NBER WORKING PAPER SERIES

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Working Paper 15624
http://www.nber.org/papers/w15624

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2009

We thank Andrew Cohn and Alec Kennedy for research assistance and Oscar Jorda for comments. The views expressed herein do not represent those of the Federal Reserve Bank of San Francisco, the Board of Governors of the Federal Reserve System, or the National Bureau of Economic Research.

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NBER Working Paper No. 15624
December 2009, Revised March 2012
JEL No. F4

ABSTRACT

This paper reconciles the persistence of aggregate real exchange rates with the faster adjustment of international relative prices in microeconomic data. Panel estimation of an error correction model using a micro data set uncovers new stylized facts regarding this puzzle. First, adjustment to purchasing power parity deviations in aggregated data is not just a slower version of adjustment to the law of one price in microeconomic data, as arbitrage occurs in different markets, in response to distinct macroeconomic and microeconomic shocks. Second, when half-lives are estimated conditional on macro shocks, micro relative prices exhibit just as much persistence as aggregate real exchange rates. These results challenge theories of real exchange rate persistence based on sticky prices and on heterogeneity across goods, and support an explanation based on the presence of distinct macro and microeconomic shocks.

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I. Introduction

The persistence of aggregate real exchange rates as they converge back to a form of purchasing power parity is a longstanding puzzle. This is especially so, since research using microeconomic data sets has demonstrated that convergence to the law of one price by disaggregated international relative prices occurs at a much faster rate. Work by Imbs et al. (2005) has documented this puzzle, as well as proposed one explanation in which heterogeneity in the convergence speeds among goods can produce an aggregation bias.

This paper presents additional new stylized facts regarding the adjustment of aggregate real exchange rates and micro prices, and we argue that any explanation for the greater persistence of real exchange rate movements should be consistent with these additional facts. Our new evidence comes from estimating panel vector error correction models jointly on macro-level and micro-level price data drawn from the Economist Intelligence Unit's *Worldwide Cost of Living Survey*. This approach enables us to decompose the real exchange rate adjustment mechanism into a nominal exchange rate component and a local currency price component as well as to identify distinct macro and micro shocks. We argue that the inconsistency between studies of aggregate real exchange rates and studies of micro prices can be reconciled if one properly conditions on the distinct types of shocks driving the aggregated and disaggregated data.

The first new stylized fact of the paper is that adjustment to the law of one price in the micro data is not just a faster version of the same adjustment process to purchasing power parity for aggregate data, but instead works through a qualitatively distinct adjustment mechanism. The theory of purchasing power parity is ambiguous as to whether parity is achieved through arbitrage in the goods market inducing goods prices to adjust, or through forces in the foreign exchange market inducing the nominal exchange rate to adjust. For aggregate data, a number of papers applying time-series analysis to aggregate real exchange rates have found that most of the adjustment takes place through the nominal exchange rate.[1] But if one wishes to investigate the role of arbitrage in the goods market, one should use price data on individual goods, where the arbitrage between home and foreign varieties of a good primarily plays out. Accordingly, a vector error correction model is estimated for each good, as well as for an aggregate price index

[1] See Fisher and Park (1991) who employ cointegration analysis, Engel and Morley (2001) who use a state-space analysis, and Cheung, Lai and Bergman (2004) who use vector error-correction analysis.

constructed over the goods in the sample. We find that in disaggregated data, local goods prices actively adjust to restore the law of one price. However, when the micro-level data are aggregated into a synthetic representation of an aggregate real exchange rate, all adjustment to restore PPP takes place through nominal exchange rates, not through local goods prices.

The qualitatively distinct channels of adjustment in disaggregated and aggregated data can be attributed to distinct microeconomic and macroeconomic shocks driving price deviations. These shocks can be identified in the context of a vector error correction model nesting together aggregated and disaggregated data and equations in a single system. Variance decompositions indicate that the idiosyncratic goods shocks are volatile, and the responses to them dominate the aggregate shocks in the disaggregated data. But the idiosyncratic shocks cancel out upon aggregation, since some shocks to price differentials are positive while others are negative. So the responses to exchange rate shocks dominate in the aggregated data.

The second stylized fact of the paper is that when half-lives are estimated in this system conditional on macroeconomic shocks, microeconomic prices are found to be just as persistent as aggregate real exchange rates. In contrast with the impression given by recent studies on microeconomic price dynamics, there is actually significant persistence contained within micro price data. We conclude that properly conditioning on shocks can resolve the inconsistency between aggregate real exchange rate studies and micro price studies. This result also implies that conventional estimates of the speed of adjustment that do not allow for the distinct responses to micro and macro shocks are subject to an omitted variable bias: the single estimated half-life is a conflation of those specific to micro and macro shocks, with that of the more volatile shock dominating.

The finding that proper estimates of persistence require conditioning on the underlying shocks cautions against an explanation for the persistence puzzle relying primarily upon aggregation bias arising from heterogeneity among goods. In particular, a significant portion of the overall heterogeneity in adjustment speeds among goods is found here to be associated with their response to macroeconomic shocks rather than to idiosyncratic goods shocks. Because macroeconomic shocks are common to goods, aggregation over heterogeneous response coefficients to macroeconomic shocks does not introduce aggregation bias. Aggregation bias applies only to the responses to idiosyncratic shocks. So a significant portion of the heterogeneity detected in past studies may be of an innocuous type when it comes to aggregation bias.

Another implication of this finding regards the usefulness of sticky price models to explain real exchange rate behavior. A conventional understanding in this theoretical literature is that PPP deviations gradually decline as firms are able to reset prices in response to the macroeconomic shocks that created the PPP deviation. But our error correction results show that prices respond quite quickly to deviations from the law of one price, and our study of the resulting impulse responses show that price adjustment accounts for a large share of corrections to these deviations. One model that perhaps could coincide better with the evidence would be a rational inattention story, where firms adjust more to shocks specific to their industry rather than to common macroeconomic shocks. For example, Mackowiak and Wiederholt (2009) show in a closed-economy rational inattention model, when idiosyncratic conditions are more variable or have larger impacts on a firm's profits and the firm has limited resources to process information about shocks, it is optimal for firms to allocate more attention to track and respond to idiosyncratic conditions than to aggregate conditions.

Carvalho and Nechio (forthcoming) present a theoretical model where aggregation over many goods with heterogeneous price stickiness generates an aggregate real exchange rate that is persistent. While this theory is a powerful explanation consistent with the empirical regularity of greater persistence in the aggregate data, it is inconsistent with the additional new facts uncovered in our empirical analysis. First, their theory implies that the qualitative mechanism of adjustment is the same in the aggregated and disaggregated sectoral data, working through goods prices; in contrast, our empirical evidence shows that aggregate adjustment is qualitatively different, working through the nominal exchange rate rather than prices. Secondly, their theory includes only aggregate shocks, so its explanation implies that micro sectoral prices adjust quickly conditional on macro shocks. In contrast, our evidence shows that the persistence of price gaps in micro data is just as high as in aggregated data when conditional on macro shocks. We conclude that their explanation for persistence cannot be the whole story, and that our evidence calls for a different type of explanation rooted in the parallel roles of micro and macro shocks.

Our work is related to recent research by Crucini and Shintani (2008), who also use EIU price data to study law-of-one-price dynamics. Our paper differs in that it decomposes deviations and adjustment by the type of shock and studies the mechanism of adjustment via local goods prices and the nominal exchange rate with an error correction mechanism. Andrade and Zachariadis (2010) also decompose micro price dynamics by shock, but their focus is on the distinction between geographically global versus local shocks rather than the macro versus micro shocks we find to be important. Further, they restrict their focus to microeconomic prices, rather than drawing implications for aggregate real exchange rates as we do. Our findings are also complementary to Broda and Weinstein (2008), who speculate that nonlinear convergence rates lead to faster adjustment among disaggregated price deviations because they are dominated by large outliers. Our findings suggest an alternative mechanism, based not on outliers, but on the distinction between idiosyncratic industry shocks and macroeconomic shocks.

The next section discusses the data set and data characteristics, including stationarity and speeds of convergence. Section 3 presents the main results in several subsections. The first compares error correction dynamics estimated separately for disaggregated and aggregated data, with the second part providing robustness checks. The third subsection estimates a combined error correction model nesting together aggregated and disaggregated data, and uses this to identify the separate roles of aggregate and idiosyncratic shocks. The last subsection revisits the autoregressive estimation of the past literature while taking different shocks into consideration, and discusses the diminished role of aggregation bias in this context. Section 4 summarizes implications for the broader literature on real exchange rates.

II. Data and Preliminary Analysis

II.A Dataset

The data are obtained from the *Worldwide Cost of Living Survey* conducted by the Economist Intelligence Unit (EIU), a proprietary service which records local prices for individual goods and services in cities worldwide.[2] The EIU data begin in 1990, and while historical data are available to subscribers at an annual frequency, data collection actually takes place twice annually. To facilitate analysis of the time-series dynamics of the panel, we were

[2] The EIU survey is used to calculate cost-of-living indexes for multinational corporations with employees located around the world. The data set is described in more detail at http://eiu.enumerate.com/asp/wcol_HelpAboutEIU.

able to obtain from the EIU semi-annual historical observations through 2007 on a one-time basis.[3]

There are distinct advantages of the EIU data that make it appealing for our time-series study. It is the most extensive survey of retail prices conducted by a single organization on a global scale that is ongoing over a long period. Most existing micro-price surveys are too infrequent to be useable for addressing time series issues, whereas the EIU data set has a sufficient length to make possible application of our time series techniques.

Another advantage of the EIU data set is that goods categories are narrowly defined, e.g. apples (1 kg), men's raincoat (Burberry type), and light bulbs (2, 60 watt). For many goods in the survey, prices are sampled separately from two different outlets, a "high-price" and "low-price" outlet. For example, food and beverage prices are sampled from supermarkets and convenience stores. We use prices from the supermarket type outlets, which are likely to be more comparable across cities. The data set also includes many service items such as telephone and line, moderate hotel (single room), and man's haircut, which would most naturally be classified as non-tradable. The degree of comparability across locations is generally high, but varies with the general availability of goods in a given city. Our sample focuses on the major city in each of 20 industrial countries, where availability might be expected to be more consistent.

Surveyors visit only outlets where items of internationally comparable quality are available. The EIU explicitly has held the aim from the beginning of its survey of maintaining ongoing consistency of its surveys across time. It has worked to keep the same stores and the same brands and sizes in obtaining the price for each item. Given that the survey takes place simultaneously in 140 cities worldwide over a two decade period, there may be substitutions or changes in the data sample. This may occur for example if a change in management leads to a correspondent being refused entrance to a store. It may occur as certain brands or sizes replace others in stores. See the data appendix of Andrade and Zachariadis (2011) for a detailed discussion of the survey methods employed by the EIU.

Documentation from the EIU website notes that there can be significant variation in prices from one survey to the next. Most of the reasons cited by the EIU for this variation correspond to economic factors of the type we model in this paper, such as exchange rate fluctuations affecting the price of imported goods, or the fact that some countries have periods of

[3] The semi-annual observations made available to us do not extend beyond 2007.

high aggregate inflation. Other factors reflect economic shocks specific to an industry of the type we try to model, such as increased competition from new entrants in the market, or local shortages of supply of a good. However, a few of the reasons provided include difficulties in maintaining consistency in an ongoing survey if goods are not consistently available, as noted in the preceding paragraphs. The EIU notes that data availability is more serious for emerging markets, especially in Chinese cities. Because our sample uses only 20 industrialized countries, it is hoped that this sampling issue will be less severe for our case. Further, we check for this problem with tests of measurement error later in the paper. We also confirm later in the paper that our results are robust to use of an alternative data sample of that from Imbs et al (2005).

We focus on bilateral prices between the major city in each of 20 industrial countries relative to the United States. The choice of countries reflects those used in past work on price aggregates (such as in Mark and Sul (2008)), and the choice of cities reflects that in Parsley and Wei (2002).[4] For these locations, the data set has full coverage for 98 tradable goods and 30 nontraded goods, as identified by Engel and Rogers (2004) in their study of price dispersion in Europe.[5] Data Appendix Tables A1, A2 and A3 list the cities and goods included in the analysis.

II.B. Preliminaries

Define $q_{ij,t}^{k}$ as the relative price of good *k* between two locations *i* and *j*, in period *t,* in logs. This may be computed as $q_{ij,t}^{k} = e_{ij,t} + p_{ij,t}^{k}$, where $e_{ij,t}$ is the nominal exchange rate (currency *j* per currency *i*), and $p_{ij,t}^{k} = p_{i,t}^{k} - p_{j,t}^{k}$ is the log difference in the price of good *k* in country *i* from that in country *j*, both in units of the local currency. As preparation for the main analysis later, we first establish that the international relative prices are stationary. We apply the cross-sectionally augmented Dickey-Fuller (CADF) test provided by Pesaran (2007) to examine the

[4] Mark and Sul (2008) use the Eurostat data from Imbs et al. (2005) for 19 goods in 10 European countries and the U.S.; we augment the data with more industrial countries to increase the power with which to reject unit roots in panel estimation. We show below that our results are robust to using Eurostat, rather than EIU, data.

[5] Engel and Rogers (2004) included only goods for which a price is recorded in every year for at least 15 of the 18 European cities in their analysis. The dataset used by Parsley and Wei (2002) contains 95 traded goods. Their set is virtually identical to that of Engel and Rogers (2004), with the difference that Parsley and Wei include yogurt, cigarettes (local brand), cigarettes (Marlboro), tennis balls, and fast food snacks, but exclude butter, veal chops, veal fillet, veal roast, women's raincoat, girl's dress, compact disc, color television, international weekly newsmagazine, paperback novel, and electric toaster.

stationarity of variables. The advantage of this test is that it controls for contemporaneous correlations across residuals. Consider the following regression:

$$\Delta q_{ij,t}^k = a_{ij}^k + b_{ij}^k(q_{ij,t-1}^k) + c_{ij}^k(\overline{q}_{t-1}^k) + d_{ij}^k(\Delta\overline{q}_t^k) + \varepsilon_{ij,t}^k$$
$$ij = 1,\ldots,N,\ k = 1,\ldots,K,\ \text{and } t = 1,\ldots,T \qquad (1)$$

where $\overline{q}_t^k = \sum_{ij=1}^{N} q_{ij,t}^k$ is the cross-section mean of $q_{ij,t}^k$ across country pairs and $\Delta\overline{q}_t^k = \overline{q}_t^k - \overline{q}_{t-1}^k$. The purpose for augmenting the cross-section mean in the above equation is to control for contemporaneous correlation among $\varepsilon_{ij,t}^k$. The null hypothesis of the test can be expressed as $H_0 : b_{ij}^k = 0$ for all *ij* against the alternative hypothesis $H_1 : b_{ij}^k < 0$ for some *ij*. The test statistic provided by Pesaran (2007) is given by:

$$CIPS^k(N,T) = N^{-1}\sum_{ij=1}^{N} t_{ij}^k(N,T)$$

where $t_{ij}^k(N,T)$ is the t statistic of b_{ij}^k in equation (1). (CIPS stands for the cross-sectionally augmented Im, Pesaran, and Shin statistic.)

