PERSISTENCE IN LAW-OF-ONE-PRICE DEVIATIONS: EVIDENCE FROM MICRO-DATA

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Persistence in Law-of-One-Price Deviations: Evidence from Micro-data

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Abstract

We study the dynamics of good-by-good real exchange rates using a micro-panel of 270 goods prices drawn from major cities in 63 countries and 258 goods prices drawn from 13 major U.S. cities. We find the half-life of deviations from the Law-of-One-Price for the average good is about 1 year. The average half-life is very similar across the OECD, the LCD and within the U.S., suggesting little in the way of nominal exchange rate regime influences. The average non-traded good has a half-life of 1.9 years compared to 1.2 years for traded-goods, for the OECD, with modest differences elsewhere. Aggregating the micro-data increases persistence in the OECD by 6 months to 1.5 years, well below levels obtained using aggregate CPI data. We attribute these differences to conceptual and methodological factors and argue in favor of increased use of micro-price data in applied theory.

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1. Introduction

Much of what is known about international relative price adjustment comes from estimates of persistence of aggregate real exchange rates constructed from consumer price indices. Typically these studies evaluate persistence in terms of half-lives of deviations from purchasing power parity – the length of time it takes for the real exchange rate to make it half of the distance back to its stationary level following a *shock*. In his cogent review of the vast literature on the topic, Rogoff (1996) places the consensus range for these half-lives at 3 to 5 years.[1]

High real exchange rate persistence is widely viewed as a litmus test of a macroeconomic theory. Consider models featuring sticky prices and imperfect competition, such as those pioneered by Obstfeld and Rogoff (1995) and Svennsson and van Wijnbergen (1989). The consensus range is frequently cited as evidence that this class of model is incapable of accounting for the time series properties of a key variable their were designed to explain, namely, the aggregate real exchange rate (see, for example, Chari, Kehoe and McGrattan (2002)).[2] Generally, the volatility and persistence of the aggregate real exchange rate is thought to pose an insurmountable empirical challenge to theoretical paradigms that presume the Law-of-One-Price holds in an approximate sense. This has led to a resurgence of interest in various forms of international market segmentation, including: transportation and distribution costs, tariff and non-tariff barriers, imperfect competition, costly

[1] This range is further confirmed by studies following Rogoff's survey. For example, Frankel and Rose (1996) utilize a panel of 150 countries and obtain strong evidence of mean-reversion of aggregate real exchange rates with a half-life of about four years. Murray and Papell (2005) conduct bias-corrections using similar data and arrive at a point estimate of 4.6 years with a confidence interval of 2.7 to 5.3 years, which nicely embraces the consensus range.

[2] The model also has difficulty generating real exchange rate variability that matches the data. This property, however, comes from an older puzzle relating to nominal exchange rate variability and the inability of the monetary approach to explain this property of the data.

search and non-traded inputs into final consumption.

Each of these models is (or should be) about heterogeneity in Law-of-One-Price deviations across goods. In models with trade costs or tariffs, the LOP deviations are constant over time and different across goods and locations.[3] In models with non-traded inputs into final consumption, it is natural for the deviations to vary over the business cycle and be common across goods within a category (i.e. traded versus non-traded). Whether the deviations persist into the steady-state is usually a maintained assumption, not a theoretical implication. Finally, the empirical targets of sticky price models are large, but rapidly decaying deviations from the Law-of-One-Price.

The goal of this paper is to bring empirical micro-foundations to the rapidly evolving open economy macroeconomic literature that emphasizes market segmentation in its various forms. We build upon Crucini, Telmer and Zachariadis (2005) who had some success relating geographic price dispersion to the economic characteristics of individual goods and services. Their study focused on major European cities using a series of extensive cross-sections of micro-prices, but lacked an explicit time series dimension. Here we study the domestic currency prices of 270 individual goods and services across 71 countries and 13 cities within the U.S. over the period 1990 to 2000. Our focus *is* the time series dimension.

Our central finding relates to the persistence of the LOP deviation for the median good. Estimating separate panel regressions for each good, pooling all international locations, we find that the median good has a half-life of about 1 year. Aggregating the micro-data using consumption expenditure shares in an attempt to emulate the construction of the CPI, the half-life rises by 6 months to 1.5 years (within the OECD).

[3] To be more precise, they may vary, but the variation is expected to be gradual over time (declining transportation costs) or abrupt (a significant trade agreement or a tariff war).

An immediate implication of this finding is that the criticism leveled at sticky-price models seems largely unwarranted, since the persistence levels exhibited by our micro-data are close to those produced by Chari, Kehoe and McGrattan's simulation experiments. A related implication is that the persistence of LOP deviations that we estimate appear more in line with micro-evidence on the frequency of price adjustment than does persistence estimated from the CPI-based real exchange rate. A prominent recent study by Bils and Klenow (2004) uses data from 1995-1997 on 350 individual good prices from the Bureau of Labor Statistics and reports an average time between price changes of only 3.3 months.[4]

Some of the goods in our cross-section appear in existing studies, inviting comparisons. Goldberg and Verboven (2005) estimate half-lives of relative price deviations for automobiles in the range of 1.3 to 1.6 years; they focus on Europe. Worldwide, we estimate half-lives of LOP deviations for automobiles ranging from 7 to 13 months. Cumby (1997) finds the half-life of international price deviations in Big Mac hamburgers to be about 1 year. The LOP for ground beef has a half-life of 11 months in our data.[5]

Moving from anecdotes to broader cross-sectional implications of our work, the half-lives of LOP deviations increase from 1.1 years to 1.4 years as we move from the average traded good to the average non-traded good, pooling all cities of the world. This finding is robust across the OECD, LDC and U.S. city sub-samples.

We find less variation in half-lives across groups of locations than across types of goods. The half-life of LOP deviations is 0.97 years for the median good in

[4] Also, Ahlin and Shintani (2006) use Mexican price data on 44 goods and report that the average monthly frequency of price changes was 28% in 1994 and as large as 50% in 1995. Blinder et al. (1998), on the other hand, use firm-level surveys and find that the median firm changes its price once a year.

[5] Related studies in this vien are: wheat, butter and charcoal (Froot, Kim and Rogoff, 1995), the Economist Magazine (Ghosh and Wolf, 1994). More comprehensive coverage of goods is found in Crownover, Pippenger and Steigerwald (1996), Isard (1977), Giovannini (1988), and Rogers and Jenkins (1995).

the panel of U.S. cities, squarely between the values for the OECD cities (1.09) and LDC cities (0.86). In our data, then, exchange rate regimes have quantitatively small and ambiguous implications for persistence. Exchange rate regimes, do, however increase the time series variability of relative prices, consistent with the work of Charles Engel (1993) and Engel and John Rogers (1996). A good description of the time series behavior of relative prices that emerges is that price deviations are moderately persistence and very volatile when a border is crossed and moderately persistent and moderately volatile when a border is not crossed.

Thus far, we have said little about the size of the absolute price deviations themselves, something absolute price data allow us to study. We consider two views: one innocuous, the other stark. The first we call *conditional price convergence;* it implies that, in the long-run, the differences in absolute prices across locations converge to a nondegenerate distribution. The second convergence concept is *absolute price convergence*; it implies that, in the long-run, the differences in absolute prices across locations disappear, the price distribution is degenerate.

