer^N)/std(rer)	0.51	0.54	0.41	0.45
msedec(rer, rer^N)	0.28	0.28	0.26	0.30
bilateral pairs	1225	378	616	231
percent of world trade	71.0	56.0	14.0	1.0

Table 4

INFLATION LEVELS
ALL BILATERAL REAL EXCHANGE RATES

Means weighted by trade

	all	**high/ high**	**high/ low**	**low/ low**
levels				
corr(rer, rer^N)	0.52	0.66	0.66	0.49
std(rer^N)/std(rer)	0.64	0.54	0.48	0.67
vdec(rer, rer^N)	0.33	0.32	0.28	0.34
4-quarter differences				
corr(rer, rer^N)	0.51	0.66	0.58	0.50
std(rer^N)/std(rer)	0.50	0.41	0.36	0.53
msedec(rer, rer^N)	0.22	0.23	0.17	0.22
16-quarter differences				
corr(rer, rer^N)	0.64	0.78	0.69	0.63
std(rer^N)/std(rer)	0.51	0.42	0.38	0.53
msedec(rer, rer^N)	0.28	0.28	0.24	0.28
bilateral pairs	1225	136	561	528
percent of world trade	71.0	0.6	10.5	59.8

Table 5

TRADE INTENSITY AND REAL EXCHANGE RATE VARIABILITY
ALL BILATERAL REAL EXCHANGE RATES

Means weighted by trade

		trade intensity		std(rer)	
	all	**high**	**low**	**high**	**low**
levels					
corr(rer, rer^N)	0.52	0.57	0.47	0.63	0.44
std(rer^N)/std(rer)	0.64	0.71	0.57	0.42	0.79
vdec(rer, rer^N)	0.33	0.37	0.29	0.24	0.39
4-quarter differences					
corr(rer, rer^N)	0.51	0.57	0.47	0.58	0.47
std(rer^N)/std(rer)	0.50	0.64	0.38	0.32	0.63
msedec(rer, rer^N)	0.22	0.28	0.16	0.13	0.27
16-quarter differences					
corr(rer, rer^N)	0.64	0.69	0.60	0.69	0.60
std(rer^N)/std(rer)	0.51	0.61	0.43	0.33	0.64
msedec(rer, rer^N)	0.28	0.33	0.23	0.18	0.34
bilateral pairs	1225	49	1176	918	307
percent world trade	71.0	32.0	38.9	29.6	41.4

Table 6

CHINA BILATERAL REAL EXCHANGE RATES

Means weighted by trade
Annual data

		income level		inflation		trade intensity		std(rer)	
	all	**high**	**low**	**high**	**low**	**high**	**low**	**high**	**low**
levels									
corr(rer, rer^N)	0.79	0.80	0.71	0.79	0.79	0.84	0.74	0.78	0.81
std(rer^N)/std(rer)	0.65	0.67	0.48	0.54	0.66	0.81	0.48	0.45	0.88
vdec(rer, rer^N)	0.46	0.47	0.34	0.41	0.46	0.59	0.32	0.30	0.64
1-year lags									
corr(rer, rer^N)	0.38	0.37	0.46	0.57	0.37	0.44	0.30	0.42	0.32
std(rer^N)/std(rer)	0.38	0.38	0.35	0.36	0.38	0.44	0.31	0.27	0.49
msedec(rer, rer^N)	0.16	0.16	0.15	0.17	0.16	0.21	0.11	0.09	0.24
4-year lags									
corr(rer, rer^N)	0.86	0.87	0.76	0.86	0.86	0.92	0.79	0.84	0.88
std(rer^N)/std(rer)	0.56	0.57	0.44	0.48	0.56	0.63	0.48	0.41	0.73
msedec(rer, rer^N)	0.48	0.49	0.33	0.39	0.48	0.60	0.35	0.29	0.69
countries	50	28	22	17	33	2	48	40	10
percent China trade	89.4	82.3	7.1	3.9	85.5	47.0	42.4	47.2	42.2