The top panel of Table 1 indicates rejection of nonstationarity at the 5% significance level for the large majority of traded goods, 72 at 10%, 63 at 5%, out of 98 traded goods in the sample. Among nontraded goods, rejection at the 5% level is supported for 11 at both 5% and 10% out of the 30 goods-- less strong than for tradeds. In addition to studying the behavior of the individual goods prices, we can also study aggregate prices, constructed as a simple average over the goods: $q_{ij,t} \equiv \sum_{k=1}^{K} q_{ij,t}^k$. This constructed aggregate provides a useful comparison to the large body of past studies of persistence in real exchange rates.[6] The bottom panel of Table 1 shows that nonstationarity can be rejected at the 1% level for the average over all traded goods. For an average over just nontraded goods, nonstationarity cannot be rejected. In the remainder of the paper, we will focus on the set of traded goods, for which there is stronger evidence of stationarity.

[6] In principle, we could also assign weights to the goods derived loosely from weights in a country's CPI. However, Crucini and Shintani (2008) find that alternative weighting schemes do not affect results for this test.

Next, we check the speed of convergence toward stationarity by estimating a second-order autoregressive model of real exchange rates with panel data.[7] To control for contemporaneous correlation of residuals, we apply the common correlated effects (CCE) regressor of Pesaran (2006) to estimate the autoregressive coefficients of real exchange rates. In other words, we estimate the equation:

$$q_{ij,t}^{k} = c_{ij}^{k} + \sum_{m=1}^{2} \rho_{ij,m}^{k} (q_{ij,t-m}^{k}) + \varepsilon_{ij,t}^{k} \text{ for } k = 1,...,K \tag{2}$$

for disaggregated data and

$$q_{ij,t} = c_{ij} + \sum_{m=1}^{2} \rho_{ij,m} (q_{ij,t-m}) + \varepsilon_{ij,t} \quad . \tag{3}$$

for aggregated data, each augmented with cross-section means of right and left hand side variables. Two different CCE estimators are proposed by Pesaran (2006). One is the mean group estimator, CCEMG, and the other is the standard pooled version of the CCE estimator, CCEP. Pesaran's (2006) Monte Carlo simulation results show that, under the assumption of slope heterogeneity, CCEP and CCEMG have the correct size even for samples as small as N = 30 and T = 20. Pesaran concludes that CCEP does slightly better in small samples, so we adopt the CCEP estimator in our empirical analysis. Both methods deliver broadly similar results here. CCEP estimates are obtained by regressing equations (2) and (3) with augmented regressors ($\bar{q}_t^k$, $\bar{q}_{t-1}^k$, $\bar{q}_{t-2}^k$) and ($\bar{q}_t$, $\bar{q}_{t-1}$, $\bar{q}_{t-2}$), respectively.[8]

Results in Table 2 indicate quick convergence speeds for disaggregated goods, with an average half-life among the goods of 1.25 years. Half-lives are computed on the basis of simulated impulse responses[9]. Adjustment for the aggregate data is distinctly slower, with a half-life of 2.10 years. While this half-life estimated for aggregate prices is lower than the values often found in previous literature for more standard aggregate data sets, it nonetheless does reproduce the finding that the aggregate half-life is longer than that for microeconomic data.[10]

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[7] Inclusion of additional lags is precluded by the short time-span of the data set.

[8] STATA code created by the authors to conduct CCEP estimations used throughout the paper are available upon request.

[9] The half-life is computed as the time it takes for the impulse responses to a unit shock to equal 0.5, as defined in Steinsson (2008). We identify the first period, t_1, where the impulse response *f(t)* falls from a value above 0.5 to a value below 0.5 in the subsequent period, t_1+1. We interpolate the fraction of a period after t_1 where the impulse response function reaches a value of 0.5 by adding $(f(t_1) - 0.5))/ (f(t_1) - f(t_1+1))$.

[10] Previous literature has tended to find even larger half-lives in aggregated data, commonly exceeding 3 years. The somewhat smaller half-life in our aggregated data is the direct result of the particular sample period, starting in

Since the second order autoregressive coefficients are not statistically significant, we also estimate a first-order autoregression, with results in the table. The conclusion is similar, with the half-life about double in aggregated data compared to the average among disaggregated data, 2.13 years compared to 1.15. The fact that half-lives at the disaggregated level are faster than for aggregates matches the finding of Imbs et al. (2005) with their data set. They hypothesize an explanation, based on the idea that speeds of adjustment are heterogeneous among goods, and that aggregation tends to give too much weight to goods with slow speeds of adjustment and hence long half-lives. The implications of our data for this hypothesis will be discussed at greater length in the following section.

III. Results

III.A. Benchmark Estimates and the Error Correction Puzzle

This section investigates the engine of convergence to the law of one price and identifies a new stylized fact. The stationarity of micro real exchange rates implies the cointegration of nominal exchange rates $(e_{ij,t})$ and relative prices $(p^k_{ij,t})$ with the cointegrating vector being (1, 1). The adjustment process of nominal exchange rates and relative prices can be studied using the following panel error-correction model (ECM):

$$\Delta e_{ij,t} = \alpha^k_{ij,e} + \rho^k_{e,ij}(q^k_{ij,t-1}) + \mu^k_{e,ij}(\Delta e_{ij,t-1}) + \mu^k_{e,ij}(\Delta p^k_{ij,t-1}) + \zeta^{e,k}_{ij,t} \qquad (4a)$$

$$\Delta p^k_{ij,t} = \alpha^k_{ij,p} + \rho^k_{p,ij}(q^k_{ij,t-1}) + \mu^k_{p,ij}(\Delta e_{ij,t-1}) + \mu^k_{p,ij}(\Delta p^k_{ij,t-1}) + \zeta^{p,k}_{ij,t}.$$ [11]

This two- equation system decomposes the good-specific real exchange rate, $q^k_{ij,t}$, into its two components, the nominal exchange rate, e_{ij}, and the relative price level, p^k_{ij}. It regresses the first difference of each of these components on the lag level of the good-specific real exchange rate, which summarizes the degree to which the law of one price is being violated in the data. Other

1990, and the broader set of countries, 20 industrial. When we compute standard CPI-based real exchange rates using the standard macroeconomic data from the IMF's *International Financial Statistics* for our sample of countries and years, the half-life is estimated at 2.05 years, very close to that of the synthetic aggregate constructed over our set of goods reported above. Extending the sample back to 1975, results in a half -life estimate of 3.34. So the aggregate half-life familiar from past real exchange rate studies is specific to the post-Bretton Woods data sample typical in these studies, and the relevant half-life is somewhat lower when the sample is limited to a more recent sample, as is necessary to compare to our micro data.

[11] Because this error correction model incorporates lags of first differences to capture short-run dynamics, this specification is analogous to the second-order autoregression estimated previously. Inclusion of additional lags is impossible due to the short time-span of the data set.

regressors in (4a) control for level effects and short run dynamics of the variables. The coefficients $\rho^k_{e,ij}$ and $\rho^k_{p,ij}$ reflect how strongly the exchange rate and prices respond to deviations from the law of one price. Because negative movements in these variables work to reduce deviations from the law of one price, they provide a measure of the speed of adjustment of nominal exchange rates and relative prices, respectively. To allow for possible cross section dependence in the errors, we computed CCEP estimators of the parameters by including as regressors the cross section averages of all variables (($\Delta\bar{e}_t$, $\bar{q}^k_{t-1}$, $\Delta\bar{e}_{t-1}$, and $\Delta\bar{p}^k_{t-1}$) and ($\Delta\bar{p}^k_t$, $\bar{q}^k_{t-1}$, $\Delta\bar{e}_{t-1}$, and $\Delta\bar{p}^k_{t-1}$) for the $\Delta e_{ij,t}$ and $\Delta p^k_{ij,t}$ equations, respectively). This pair of ECM equations is estimated for our panel of city pairs, for each of the 98 traded goods.

We also estimate the following aggregate version of the two equation system, where the good-specific relative price for good k , p_k, is replaced by the average across all goods, p:

$$\Delta e_{ij,t} = \alpha_{ij,e} + \rho_{e,ij}(q_{ij,t-1}) + \mu_{e,ij}(\Delta e_{ij,t-1}) + \mu_{e,ij}(\Delta p_{ij,t-1}) + \zeta^e_{ij,t} \tag{4b}$$

$$\Delta p_{ij,t} = \alpha_{ij,p} + \rho_{p,ij}(q_{ij,t-1}) + \mu_{p,ij}(\Delta e_{ij,t-1}) + \mu_{p,ij}(\Delta p_{ij,t-1}) + \zeta^p_{ij,t}\,.$$

As a basis of comparison with past research, consider first the constructed aggregate prices. Fisher and Park (1991) found for aggregate CPI-based real exchange rates that the speed of adjustment is significant for exchange rate and insignificantly different from zero for price, concluding that adjustment takes place primarily through the exchange rate. Our method of estimating the error correction mechanism differs from theirs, pooling across countries with panel data for each equation in (4), but our conclusion for aggregate data agrees with theirs. As reported in panel a of Table 3, the speed of adjustment for price, ρ_p, is just 0.04, while that for the exchange rate, ρ_e, is much larger at 0.13. [12]

The result is entirely different at the disaggregated goods level. Now we estimate the error correction regression (4) as a panel over city pairs, once for each of the traded goods in the sample. Table A4 in the data appendix shows results for each good separately, and Table 3 summarizes by reporting mean values over all goods. The role of the two variables is reversed

[12] Due to our panel methodology, both coefficients are statistically significant, so we cannot conclude that the price coefficient equals zero as found in past work. But the much larger coefficient (in absolute value) in the exchange rate equation indicates that the exchange rate responds much more strongly than does price. Because the two equations in (4) are estimated individually, we do not have the joint distribution of response coefficients needed to conduct a formal F test.

from that with the aggregate data: the mean speed of adjustment for the price ratio, ρ_p^k, is large, 0.20, while that for the exchange rate, ρ_e^k, is much smaller, 0.03.

Judging by speeds of adjustment, the dynamic adjustment appears to be very different at the disaggregated level than at the aggregated level. While at the aggregate level it is nominal exchange rate movements that facilitate dynamic adjustment to restore PPP, at the disaggregated level it is movements in the price in the goods market that does the adjustment. It probably should not be surprising that the nominal exchange rate cannot serve the function of adjustment for individual goods, given Crucini et al. (2005) has showed that for European country pairs there are many goods overpriced as well as underpriced. The same appears to be true for our country pairs. Given that adjustment requires movements in opposite directions for these two groups of goods, there is no way that the exchange rate component of these relative prices can make them move in the necessary directions simultaneously. However, what is surprising is that goods prices do facilitate adjustment at the goods level, and in fact adjustment is faster than for aggregate prices that have the exchange rate to move them.

III.B. Robustness Checks

In a dynamic panel model with cross-sectional dependence, conventional estimators, such as fixed effect estimators, generalized method of moment estimators, instrumental-variable estimators, and CCEP estimators are inconsistent for finite T even as N becomes infinite, but they are consistent when both T and N become infinite (Philips and Sul, 2007; Sarafidis and Robertson, 2009; Groote and Everaert, 2011). The Technical Appendix provides a detailed Monte Carlo study showing this conclusion applies also to a panel VECM specification. Two main findings are as follows. First, the mean biases of the estimated responses to the error correction term, the parameters of most interest to us, are positive, indicating that the CCEP estimates tend to be biased upward, implying they overstate the true speed of adjustment (in absolute value). Second, an increase in N, for a given T, has only limited effect on mean bias but it decreases the standard deviation and root mean squared error of estimates. However, an increase in T for a given N decreases the magnitude of the bias as well as that of the other above-mentioned statistics.

In addition, we also conduct an experiment with simulated data that closely resembles our actual data set. Data were generated using the coefficient estimates together with the residuals from the CCEP estimation of the two-equation system (4b) for aggregated data, including allowing for heterogeneous error correction adjustment coefficients. In each of 1000 replications, a sequence of innovations for 20 country pairs covering 34 periods was drawn from the residuals of the exchange rate and price equations, and these were used to generate simulated series for price and exchange rate (as well as real exchange rate), using actual observations as starting values. The generated data were then used to estimate the model by CCEP. Results in Table 4 indicate that CCEP tends to overstate the true speed of adjustment parameter (in absolute value), but it is somewhat smaller than in the Monte Carlo study described above.

To show that our results are robust to controlling for potential bias in our estimates, we will employ the standard double bootstrap procedure of Kilian (1998) with 1000 replications to obtain the bias-adjusted estimates. Results for the VECM system are reported in panel (b) of table 3. While the estimates of the speed of adjustment are somewhat lower under the bias correction, all conclusions are the same as for the unadjusted CCEP results: for aggregated data the speed of adjustment for the nominal exchange rate is much larger than that for the price level; for disaggregated the speed of adjustment in prices is faster.

To check the sensitivity of our result to our particular data set, we conduct the same error correction estimation using the data set used by Imbs et al. (2005).[13] While the values of adjustment parameters reported in Table 5 are lower across the board, the pattern of relative rankings is the same. In disaggregated industry level data the speed of adjustment for prices is more than twice that for the nominal exchange rate; for aggregated data the reverse is true, with the speed of adjustment for prices being half of that for the nominal exchange rate.

We here rule out two potential explanations for the puzzle. The first thing to rule out is measurement error in the disaggregated price observations. This would seem plausible, given that the price ratio data rely upon survey takers to subjectively choose representative goods within some categories. If the measurement error is corrected or reversed in subsequent observations of prices, it might appear as if prices are adjusting to correct the price deviation. (Of course, the exchange rate data would not be subject to the errors of survey collection.) To test this explanation, a Hausman test is conducted, estimating a first-order autoregression of $q_{ij,t}^{k}$ for

[13] The Imbs et al. (2005) benchmark dataset we use consists of monthly observations extending from 1981 to 1995 for the U.S. and 10 European countries (we exclude Finland in order to maintain a balanced panel, as required for our estimation methodology).

each cross-sectional item (country-goods) by two methods, OLS and two stage least squares using lagged values as instruments, and testing the hypothesis of no measurement error. Among the 1843 country-good series, only 233 reject consistency at the 5% level. This indicates that measurement error is not a problem for most of our observations.

Another potential explanation for our result is that the type of aggregation bias Imbs et al. (2005) described for autoregressions, like our equation (2), could have an analog for our error correction equation (3). Imbs et al. (2005) argued that heterogeneity in the speeds of convergence in the real exchange rate among disaggregated goods can lead to an overestimate of the persistence in the aggregate real exchange rate, under conditions where those goods with slow speeds of adjustment receive too much weight in computing the aggregate price level.[14] To translate this argument into an explanation for our error correction estimation, aggregation would need to lead to a bias underestimating the aggregate adjustment speed in one variable, the prices, but at the same time an overestimate of the speed of adjustment in another variable, the nominal exchange rate. On one hand, we can confirm that there is heterogeneity among the goods *k* in terms of the size of ρ_e^k and ρ_p^k, so larger weights on some goods could lead to estimates of the aggregate that are different from the average among the goods. However, there is no heterogeneity among goods in terms of the fact that $|\rho_e^k| < |\rho_p^k|$; this is true for all 98 of the goods in the sample. We can conceive of no weighting of goods when aggregating that could reverse this inequality in the aggregate.