We find the null hypothesis of *absolute price convergence* is rejected for virtually all goods in the international data, but is not rejected for most of the goods within the U.S. (results against absolute convergence are stronger across cities within LDC than across cities within the OECD). Given the fact that absolute LOP deviations are numerically smaller within the U.S. compared to internationally and that the number of observations (i.e. location pairs) is also much smaller for the U.S., our inability to reject the null of absolute price convergence in the U.S. may reflect a combination of the smaller absolute deviations and greater sampling variance. However, it seems safe to say that the long-run, cross-sectional variance of prices at the level of the individual good is lower intranationally than internationally, for virtually all goods.

These results may be summarized very succinctly as follows: the primary feature of relative price behavior that distinguishes locations within countries from what we observe internationally is not the persistence of the stochastic fluctuations of relative prices around their long-run levels, but rather the magnitude of the long-run deviations themselves and the voracity of the shocks that impinge upon them.[6]

The remainder of the paper is organized as follows. Section 2 presents a simple model of retail prices and introduces convergence concepts. Section 3 describes the data. Section 4 examines the long-run stationary and convergence questions. Section 5 contains the main results, dealing with persistence of LOP deviations. We provide discussion of robustness in Section 6 and concluding remarks in Section 7.

2. Conceptual Framework

We organize our data using the framework Crucini, Telmer and Zachariadis (2005) applied to study microeconomic price dispersion in a cross-section of European capital cities. Retail firms combine traded and non-traded inputs and sell the resulting composite good to consumers residing in the same location. In effect, final consumption is completely home biased unless consumers bypass the local retailer. The home bias of retailers, in contrast, varies with the proportion of their marginal cost attributable to local inputs.

Formally, the cost function for the retail firm in location i, selling good m, is

[6] The intranational part of our analysis is most closely related to work by Parsley and Wei (1996) and Cecchetti, Mark and Sonora (2002). Parsley and Wei uses 51 retail prices across 48 U.S. cities and find relatively rapid price convergence for traded goods. In contrast, Cecchetti, Mark and Sonora uses an almost century long panel of U.S. CPI data and find extremely slow adjustment. Our estimates are much more closer to the results of Parsley and Wei who also use micro-data.

the solution to the following cost minimization problem solved at each date:

$$\begin{aligned}\min_{\{N_i^m, X_i^m\}} C_i^m &= W_i N_i^m + T_i^m X_i^m \\ \text{s.t. } Y_i^m &\equiv (N_i^m)^{\alpha_m} (X_i^m)^{(1-\alpha_m)}\end{aligned}$$

where C_i^m is the cost of producing good m in location i, Y_i^m is the physical output level, N_i^m is the labor input, X_i^m is the traded intermediate input, W_i and T_i^m are the respective input prices, and $0 < \alpha_m < 1$.[7]

We have adopted two assumptions. First, that factor mobility is sufficiently high across sectors within a location that W_i is location-specific, not good-specific. The wage would also lose location-specificity if labor was highly mobile across locations. The second assumption is that retailers in all locations produce good m using the same technology; α_m is good-specific, not location-specific.

Under constant returns to scale and allowing for a markup over marginal cost, $B_i^m \geq 1$, the per unit retail price of good m faced by a consumer in location i, P_i^m, is:

$$P_i^m = B_i^m (W_i)^{\alpha_m} (T_i^m)^{1-\alpha_m} \tag{2.1}$$

The bilateral real exchange rate for good m across city pair i and j (in logs) is therefore:

$$q_{ij}^m = \ln P_i^m - \ln P_j^m = b_{ij}^m + \alpha_m w_{ij} + (1-\alpha_m)\tau_{ij}^m. \tag{2.2}$$

Equation (2.2) says that prices will differ across locations due to differences in markups, wages and traded input prices. Theoretical counterparts to these wedges are imperfect competition, the Balassa-Samuelson hypothesis, transportation costs and tariffs, among others.

[7] Allowing for non-traded inputs beyond labor services (e.g., retail space, utilities, advertising, among others) and multiple traded inputs does not alter the key implications of the theory, we would simply treat N_i^m and X_i^m as composites of local and traded inputs.

2.1. Conditional and Absolute Price Convergence

Theory places stark restrictions on the right-hand-side of equation (2.2). It is near universal to assume the deviations are constant in the long run, something we provide evidence on in the section immediately following this one. Where theories differ is in their assumptions about the sources and magnitudes of the long run deviations. We contrast two prominent viewpoints. One we call conditional convergence: the notion that relative prices converge to a fixed distribution as the time period goes to infinity and all shocks are set to their unconditional mean of zero. The other we call absolute convergence: the notion that the long run distribution of relative prices is degenerate (i.e. the price of a good converges to the same level across locations when expressed in a common currency).

Definition 1. *Conditional price convergence.* $T^{-1}\sum_{t=1}^{T} q_{ijt}^{m}$ *converges to a random variable* q_{ij}^{m} *in distribution as* $T \to \infty$.

From the definition of convergence in distribution, conditional price convergence is equivalent to the convergence of the cumulative distribution function $F_T^m(x)$ of $T^{-1}\sum_{t=1}^{T} q_{ijt}^{m}$ to $F^m(x)$ of q_{ij}^{m} as $T \to \infty$, where q_{ij}^{m} is determined by the linear combination of the long-run levels of markups, wages and trade costs across locations.

Definition 2. *Absolute price convergence.* $T^{-1}\sum_{t=1}^{T} q_{ijt}^{m}$ *converges to zero in probability, for all* i*, as* $T \to \infty$.

This definition formalizes the absolute version of the Law-of-One-Price in a cross-section of locations. It is a special case of conditional price convergence. In addition to requirement that $F_T^m(x)$ of $T^{-1}\sum_{t=1}^{T} q_{ijt}^m$ converges to $F^m(x)$ of q_{ij}^m as $T \to \infty$, the distribution of q_{ij}^m is now degenerate at zero: $F^m(x) = 1$ for $x \geq 0$ and 0 for $x < 0$ for all i.

The conditions necessary for absolute convergence are stringent. In the long run we would need to observe: identical markups of price over marginal cost, equal wages across location and a complete absence of trade costs and tariffs on traded intermediate inputs.

In modeling deviations of relative prices from their long-run levels, we follow much of the existing PPP literature and estimate a first-order autoregressive model (here we use i to denote a bilateral pair):[8]

$$q_{it}^m - q_i^m = \rho_m(q_{it-1}^m - q_i^m) + v_{it}^m \tag{2.3}$$

or equivalently,

$$q_{it}^m = \eta_i^m + \rho_m q_{it-1}^m + v_{it}^m\ . \tag{2.4}$$

Assuming $|\rho_m| < 1$, $q_i^m = \eta_i/(1-\rho_m)$ defines the time-invariant individual city-specific effect, assumed to have variance σ_η^2. It may be viewed as the steady state level of q_{it}^m in the sense that it is the sample mean of q_{it}^m conditional on η_i^m for large t. Provided that $\sigma_\eta^2 > 0$, the model is consistent with the conditional convergence hypothesis. Evidently, it reduces to the model of absolute convergence for goods satisfying the restriction $\eta_i^m = 0$ for all i.

The error terms v_{it}^m are innovations to the transitory deviations of relative prices from their long-run levels. We assume the v_{it}^m have mean zero conditional on η_i^m and lagged q_{it}^m's and variance σ_v^2.

Having laid out our conceptual framework, we now describe the data.

[8] Goldberg and Verboven (2005) also consider covergence toward the relative and absolute versions of Law-of-One-Price by using specifications with and without allowing individual effects.