Table 7

TRADE BLOCS
US BILATERAL REAL EXCHANGE RATES

Means weighted by trade

	all	EU	non-EU	NAFTA	non-NAFTA	other
levels						
corr(rer, rer^N)	0.60	0.27	0.71	0.81	0.52	0.63
std(rer^N)/std(rer)	0.46	0.32	0.51	0.55	0.42	0.48
vdec(rer, rer^N)	0.30	0.10	0.36	0.49	0.20	0.26
4-quarter differences						
corr(rer, rer^N)	0.60	0.41	0.66	0.69	0.55	0.63
std(rer^N)/std(rer)	0.41	0.22	0.47	0.50	0.37	0.45
msedec(rer, rer^N)	0.20	0.05	0.25	0.33	0.14	0.19
16-quarter differences						
corr(rer, rer^N)	0.73	0.57	0.79	0.80	0.70	0.78
std(rer^N)/std(rer)	0.39	0.22	0.44	0.49	0.34	0.41
msedec(rer, rer^N)	0.24	0.07	0.29	0.39	0.17	0.22
countries	49	14	35	2	47	33
percent US trade	87.2	21.0	66.2	28.6	58.6	37.6

Table 8

TRADE BLOCS
ALL BILATERAL REAL EXCHANGE RATES

Means weighted by trade

	all	EU/ EU	EU/ NAFTA	EU/ other	NAFTA/ NAFTA	NAFTA/ other	other/ other
levels							
corr(rer, rer^N)	0.52	0.35	0.30	0.54	0.81	0.63	0.67
std(rer^N)/std(rer)	0.64	0.88	0.33	0.59	0.54	0.49	0.57
vdec(rer, rer^N)	0.33	0.35	0.11	0.32	0.48	0.27	0.38
4-quarter differences							
corr(rer, rer^N)	0.51	0.43	0.41	0.44	0.69	0.63	0.60
std(rer^N)/std(rer)	0.50	0.71	0.22	0.37	0.50	0.44	0.42
msedec(rer, rer^N)	0.22	0.27	0.06	0.15	0.33	0.19	0.21
16-quarter differences							
corr(rer, rer^N)	0.64	0.57	0.55	0.56	0.80	0.78	0.69
std(rer^N)/std(rer)	0.51	0.72	0.24	0.43	0.49	0.41	0.44
msedec(rer, rer^N)	0.28	0.33	0.08	0.23	0.38	0.23	0.31
bilateral pairs	1225	91	42	462	3	99	528
percent world trade	71.0	23.1	6.6	12.3	7.9	11.3	9.8

Table 9

DIFFERENCES IN MEANS: T TESTS

Means that are different at 0.05 significance level

Table 2 US bilateral RERs	income level: none inflation: none trade intensity: all std(rer): all expect for corr levels, corr 4-qtr diffs, corr 16-qtr diffs
Table 3 Income levels: all bilateral RERs	high/high: all except vardec levels, corr 16-qtr diffs high/low: all except vardec levels, corr 16-qtr diffs low/low: none except msedec 4-qtr diffs, sdratio 16-qtr diffs, msedec 16-qtr diffs
Table 4 Inflation levels: all bilateral RERs	high/high: none except corr 4-qtr diffs, corr 16-qtr diffs high/low: all low/low: all
Table 5 Trade intensity & RER variability: all bilateral RERs	trade intensity: all std(rer): all
Table 6 China bilateral RERs	income: none except corr levels, corr 16-qtr diffs inflation: none trade intensity: all std(rer): all except corr levels, corr 16-qtr diffs
Table 7 Trade blocs: US bilateral RERs	EU: all NAFTA: all other: none
Table 8 Trading blocs: all bilateral RERs	EU/EU: all EU/NAFTA: all EU/other: all except corr levels, sdratio levels, vardec levels NAFTA/NAFTA: all except sdratio 4-qtr diffs, sdratio 16-qtr diffs NAFTA/other: all other/other: all except msedec 4-qtr diffs
Table 10 All bilateral RERs: unweighted means	trade intensity: all except corr levels, corr 4-qtr diffs, corr 16-qtr diffs std(rer): all except vardec levels EU/EU: all except corr 4-qtr diffs, corr 16-qtr diffs EU/NAFTA: all except corr levels, corr 4-qtr diffs, corr 16-qtr diffs EU/other: all NAFTA/NAFTA: none NAFTA/other: none except vardec levels other/other: all