III.C. The Role of Distinct Shocks

The finding above, that aggregated and disaggregate price deviations have qualitatively distinct adjustment mechanisms, suggests that the two types of price deviations may have qualitatively different origins. We conjecture that there are idiosyncratic shocks at the good level that are distinct from macroeconomic shocks occurring at the aggregate level. Accordingly, we apply the CCEP estimator to a modified three-variable vector error correction model, which takes the novel step of nesting together aggregate and disaggregated price data series:

$$\begin{aligned}\Delta e_{ij,t} &= \alpha_{ij,e}^k + \rho_{e,ij}^{k1}(q_{ij,t-1}^k - q_{ij,t-1}) + \rho_{e,ij}^{k2}(q_{ij,t-1}) \\ &\quad + \mu_{e,ij,1}^k(\Delta e_{ij,t-1}) + \mu_{e,ij,2}^k(\Delta p_{ij,t-1}^k) + \mu_{e,ij,3}^k(\Delta p_{ij,t-1}) + \zeta_{e,ij,t}^k\end{aligned} \tag{5}$$

[14] This argument has been critiqued by Chen and Engel (2005) among others.

$$\Delta p_{ij,t} = \alpha^k_{p,ij} + \rho^{k1}_{p,ij}(q^k_{ij,t-1} - q_{ij,t-1}) + \rho^{k2}_{p,ij}(q_{ij,t-1}) + \mu^k_{pkij,1}(\Delta e_{ij,t-1}) + \mu^k_{p,ij,2}(\Delta p^k_{ij,t-1}) + \mu^k_{p,ij,3}(\Delta p_{ij,t-1}) + \zeta^k_{p,ij,t}$$

$$\Delta p^k_{ij,t} = \alpha^k_{pk,ij} + \rho^{k1}_{pk,ij}(q^k_{ij,t-1} - q_{ij,t-1}) + \rho^{k2}_{pk,ij}(q_{ij,t-1}) + \mu^k_{pk,ij,1}(\Delta e^k_{ij,t-1}) + \mu^k_{pk,ij,2}(\Delta p^k_{ij,t-1}) + \mu^k_{pk,ij,3}(\Delta p_{ij,t-1}) + \zeta^k_{pk,ij,t}$$

There are two cointegrating vectors in this system over the variables *e*, p^k, and *p*: [1 0 1] and [0 1 -1]. This system allows for a distinct response to the aggregate price deviation $q_{ij,t-1}$, which is the average across all goods, and a distinct response to the purely idiosyncratic price wedge, specified as $q^k_{ij,t-1} - q_{ij,t-1}$, the difference between the price wedge for one good and the average wedge across all goods. Given the definition of *q* and q^k, the latter difference alternately may be written: $q^k_{ij,t-1} - q_{ij,t-1} = p^k_{ij,t-1} - p_{ij,t-1}$.

Estimates of the response parameters in the expanded VECM, reported in Table 6, support and extend the results found earlier when estimating separate VECM systems for aggregates and disaggregated data. Again p_k responds to $q^k - q$ ($p^k - p$) deviations, and now we see explicitly that it does not respond to *q* deviations. We see that *e* responds to aggregate *q* deviations but not to $q^k - q$ ($p^k - p$) deviations. And finally, *p* responds only to *q* deviations. These conclusions are the same for the bias-corrected estimates reported in panel b of table 6, which were computed using the method of Kilian (1998).

The main benefit of estimating equation (5) is that it provides a way to identify idiosyncratic shocks as separate from macroeconomic shocks. We use a Cholesky ordering of the variables *e*, *p*, and p^k, which defines an industry shock as an innovation to p^k for a particular good that has no contemporaneous effect on aggregate *p* (or *e*). We believe this is a case where a Cholesky identification of shocks is particularly well suited. An aggregate shock is one that makes both p^k and *p* move contemporaneously, as it affects goods prices on average. If desired, these aggregate shocks may be divided into shocks to the foreign exchange market, identified as all innovations to *e*, or shocks to the aggregate goods market, identified as innovations to *p* with no contemporaneous effect on *e*. This estimation is run for each of the 98 goods, and variance decompositions and impulse responses are generated for each.

Figures 1 and 2 report the variance decompositions of the variables by shock, where the numbers reported for disaggregated data are the averages among the 98 goods. Not surprisingly, variation in the aggregate real exchange rate, q, is due mainly to nominal exchange rate shocks, accounting for over 80% of variation, with a secondary role played by aggregate price shocks, and virtually no role at all played by idiosyncratic shocks. In contrast, variation in LOP deviations in disaggregated data, q^k, are due largely to idiosyncratic industry price shocks to p^k, accounting for about 80% of variation, with exchange rate shocks playing a much lesser role.

Impulse responses reported in Figures 3-5 help identify the mechanisms of adjustment. The figures report impulse responses from simulations of the system (5), where parameter values are the averages of the estimates derived for the 98 goods. Recall from the variance decompositions above that most movements in q^k appear to be due to idiosyncratic shocks. The bottom panel of Figure 3 shows that the dynamics of q^k resemble that for p^k, whereas the nominal exchange does not move. Since $q^k = e + p^k$, this observation suggests that the goods price does most of the adjusting to restore LOP. Next, recall from variance decompositions that most of the movements in the real exchange rate, q, were due to nominal exchange rate shocks, with aggregate price shocks in a secondary role. The top panel of Figure 4 shows that the response of q to exchange rate shocks looks like that of the e component; this indicates the nominal exchange rate does the adjusting. Interestingly, for an aggregated price shock, the top panel of Figure 5 shows that the response of q looks like e; again, the nominal exchange rate does most of the adjusting, even though the shock was an innovation to p orthogonal to innovations to e.

These conclusions regarding adjustment dynamics are formalized in Table 7 following the methodology of Cheung et al. (2004). Defining the impulse response of variable m to shock n as $\psi_{m,n}(t)$, note that $\psi_{q_k,n}(t) = \psi_{e,n}(t) + \psi_{p_k,n}(t)$ for disaggregated data and $\psi_{q,n}(t) = \psi_{e,n}(t) + \psi_{p,n}(t)$ for aggregated data. Then $g^{q_k}_{e,n}(t) = \Delta\psi_{e,n}(t) / \Delta\psi_{q_k,n}(t)$ measures the proportion of adjustment in LOP deviations explained by nominal exchange rate adjustment, and $g^{q_k}_{p_k,n}(t) = \Delta\psi_{p_k,n}(t) / \Delta\psi_{q_k,n}(t)$ measures the proportion explained by price adjustment, such that $g^{q_k}_{e,n}(t) + g^{q_k}_{p_k,n}(t) = 1$. The analogs for decomposing adjustment for aggregated data are $g^{q}_{e,n}(t) = \Delta\psi_{e,n}(t) / \Delta\psi_{q,n}(t)$ and $g^{q}_{p,n}(t) = \Delta\psi_{p,n}(t) / \Delta\psi_{q,n}(t)$. The values in Table 7 support the conclusions above. Adjustment of aggregated data takes place mainly via adjustment in the nominal exchange rate regardless of shock. Adjustment of disaggregated data depends upon the shock; for aggregate shocks (*e* and *p*), adjustment takes place mainly via nominal exchange rate adjustment, but for idiosyncratic shocks adjustment takes place via price adjustment.

Overall, we conclude that price deviations at the aggregated and disaggregated levels are very different. First they differ in terms of the shocks that drive them. Further, the dynamic responses differ according to shock: movements in disaggregated q_k are dominated by movements in the p^k component as it adjusts in response to p_k shocks, while movements in the aggregate q are dominated by movements in e adjusting in response to e and p shocks. This indicates to us that the apparent inconsistency in adjustment dynamics observed for aggregated and disaggregated data comes from the distinction between the particular shocks that dominate at different levels of aggregation.

III.D. Implications for the Convergence Speed Puzzle

The hypothesis that different shocks and adjustment mechanisms are at work at different levels of aggregation also offers a promising explanation for the persistence puzzle popularized in Imbs et al. (2005) and others. Why does the half-life of aggregated real exchange rates appear to be longer than for disaggregated data? The error correction models estimated in the previous section provide an answer. Figures 3-5 indicates that the half-lives of disaggregated real exchange rates vary by the shock to which they are adjusting. Table 8 computes the half-life of adjustment of the aggregate and disaggregated real exchange rates, conditional on the shock.[15] The half-lives for aggregated real exchange rates, q, and disaggregated, q_k , are quite similar to each other when conditioned on aggregate e and p shocks, with values in the neighborhood of 2 years. But when conditioned on idiosyncratic shocks, the half-life of disaggregated real exchange rates falls dramatically, to a value about half of that for aggregate shocks.[16] The main lesson is that when conditioned on aggregate shocks, there is no longer a contrast in persistence between aggregate and disaggregated real exchange rates. Instead, the contrast is between aggregate and disaggregate shocks; disaggregated data respond slowly to the first and quickly to the latter. This

[15] Half-lives are generated from simulated impulse responses. System (5) was simulated 1000 times using random draws of system parameters, where the mean and standard errors of the distribution are the average estimates among the goods. Half-lives are computed for aggregated and disaggregated data in each simulation, and the table reports the mean of these. Confidence intervals are not reported for the half lives because the impulse responses for the 3-equation system involve a large number of parameters, each with their own confidence band, leading to an accumulation of uniformly very wide confidence intervals for statistics related to the impulse responses.
[16] No half-life is reported for the aggregate real exchange rate, since idiosyncratic shocks have essentially no effect on this variable.

indicates that once half-lives are conditioned on shocks, there appears to be no micro-macro disconnect puzzle. The finding in past work estimating half-lives that disaggregated real exchange rates adjust faster can be attributed to the dominance of a different composition of shocks for disaggregated data.

Panel (b) of the table reports halflives computed from the bias-corrected estimates from panel (b) of table 6, using the method of Kilian (1998). The bias-corrected halflives are longer due to the lower estimates of the speed of adjustment parameters reported in panel (b) of table 6. This implies that our model is actually closer to explaining the high degree of persistence reported in past studies than it may have appeared when using uncorrected estimates. These results continue to support our main conclusion, that when conditional on aggregate shocks, there is no longer a contrast in the persistence between aggregated and disaggregated real exchange rates.

This basic lesson can be translated from terms of error corrections into the more familiar terms of autoregressions estimated in most past research. Consider the following aggregation exercise. Given that $q_{ij,t}$ is the aggregation of $q_{ij,t-1}^{k}$ over goods, it is viewed as a puzzle that estimates of their adjustment speeds are so different. Aggregating an AR(1) version of equation (2) over goods:

$$\frac{1}{K}\sum_{k=1}^{K} q_{ij,t}^{k} = \frac{1}{K}\sum_{k=1}^{K}\left(c_{ij}{}^{k} + \rho_{ij}^{k} q_{ij,t-1}^{k} + \varepsilon_{ij,t}^{k}\right)$$

$$q_{ij,t} = \frac{1}{K}\sum_{k=1}^{K}\left(c_{ij}{}^{k}\right) + \frac{1}{K}\sum_{k=1}^{K}\left(\rho_{ij}^{k} q_{ij,t-1}^{k}\right) + \frac{1}{K}\sum_{k=1}^{K}\varepsilon_{ij,t}^{k} \tag{6}$$

Work by Imbs et al. (2005) has focused on the role of heterogeneity of adjustment speeds among the goods. If we allow for heterogeneity in the autoregressive coefficient ρ_{ij}^{k} among goods, equation (6) differs from an AR(1) version of the aggregate equation (3) because $\frac{1}{K}\sum_{k=1}^{K}\left(\rho_{ij}^{k} q_{ij,t-1}^{k}\right) \neq \rho_{ij} q_{ij,t-1}$. If there is a correlation between the variation in ρ_{ij}^{k} and $q_{ij,t-1}^{k}$ among goods, so that slowly adjusting goods have larger price deviations, then this will bias upward estimates of the average speed of adjustment.

However, the vector error correction exercise demonstrated that the mechanism by which a good’s price deviation is eliminated differs in response to the component of the price deviation that is common across goods and the component that is idiosyncratic to the particular good. If this distinction in adjustment mechanism affects the speed of adjustment, this suggests that the specification of the autoregression should be expanded as follows to allow for this distinction:

$$q_{ij,t}^{k} = c_{qk,ij}^{k} + \rho_{qk,ij}^{k1}\left(q_{ij,t-1}^{k} - q_{ij,t-1}\right) + \rho_{qk,ij}^{k2} q_{ij,t-1} + \varepsilon_{qk,ij,t}^{k} \tag{7a}$$

or equivalently

$$q_{ij,t}^{k} = c_{qk,ij}^{k} + \rho_{qk,ij}^{k1} q_{ij,t-1}^{k} + \left(\rho_{qk,ij}^{k2} - \rho_{qk,ij}^{k1}\right) q_{ij,t-1} + \varepsilon_{qk,ij,t}^{k} \,. \tag{7b}$$

Here $\rho_{qk,ij}^{k2}$ captures the adjustment in relative price of good *k* to aggregate macroeconomic price deviations, and ρ_{ij}^{k1} captures the response to price deviations that are specific to the good *k*. For completeness, an analogous expansion of an AR(1) version of the aggregate equation (3) can be defined (for each *k*).

$$q_{ij,t} = c_{q,ij}^{k} + \rho_{q,ij}^{k1}\left(q_{ij,t-1}^{k} - q_{ij,t-1}\right) + \rho_{q,ij}^{k2} q_{ij,t-1} + \varepsilon_{q,ij,t} \,. \tag{8}$$

Now aggregate up equation (7a):

$$\frac{1}{K}\sum_{k=1}^{K} q_{ij,t}^{k} = \frac{1}{K}\sum_{k=1}^{K}\left(c_{qk,ij}^{k} + \rho_{qk,ij}^{k1}\left(q_{ij,t-1}^{k} - q_{ij,t-1}\right) + \rho_{qk,ij}^{k2} q_{ij,t-1} + \varepsilon_{qk,ij,t}^{k}\right)$$

$$q_{ij,t} = \frac{1}{K}\sum_{k=1}^{K} c_{qk,ij}^{k} + \underbrace{\frac{1}{K}\sum_{k=1}^{K}\rho_{qk,ij}^{k1}\left(q_{ij,t-1}^{k} - q_{ij,t-1}\right)}_{\text{Term A}} + \underbrace{q_{ij,t-1}\frac{1}{K}\sum_{k=1}^{K}\rho_{qk,ij}^{k2}}_{\text{Term B}} + \frac{1}{K}\sum_{k=1}^{K}\varepsilon_{qk,ij,t}^{k} \tag{9}$$

One observation is that, while heterogeneity in $\rho_{qk,ij}^{k1}$ can lead to a heterogeneity bias in Term A in the same way as seen in equation (6), in contrast, heterogeneity in $\rho_{qk,ij}^{k2}$ has no impact on aggregation of Term B, as the common component $q_{ij,t-1}$ passes through the summation operator. So part of the heterogeneity among goods in terms of adjustment speed documented by Imbs et al. (2005) may be of an innocuous type, depending on how much applies to adjustment to aggregate $q_{ij,t}$ deviations, and how much to good specific deviations to $q_{ij,t}^{k}$.