3. The Data

The source of our retail price data is the Economist Intelligence Unit's *Worldwide Cost of Living Survey.*[9] To our knowledge this is the most extensive ongoing survey of international retail prices in the sense that it covers a significant fraction of retail items that urban residents consume and spans cities in virtually every country, including multiple cities within a select number of countries. Given our time series focus, a significant advantage over other price surveys that have similar coverage of goods and locations is its annual frequency and early starting date, 1990. Most existing surveys are so infrequent as to render them useless for addressing time series issues.

Turning to the details, the number of cities included in the survey is 122 and these cities span 78 countries. The maximum number of goods and services priced in any given year is 301. Our sample runs annually from 1990 to 2000.

We conduct our international analysis using one city from each country. We chose the continental U.S. for our intranational analysis for the simple reason that it contains by far the largest number of cities surveyed at 13. The next largest number of cities surveyed equals 5 in Australia, China and Germany.

In our dynamic panel estimation we pool our data across locations and time and run a separate regression for each good. Since the raw data contain a number of missing observations and we want to work with balanced panels, we select goods and locations in the following way. First, if the country underwent a currency reform we eliminate it from the sample.[10] Second, for each good, cities that contain

[9] The target market for the data source is corporate human resource managers who use it to help determine compensation levels of their employees residing in different cities of the world. While the goods and services reflect this objective to some extent, the sample is extensive enough to overlap significantly with what appears in a typical urban consumption basket.

[10] The excluded countries are: Argentina, Brazil, Ecuador, Mexico, Peru, Poland, Russia, and Uruguay.

missing observations are removed. In selecting the city to use when more than one city is available our default choice is the city that comes first alphabetically. When a price observation is not available for the first city in the alphabet, we move on down the list alphabetically until we either find a price observation or exhaust the available cities in that country.

After applying these rules, the number of cities utilized to estimate the persistence of an individual good's relative price ranges from 22 to 62, in the international panel, with the median number of cities used equal to 54. In the U.S. panel, the number of cities utilized ranges from 10 to 13 and the median number used (after rounding) is also 13, reflecting the fact that the U.S. panel contains very few missing observations.

Table 1 presents the 82 cities, located in 63 countries, that survived our selection criterion. We organize countries into four major groups. The first group we call the 'World' since it comprises all international locations for which data is available for a particular good spanning all 11 years. The second and third groups are sub-groups of the World: the OECD and the remaining 40 countries we refer to as the 'LDC.' (see Table 1 for a detailed listing). The fourth group of locations are the 13 cities of the U.S., used for our *intranational* analysis.

The number of goods for which a particular city is used in the panel estimation is noted in parentheses in Table 1. Descriptions of the individual goods and services used in our analysis is provided in Table A1 of the Appendix. After constructing our panel data we end up with 270 goods, however 58 goods are priced in two different types of outlets. Thus, there are essentially 154 different goods.

While we use bilateral relative prices in what follows, it is instructive to examine the sample distribution of:

$$q_{kt}^m = \ln P_{kt}^m - n_k^{-1} \sum_{k=1}^{n_k} \ln P_{kt}^m \tag{3.1}$$

which is the deviation of the price of good m in city k from its geometric average price across all cities (there are n_k locations that have price observations for good k).

The international price data exhibits extraordinary geographic price dispersion. Pooling all the available international data, the standard deviation of q_{kt}^m is 0.66 in 1990 and 0.60 in 2000. The dispersion in prices across U.S. cities is, understandably, much lower, with a standard deviation of 0.28 in 1990 and 0.25 in 2000. What is important to note is that the implied geographic dispersion in all of these settings exceeds what might be reasonably attributed to transportation costs and tariffs. For example, Hummels (1999) finds that trade costs for U.S. imports are typically less than 10%, well below the 25% or 60% needed to account for retail price dispersion.

A number of theoretical perspectives predict price dispersion should be higher for non-traded goods than traded goods. Figure 1 elucidates this property of the micro-data, plotting the distribution of Law-of-One-Price deviations in 2000 for traded and non-traded goods for international cities and U.S. cities. An unexpected feature is the lower dispersion of *non-traded* goods prices across U.S. cities relative to the prices of *traded* goods internationally (their respective standard deviations are 0.32 and 0.53). The retail model attributes this phenomenon to the fact that traded goods have non-traded cost components and this generates higher international price dispersion even among so-called traded goods.

While the comparisons of price distributions across groups of countries and types of goods is instructive, it is impossible to infer how much of the observed dispersion is due to long-run deviations from the LOP and how much is due to transitory fluctuations away from those long-run deviations. To address this question we turn to our time series model.

4. Long-run Properties

Beginning with the long-run properties of LOP deviations, we test for stationarity and the type of long-run convergence. Our estimation is conducted at the level of the relative price of an individual good across a city pair, pooling all locations falling into the following four groups: i) all international cities, ii) cities located in OECD countries, iii) cities located in less developed countries, and iv) U.S. cities. Up to the issue of missing data, the OECD and the non-OECD countries (the 'LDC') together make up the group: all international cities (the 'World').

4.1. Testing for a unit root in Law-of-One-Price deviations

We begin with tests of the unit root null: $\rho_m = 1$ at the level of an individual good, pooling $N = n(n-1)/2$ bilateral pairs, where n is the number of cities with a complete set of time series observations for the price of good m in the group of locations under investigation.

Since we have a large cross-sectional dimension (i.e., bilateral pairs), but a limited time series dimension (11 years), it is inappropriate to employ conventional panel unit root tests that rely on large T asymptotics. Instead, we employ a unit root test for short panels developed by Harris and Tzavalis (1999). The test statistics are based on the least squares dummy variable (LSDV) estimator of ρ_m in (2.4) and converge to a standard normal distribution under the null hypothesis of a unit root, as N grows to infinity with fixed T.

Table 2 summarizes the results of these tests. Using the international data based on all the available cities in the world, we are able to reject the null hypothesis of a unit root for virtually every good. The test with a constant is based on the LSDV estimator. Here we reject the unit root hypothesis for 99% of the 270 goods at the 1% level. Interestingly, the two goods for which we are unable to reject the unit root null are the both labor services: the average cost of labour per hour and hourly wages paid to a baby-sitter.

If absolute price convergence, $\eta_i^m = 0$ for all i in (2.4) is valid, applying this restriction is likely to increase the power of the test. For this reason, we also report the results of the test without a constant in Panel B of Table 2. These tests are based on the simple least squares pooled estimator without including dummy variables (i.e., imposing the restriction, $\eta_i^m = 0$). We now reject the unit root null for all goods at the 1% level of significance except for the cost of labour per hour. The results are only slightly weaker in the context of the OECD and LDC sub-groups, the proportions of goods for which the unit root null is rejected remains above 97%.

The null hypothesis of a unit root is also rejected for most of the goods in the U.S. panel (93% of 258 goods at 1% level in the test with a constant). The modest reduction in the fraction of rejections that occurs as we move from international to intranational data may simply reflect lower power of the test with a smaller sample size in the U.S. panel ($N = 78$).

In summary, we find overwhelming support for the hypothesis that when a disturbance alters the relative price of a good from its location-specific mean, the deviations are temporary, not permanent. This conclusion holds both within and across countries.

4.2. Absolute versus conditional price convergence

Having established that relative prices are level stationary, good-by-good, and with absolute price data in hand, we are now in a position to consider the alternatives of absolute and conditional price convergence.

First, we review some econometric issues. It is necessary to model the long-run and transitory deviations from the long-run in any attempt to assess the relative merits of the absolute and conditional price convergence paradigms. Moreover, the validity of the instruments will depend on which null hypothesis we consider.