Table 10

ALL BILATERAL REAL EXCHANGE RATES

Unweighted means

		trade intensity		std(rer)		trading blocs					
	all	high	low	high	low	EU/ EU	EU/ NAFTA	EU/ other	NAFTA/ NAFTA	NAFTA/ other	other/ other
levels											
corr(rer, rer^N)	0.59	0.56	0.60	0.66	0.39	0.52	0.50	0.56	0.74	0.60	0.65
std(rer^N)/std(rer)	0.59	0.87	0.58	0.53	0.77	0.85	0.34	0.54	0.42	0.53	0.63
vdec(rer, rer^N)	0.35	0.40	0.35	0.34	0.36	0.41	0.14	0.30	0.30	0.30	0.40
4-quarter differences											
corr(rer, rer^N)	0.51	0.52	0.51	0.55	0.39	0.47	0.51	0.49	0.59	0.54	0.53
std(rer^N)/std(rer)	0.43	0.72	0.42	0.38	0.58	0.70	0.24	0.37	0.40	0.46	0.45
msedec(rer, rer^N)	0.20	0.27	0.20	0.18	0.24	0.28	0.07	0.16	0.22	0.20	0.23
16-quarter differences											
corr(rer, rer^N)	0.59	0.62	0.59	0.62	0.48	0.60	0.57	0.56	0.65	0.63	0.60
std(rer^N)/std(rer)	0.46	0.70	0.45	0.42	0.60	0.70	0.26	0.40	0.39	0.47	0.49
msedec(rer, rer^N)	0.28	0.35	0.28	0.27	0.31	0.36	0.09	0.23	0.24	0.27	0.33
bilateral pairs	1225	49	1176	918	307	91	42	462	3	99	528
percent world trade	71.0	32.0	38.9	29.6	41.4	23.1	6.6	12.3	7.9	11.3	9.8

Table 11

TRADE WEIGHTED REGRESSIONS

Standard errors in parentheses

	sum income	**diff income**	**sum inflation**	**diff inflation**	**trade intensity**	**std(rer)**	**EU/ EU**	**EU/ NAFTA**	**EU/ other**	**NAFTA/ NAFTA**	**NAFTA/ other**	**constant**	**R^2**
levels													
corr(rer, rer^N)	–0.004	–0.011	–0.200	0.044	0.314*	1.617*	–0.099*	–0.268*	–0.024	0.091	–0.013	0.382	0.292
	(0.018)	(0.021)	(0.131)	(0.151)	(0.117)	(0.165)	(0.037)	(0.044)	(0.037)	(0.080)	(0.037)	(0.380)	
std(rer^N)/std(rer)	–0.019	0.064*	0.066	0.392*	0.821*	–2.813*	–0.001	–0.236*	–0.0414	–0.714*	–0.197*	1.336*	0.363
	(0.020)	(0.023)	(0.142)	(0.163)	(0.127)	(0.179)	(0.040)	(0.047)	(0.040)	(0.087)	(0.040)	(0.412)	
vdec(rer, rer^N)	–0.015	0.011	–0.048	0.202*	0.230*	–0.878*	–0.121*	–0.264*	–0.074*	–0.088	–0.144*	0.821*	0.242
	(0.011)	(0.013)	(0.080)	(0.092)	(0.071)	(0.101)	(0.022)	(0.027)	(0.022	(0.049)	(0.022)	(0.232)	
4-quarter lags													
corr(rer, rer^N)	0.001	–0.070*	–0.116	0.035	0.003	1.520*	–0.029	–0.173*	–0.098*	0.181*	0.058*	0.352	0.419
	(0.009	(0.011)	(0.067)	(0.077)	(0.060)	(0.085)	(0.019)	(0.022)	(0.019	(0.041)	(0.019)	(0.195)	
std(rer^N)/std(rer)	–0.011	0.099*	0.072	0.100	1.016*	–2.631*	0.012	–0.169*	–0.084*	–0.712*	–0.096*	0.951*	0.313
	(0.021	(0.024)	(0.148)	(0.170)	(0.132)	(0.186)	(0.041)	(0.049)	(0.041	(0.090)	(0.041)	(0.428)	
msedec(rer, rer^N)	–0.008	0.021*	0.035	0.058	0.235*	–0.965*	–0.048*	–0.155*	–0.081*	–0.088*	–0.050*	0.519*	0.354
	(0.008	(0.009)	(0.054)	(0.062)	(0.048)	(0.068)	(0.015)	(0.018)	(0.015	(0.033)	(0.015)	(0.157)	
16-quarter lags													
corr(rer, rer^N)	–0.007	–0.092*	–0.173*	0.246*	0.218*	1.358*	–0.018	–0.129*	–0.071*	0.041	0.080*	0.616*	0.333
	(0.011	(0.013)	(0.076)	(0.088)	(0.068)	(0.096)	(0.021)	(0.026)	(0.021	(0.047)	(0.021)	(0.221)	
std(rer^N)/std(rer)	–0.011	0.098*	0.104	0.060	0.406*	–2.524*	0.033	–0.198*	–0.080*	–0.351*	–0.097*	1.014*	0.301
	(0.019	(0.023)	(0.139)	(0.159)	(0.123)	(0.175)	(0.039)	(0.046)	(0.039	(0.085)	(0.039)	(0.402)	
msedec(rer, rer^N)	–0.016	0.026*	–0.034	0.229*	0.297*	–1.111*	–0.076*	–0.208*	–0.090*	–0.159*	–0.110*	0.778*	0.314
	(0.009	(0.011)	(0.067)	(0.077)	(0.060)	(0.085)	(0.019)	(0.022)	(0.019	(0.041)	(0.019)	(0.195)	