Table 9 shows the results of estimating equations (7a) and (8). The first result is that the apparent inconsistency of the equations (2) and (3) has disappeared, when estimated in the augmented form of equations (7a) and (8). If we focus on the response to aggregate deviations $q_{ij,t-1}$, the average response coefficients in the two equations are nearly the same. In the disaggregated equation the average coefficient is $\frac{1}{K}\sum_{k=1}^{K}\rho_{qk,ij}^{k2}$ =0.79, and in the aggregate equation the average coefficient is $\frac{1}{K}\sum_{k=1}^{K}\rho_{q,ij}^{k2}$ =0.80. So if one focuses just on responses to aggregate deviations, the aggregation puzzle disappears.

Further, Table 9 indicates the degree of heterogeneity in the coefficients in terms of the standard deviation of the estimates across goods. By this measure, the heterogeneity for the coefficient on the aggregated real exchange rate (*q*) appears to be of similar magnitude to that for the idiosyncratic deviation (q_k-q). Recall that it is only heterogeneity in the latter coefficient that fails to cancel out upon aggregation and thereby could lead to aggregation bias of the type described by Imbs et al.

Equation (7a) also suggests that the estimations by Imbs et al. (2005) of an equation like (2) are subject to a potentially large omitted variable bias. Write equation (7b) as

$$\begin{aligned} q_{ij,t}^{k} &= c_{qk,ij}^{k} + \rho_{qk,ij}^{k1} q_{ij,t-1}^{k} + \rho_{qk,ij}^{k3} q_{ij,t-1} + \varepsilon_{qk,ij,t}^{k} \\ \text{where } \rho_{qk,ij}^{k3} &\equiv \rho_{qk,ij}^{k2} - \rho_{qk,ij}^{k1} \end{aligned} \tag{10}$$

Estimating equation (2) ignores the second term. Generalizing the standard omitted variable bias formula to the case of our panel data, the bias would be:

$$\begin{aligned} E\left[\hat{\rho}^{k1}\right] = \rho^{k1} &+ \left(\sum_{ij=1}^{N} Q_{ij,-1}^{k'} M_w Q_{ij,-1}^{k}\right)^{-1} \left(\sum_{ij=1}^{N} Q_{ij,-1}^{k'} M_w \bar{Q}_{-1}\right)\tau \;+ \\ &\left(\sum_{ij=1}^{N} Q_{ij,-1}^{k'} M_w Q_{ij,-1}^{k}\right)^{-1} \left(\sum_{ij=1}^{N} Q_{ij,-1}^{k'} M_w Q_{ij,-1}\right)\rho^{k3} \end{aligned} \tag{11}$$

where

$$Q_{ij,-1}^{k} = (q_{ij,1}^{k}, q_{ij,2}^{k}, \ldots, q_{ij,T-1}^{k})';\; M_w = I - W(W'W)^{-1}W';\; W = (W_2', W_3', \ldots W_T')';$$
$$W_t = (1,\; \bar{q}_t^{k},\; \bar{q}_{t-1}^{k});\; \bar{Q}_{-1} = (\bar{q}_2,\; \bar{q}_3, \ldots, \bar{q}_T)';\; Q_{ij,-1} = (q_{ij,1}, q_{ij,2}, \ldots, q_{ij,T-1})'.$$

and τ is the coefficient of the cross-sectional mean in the augmented equation of (10) (see the appendix for the derivation).

Our findings also bring evidence to bear on the conjecture by Broda and Weinstien (2008) that lower persistence in disaggregated relative prices may be due to nonlinear adjustment. Previous work has demonstrated significant nonlinearities in aggregate real exchange rate adjustment, where convergence is faster for real exchange rate deviations that are large.[17] This may reflect the presence of costs of engaging in arbitrage, discouraging arbitrage responses to

[17] See Parsley and Wei (1996), Taylor et al. (2001), and Wu et al. (2009).

price deviations too small to generate sufficient profits to cover these costs. Broda and Weinstein (2008) suggest that if there is heterogeneity among goods in terms of the volatility of their price deviations, OLS estimates of convergence speed will place a heavy weight on the observations where the absolute value of deviations is large, thereby tending to find fast convergence. But as data are aggregated, they conjecture, large positive and negative price deviations are likely to cancel, so the weight given to small price deviations will increase, thereby tending to find slower convergence.

Our empirical work supports the idea, in a general sense, that faster convergence in disaggregated data is associated with greater volatility. When we compute the standard deviations of real exchange rate deviations at the goods level for each of the 98 goods in our data set, their average standard deviation is 4.8 times that of the aggregate real exchange rate (10.67% and 2.22% respectively). However, we do not find much heterogeneity among goods in this regard. For every one of our 98 goods, the standard deviation of price deviations exceeds that of the aggregate real exchange rate; the heterogeneity among goods is small compared to the gap between their average and the aggregate data. The same conclusion holds for convergence speeds: even though there is some variation in the convergence speeds among the goods in our sample when estimating equation (2), the price gap for every one of the 98 goods in our sample has a faster convergence speed than does the aggregate real exchange rate.

Instead of pointing to a distinction among goods, where certain goods with smaller volatility and slower convergence do not cancel out upon aggregation, our results instead point to distinct components of each good's price deviation, due to aggregate and idiosyncratic shocks, respectively, where the latter can reasonably be expected to have larger volatility and faster convergence, as well as to cancel out upon aggregation. This would seem to be a helpful way of reframing the role of nonlinearity conjectured in Broda and Weinstein (2008); the distinction between aggregate and idiosyncratic shocks makes this conjecture operational.

Finally, our findings have revealing implications for the use of sticky price models to describe real exchange rate behavior. Cheung et al. (2004) argued against sticky price models, emphasizing that the adjustment dynamics of the aggregate real exchange rate are dictated by the adjustment dynamics of the nominal exchange rate, not those of gradually adjusting sticky prices. On the one hand our result contrasts with this finding, showing that the adjustment in disaggregated real exchange rates is dictated by the dynamics of prices in the goods market.

Nonetheless, our finding supports the overall conclusion of Cheung et al; it does not bolster the case for conventional types of sticky price models. Our result indicates that prices actually adjust quite quickly at the disaggregated level, indicating small menu costs or frequent Calvo signals to reset price.

IV. Conclusions

Past papers have been surprised that international price deviations at the goods level adjust faster than do aggregate real exchange rates. The first contribution of the paper is to offer a deeper understanding of this macro-micro disconnect. This paper shows that adjustment in real exchange rates to purchasing power parity is not just a slower version of the adjustment in micro-level prices back to the law of one price: while the nominal exchange rate does the adjusting at the aggregate level, it is the price that does the adjusting at the disaggregated level. The reason is that there are distinct shocks driving price deviations at these two levels of aggregation. The disaggregated level is dominated by idiosyncratic shocks specific to the good, which cancel out upon aggregation and have minimal impact upon aggregate dynamics.

The second contribution of the paper is to offer a resolution to the micro-macro disconnect. Once half-lives are estimated conditional on macroeconomic shocks, microeconomic prices are found to be just as persistent as aggregate real exchange rates. In contrast with the impression given by recent studies on microeconomic price dynamics, there is actually significant persistence contained within micro price data.

The third contribution is to caution against an explanation for the persistence puzzle relying primarily upon heterogeneity among goods and aggregation bias. In particular, a significant portion of the overall heterogeneity in adjustment speeds among goods is found here to be associated with their response to the macroeconomic shocks rather than to idiosyncratic goods shocks. Because the macroeconomic shocks are common to goods, heterogeneity in these coefficients will cancel out upon aggregation. So a significant portion of the heterogeneity detected in past studies may be of an innocuous type when it comes to aggregation bias

Finally, the analysis has important implications for the widespread use of sticky price models to explain real exchange rate behavior. We see evidence that there is rapid adjustment in prices to arbitrage opportunities at the microeconomic level, indicating a fair degree of price flexibility. However, these price movements selectively respond mainly to idiosyncratic shocks at the goods level, and appear to cancel out upon aggregation with minimal implications for aggregate variables like the aggregate real exchange rate. This finding does not coincide well with standard sticky price models of real exchange rate behavior, where stickiness results from the inability to reset prices rapidly and does not distinguish between shocks. A model that potentially could coincide better with the evidence would be a rational inattention or sticky information story, where firms adjust to shocks specific to their industry rather than common macroeconomic shocks. If a firm has limited resources to process information about shocks, and if industry specific shocks are more variable or have larger impacts on a firm's profits, it can be optimal for firms to allocate more attention to track and respond to idiosyncratic conditions than to aggregate conditions. Our empirical result suggests the usefulness of future theoretical work in this direction.

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Table 1: Stationarity of relative prices

Sample	(mean) b	(mean) t-stat	(mean) # obs.	significance 1%	5%	10%
Disaggregated data:						
Traded: (out of 98)	-0.316	-2.434	621	47	63	72
Nontraded (out of 30)	-0.242	-2.121	636	8	11	11
Aggregated data:						
Traded:	-0.284	-2.447	660	Yes	Yes	Yes
Non-traded	-0.220	-1.868	660	No	No	No

Note: For disaggregated data, the table reports estimates of *b* in the equation:

$$\Delta q_{ij,t}^{k} = a_{ij}^{k} + b_{ij}^{k}(q_{ij,t-1}^{k}) + c_{ij}^{k}(\bar{q}_{t-1}^{k}) + d_{ij}^{k}(\Delta\bar{q}_{t}^{k}) + \varepsilon_{ij,t}^{k}$$

$$ij = 1,...,N,\ k = 1,...,K, \text{ and } t = 1,...,T$$

where $\bar{q}_{t}^{k} = \sum_{ij=1}^{N} q_{ij,t}^{k}$ is the cross-section mean of $q_{ij,t}^{k}$ across country pairs and $\Delta\bar{q}_{t}^{k} = \bar{q}_{t}^{k} - \bar{q}_{t-1}^{k}$.The null hypothesis of the test is $H_0 : b_{ij}^{k} = 0$ for all *ij* against the alternative hypothesis $H_1 : b_{ij}^{k} < 0$ for some *ij*. The *b* coefficients and t-stats are calculated as means over the individual goods results, and significance results report the number of goods that reject nonstationarity at the specified significance level. For aggregated data, the table reports estimates of the equation:

$$\Delta q_{ij,t} = a_{ij} + b_{ij}(q_{ij,t-1}) + c_{ij}(\bar{q}_{t-1}) + d_{ij}(\Delta\bar{q}_{t}) + \varepsilon_{ij,t}$$

$$ij = 1,...,N \text{ and } t = 1,...,T$$

where $\bar{q}_{t} = \sum_{ij=1}^{N} q_{ij,t}$ is the cross-section mean of $q_{ij,t}$ across country pairs and $\Delta\bar{q}_{t} = \bar{q}_{t} - \bar{q}_{t-1}$.

Table 2. Half-lives in autoregressions of real exchange rates

Sample	(Mean) ρ_1	(Mean) t-stat	(Mean) ρ_2	(Mean) t-stat	(Mean) #obs.	(Mean) Half-life
AR(2):						
Disaggregated data	0.715	10.620	0.050	0.696	621	1.25
Aggregated data	0.896	13.879	-0.054	-1.195	660	2.10
AR(1):						
Disaggregated data	0.739	14.250			621	1.15
Aggregated data	0.850	20.399			660	2.13

Note: For disaggregated data, the table reports estimates of ρ in the equation $q_{ij,t}^k = c_{ij}^k + \sum_{m=1}^{2} \rho_{ij,m}^k (q_{ij,t-m}^k) + \varepsilon_{ij,t}^k$ for $k = 1,...,K$. The ρ coefficients and t-stats are calculated as mean values of ρ_1^k , ρ_2^k and their associated t-statistics across all goods *k*. Estimates for aggregated data are based on the equation $q_{ij,t} = c_{ij} + \sum_{m=1}^{2} \rho_{ij,m} (q_{ij,t-m}) + \varepsilon_{ij,t}$ Half-life in years are calculated from simulated impulse responses derived from the parameter estimates.

Table 3: Vector error correction estimates

	(mean) ρ	(mean) t-stat	Heterogeneity (Std.Dev.)	#obs.
a) CCEP Estimates:				
Disaggregated Data (for 98 traded goods):				
Exchange rate equation	-0.028	-2.260	0.015	621
Price ratio equation	-0.203	-4.074	0.087	
Aggregated Data:				
Exchange rate equation	-0.126	-3.520		660
Price ratio equation	-0.044	-3.377		
b) Bias-Corrected CCEP Estimates:				
Disaggregated Data (for 98 traded goods):				
Exchange rate equation	-0.019	-1.458	0.013	621
Price ratio equation	-0.143	-3.049	0.087	
Aggregated Data:				
Exchange rate equation	-0.096	-2.839		660
Price ratio equation	-0.035	-3.007		

Note: The table reports estimates with disaggregated data for the equation system:

$$\Delta e_{ij,t} = \alpha^k_{ij,e} + \rho^k_{e,ij}(q^k_{ij,t-1}) + \mu^k_{e,ij}(\Delta e_{ij,t-1}) + \mu^k_{e,ij}(\Delta p^k_{ij,t-1}) + \zeta^{e,k}_{ij,t}$$

$$\Delta p^k_{ij,t} = \alpha^k_{ij,p} + \rho^k_{p,ij}(q^k_{ij,t-1}) + \mu^k_{p,ij}(\Delta e_{ij,t-1}) + \mu^k_{p,ij}(\Delta p^k_{ij,t-1}) + \zeta^{p,k}_{ij,t}.$$

and with aggregate data for the system:

$$\Delta e_{ij,t} = \alpha_{ij,e} + \rho_{e,ij}(q_{ij,t-1}) + \mu_{e,ij}(\Delta e_{ij,t-1}) + \mu_{e,ij}(\Delta p_{ij,t-1}) + \zeta^{e}_{ij,t}$$

$$\Delta p_{ij,t} = \alpha_{ij,p} + \rho_{p,ij}(q_{ij,t-1}) + \mu_{p,ij}(\Delta e_{ij,t-1}) + \mu_{p,ij}(\Delta p_{ij,t-1}) + \zeta^{p}_{ij,t}.$$

For the disaggregated data, the ρ coefficients for the exchange rate and price equations are calculated as means of $\rho^k_{e,}$, ρ^k_p across goods, respectively. The reported standard deviation of ρ estimates across goods is provided as a measure of heterogeneity among goods. The bias correction is carried out via the Kilian (1998) bootstrap method with 1000 iterations. The t-statistics are computed from standard errors derived using the double-bootstrap method of Kilian (1998).