The parameter of interest is ρ_m. To allow for conditional convergence, one may employ the LSDV estimator using the dummy variable to capture η_i^m. The LSDV estimator, however, does not provide a consistent estimator when time dimension T is small and fixed.[11] For this reason, our benchmark estimator is Arellano and Bond's (1991) generalized method of moments (GMM) estimator. As a robustness check, we will report LSDV estimates in a subsequent section.

The two-step GMM estimator of ρ_m is based upon the first difference transformation of (2.4),

$$q_{it}^m - q_{i,t-1}^m = \rho_m \left(q_{i,t-1}^m - q_{i,t-2}^m \right) + \left(v_{it}^m - v_{i,t-1}^m \right) \quad \text{for } t = 3, ..., T, \tag{4.1}$$

with instruments selected from the following orthogonality conditions,

$$E\left[q_{is}^m \left(v_{it}^m - v_{i,t-1}^m \right) \right] = 0 \quad \text{for } s = 1, ..., t-2 \text{ and } t = 3, ..., T. \tag{4.2}$$

This choice of instruments, originally proposed by Holtz-Eakin, Newey, and Rosen (1988) and Arellano and Bond (1991), is known to provide a consistent estimator for fixed T and large N under fairly general assumptions.[12]

The GMM estimator for the dynamic panel model based on the moment conditions (4.2) is valid under price convergence to any long-run level, whether it is characterized by absolute or conditional price convergence. However, in the case of absolute price convergence, the lack of individual effect, or $\eta_i^m = 0$, in

[11] Our panel unit root test based on LSDV estimator works with fixed T since the test statistics are corrected for asymptotic bias.

[12] We also follow Arellano and Bond (1991) for the choice of a weighting matrix in the first-step of the GMM estimation.

(2.4) provides $T-1$ additional valid moment conditions $E\left[q_{it}^{m} v_{i,t-1}^{m}\right] = 0$ for $t = 2, ..., T$ (see Holtz-Eakin, 1988, for more on this issue). We can thus employ another GMM estimator that incorporates the new moment conditions in addition to those listed as equation (4.2) to estimate persistence under the null of absolute convergence. The distance between the GMM objective functions using these two alternative GMM estimates provides the inputs necessary to test the absolute price convergence hypothesis (the details of this test are provided in the Appendix).

The upper panel of Table 3 reports the GMM estimates under the null hypothesis of absolute convergence, using the additional moment conditions that come with that assumption. The lower panel reports the results of the test for absolute price convergence.

Beginning with the persistence estimates under the restriction of no individual effect (the upper panel of Table 3) we see estimates above 0.8, consistent with half-lives in the range of 3.4 to 7.5 years using the medians. Note that all the statistics reported in this table are averages or standard deviations of good-by-good estimates of ρ^{m}.

While the medians of the half-lives of individual goods and services are in the ballpark of the consensus estimates for PPP deviations of 3 to 5 years, our micro-estimates are likely to be biased upward. The bias results from the fact that the restriction that $\eta_{i}^{m} = 0$ (absolute convergence) appears not to be valid. As the lower panel of the table reports, we reject the absolute convergence hypothesis resoundingly in the international context: for 99% of the goods we reject at the 1% level of significance. The rejection frequency falls off somewhat, to 77%, as we move to the LDC group and even further to 19% and 4% as move to the OECD and U.S. groups, respectively.

Even within the OECD group, however, the absolute convergence hypothesis is rejected for about one half of the goods in the sample at the 10% level of significance. While the evidence against the null is weaker in the U.S. case, this finding may be partly the result of low power of the test since we have far fewer U.S. city pairs than we have international city pairs. In any case, it seems fair to say that the absolute convergence hypothesis is flagrantly violated in the global economy and is finds some support within the U.S..

Since physical commodities and services are not traded in a frictionless environment, rejection of absolute convergence is not too surprising. Based on these findings, the remainder of our analysis allows for long-run deviations (i.e., our benchmark model is conditional convergence).

5. Short-run Properties

We are interested in three issues related to the rate at which international relative prices move back to their steady-state levels following a 'shock.' First, we explore the persistence of the average good in each cross-section of locations. Second, we consider potential explanations for differences in persistence across goods. Third, we address the relationship between the time series properties of LOP and PPP using our micro-data as an empirical laboratory.

5.1. Persistence of Law-of-One-Price Deviations

Table 4 presents summary statistics on LOP persistence. We see, first of all, that the average persistence level is remarkably close to 0.5 in all four groupings. This corresponds to a half-life of one year, a full 2 years shy of the lower bound of the 3 to 5 year consensus range for PPP. Relative prices adjust even quicker across the LDC cities, where the half-life falls to 10 months. The latter finding is consistent with the view that greater volatility of nominal exchange rates and more rapid inflation gives rise to faster price adjustment in LDC countries.[13]

The median estimates are close to the means suggesting the distribution of parameter estimates is not strongly skewed. The standard deviation of the estimates across goods is high, for all groups of locations, ranging from 0.14 in the LDC group to 0.19 for the OECD. This heterogeneity in persistence across goods is obvious in Figure 2, which displays the entire distribution of estimates for each group. Individual estimates based on all available world cities are presented in Table A1 of the Appendix.

The first and third quartile of parameter estimates for all international pairs, are 0.41 and 0.61, respectively. In half-lives these numbers translate to 0.8 years and 1.4 years, respectively. Since our standard errors are typically below 0.03, one cannot ascribe much of this heterogeneity to sampling error. Moreover, if sampling error was to blame one would expect each distribution to resemble a normal distribution. The tails of all the distributions are fatter than those of a normal distribution. The distribution of OECD estimates looks bimodal, suggestive of a mixture of distributions.

A second striking feature is that persistence differs much more across goods than groups of locations.[14] Consider the fact that the persistence of LOP deviations for the median good in the U.S. panel lies exactly midway between the median for the LDC and OECD estimates. The differences across the groups are minor. From the perspective of the persistence of LOP deviations the nominal exchange rate regime appears to have little impact, contrary to what is often found in the international finance literature.

[13] This faster adjustment in LDCs was also observed in the cross country study of PPP by Cheung and Lai (2000).

[14] This suggests that small changes in the micro-samples underlying the CPI could have large effects on estimates of aggregate persistence.

5.2. Compositional Bias

Having found substantial differences in persistence across goods we would like to offer an explanation for it. We propose compositional bias, which arises from the fact that each retail good is a composite of non-traded and traded intermediate inputs.[15] Since non-traded inputs are expected to experience larger and more persistent deviations from the LOP than traded inputs, 'compositional bias' in persistence of retail goods is expected to arise. The extent of the bias should depend upon the cost-share parameter, α_m.

Using OECD input-output tables, Crucini, Lee, Shintani and Telmer (2006) estimate the cost-share of non-traded inputs into production. Placing each good in the micro-sample into an input-output sector they find that most goods in the EIU sample tend to fall into one of two categories, those with high non-traded inputs shares (0.85) and those with low non-traded input shares, (0.18).[16] Moreover, when retail items are divided into the familiar dichotomous categories, traded goods and non-traded services, the partition that results is very similar to the one resulting from the alternative dichotomous partition of goods into high and low non-traded input shares.

As a reflection of these empirical facts, in what follows we use label 'non-traded good' to refer to a retail item that is not traded and has a non-traded input cost share of $\alpha_n = 0.85$. We use the term 'traded good' to refer to a retail item that is traded and has a non-traded input cost share of $\alpha_t = 0.15$. Note we have adjusted the share for the traded good slightly so that the weights of traded and non-traded inputs across the two types of goods are mirror images (this simplifies the notation).