Table 12

MISSING VALUES IN THE DATA

	Quarterly Missing Values	Annual Missing Values
Argentina	PPI: 1980Q1–1993Q4	PPI: 1980–1992
China (P.R.C.)		CPI: 1980–1984
Hong Kong (P.R.C.)	PPI: 1980Q1–1992Q4, CPI: 1980Q1–1989Q4	PPI: 1980–1989, CPI: 1980
Greece		PPI: 1981–1982
Italy	PPI: 1980Q1–1980Q4	PPI: 1980
Jordan	PPI: 1986Q1–1986Q3	
Malaysia	PPI: 1980Q1–1983Q4	PPI: 1980–1983
Mexico	PPI: 1980Q1–1980Q4	PPI: 1980
Philippines	PPI: 1980Q1–1992Q4	PPI: 1980–1992
Saudi Arabia	PPI: 1980Q1–1985Q1	PPI: 1980–1984
Trinidad and Tobago	PPI: 2000Q2–2000Q3	
Turkey	PPI: 1980Q1–1984Q3, 1985Q4	PPI: 1980

Figure 1.

Chile-United States real exchange rate

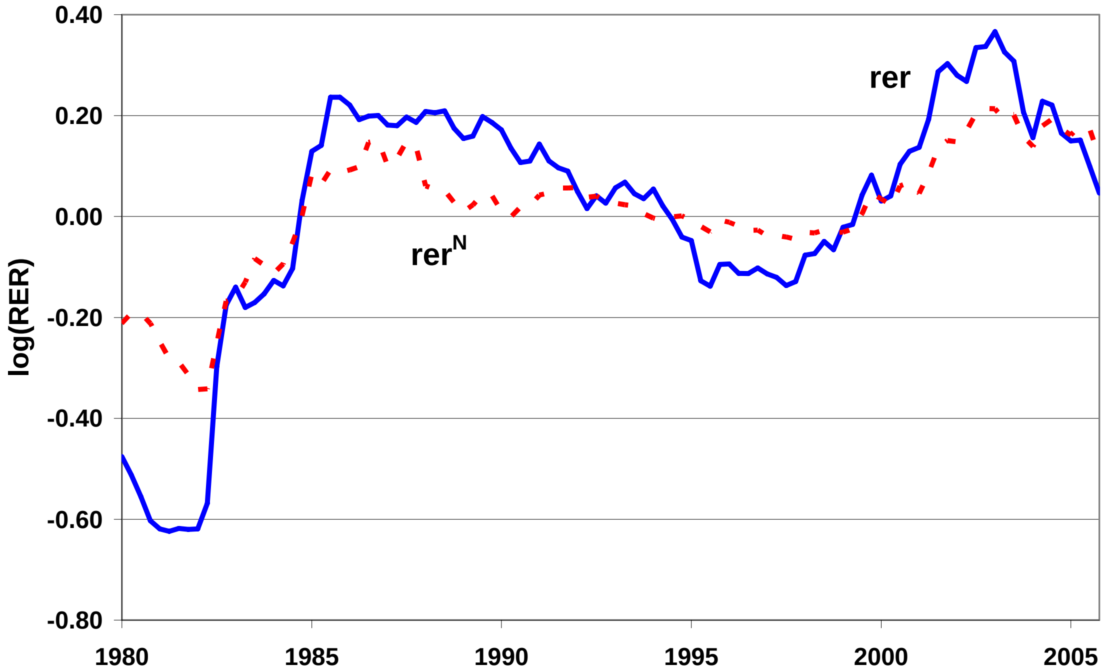

Figure 2.