Table 4: Monte Carlo experiment for CCEP estimator

	Pesaran Coefficient	Average Monte Carlo Coefficient	5%	95%
Exchange rate equation	-0.126	-0.156	-0.216	-0.099
Price ratio equation	-0.044	-0.053	-0.073	-0.035

Note: Data were generated using the system:

$$\Delta e_{ij,t} = \hat{\rho}_{e,ij}(q_{ij,t-1}) + \hat{\mu}_{e,ij}(\Delta e_{ij,t-1}) + \hat{\mu}_{e,ij}(\Delta p_{ij,t-1}) + \zeta^{e}_{ij,t}$$

$$\Delta p_{ij,t} = \hat{\rho}_{p,ij}(q_{ij,t-1}) + \hat{\mu}_{p,ij}(\Delta e_{ij,t-1}) + \hat{\mu}_{p,ij}(\Delta p_{ij,t-1}) + \zeta^{p}_{ij,t}.$$

where the Pesaren coefficient values for ρ_e and ρ_p are taken from CCEP estimation of the two-equation system (4b) with aggregated data, reported in Table 3, panel a. . In each of 1000 replications, a sequence of innovations for 20 country pairs covering 34 periods were drawn from the (demeaned) residuals of the estimated exchange rate and price equations, and these were used to generate series for price and exchange rate (as well as for the real exchange rate), using actual observations as starting values. The generated data were then used to re-estimate the model by CCEP. The "Monte Carlo coefficients" denote the average coefficients across the 1000 replications, as well as the 5% and 95% cutoffs of the distribution of estimates.

Table 5: Vector error correction estimates using data set from Imbs et al. (2005)

	(mean) ρ	(mean) t-stat
Disaggregated Data:		
Exchange rate equation	-0.016	-2.540
Price ratio equation	-0.036	-3.606
Aggregated Data:		
Exchange rate equation	-0.025	-2.836
Price ratio equation	-0.016	-2.771

Notes: The table reports estimates with disaggregated data for the equation system:

$$\Delta e_{ij,t} = \alpha^k_{ij,e} + \rho^k_{e,ij}(q^k_{ij,t-1}) + \mu^k_{e,ij}(\Delta e_{ij,t-1}) + \mu^k_{e,ij}(\Delta p^k_{ij,t-1}) + \zeta^{e,k}_{ij,t}$$

$$\Delta p^k_{ij,t} = \alpha^k_{ij,p} + \rho^k_{p,ij}(q^k_{ij,t-1}) + \mu^k_{p,ij}(\Delta e_{ij,t-1}) + \mu^k_{p,ij}(\Delta p^k_{ij,t-1}) + \zeta^{p,k}_{ij,t} .$$

and with aggregate data:

$$\Delta e_{ij,t} = \alpha_{ij,e} + \rho_{e,ij}(q_{ij,t-1}) + \mu_{e,ij}(\Delta e_{ij,t-1}) + \mu_{e,ij}(\Delta p^k_{ij,t-1}) + \zeta^{e}_{ij,t}$$

$$\Delta p_{ij,t} = \alpha_{ij,p} + \rho_{p,ij}(q_{ij,t-1}) + \mu_{p,ij}(\Delta e_{ij,t-1}) + \mu_{p,ij}(\Delta p_{ij,t-1}) + \zeta^{p}_{ij,t} .$$ [18]

For disaggregated data, the ρ coefficients for the exchange rate and price equations are calculated as means of $\rho^k_{e,}$, ρ^k_p across goods, respectively

[18] Because this error correction model incorporates lags of first differences to capture short-run dynamics, this specification is analogous to the second-order autoregression estimated previously. Inclusion of additional lags is impossible due to the short time-span of the data set.

Table 6: 3-Equation vector error correction estimates

	Response to q_k-q			Response to q			
	Mean ρ	Mean t-stat	Hetero-geneity: StdDev[1]	Mean ρ	Mean t-stat	Hetero-geneity: StdDev	Mean #obs.
a) CCEP estimates:							
Exchange rate equation	-0.002	-0.095	0.017	-0.163	-3.688	0.035	621
Aggregated Price equation	0.001	0.006	0.011	-0.055	-2.614	0.012	
Disaggregated Price equation	-0.301	-3.612	0.117	-0.065	-0.543	0.106	
b) Bias-corrected CCEP estimates:							
Exchange rate equation	-0.001	-0.050	0.017	-0.117	-2.433	0.040	621
Aggregated Price equation	0.000	-0.090	0.012.	-0.040	-2.400	0.014.	
Disaggregated Price equation	-0.208	-2.843	0.120	-0.048	-0.625	0.111	

Notes: The table reports estimates with disaggregated data for the equation system:

$$\Delta e_{ij,t} = \alpha^{k}_{ij,e} + \rho^{k1}_{e,ij}(q^{k}_{ij,t-1} - q_{ij,t-1}) + \rho^{k2}_{e,ij}(q_{ij,t-1}) + \mu^{k}_{e,ij,1}(\Delta e_{ij,t-1}) + \mu^{k}_{e,ij,2}(\Delta p^{k}_{ij,t-1}) + \mu^{k}_{e,ij,3}(\Delta p_{ij,t-1}) + \zeta^{k}_{e,ij,t}$$

$$\Delta p_{ij,t} = \alpha^{k}_{p,ij} + \rho^{k1}_{p,ij}(q^{k}_{ij,t-1} - q_{ij,t-1}) + \rho^{k2}_{p,ij}(q_{ij,t-1}) + \mu^{k}_{pkij,1}(\Delta e_{ij,t-1}) + \mu^{k}_{p,ij,2}(\Delta p^{k}_{ij,t-1}) + \mu^{k}_{p,ij,3}(\Delta p_{ij,t-1}) + \zeta^{k}_{p,ij,t}$$

$$\Delta p^{k}_{ij,t} = \alpha^{k}_{pk,ij} + \rho^{k1}_{pk,ij}(q^{k}_{ij,t-1} - q_{ij,t-1}) + \rho^{k2}_{pk,ij}(q_{ij,t-1}) + \mu^{k}_{pk,ij,1}(\Delta e^{k}_{ij,t-1}) + \mu^{k}_{pk,ij,2}(\Delta p^{k}_{ij,t-1}) + \mu^{k}_{pk,ij,3}(\Delta p_{ij,t-1}) + \zeta^{k}_{pk,ij,t}$$

The ρ coefficients for exchange rate, aggregate price, and disaggregated price responses are calculated as the means of ρ^{k1}_{e}, ρ^{k2}_{e}, ρ^{k1}_{p}, ρ^{k2}_{p}, ρ^{k1}_{pk} ρ^{k2}_{pk} across goods, respectively. The reported standard deviation of ρ parameter estimates provides a measure of heterogeneity across goods.
The bias correction is carried out via the Kilian (1998) bootstrap method with 1000 replications. The t-statistics are computed from standard errors derived using the double-bootstrap method of Kilian (1998).

Table 7: Relative contributions of nominal exchange rate and price adjustments to PPP and LOP Reversion

		With an exchange rate shock		with an aggregate price shock		with a disaggregate price shock	
Disaggregated q_k:	years	$g^{q_k}_{e,e}$	$g^{q_k}_{p_k,e}$	$g^{q_k}_{e,p}$	$g^{q_k}_{p_k,p}$	$g^{q_k}_{e,p_k}$	$g^{q_k}_{p_k,p_k}$
	1	0.73	0.27	0.64	0.36	0.01	0.99
	2	0.78	0.22	0.71	0.29	0.01	0.99
	3	0.80	0.20	0.73	0.27	0.00	1.00
	5	0.84	0.16	0.78	0.22	-0.02	1.02
	10	0.93	0.07	0.88	0.12	-0.08	1.08
Aggregated q:	years	$g^{q}_{e,e}$	$g^{q}_{p,e}$	$g^{q}_{e,p}$	$g^{q}_{p,p}$	g^{q}_{e,p_k}	g^{q}_{p,p_k}
	1	0.77	0.23	0.76	0.24	---	---
	2	0.79	0.21	0.79	0.21	---	---
	3	0.79	0.21	0.79	0.21	---	---
	5	0.79	0.21	0.79	0.21	---	---
	10	1.79	0.21	0.79	0.21	---	---

Note: The columns $g^{q_k}_{i,j}$ indicates the proportion of adjustment in the relative price q_k explained by adjustment in variable i, conditional on shock j. The columns $g^{q}_{i,j}$ indicate the same proportion for adjustment in the aggregated real exchange rate q.

Table 8. Estimates of half-lives conditional on the shock

	e shock	*p* shock	p_k shock
CCEP Estimation:			
Disaggregated q_k	1.76	1.65	1.12
Aggregated *q*	1.57	1.71	---
CCEP Bias-Corrected Estimation:			
Disaggregated q_k	2.61	2.72	1.70
Aggregated *q*	2.27	2.46	---

Note: Half-lives in years, estimated from impulse responses of the equation system:

$$\Delta e_{ij,t} = \alpha^k_{ij,e} + \rho^{k1}_{e,ij}(q^k_{ij,t-1} - q_{ij,t-1}) + \rho^{k2}_{e,ij}(q_{ij,t-1}) + \mu^k_{e,ij,1}(\Delta e_{ij,t-1}) + \mu^k_{e,ij,2}(\Delta p^k_{ij,t-1}) + \mu^k_{e,ij,3}(\Delta p_{ij,t-1}) + \zeta^k_{e,ij,t}$$

$$\Delta p_{ij,t} = \alpha^k_{p,ij} + \rho^{k1}_{p,ij}(q^k_{ij,t-1} - q_{ij,t-1}) + \rho^{k2}_{p,ij}(q_{ij,t-1}) + \mu^k_{pkij,1}(\Delta e_{ij,t-1}) + \mu^k_{p,ij,2}(\Delta p^k_{ij,t-1}) + \mu^k_{p,ij,3}(\Delta p_{ij,t-1}) + \zeta^k_{p,ij,t}$$

$$\Delta p^k_{ij,t} = \alpha^k_{pk,ij} + \rho^{k1}_{pk,ij}(q^k_{ij,t-1} - q_{ij,t-1}) + \rho^{k2}_{pk,ij}(q_{ij,t-1}) + \mu^k_{pk,ij,1}(\Delta e^k_{ij,t-1}) + \mu^k_{pk,ij,2}(\Delta p^k_{ij,t-1}) + \mu^k_{pk,ij,3}(\Delta p_{ij,t-1}) + \zeta^k_{pk,ij,t}$$

The bias correction is carried out via the Kilian (1998) bootstrap method using 1000 replications.

Table 9. Estimates of speeds of adjustment in expanded autoregression

	Response to q_k-q			Response to q			
	Mean ρ	Mean t-stat	Hetero-geneity: StdDev[1]	Mean ρ	Mean t-stat	Hetero-geneity: StdDev[1]	#obs.
Disaggregated data	0.678	9.552	0.131	0.787	7.198	0.111	621
Aggregated data	-0.001	-0.042	0.018	0.803	16.860	0.039	621

Note: Estimates for disaggregated data from the equation:

$$q_{ij,t}^{k} = c_{qk,ij}{}^{k} + \rho_{qk,ij}^{k1}\left(q_{ij,t-1}^{k} - q_{ij,t-1}\right) + \rho_{qk,ij}^{k2} q_{ij,t-1} + \varepsilon_{qk,ij,t}^{k}$$

and for aggregated data from:

$$q_{ij,t} = c_{q,ij}{}^{k} + \rho_{q,ij}^{k1}\left(q_{ij,t-1}^{k} - q_{ij,t-1}\right) + \rho_{q,ij}^{k2} q_{ij,t-1} + \varepsilon_{q,ij,t}.$$

Standard deviation of parameter estimates are reported across goods.