[15] Burstein et al (2003) develop a model of distribution costs to explain multi-stage exchange rate pass-through in the context of exchange rate stabilizations.

[16] These numbers are taken from Crucini, Lee, Shintani and Telmer (2006).

For compositional bias to matter for persistence, it must be the case that persistence differs across non-traded and traded components of cost. It seems natural to assume that $\rho_w > \rho_\tau$, where the subscripts denote non-traded (i.e. wage) and intermediate traded inputs.

According to the retail model, the LOP deviation for a prototype retail good is (suppressing the location indices):

$$q_t^m = \alpha_m w_t + (1 - \alpha_m)\tau_t^m,$$

For a prototypical non-traded good, persistence is given by:

$$\rho_n = \alpha^2 \rho_w \frac{\sigma_w^2}{\sigma_{q_n}^2} + (1 - \alpha)^2 \rho_\tau \frac{\sigma_\tau^2}{\sigma_{q_n}^2}$$

while for the prototypical traded good, it is :

$$\rho_t = (1 - \alpha)^2 \rho_w \frac{\sigma_w^2}{\sigma_{q_t}^2} + \alpha^2 \rho_\tau \frac{\sigma_\tau^2}{\sigma_{q_t}^2}$$

where $\sigma_{q_z}^2$ is the variability of the LOP deviation for the retail good where $z = n, t$ denoting non-traded and traded goods, respectively. We are assuming simple first-order autoregressive structures for the inputs here as well. Thus, as expected the non-traded good has a large weight, α^2 on the wage persistence, while the mirror image is true for the traded good.[17] As $\alpha \to 1$, the persistence of LOP deviations for the non-traded retail good will converge to the persistence of the wage cost. The persistence of the traded good will equal that of an imported intermediate good (since there is no longer any value added at the retail level).

Table 5 reports average persistence estimates for goods we classify as non-traded and traded in our panel. The persistence of non-traded retail goods is significantly higher than traded retail goods for the international city pairs, but

[17]If it were not for the denominators, the variances of the actual retail goods, these two expressions would be exact mirror images of one another.

only slightly so for the U.S. city pairs. The average OECD half-life approximately doubles from 1.2 to 2 years as we move from traded to non-traded goods. Keep in mind that these are averages across goods within each category and as Figures 3 and 4 show, there is also considerable variability within each group. Despite the considerable overlap of the distributions, there is a pronounced rightward shift in the distribution of persistence among the non-traded goods; it is particularly pronounced for the OECD.

Using $\alpha = 0.85$, and assuming the covariance of the innovations to traded and non-traded costs is zero, and using the OECD mean estimates for traded and non-traded retail price persistence of 0.49 and 0.63 as proxies for the persistence of the underlying input persistence levels we predict $\widehat{\rho}_n = 1.26\widehat{\rho}_t$. The ratio of the persistence of the non-traded and traded goods we started with was $0.63/0.49 = 1.28$. The difference in persistence in moving from inputs prices to final goods prices is thus less than 2% when evaluated at the unconditional group means.

We note that the range of persistence when we go from the prototypical traded good to the prototypical non-traded good, 0.49 to 0.63, only slightly less than the difference between the 25th and 75th percentile of persistence estimates in the OECD distribution. Thus, compositional bias has the potential to explain a substantial fraction of the cross-sectional heterogeneity in micro-persistence.

5.3. Aggregation Bias

In the context of persistence, aggregation bias refers to the fact that the persistence of an aggregate series need not equal the mean of the persistence of the individual series used to construct that aggregate. In other words, there is a non-linear transformation in going from micro-persistence to macro-persistence. Since we have the luxury of micro-data, our approach to evaluating aggregation bias is direct. We aggregate our data and re-estimate the model. Comparisons of the first-order autocorrelation at the micro-level and the macro-level is how we summarize the impact of aggregation.

Individual goods are placed into consumption categories at the level of aggregation of the available consumption expenditure weights. Our OECD city aggregate price levels are based on 174 prices for the same 23 OECD cities we have used to this point. The aggregate city price levels for the LDC group uses 64 prices and is computed for only 19 countries (Cote d'Ivoire, Egypt, Kenya, Morocco, Senegal, Tunisia, Hong Kong, Indonesia, Pakistan, Philippines, Singapore, Sri Lanka, Thailand, Chile, Panama, Venezuela, Bahrain, Hungary, and Israel).[18] We use the same set of goods to construct the aggregates across countries within each group to ensure the baskets are comparable. We do this to avoid having aggregate persistence confounding true price level inertia with compositional differences in the CPI-basket across countries. Given the large differences in persistence found in the micro-data this seems a worthwhile precaution. The substantial reduction in goods in the LDC case is a reflection of this choice, whereas the significant drop in locations is primarily dictated by the scope of the ICP. The aggregate price indices for the 13 U.S. cities are based on 191 prices and were constructed using city-level consumption expenditure weights provided to us by the Bureau of Labor Statistics.[19]

Table 6 shows the results of GMM estimation applied after the micro-data has been aggregated using each of three following weighting methods: (i) CPI-weights, (ii) equal weights, (ii) good-specific weights. Good-specific weights are within-group cross-country averages of country-specific expenditure weights, category-by-category. Effectively this ensures a common basket, as does equal weighting,

[18] The 1990 weights for 78 expenditure categories are used for the OECD and the 1996 weights for 26 expenditure categories are used for the LDC.

[19] The 1994 weights for 210 ELI (Entry Level Items) categories are used for the U.S. We thank Randy Verbrugge at the BLS for providing us with these data.

but it keeps the weight on individual goods at the levels indicated by average expenditure shares across locations for those goods. To assess various forms of aggregation bias we also report the persistence of the median good. Note that this median is slightly different than what is reported in early tables because we restrict the average to be taken over goods that are actually used in our construction of price levels.

In attempting to reconcile our median estimates at the level of goods with CPI-based PPP measures, the construct that is conceptually similar to what national statistical agencies do is contained in the row labelled CPI-weights. Comparing the half-lives using CPI-weights to the median estimates, we see the OECD rises from 1 year to 1.53 years, while the LDC half-lives are basically unchanged and the U.S. half-lives fall. Results are also sensitive to the weighting method.

Imbs et al. (2005) provide a theoretical result that aggregation bias is positive when the variance and persistence of the individual price series are positively correlated across goods. We checked this correlation for our data set and found it to be positive within the OECD and LDC groups, but small and negative within the U.S. While their analytical result is specific to the estimation strategy they pursue, it is at least consistent with the significant elevation of persistence in the OECD setting.[20]

Imbs et al (2005) use sub-indices and the overall CPI across, mostly, European Union countries. Obviously, the persistent of aggregate CPI-based real exchange rates match up with the consensus estimates (though their estimation procedures and sample periods differ somewhat from the existing literature). However, their sub-indicies exhibit less persistence than the overall CPI, which they attribute to

[20] Evidence of aggregation bias in the LDC and US case is mixed. The small difference in the parameter estimate for the LDC across the median and equal weighted version suggests an absence of aggregation bias despite the positive signal of the Imbs et al correlation. The small negative correlation in the US case suggests a lack of aggregation bias, despite an elevated persistence in going from the median good to the equally weighting prices in the micro-data.

aggregation bias.