Correlations

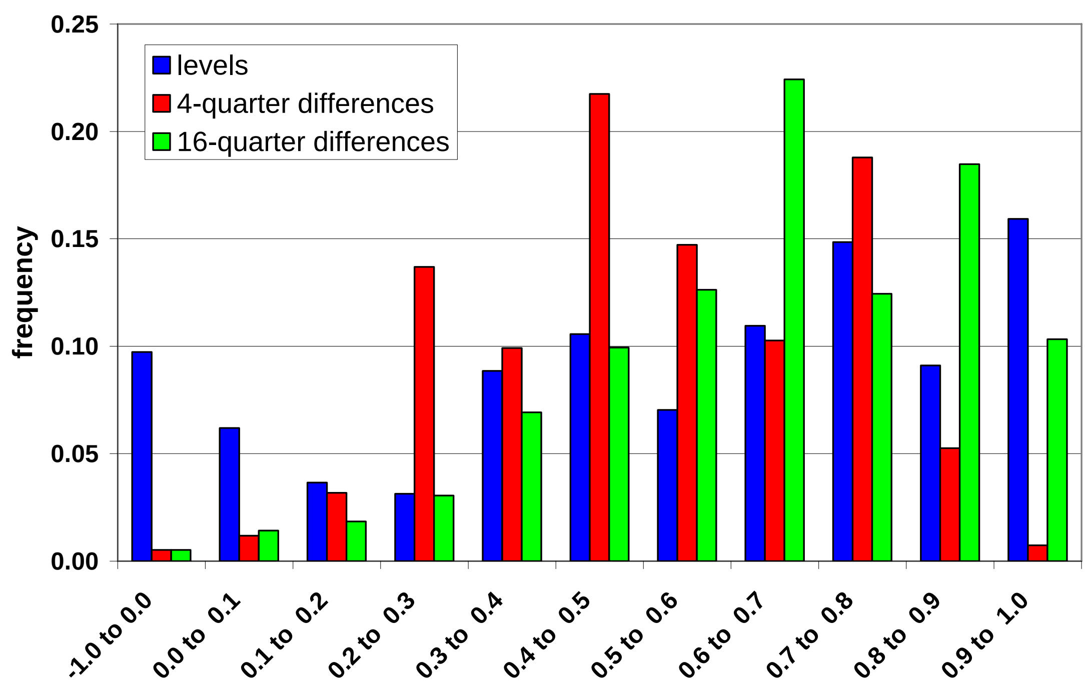

Figure 3.

Relative standard deviations

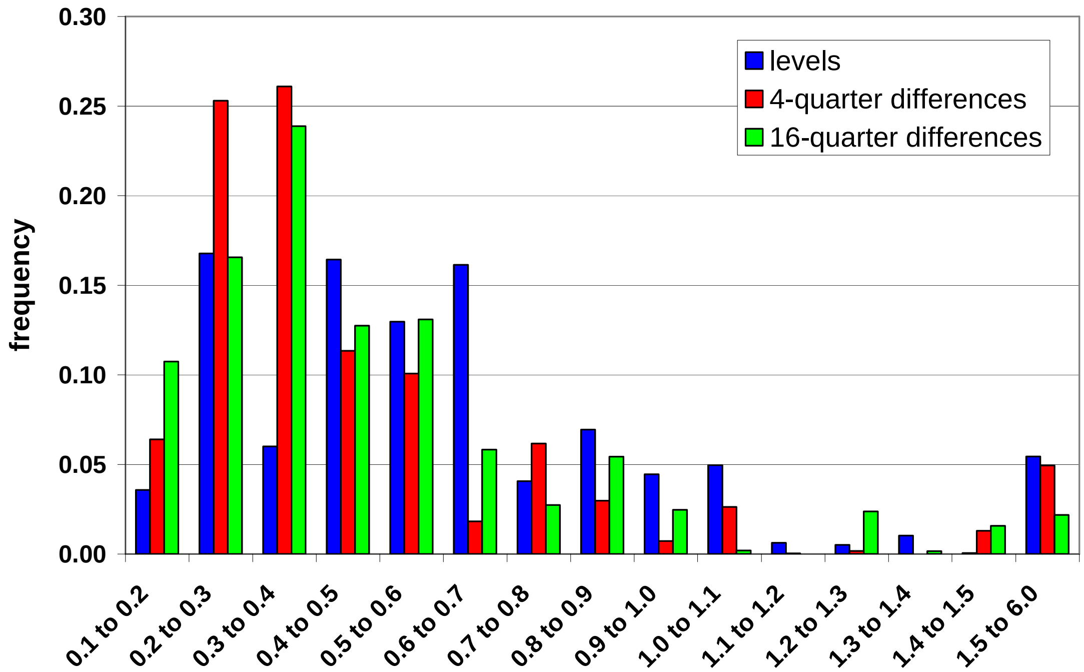

Figure 4.

Variance / mean squared error decompositions