Fig. 1 Variance decomposition of q_k

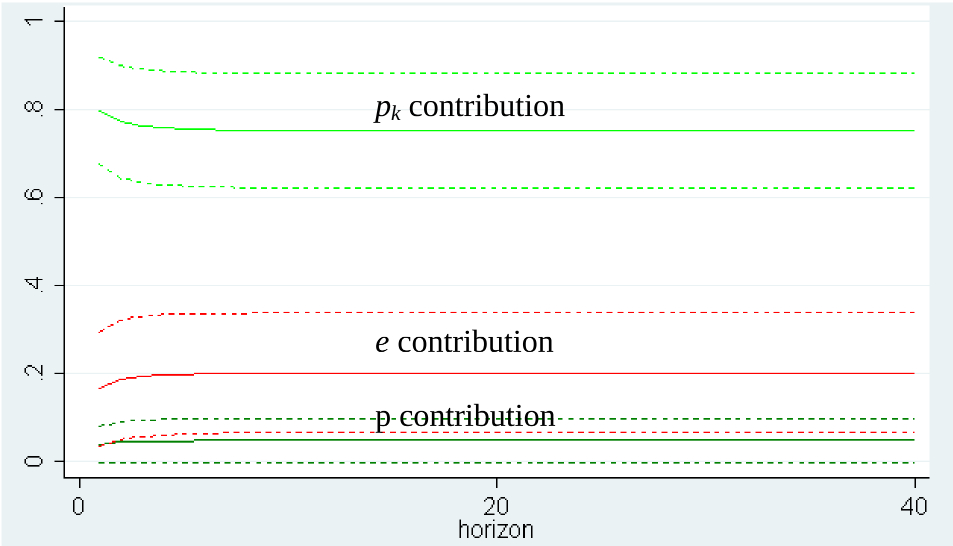


Fig. 2 Variance decomposition of q

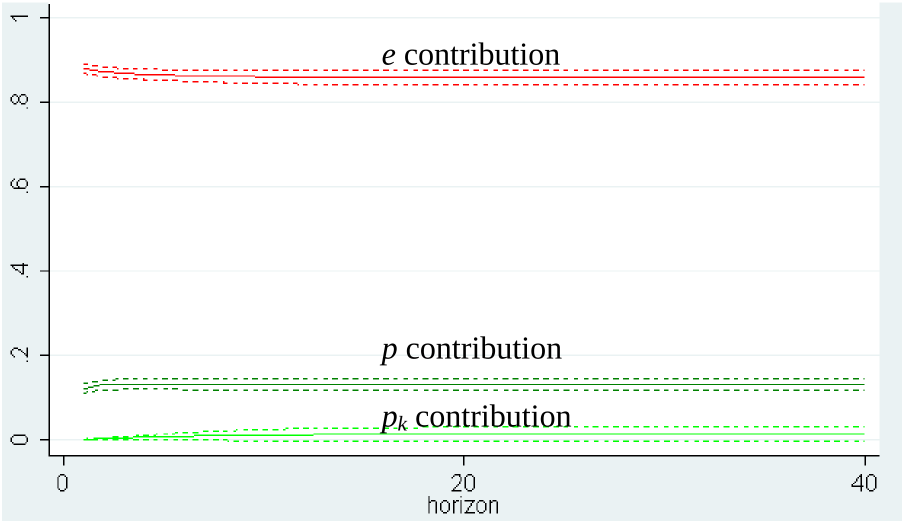


Fig. 3. Impulse response to p_k shock

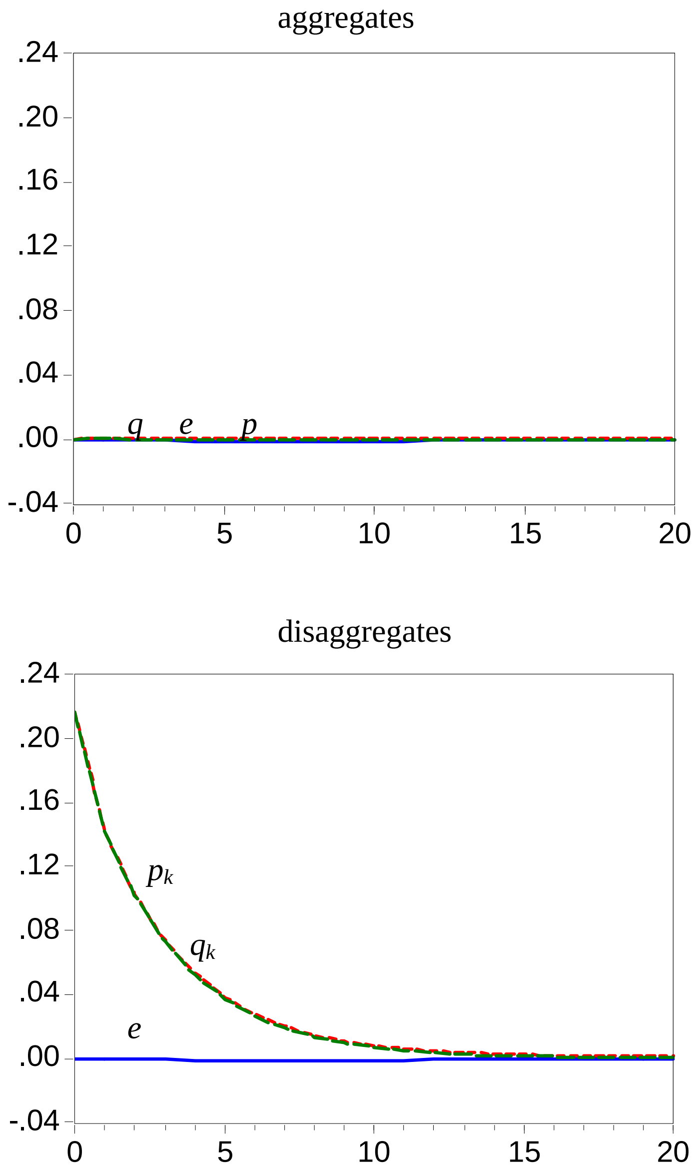
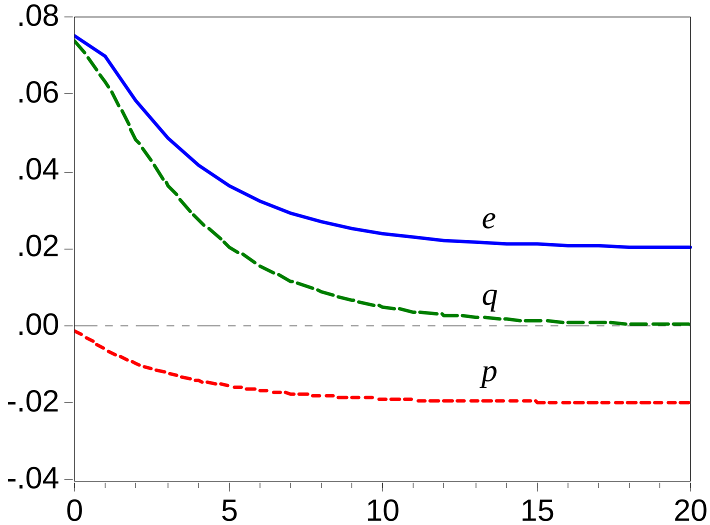


Fig. 4. Impulse response to *e* shock

aggregates



disaggregates

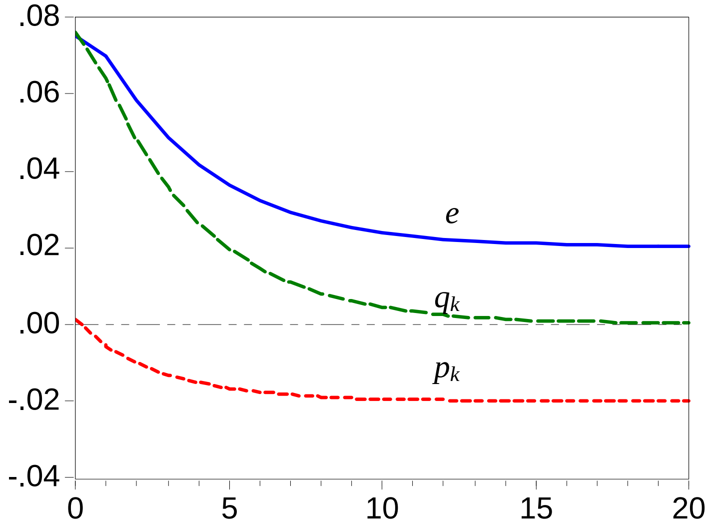
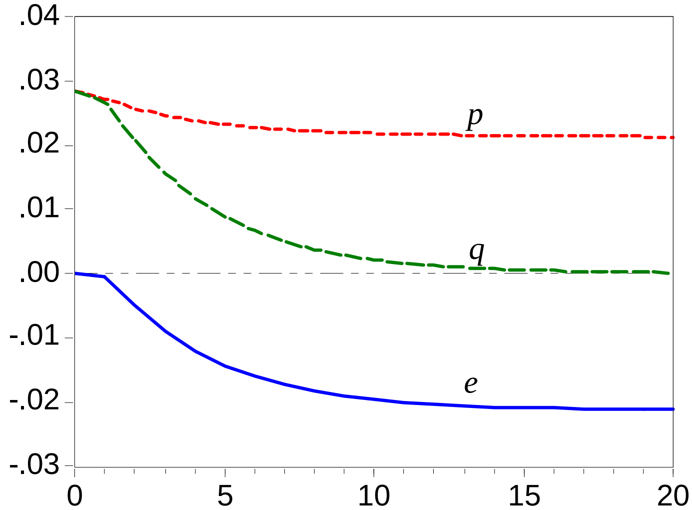
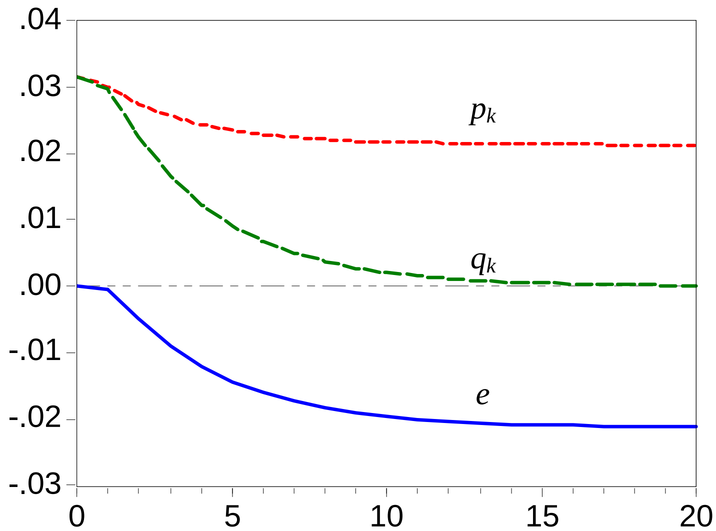


Fig. 5. Impulse response to *p* shock

aggregates



disaggregates



Data Appendix

Table A1. Cities in sample of 20 industrial countries and U.S.

City	Country
Amsterdam	Netherlands
Athens	Greece
Auckland	New Zealand
Berlin	Germany
Brussels	Belgium
Copenhagen	Denmark
Helsinki	Finland
Lisbon	Portugal
London	United Kingdom
Luxembourg	Luxembourg
Madrid	Spain
Oslo	Norway
Paris	France
Rome	Italy
Stockholm	Sweden
Sydney	Australia
Tokyo	Japan
Toronto	Canada
Vienna	Austria
Zurich	Switzerland
New York	United States

Table A2. Traded items in sample, by category

Food and non-alcoholic beverages: perishable

White bread (1 kg)
Butter (500 g)
Margarine (500 g)
Spaghetti (1 kg)
Flour, white (1 kg)
Sugar, white (1 kg)
Cheese, imported (500 g)
Cornflakes (375 g)
Milk, pasteurised (1 l)
Potatoes (2 kg)
Onions (1 kg)
Tomatoes (1 kg)
Carrots (1 kg)
Oranges (1 kg)
Apples (1 kg)
Lemons (1 kg)
Bananas (1 kg)
Lettuce (one)
Eggs (12)
Beef: filet mignon (1 kg)
Beef: steak, entrecote (1 kg)
Beef: stewing, shoulder (1 kg)
Beef: roast (1 kg)
Beef: ground or minced (1 kg)
Veal: chops (1 kg)
Veal: fillet (1 kg)
Veal: roast (1 kg)
Lamb: leg (1 kg)
Lamb: chops (1 kg)
Lamb: stewing (1 kg)
Pork: chops (1 kg)
Pork: loin (1 kg)
Ham: whole (1 kg)
Bacon (1 kg)
Chicken: fresh (1 kg)
Fresh fish (1 kg)
Orange juice (1 l)

Food and non-alcoholic beverages: Non-perishable

White rice (1 kg)
Olive oil (1 l)
Peanut or corn oil (1 l)
Peas, canned (250 g)
Tomatoes, canned (250 g)
Peaches, canned (500 g)
Sliced pineapples, can (500 g)
Chicken: frozen (1 kg)
Frozen fish fingers (1 kg)
Instant coffee (125 g)
Ground coffee (500 g)
Tea bags (25 bags)
Cocoa (250 g)
Drinking chocolate (500 g)
Coca-Cola (1 l)
Tonic water (200 ml)
Mineral water (1 l)

Clothing and footwear

Business suit, two piece, med. wt.
Business shirt, white
Men's shoes, business wear
Mens raincoat, Burberry type
Socks, wool mixture
Dress, ready to wear, daytime
Women's shoes, town
Women's cardigan sweater
Women's raincoat, Burberry type
Tights, panty hose
Child's jeans
Child's shoes, dresswear
Child's shoes, sportswear
Girl's dress
Boy's jacket, smart
Boy's dress trousers

Alcoholic beverages

Wine, common table (750 ml)
Wine, superior quality (750 ml)
Wine, fine quality (750 ml)
Beer, local brand (1 l)
Beer, top quality (330 ml)
Scotch whisky, six yrs old (700 ml)
Gin, Gilbey's or equivalent (700 ml)
Vermouth, Martini & Rossi (1 l)
Cognac, French VSOP (700 ml)
Liqueur, Cointreau (700 ml)

Recreation

Compact disc album
Television, colour (66 cm)
Kodak colour film (36 exposures)
Intl. weekly news magazine (Time)
Inttl foreign daily newspaper
Paperback novel (at bookstore)

Personal care

Aspirins (100 tablets)
Razor blades (five pieces)
Toothpaste with fluoride (120 g)
Facial tissues (box of 100)
Hand lotion (125 ml)
Lipstick (deluxe type)

Household supplies

Toilet tissue (two rolls)
Soap (100 g)
Laundry detergent (3 l)
Dishwashing liquid (750 ml)
Insect-killer spray (330 g)
Light bulbs (two, 60 watts)
Frying pan (Teflon or equivalent)
Electric toaster (for two slices)
Batteries (two, size D/LR20)

Table A3. Non-traded items

Laundry (one shirt)	Domestic cleaning help	Regular unleaded petrol
Dry cleaning, man’s suit	Maid’s monthly wages	Taxi: initial meter charge
Dry cleaning, woman’s dress	Babysitter	Taxi rate per additional kilometre
Dry cleaning, trousers	Developing 36 colour pictures	Taxi: airport to city centre
Man’s haircut	Daily local newspaper	Two-course meal for two people
Woman’s cut & blow dry	Three-course dinner	Hire car
Telephone and line	Seats at theatre or concert	
Electricity	Seats at cinema	
Gas Tune-up	Road tax or registration fee	
Water	Moderate hotel, single room	
Business trip, daily cost	One drink at bar of hotel	
Hilton-type hotel, single room	Simple meal for one person	

Table A4: Error Correction results detailed by good

Product Description	e-coef	t-stat	p-coef	t-stat
Instant coffee (125 g) (supermarket)	-0.040	-2.779	-0.186	-3.799
Coca-Cola (1 l) (supermarket)	-0.044	-3.520	-0.183	-2.376
Tonic water (200 ml) (supermarket)	-0.031	-2.657	-0.144	-3.249
Mineral water (1 l) (supermarket)	-0.037	-4.252	-0.179	-5.701
Orange juice (1 l) (supermarket)	-0.020	-1.151	-0.169	-1.417
Ground coffee (500 g) (supermarket)	-0.020	-1.671	-0.183	-4.995
Tea bags (25 bags) (supermarket)	-0.034	-4.603	-0.170	-4.755
Cocoa (250 g) (supermarket)	-0.023	-1.339	-0.163	-4.869
Drinking chocolate (500 g) (supermarket)	-0.056	-3.394	-0.204	-5.699
Peas, canned (250 g) (supermarket)	-0.025	-2.861	-0.228	-5.175
Tomatoes, canned (250 g) (supermarket)	-0.024	-2.162	-0.117	-2.396
Peaches, canned (500 g) (supermarket)	-0.021	-1.422	-0.138	-1.041
Sliced pineapples, canned (500 g) (supermarket)	-0.017	-1.626	-0.205	-2.448
Potatoes (2 kg) (supermarket)	-0.009	-1.704	-0.444	-7.576
Oranges (1 kg) (supermarket)	-0.015	-3.529	-0.333	-2.421
Apples (1 kg) (supermarket)	0.001	0.131	-0.339	-4.770
Lemons (1 kg) (supermarket)	-0.018	-4.107	-0.249	-4.189
Bananas (1 kg) (supermarket)	-0.020	-2.185	-0.535	-7.828
Lettuce (one) (supermarket)	-0.035	-4.420	-0.373	-9.018
Eggs (12) (supermarket)	-0.015	-1.128	-0.257	-5.424
Onions (1 kg) (supermarket)	-0.022	-2.335	-0.471	-6.222
Tomatoes (1 kg) (supermarket)	-0.017	-2.763	-0.379	-3.665
Carrots (1 kg) (supermarket)	-0.010	-2.115	-0.457	-7.153
Beef: filet mignon (1 kg) (supermarket)	-0.014	-1.142	-0.208	-8.700
Veal: chops (1 kg) (supermarket)				
Veal: fillet (1 kg) (supermarket)	-0.017	-0.531	-0.255	-5.083
Veal: roast (1 kg) (supermarket)				
Lamb: leg (1 kg) (supermarket)	-0.011	-1.060	-0.196	-3.273
Lamb: chops (1 kg) (supermarket)	-0.036	-3.273	-0.290	-6.405
Lamb: stewing (1 kg) (supermarket)	-0.001	-0.238	-0.190	-2.115
Pork: chops (1 kg) (supermarket)	-0.040	-4.236	-0.198	-3.149
Pork: loin (1 kg) (supermarket)	-0.033	-4.955	-0.256	-4.581
Ham: whole (1 kg) (supermarket)	-0.018	-1.214	-0.214	-2.596
Bacon (1 kg) (supermarket)	-0.016	-1.649	-0.164	-3.255
Beef: steak, entrecote (1 kg) (supermarket)	-0.037	-1.996	-0.176	-2.396
Chicken: frozen (1 kg) (supermarket)				
Chicken: fresh (1 kg) (supermarket)	-0.038	-3.920	-0.237	-4.833
Frozen fish fingers (1 kg) (supermarket)	-0.010	-1.297	-0.317	-4.374
Fresh fish (1 kg) (supermarket)	-0.009	-0.795	-0.135	-4.528
Beef: stewing, shoulder (1 kg) (supermarket)	-0.028	-3.092	-0.297	-4.657
Beef: roast (1 kg) (supermarket)	-0.021	-2.197	-0.213	-3.500
Beef: ground or minced (1 kg) (supermarket)	-0.025	-1.973	-0.224	-4.567
White bread, 1 kg (supermarket)	-0.023	-1.884	-0.114	-3.050
Flour, white (1 kg) (supermarket)	-0.035	-2.292	-0.125	-2.533
Sugar, white (1 kg) (supermarket)	-0.069	-2.698	-0.305	-7.383