While our aggregated OECD micro-data exhibits higher persistence than the median persistence of the goods used in its construction, aggregate persistence remains well below the consensus range. In this sense, our estimate of aggregation bias is modest, as anticipated by the simulation procedures used by Chen and Engel (2005). The question then becomes: What accounts for the difference between our estimates of the aggregate real exchange rate (and its persistence) and the one computed from price indices produced by the national statistical agencies?

One obvious candidate explanation is that the sample of prices in our world-wide survey is simply not representative of the overall consumption basket. An alternative explanation is that we cannot emulate the procedures used by national statistical agencies to construct the CPI, despite a valiant effort. On the first point, the goods in the survey are, in fact, disproportionately goods relative to services (traded goods out number non-traded goods 3 or 4 to one in our micro-data). However, even if we stack the deck in favor of non-traded goods and aggregate only non-traded goods, the highest half-life is 3.68 years (see Table 7) and only then do we enter the consensus range of PPP estimates. Unfortunately, this number is obtained by using common expenditure weights across the OECD, which are not the weights used by each national statistical agency to construct their respective CPIs. If we restrict ourselves to CPI-weighted aggregates of non-traded goods, the longest half-life is 2.32 years (again the OECD), again below the consensus range.

A more plausible explanation for the differences in our EIU-based real exchanges and those computed from official CPI data is simply that the two surveys are pursuing different ends by different means. The goal of national statistical agencies is to measure the price of a basket of goods representative of what consumers purchase locally. The contents of the baskets are allowed to change gradually over time. The BLS and other statistical agencies also adjusts market prices for changes in quality and other considerations. They often estimate and treat entire consumption categories differently, such as the imputation of rental costs. Thus, in many cases, market prices are not really the raw inputs into the CPI construct. Yet market prices are what the Economist Intelligence Unit provide and the items are intended to be comparable across locations and stable over time. The goal in terms of the location dimension is to price a standardized international basket. Such a procedure is counterproductive for a national statistical agency intending to make the basket representative of local consumption patterns. One look inside the contents of the food components of the CPIs of the United States and Mexico makes this difference patently obvious.[21]

Where does this leave us? In terms of the persistence question, the evidence presented here is consistent with frequent price adjustment documented by Bils and Klenow (2004) as well as more frequent price changes for traded goods than for services. At a conceptual level, comparing the prices of the same items across locations and using a standardized international consumption basket is more in the spirit of the LOP and PPP propositions. Here the EIU data and results seem more intellectually satisfying.

6. Robustness

In this section we discuss the robustness of our estimates.

[21] Related to this is what might be dubbed "structural shfits," changes in the content or structure of expenditure and prices that cause abrupt or gradual deviations from parity. Papell (2002) shows that trend breaks may be responsible for much of the persistence in the U.S. real exchange rate. Given our short time frame of analysis, it may be that we avoid this low frequency changes and therefore arrive at a lower estimate of persistence.

6.1. An Alternative Estimator

Table 8 shows the results based on the LSDV estimator. Overall, the numbers are very similar to the GMM estimates despite the presence of asymptotic bias in the LSDV estimator. The notable exception is the LDC group where both the average and median half-lives are now in excess of one year. However, like the GMM result, the average adjustment speed in terms of the LDC half-life is still faster than the OECD groups and the U.S. cities. We conclude that rapid price adjustment with half-life of about a year is a robust result, given the insensitivity of the estimates to the choice of an alternative estimator.

Table 9 presents the results for traded and non-traded goods. The results are again, quite consistent with what we found using the GMM estimator. One exception is that the traded and non-traded persistent levels now look more heterogeneous in the U.S. case. Thus, it could be that traded and non-traded price dynamics are not as similar within countries as our GMM estimates had led us to believe, but rather are more consistent with what we observe across international cities, namely more persistence in non-traded goods relative prices than in traded goods relative prices.

6.2. Small Sample Bias

For the LSDV estimator, the finite time series observation T is known to cause downward bias, even if N tends to infinity.[22] Such an asymptotic bias of the LSDV estimator $\widehat{\rho}$ can be evaluated using the well-known formula for the dynamic panel

[22] Correcting bias caused by finite T in the least-squares persistence estimates of real exchange rates has been considered in studies by Andrews (1993), Murray and Papell (2002), and Choi, Mark and Sul (2005), among others.

derived by Nickell (1981),

$$\begin{aligned}
\operatorname*{p\,lim}_{N\to\infty}(\widehat{\rho}-\rho) &= \frac{-(1+\rho)}{T-1}\frac{A}{\left\{1-\frac{2\rho A}{(1-\rho)(T-1)}\right\}} \\
\text{where } A &\equiv 1-\frac{1}{T}\frac{(1-\rho^{T})}{(1-\rho)}\ .
\end{aligned}$$

In contrast, there is no asymptotic bias in the GMM estimator we employ as long as N tends to infinity. Of course, GMM may suffer from bias when N is finite. Unfortunately, no closed form bias formula is available to make the adjustment. To evaluate the effect of this finite sample bias we employed a Monte Carlo procedure. We obtained key parameters, ρ, σ_{η}^{2}, and σ_{v}^{2} from our estimated dynamic panel model and evaluated the extent of the bias with N set equal the values available in our sample and repeatedly estimating the persistence parameters using the artificially generated data. We found that finite sample bias had a very minor impact on our results.[23]

6.3. Measurement Error

The fact that we are using micro data collected across quite distinct markets makes the possibility of measurement error a concern in our estimation. The presence of measurement error in q_{it}^{m} produces a correlation between instruments dated $t-2$ and the error in first difference, $v_{it}^{m}-v_{i,t-1}^{m}$, and thus the moment conditions (4.2) become invalid (see Holtz-Eakin, Newey, and Rosen, 1988, for more on the reasoning). In such a case, we may still use instruments dated $t-3$ and earlier. To consider the issue of measurement error, we also used the measurement-error-robust estimator based on this reduced number of moment conditions. We found rapid convergence, very similar to the results we report in the text. For this

[23] An ealier version of our paper reported significant downward bias in the persistence estimates, but this was found to be due to a small programming error in the code for our Monte Carlo procedure.

reason, we conclude that measurement error is an implausible explanation for the low persistence implied by our parameter estimates.

7. Conclusion

We have unearthed a number of novel findings relating to the size of absolute price deviations, their persistence over time and how these features differ across traded and non-traded goods or when a border is crossed. The richness of the Economist Intelligence Unit data and other archives currently being developed continue to improve our understanding of price dispersion and dynamics.

The analysis conducted in this paper has also uncovered large disparities in the facts that arise using official CPI data and aggregated micro-data. Our hunch is that some of this gap will turn out to rationalize the often stated concerns by economists about the pitfalls of using the CPI index for international price comparisons. We have argued here and previously, in Crucini, Telmer and Zachariadis (2005), that micro-data is necessary because the CPI averages away many sources of cross-sectional variation implied by economic theory. The faster speed of relative price adjustment at the level of individual goods and aggregated micro-price data compared to what the CPI-based real exchange rate suggests is yet another major concern.

It is our hope that the micro-data used here and the facts developed with this data will help to bring measurement closer to the existing theoretical frontier. Much remains to be done.