Cheese, imported (500 g) (supermarket)	-0.026	-2.459	-0.249	-5.500
Cornflakes (375 g) (supermarket)	-0.025	-2.054	-0.269	-3.390
Milk, pasteurised (1 l) (supermarket)	-0.054	-3.187	-0.183	-4.141
Olive oil (1 l) (supermarket)	-0.017	-1.211	-0.272	-4.571
Peanut or corn oil (1 l) (supermarket)	-0.023	-2.999	-0.070	-1.757
Butter, 500 g (supermarket)	-0.031	-1.728	-0.192	-3.022
Margarine, 500 g (supermarket)	-0.050	-4.268	-0.229	-3.622
White rice, 1 kg (supermarket)	-0.018	-1.854	-0.206	-3.101
Spaghetti (1 kg) (supermarket)	-0.031	-3.122	-0.254	-4.769
Wine, common table (1 l) (supermarket)	-0.027	-1.653	-0.160	-1.770
Scotch whisky, six years old (700 ml) (supermarket)	-0.055	-2.859	-0.179	-4.692
Gin, Gilbey's or equivalent (700 ml) (supermarket)	-0.040	-1.743	-0.096	-1.825
Vermouth, Martini & Rossi (1 l) (supermarket)	-0.028	-2.461	-0.096	-0.892
Cognac, French VSOP (700 ml) (supermarket)	-0.012	-0.583	-0.188	-4.332
Liqueur, Cointreau (700 ml) (supermarket)	-0.052	-1.915	-0.154	-5.943
Wine, superior quality (700 ml) (supermarket)	-0.021	-1.826	-0.179	-2.856
Wine, fine quality (700 ml) (supermarket)	-0.009	-0.497	-0.186	-3.406
Beer, local brand (1 l) (supermarket)	-0.039	-2.189	-0.126	-2.514
Beer, top quality (330 ml) (supermarket)	-0.038	-3.279	-0.237	-5.950
Soap (100 g) (supermarket)	-0.006	-0.506	-0.129	-4.614
Light bulbs (two, 60 watts) (supermarket)	-0.018	-1.040	-0.228	-5.955
Batteries (two, size D/LR20) (supermarket)	-0.026	-2.007	-0.170	-2.952
Frying pan (Teflon or good equivalent) (supermarket)	-0.053	-5.538	-0.242	-6.340
Electric toaster (for two slices) (supermarket)	-0.027	-1.076	-0.133	-4.644
Laundry detergent (3 l) (supermarket)	-0.016	-3.146	-0.137	-4.626
Toilet tissue (two rolls) (supermarket)	-0.034	-1.506	-0.283	-5.036
Dishwashing liquid (750 ml) (supermarket)	-0.025	-1.445	-0.136	-3.014
Insect-killer spray (330 g) (supermarket)	-0.029	-2.452	-0.219	-5.818
Aspirins (100 tablets) (supermarket)	-0.022	-1.958	-0.150	-3.605
Lipstick (deluxe type) (supermarket)	-0.019	-0.860	-0.108	-2.281
Razor blades (five pieces) (supermarket)	-0.022	-3.112	-0.067	-1.125
Toothpaste with fluoride (120 g) (supermarket)	-0.047	-3.687	-0.199	-4.768
Facial tissues (box of 100) (supermarket)	-0.009	-0.757	-0.171	-6.593
Hand lotion (125 ml) (supermarket)	-0.025	-3.502	-0.154	-3.216
Child's jeans (chain store)	-0.021	-1.928	-0.137	-2.101
Boy's dress trousers (chain store)	-0.031	-1.810	-0.201	-3.214
Child's shoes, dresswear (chain store)	-0.044	-2.681	-0.153	-4.611
Child's shoes, sportswear (chain store)	-0.011	-0.913	-0.186	-6.483
Girl's dress (chain store)	-0.018	-1.785	-0.222	-3.660
Boy's jacket, smart (chain store)	-0.027	-3.380	-0.224	-5.385
Business suit, two piece, medium weight (chain store)	-0.024	-2.776	-0.060	-1.856
Business shirt, white (chain store)	-0.023	-2.336	-0.221	-2.951
Men's shoes, business wear (chain store)	-0.029	-2.679	-0.204	-3.372
Men's raincoat, Burberry type (chain store)	-0.018	-2.974	-0.158	-2.502
Socks, wool mixture (chain store)	-0.024	-1.996	-0.165	-2.639
Dress, ready to wear, daytime (chain store)	-0.019	-1.404	-0.054	-0.855
Women's shoes, town (chain store)	-0.048	-4.697	-0.152	-5.585
Women's cardigan sweater (chain store)	-0.029	-2.399	-0.301	-7.125

Women's raincoat, Burberry type (chain store)	-0.018	-1.885	-0.197	-4.698
Tights, panty hose (chain store)	-0.016	-1.030	-0.163	-4.493
Compact disc album (average)	-0.077	-2.059	-0.130	-5.062
Television, colour (66 cm) (average)	-0.024	-1.392	-0.102	-1.903
International foreign daily newspaper (average)	-0.055	-3.085	-0.141	-3.789
International weekly news magazine (Time) (average)	-0.056	-1.948	-0.240	-2.022
Paperback novel (at bookstore) (average)	-0.028	-1.473	-0.084	-1.197
Kodak colour film (36 exposures) (average)	-0.056	-2.341	-0.158	-3.911
Averages: Mean	-0.028	-2.260	-0.203	-4.074
Averages: Median	-0.024	-2.057	-0.187	-4.026

Technical Appendix:

A. Monte Carlo Simulations

The purpose of this appendix is to evaluate the bias of CCEP estimates for parameter configurations based on a VECM model. The data generating process (DGP) is given by the following two-variable system of equations:

$$\begin{aligned} \Delta y_{i,1,t} &= \alpha_{i,1} + \rho_{1,1}(ec_{i,t-1}) + \delta_{1,1}(\Delta y_{i,1,t-1}) + \delta_{1,2}(\Delta y_{i,2,t-1}) + \gamma_i f_t + \varepsilon_{i,1,t}, \\ \Delta y_{i,2,t} &= \alpha_{i,2} + \rho_{2,1}(ec_{i,t-1}) + \delta_{2,1}(\Delta y_{i,1,t-1}) + \delta_{2,2}(\Delta y_{i,2,t-1}) + \gamma_i f_t + \varepsilon_{i,2,t}, \\ f_t &= \theta f_{t-1} + \eta_t \end{aligned} \qquad \text{(A1)}$$

which can be represented in matrix form as

$$\begin{aligned} \Delta \mathbf{Y}_{i,t} &= \boldsymbol{\alpha}_i + \boldsymbol{\Psi}\mathbf{A}' Y_{i,t-1} + \boldsymbol{\Gamma}\Delta\mathbf{Y}_{i,t-1} + \mathbf{u}_{i,t}, \; i = 1,\dots N, \; t = 1,\dots T, \\ \mathbf{u}_{i,t} &= \gamma_i f_t \mathbf{i}_2 + \boldsymbol{\varepsilon}_{i,t}, \\ f_t &= \theta f_{t-1} + \eta_t, \end{aligned} \qquad \text{(A2)}$$

where $\Delta \mathbf{Y}_{i,t} = (\Delta y_{i,1,t}, \Delta y_{i,2,t})'$, $\boldsymbol{\alpha}_i = (\alpha_{i,1}, \alpha_{i,2})'$, $\alpha_{i,j} \sim i.i.d.\, N(0,1)$ for j=1, 2, $\mathbf{i}_2 = (1,1)'$, f_t is an unobservable common factor across cross-section units i, γ_i is the heterogeneous factor loading, $\boldsymbol{\varepsilon}_{i,t} = (\varepsilon_{i,t,1}, \varepsilon_{i,t,2})$ is a vector of idiosyncratic errors with $\boldsymbol{\Omega} \equiv E(\boldsymbol{\varepsilon}'_{i,t}\boldsymbol{\varepsilon}_{i,t}) = \begin{bmatrix} 1 & \kappa \\ \kappa & 1 \end{bmatrix}$. $\mathbf{A}' = (1,\; 1)$ is the cointegrating vector, $\boldsymbol{\Psi} = \left(-0.12,\; -0.04\right)'$, and $\boldsymbol{\Gamma} = \begin{bmatrix} 0.12 & 0.12 \\ -0.02 & 0.04 \end{bmatrix}$ are coefficient matrices calibrated from the estimation results of (A1) based on our aggregate data (e.g. , see Table 3, panel a for the elements of $\boldsymbol{\Psi}$).[19] The common factor f_t is assumed to follow an AR(1) process with the disturbance η_t being identically, independently and normally distributed with a mean zero and variance one, i.e. i.i.d. N(0,1), and is also independent of $\boldsymbol{\varepsilon}_{i,t}$ and γ_i.[20]

[19] Our calibration of $\boldsymbol{\Psi}$ and $\boldsymbol{\Gamma}$ implies $\rho_{1,1} = -.12,\; \rho_{2,1} = -.04$, $\delta_{1,1} = .12,\; \delta_{1,2} = 0.12,\; \delta_{2,1} = -.02,\; \delta_{2,2} = .04$.

[20] In terms of the variables in our paper $\Delta \mathbf{Y}_{i,t} = (\Delta e_{ij,t}, \Delta p_{ij,t})'$, where the cross-section unit index i corresponds to the ij index of country pairs in the empirical analysis.

The factor loading γ_i characterizes the degree of cross dependence of variables ($\Delta \mathbf{Y}_{i,t}$) across units and is assumed to be distributed i.i.d. U[-1,3] for the case of high cross dependence, i.i.d. U[0, 0.2] for low cross dependence. The persistence of the factor measured by θ is assumed to be 0.2 and 0.8 for low and high persistence, respectively. The coefficient κ in the covariance matrix, $\mathbf{\Omega}$, reflects the degree of contemporaneous correlation of $\Delta y_{i,1,t}$ and $\Delta y_{i,2,t}$ and is assumed to be 0.2 and 0.8 for low and high contemporaneous correlation. The coefficient matrices $\mathbf{\Gamma}$, $\mathbf{\Omega}$, $\mathbf{\Psi}$, $\mathbf{A}$ are invariant across i and imply that $\mathbf{\Psi A}'$ has a reduced rank. Therefore, one root of the model is equal to one and the other three are greater than one in absolute value. The time and cross-section dimensions of the panel, T and N, respectively, are allowed take the following values: {35, 50, 100} and {20, 50}. The estimators are compared in terms of mean bias (mb), root mean squared error (rmse), standard deviation (stdv), and mean estimated standard error (stde).[21]

The simulation procedure involves the following steps:

1. Drawing idiosyncratic residuals $\boldsymbol{\varepsilon}_{i,t}$ from the bivariate normal distribution function, $N(\mathbf{0},\mathbf{\Omega})$, and common factor shocks η_t from a standard normal distribution, i.i.d. N(0,1), we generate a dataset $Y_{i,t} = (y_{i,1,t}, y_{i,2,t})'$ for i=1,…N and t =1,…T, based on the DGP described in equation (A1).[22]
2. We estimate the following equations with Pesaran's CCEP method including cross-sectional means of the regressand and regressors:

$$\begin{aligned} \Delta y_{i,1,t} &= \alpha_{i,1} + \rho_{1,1}(ec_{i,t-1}) + \delta_{1,1}(\Delta y_{i,1,t-1}) + \delta_{1,2}(\Delta y_{i,2,t-1}) + u_{i,1,t}, \\ \Delta y_{i,2,t} &= \alpha_{i,2} + \rho_{2,1}(ec_{i,t-1}) + \delta_{2,1}(\Delta y_{i,1,t-1}) + \delta_{2,2}(\Delta y_{i,2,t-1}) + u_{i,2,t}, \end{aligned} \quad \text{(A3)}$$

where, $ec_{i,t-1} = y_{i,1,t-1} + 1.0 y_{i,2,t-1}$ and obtain estimates of the vector of slope parameters $\Phi = (\rho_{1,1}, \rho_{2,1}, \delta_{1,1}, \delta_{1,2}, \delta_{2,1}, \delta_{2,2})$.

[21] Denoting $\hat{\Phi}$ as the estimate of Φ, we can define the mean bias of estimates as the average of $\Phi - \hat{\Phi}$, stde as the average of the standard error of $\hat{\Phi}$, stdv = $\sqrt{\sum_{i=1}^{R} (\hat{\Phi} - \bar{\hat{\Phi}})^2 / R}$, and $rmse = \sqrt{\sum_{i=1}^{R} (\hat{\Phi} - \Phi)^2 / R}$, where R is the number of iterations.

[22] We initialize the first two time series observations using values in our actual dataset.

3. Repeating steps 1 and 2 2000 times, we construct the mean bias, root mean squared error of estimates, standard deviation and mean estimated standard error across all iterations.