Appendix: GMM-based test for absolute price convergence

In what follows, we drop the good index m since all of our estimation is good-by-good pooling across all available city pairs $i = 1, ..., N$. The first-differenced

GMM estimator of AR coefficient ρ based on $(T-1)(T-2)/2$ total moment conditions can be written as

$$\widehat{\rho} = (\mathbf{X}'\mathbf{Z}\widehat{\mathbf{W}}_N\mathbf{Z}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Z}\widehat{\mathbf{W}}_N\mathbf{Z}'\mathbf{Y}$$

where $\mathbf{Z}' = (\mathbf{Z}_1', \mathbf{Z}_2', ..., \mathbf{Z}_N')$ is the $(T-1)(T-2)/2 \times N(T-2)$ matrix with

$$\mathbf{Z}_i = \begin{bmatrix} q_{i1} & 0 & 0 & \cdots & 0 & \cdots & 0 \\ 0 & q_{i1} & q_{i2} & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & & \vdots & & \vdots \\ 0 & 0 & 0 & \cdots & q_{i1} & \cdots & q_{iT-2} \end{bmatrix},$$

$\mathbf{Y}' = (\mathbf{\Delta q}_1', \mathbf{\Delta q}_2', ..., \mathbf{\Delta q}_N')$ is the $N(T-2)$ vector with

$$\mathbf{\Delta q}_i = (\Delta q_{i3}, \Delta q_{i4}, ..., \Delta q_{i,T})',$$

$\mathbf{X}' = (\mathbf{\Delta q}_{1,-1}', \mathbf{\Delta q}_{2,-1}', ..., \mathbf{\Delta q}_{N,-1}')$ is the $N(T-2)$ vector with

$$\mathbf{\Delta q}_{i,-1} = (\Delta q_{i2}, \Delta q_{i3}, ..., \Delta q_{i,T-1})',$$

and $\widehat{\mathbf{W}}_N = \mathbf{S}_N^{-1}$ is an optimal weighting matrix. Following Arellano and Bond (1991), we employ

$$\mathbf{S}_N = \left(N^{-1} \sum_{i=1}^{N} \mathbf{Z}_i'\mathbf{H}\mathbf{Z}_i \right)^{-1}$$

where

$$\mathbf{H} = \begin{bmatrix} 2 & -1 & 0 & \cdots & 0 \\ -1 & 2 & 0 & \cdots & 0 \\ 0 & -1 & 2 & \cdots & 0 \\ \vdots & \vdots & \vdots & & \vdots \\ 0 & 0 & 0 & \cdots & 2 \end{bmatrix}$$

for the first-step estimator. For the second-step estimation, we use

$$\mathbf{S}_N = \left(N^{-1} \sum_{i=1}^{N} \mathbf{Z}_i'\widehat{u}_i\widehat{u}_i'\mathbf{Z}_i \right)^{-1}$$

where $\widehat{u}_i$ are residual vectors from the first-step estimator.

For the GMM estimation without individual effects, $T-1$ additional moment conditions are available since total of $T(T-1)/2$ moment conditions are implied by

$$E\left[q_{is}v_{it}\right] = 0 \quad \text{for } s = 1, ..., t-1 \text{ and } t = 2, ..., T.$$

The GMM estimator without individual effects is given by

$$\widehat{\rho}^* = (\mathbf{X}^{*\prime}\mathbf{Z}^*\widehat{\mathbf{W}}_N^*\mathbf{Z}^{*\prime}\mathbf{X}^*)^{-1}\mathbf{X}^{*\prime}\mathbf{Z}^*\widehat{\mathbf{W}}_N^*\mathbf{Z}^{*\prime}\mathbf{Y}^*$$

where $\mathbf{Z}^{*\prime} = (\mathbf{Z}_1^{*\prime}, \mathbf{Z}_2^{*\prime}, ..., \mathbf{Z}_N^{*\prime})$ is the $T(T-1)/2 \times N(T-2) + (T-1)$ matrix with

$$\mathbf{Z}_i^* = \begin{bmatrix} \mathbf{Z}_i & 0 & \cdots & 0 \\ 0 & q_{i1} & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & q_{iT-1} \end{bmatrix},$$

$\mathbf{Y}^{*\prime} = (\mathbf{\Delta q}_1^{*\prime}, \mathbf{\Delta q}_2^{*\prime}, ..., \mathbf{\Delta q}_N^{*\prime})$ is the $N(T-2) + (T-1)$ vector with

$$\mathbf{\Delta q}_i^* = (\mathbf{\Delta q}_i', q_{i2}, ..., q_{i,T})',$$

$\mathbf{X}^{*\prime} = (\mathbf{\Delta q}_{1,-1}^{*\prime}, \mathbf{\Delta q}_{2,-1}^{*\prime}, ..., \mathbf{\Delta q}_{N,-1}^{*\prime})$ is the $N(T-2) + (T-1)$ vector with

$$\mathbf{\Delta q}_{i,-1}^* = (\mathbf{\Delta q}_{i,-1}', q_{i1}, ..., q_{i,T-1})',$$

and $\widehat{\mathbf{W}}_N^* = \mathbf{S}_N^{*-1}$ is an optimal weighting matrix. Test statistic for the null hypothesis of no individual effects can be constructed based on the test of the validity of $T-1$ additional restrictions (see Holtz-Eakin, 1988). Under the null hypothesis,

$$L = J^* - J$$

where J^* is the GMM criterion function for $\widehat{\rho}^*$ and J is the GMM criterion function for $\widehat{\rho}$ with weighting matrix obtained from the submatrix of $\mathbf{S}_N^*$, follows chi-squared distribution with $T-1$ degree of freedom as $N \to \infty$. This test statistic can be used for testing the absolute price convergence in our context since it corresponds to no individual effect.

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Table 1. Locations

Asia	Tunis, Tunisia (186) †	**Central America**
Bahrain, Bahrain (230) †	Harare, Zimbabwe (200)	San Jose, Costa Rica (230)
Dhaka, Bangladesh (133)	**Europe**	Guatemala City, Guatemala (221)
Beijing, China (144)	Vienna, Austria (263) *	Panama City, Panama (242) †
Hong Kong, Hong Kong (242) †	Brussels, Belgium (263) *	**Oceania**
New Delhi, India (57)	Prague, Czech (188)	Adelaide, Australia (251) *
Mumbai, India (146)	Copenhagen, Denmark (264) *	Brisbane, Australia (12) *
Jakarta, Indonesia (183) †	Helsinki, Finland (255) *	Melbourne, Australia (2) *
Tehran, Iran (181)	Lyon, France (261) *	Perth, Australia (2) *
Tel Aviv, Israel (255) †	Paris, France (7) *	Sydney, Australia (2) *
Osaka Kobe, Japan (244) *	Berlin, Germany (265) *	Auckland, New Zealand (257) *
Tokyo, Japan (7) *	Dusseldorf, Germany (5) *	Wellington, New Zealand (5) *
Amman, Jordan (137)	Athens, Greece (247) *	**North America**
Seoul, Korea (167)	Budapest, Hungary (255) †	Calgary, Canada (250) *
Kuala Lumpur,Malaysia (244)	Dublin, Ireland (248) *	Montreal, Canada (15) *
Karachi, Pakistan (192) †	Milan, Italy (263) *	Toronto, Canada (3) *
Manila,Philippines (211) †	Rome, Italy (5) *	Atlanta, USA (249) *
Al Khobar, Saudi Arabia (203)	Luxembourg, Luxembourg (260) *	Boston, USA (11) *
Jeddah, Saudi Arabia (17)	Amsterdam, Netherlands (260) *	Chicago, USA (5) *
Singapore, Singapore (256) †	Oslo, Norway (233) *	Cleveland, USA (3) *
Colombo, Sri Lanka (212) †	Lisbon, Portugal (267) *	New York, USA (1) *
Taipei, Taiwan (215)	Bucharest, Romania (1)	**United States**
Bangkok, Thailand (257) †	Barcelona, Spain (268) *	Atlanta (248)
Abu Dhabi, UAE (238)	Stockholm, Sweden (252) *	Boston (257)
Dubai, UAE (11)	Geneva, Switzerland (262) *	Chicago (251)
	Zurich, Switzerland (6) *	Cleveland (249)
Africa	Istanbul, Turkey (253) *	Detroit (260)
Abidjan, Cote dIvoire (242) †	London, UK (261) *	Houston (250)
Cairo, Egypt (197) †	Belgrade, Yugoslavia (105)	Los Angeles (248)
Nairobi, Kenya (233) †		Miami (253)
Tripoli, Libya (51)	**South America**	New York (234)
Casa Blanca, Morocco (199) †	Santiago, Chile (257) †	Pittsburgh (235)
Lagos, Nigeria (204)	Bogota, Columbia (235)	San Francisco (230)
Dakar, Senegal (197) †	Asuncion, Paraguay (250)	Seattle (252)
Johannesburg, South Africa (253)	Caracas, Venezuela (238) †	Washington DC (255)