Simulation results are reported in Tables A1 – A4 for different configurations of underlying parameters and dimensions of time series length and cross-section size. Results from the benchmark model with high cross dependence of variables across units ($\gamma_i \sim$ i.i.d. $U[-1,3]$) , low persistence of common factor movements (θ = 0.2), and low contemporaneous correlation among variables(κ =0.2) are reported in Table A1 for different panel dimensions.. Table A2 reports results with low cross-dependence across *i* (low γ_i) , while leaving the other parameters the same as in Table A1. Tables A3 and A4 report results with high γ_i and θ, but low κ, and with high γ_i and κ, but low θ, respectively.

Summarizing the most salient results: (i) An increase in panel size *N*, for a given *T*, has only a limited effect on the magnitude of mean bias, but it decreases the standard deviation and root mean squared error of estimates. However, an increase in time dimension *T*, for a given *N*, decreases the magnitude of the bias as well as that of the other above-mentioned statistics; (ii) The mean estimated standard error is generally very close to the standard deviation, implying that it may be appropriate to use the standard error of CCEP estimates for statistical inference; and (iii) For the estimated responses to the error correction terms, $\rho_{1,1}$, $\rho_{2,1}$, our main variables of interest, the mean biases are always positive, implying the CCEP estimates tend to overstate the true speed of adjustment (in absolute value). Moreover the magnitude of the mean bias as well as the standard errors associated with these coefficient estimates are comparable.

B. Derivation of omitted variable bias:

Consider the following equation:

$$q_{ij,t}^{k} = c_{qk,ij}^{k} + \rho_{qk,ij}^{k1} q_{ij,t\text{-}1}^{k} + \rho_{qk,ij}^{k3} q_{ij,t\text{-}1} + \varepsilon_{qk,ij,t}^{k}. \quad \text{(A1)}$$

Omitting $\mathrm{q}_{\mathrm{ij,t-1}}$ from (A1) and then augmenting the resulting equation with cross-section means:

$$q_{ij,t}^{k} = W_t \gamma_{ij}' + \rho_{qk,ij}^{k1} q_{ij,t-1}^{k} + v_{qk,ij,t}^{k}, \quad \text{(A2)}$$

where $W_t = (1,\ \bar{q}_t^k,\ \bar{q}_{t\text{-}1}^k)$ and $\gamma_{ij} = (c_{qk,ij}^k, \delta_{ij}^1, \delta_{ij}^2)$. The matrix representation of equation (A2) is:

$$Q_{ij}^{k} = W\gamma_{ij}' + Q_{ij,-1}^{k}\rho_{qk,ij}^{k1} + V_{ij}^{k},$$

where, $Q_{ij}^{k} = (q_{ij,2}^{k}, q_{ij,3}^{k}, ..., q_{ij,T}^{k})'$; $W = (W_2', W_3', ...W_T')'$; $Q_{ij,-1}^{k} = (q_{ij,1}^{k}, q_{ij,2}^{k}, ..., q_{ij,T-1}^{k})'$;

$V_{ij}^{k} = (v_{ij,2}^{k}, v_{ij,3}^{k}, ...v_{ij,T}^{k})'$;

Based on equation (A1), the regression equation augmented with cross-section means is:

$$q_{ij,t}^{k} = R_t\kappa_{ij}' + \rho_{qk,ij}^{k1} q_{ij,t-1}^{k} + \rho_{qk,ij}^{k3} q_{ij,t-1} + \varepsilon_{qk,ij,t}^{k},$$

where, $R_t = (W_t, \bar{q}_{t\text{-}1})$; $\kappa_{ij} = (c_{qk,ij}^{k}, \delta_{ij}^{1}, \delta_{ij}^{2}, \tau_{ij}) = (\gamma_{ij}, \tau_{ij})$. The matrix representation of the above equation is :

$$Q_{ij}^{k} = R\kappa_{ij}' + Q_{ij,\text{-}1}^{k}\rho_{qk,ij}^{k1} + Q_{ij,\text{-}1}\rho_{qk,ij}^{k3} + \xi_{ij}^{k} \quad . \qquad \text{(A3)}$$

where $R = (R_2', R_3', ...R_T')'$; $Q_{ij,\text{-}1} = (q_{ij,1}, q_{ij,2}, ..., q_{ij,T-1})'$; $\xi_{ij}^{k} = (\varepsilon_{ij,2}^{k}, \varepsilon_{ij,3}^{k}, ...\varepsilon_{ij,T}^{k})'$.

Plugging equation (A3) into the pooling estimates of $\hat{\rho}^{k1}$ from equation (A2), one can derive the following equation with some simple manipulation.

$$\hat{\rho}^{k1} = (\sum_{ij=1}^{N} Q_{ij,-1}^{k'} M_w Q_{ij,-1}^{k})^{-1} \sum_{ij=1}^{N} Q_{ij,-1}^{k'} M_w \bar{Q}_{-1}\tau + (\sum_{ij=1}^{N} Q_{ij,-1}^{k'} M_w Q_{ij,-1}^{k})^{-1} (\sum_{ij=1}^{N} Q_{ij,-1}^{k'} M_w Q_{ij,-1}\rho^{k3})$$
$$+ (\sum_{ij=1}^{N} Q_{ij,-1}^{k'} M_w Q_{ij,-1}^{k})^{-1} (\sum_{ij=1}^{N} Q_{ij,-1}^{k'} M_w \xi_{ij}^{k}) + \rho^{k1}$$

where, $M_w = I - W(W'W)^{-1}W'$; $\bar{Q}_{\text{-}1} = (\bar{q}_2, \bar{q}_3, ..., \bar{q}_T)'$.

$$E\left[\hat{\rho}^{k1}\right] = \rho^{k1} + (\sum_{ij=1}^{N} Q_{ij,\text{-}1}^{k'} M_w Q_{ij,\text{-}1}^{k})^{-1} (\sum_{ij=1}^{N} Q_{ij,-1}^{k'} M_w \bar{Q}_{-1})\tau + (\sum_{ij=1}^{N} Q_{ij,-1}^{k'} M_w Q_{ij,-1}^{k})^{-1} (\sum_{ij=1}^{N} Q_{ij,-1}^{k'} M_w Q_{ij,-1})\rho^{k3}$$

$$= \rho^{k1} + \text{Bias}$$

Table A1: Simulation results with high γ_i, low θ and low κ

T	N		ρ_{11}	δ_{11}	δ_{12}	ρ_{21}	δ_{21}	δ_{22}
35	20	mb	0.046	0.023	-0.038	0.045	-0.040	0.032
		stdv	0.023	0.044	0.046	0.023	0.043	0.047
		stde	0.022	0.040	0.043	0.023	0.041	0.043
		rmse	0.052	0.049	0.060	0.051	0.059	0.057
50	20	mb	0.031	0.014	-0.026	0.029	-0.027	0.022
		stdv	0.017	0.036	0.039	0.018	0.035	0.038
		stde	0.016	0.033	0.035	0.016	0.032	0.035
		rmse	0.035	0.038	0.047	0.034	0.044	0.044
100	20	mb	0.014	0.007	-0.014	0.013	-0.014	0.010
		stdv	0.010	0.024	0.025	0.010	0.023	0.026
		stde	0.009	0.022	0.024	0.009	0.022	0.024
		rmse	0.017	0.025	0.029	0.017	0.027	0.028
35	50	mb	0.046	0.022	-0.038	0.043	-0.038	0.032
		stdv	0.016	0.027	0.029	0.017	0.026	0.029
		stde	0.014	0.026	0.027	0.015	0.025	0.027
		rmse	0.049	0.035	0.048	0.046	0.046	0.043
50	50	mb	0.030	0.015	-0.026	0.029	-0.028	0.022
		stdv	0.011	0.022	0.023	0.011	0.022	0.023
		stde	0.010	0.021	0.022	0.011	0.021	0.022
		rmse	0.032	0.027	0.035	0.031	0.035	0.032
100	50	mb	0.014	0.007	-0.013	0.013	-0.013	0.010
		stdv	0.006	0.015	0.016	0.006	0.014	0.016
		stde	0.006	0.014	0.015	0.006	0.014	0.015
		rmse	0.015	0.016	0.020	0.015	0.020	0.019

Notes: mb, stdv, stde, and rmse denote the mean bias, standard deviation, mean estimated standard error, and root mean square of CCEP estimates of equation system (A3) for parameters γ_i ~i.i.d. U[-1,3], κ =0.2, θ = 0.2. T and N are the number of time-series observations and cross-section units, respectively.

Table A2: Simulation results with low γ_i, low θ, and low κ

T	N		ρ_{11}	δ_{11}	δ_{12}	ρ_{21}	δ_{21}	δ_{22}
35	20	mb	0.045	0.021	-0.038	0.043	-0.037	0.029
		stdv	0.022	0.042	0.044	0.023	0.041	0.045
		stde	0.022	0.040	0.042	0.022	0.040	0.043
		rmse	0.050	0.047	0.058	0.049	0.056	0.054
50	20	mb	0.029	0.014	-0.025	0.028	-0.027	0.022
		stdv	0.016	0.035	0.036	0.016	0.033	0.037
		stde	0.016	0.032	0.035	0.016	0.032	0.035
		rmse	0.033	0.037	0.044	0.033	0.042	0.043
100	20	mb	0.014	0.006	-0.014	0.013	-0.013	0.010
		stdv	0.009	0.023	0.025	0.010	0.023	0.025
		stde	0.009	0.022	0.024	0.010	0.022	0.024
		rmse	0.017	0.024	0.028	0.016	0.026	0.027
35	50	mb	0.044	0.022	-0.037	0.042	-0.037	0.031
		stdv	0.016	0.027	0.029	0.016	0.026	0.029
		stde	0.014	0.025	0.027	0.014	0.025	0.027
		rmse	0.047	0.035	0.047	0.045	0.045	0.042
50	50	mb	0.029	0.014	-0.026	0.028	-0.026	0.021
		stdv	0.011	0.021	0.023	0.011	0.022	0.023
		stde	0.010	0.021	0.022	0.010	0.020	0.022
		rmse	0.031	0.026	0.034	0.029	0.034	0.031
100	50	mb	0.014	0.006	-0.013	0.013	-0.013	0.010
		stdv	0.006	0.014	0.015	0.006	0.014	0.015
		stde	0.006	0.014	0.015	0.006	0.014	0.015
		rmse	0.015	0.016	0.020	0.014	0.020	0.018

Notes: mb, stdv, stde, and rmse denote the mean bias, standard deviation, mean estimated standard error, and root mean square of CCEP estimates for the parameter set γ_i ~i.i.d. U[0, 0.2], κ =0.2, θ = 0.2. T and N are the number of time-series observations and cross-section units, respectively.

Table A3: Simulation results with high γ_i, high θ, and low κ

T	N		ρ_{11}	δ_{11}	δ_{12}	ρ_{21}	δ_{21}	δ_{22}
35	20	mb	0.059	0.031	-0.049	0.057	-0.047	0.040
		stdv	0.027	0.046	0.047	0.028	0.046	0.048
		stde	0.024	0.041	0.044	0.024	0.040	0.043
		rmse	0.064	0.055	0.068	0.063	0.066	0.062
50	20	mb	0.038	0.021	-0.036	0.036	-0.034	0.027
		stdv	0.018	0.036	0.037	0.018	0.036	0.038
		stde	0.017	0.033	0.035	0.018	0.033	0.035
		rmse	0.042	0.042	0.052	0.040	0.049	0.046
100	20	mb	0.017	0.009	-0.018	0.016	-0.017	0.012
		stdv	0.011	0.024	0.027	0.010	0.024	0.027
		stde	0.010	0.022	0.024	0.010	0.022	0.024
		rmse	0.020	0.026	0.032	0.019	0.029	0.029
35	50	mb	0.060	0.031	-0.047	0.057	-0.048	0.042
		stdv	0.019	0.029	0.029	0.020	0.028	0.029
		stde	0.015	0.026	0.027	0.016	0.025	0.027
		rmse	0.063	0.042	0.055	0.060	0.055	0.052
50	50	mb	0.038	0.022	-0.032	0.036	-0.032	0.028
		stdv	0.012	0.022	0.023	0.012	0.022	0.023
		stde	0.011	0.021	0.022	0.011	0.021	0.022
		rmse	0.040	0.031	0.040	0.038	0.038	0.036
100	50	mb	0.017	0.010	-0.016	0.016	-0.016	0.014
		stdv	0.006	0.015	0.016	0.006	0.015	0.016
		stde	0.006	0.014	0.015	0.006	0.014	0.015
		rmse	0.018	0.018	0.022	0.017	0.021	0.021

Notes: mb, stdv, stde, and rmse denote the mean bias, standard deviation, mean estimated standard error, and root mean square of CCEP estimates for the parameter set γ_i ~i.i.d. U[-1, 3], κ =0.2, θ = 0.8. T and N are the number of time-series observations and cross-section units, respectively.

Table A4: Simulation results with high γ_i, low θ and high κ

T	N		ρ_{11}	δ_{11}	δ_{12}	ρ_{21}	δ_{21}	δ_{22}
35	20	mb	0.046	0.008	-0.023	0.043	-0.049	0.042
		stdv	0.021	0.066	0.072	0.021	0.067	0.074
		stde	0.020	0.062	0.069	0.020	0.062	0.069
		rmse	0.050	0.066	0.076	0.048	0.083	0.085
50	20	mb	0.031	0.006	-0.017	0.029	-0.032	0.026
		stdv	0.014	0.054	0.061	0.015	0.054	0.061
		stde	0.014	0.050	0.056	0.014	0.050	0.056
		rmse	0.034	0.055	0.064	0.032	0.062	0.066
100	20	mb	0.014	0.003	-0.009	0.013	-0.016	0.013
		stdv	0.008	0.037	0.041	0.008	0.037	0.041
		stde	0.008	0.034	0.039	0.008	0.034	0.039
		rmse	0.017	0.037	0.042	0.016	0.040	0.043
35	50	mb	0.046	0.010	-0.024	0.043	-0.046	0.041
		stdv	0.015	0.043	0.044	0.015	0.043	0.044
		stde	0.013	0.039	0.043	0.013	0.039	0.043
		rmse	0.048	0.044	0.050	0.046	0.063	0.061
50	50	mb	0.030	0.007	-0.016	0.028	-0.031	0.027
		stdv	0.010	0.035	0.037	0.010	0.034	0.036
		stde	0.009	0.031	0.035	0.009	0.031	0.035
		rmse	0.032	0.035	0.040	0.030	0.046	0.046
100	50	mb	0.014	0.003	-0.008	0.013	-0.016	0.014
		stdv	0.005	0.022	0.025	0.005	0.022	0.025
		stde	0.005	0.022	0.024	0.005	0.021	0.024
		rmse	0.015	0.022	0.026	0.014	0.027	0.028

Notes: mb, stdv, stde, and rmse denote the mean bias, standard deviation, mean estimated standard error, and root mean square of CCEP estimates for the parameter set γ_i ~i.i.d. U[-1,3], $\theta = 0.2$, $\kappa = 0.8$. T and N are the number of time-series observations and cross-section units, respectively.