Note: Number in parentheses are the number of goods in the analysis for which that city is used.
 * indicates city belongs to OECD group.† indicates selected LDCs for CPI construction.

Table 2. Panel Unit Root Tests for Individual Goods

	World	OECD	LDC	US
Panel A: Rejection frequencies of test with constant				
10% level	0.99	0.99	0.99	0.95
5% level	0.99	0.99	0.98	0.94
1% level	0.99	0.97	0.98	0.93
Panel B: Rejection frequencies of test without constant				
10% level	1.00	0.99	0.99	0.97
5% level	1.00	0.99	0.98	0.97
1% level	1.00	0.98	0.97	0.95
Goods	270	270	270	258
Observations	1431	253	465	78

Notes: Based on panel data with time-dimension $T = 11$ (1990-2000) and cross-sectional dimension N (the number of city pairs) which may vary from good to good. M is the total number of goods and unit root test statistics available for each group of countries. The number shows the proportion of goods for which the null hypothesis of unit root is rejected using the panel unit root test of Harris and Tzavalis (1999). The test with constant is based on the LSDV estimator and test without constant is based on the simple OLS estimator without dummy variables.

Table 3. Persistence of Law-of-One-Price Deviations

Under Absolute Convergence and Tests of Absolute Convergence

	World	OECD	LDC	US
Persistence ($\widehat{\rho}$)				
Mean	0.89	0.90	0.87	0.80
Median	0.89	0.91	0.88	0.82
Standard deviation	0.05	0.06	0.06	0.13
Half-lives (years)				
Mean	7.18	9.49	6.82	10.7
Median	6.12	7.52	5.28	3.41
Standard deviation	5.78	8.02	9.82	50.0
Rejections of absolute convergence				
10% level	1.00	0.48	0.87	0.04
5% level	1.00	0.38	0.83	0.04
1% level	0.99	0.19	0.77	0.04
Goods	270	270	270	258
Observations	1431	253	465	78

Notes: In the upper two panels, the mean, median and standard deviation are taken across the goods used in the estimation. Thus the mean $\widehat{\rho}$ is the average of the persistence estimates across goods, with each estimate obtained by pooling all locations in the group indicated by the column heading. The lower panel contains the proportion of goods for which the null hypothesis of no individual effects is rejected using the test based on the distance between GMM objective functions evaluated at estimates under both conditional and absolute convergence. The half-life is computed as $h_m = \ln(0.5)/\ln \rho_m$.

Table 4. Persistence of Law-of-One-Price Deviations

	World	OECD	LDC	US
Persistence ($\widehat{\rho}$)				
Mean good	0.50	0.52	0.45	0.48
Median good	0.52	0.53	0.45	0.49
Standard deviation	0.14	0.19	0.14	0.18
Half-lives (years)				
Mean good	1.12	1.37	0.95	1.20
Median good	1.04	1.09	0.86	0.97
Standard deviation	0.47	0.92	0.41	0.99
Goods	270	270	270	258
Observations	1431	253	465	78

Note: In the upper two panels, the mean, median and standard deviation are taken across the goods used in the estimation. Thus the mean $\widehat{\rho}$ is the average of the persistence estimates across goods, with each estimate obtained by pooling all locations in the group indicated by the column heading. Observations refers to median number of bilateral prices across goods.

Table 5. Persistence of Law-of-One-Price Deviations For Traded and Non-Traded Goods

	World		OECD		LDC		US	
	Traded	Non-traded	Traded	Non-traded	Traded	Non-traded	Traded	Non-traded
Persistence ($\widehat{\rho}$)								
Mean	0.49	0.57	0.49	0.63	0.44	0.50	0.48	0.51
Median	0.50	0.57	0.50	0.66	0.43	0.50	0.48	0.52
Standard deviation	0.13	0.13	0.18	0.17	0.13	0.13	0.17	0.21
Half lives (years)								
Mean	1.06	1.35	1.20	1.94	0.91	1.10	1.16	1.35
Median	1.00	1.23	1.01	1.67	0.83	1.01	0.95	1.07
Standard deviation	0.43	0.53	0.77	1.16	0.38	0.48	0.99	0.97
Goods	213	60	210	60	210	60	204	54
Observations	1431	1485	253	253	465	545	78	78

Note: See notes to Table 4.

Table 6. Persistence of Purchasing Power Parity Deviations

	OECD	LDC	US
Persistence ($\widehat{\rho}$)			
Median good	0.51	0.54	0.52
CPI-weights	0.64	0.51	0.45
	(0.02)	(0.02)	(0.03)
Equal weights	0.62	0.55	0.61
	(0.01)	(0.01)	(0.02)
Common weights	0.77	0.65	0.67
	(0.01)	(0.01)	(0.02)
Half-lives (years)			
Median good	1.01	1.14	1.05
CPI-weights	1.53	1.04	0.86
	(0.08)	(0.05)	(0.08)
Equal weights	1.46	1.18	1.39
	(0.05)	(0.03)	(0.12)
Common weights	2.71	1.58	1.72
	(0.17)	(0.05)	(0.14)
Goods	174	64	191
Observations	253	171	78

Note: See notes to Table 4.

Table 7. Persistence of Purchasing Power Parity Deviations For Traded and Non-Traded Aggregates

	OECD		LDC		US	
	Traded	Non-traded	Traded	Non-traded	Traded	Non-traded
Persistence ($\widehat{\rho}$)						
Median good	0.49	0.64	0.53	0.56	0.49	0.58
CPI-weights	0.68	0.74	0.61	0.68	0.28	0.64
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)
Equal weights	0.60	0.77	0.49	0.61	0.62	0.49
	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)
Common weights	0.69	0.83	0.66	0.59	0.37	0.71
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Half lives (years)						
Median good	0.96	1.57	1.08	1.21	0.96	1.27
CPI-weights	1.82	2.32	1.41	1.82	0.54	1.57
	(0.09)	(0.11)	(0.05)	(0.07)	(0.04)	(0.09)
Equal weights	1.36	2.68	0.97	1.40	1.43	0.98
	(0.05)	(0.20)	(0.03)	(0.04)	(0.08)	(0.04)
Common weights	1.86	3.68	1.69	1.29	0.70	1.99
	(0.08)	(0.32)	(0.07)	(0.04)	(0.04)	(0.08)
Goods	139	35	44	20	160	31
Observations	253	253	171	171	78	78

Note: See notes to Table 4.

Table 8. Persistence of Law-of-One-Price Deviations
Assuming Conditional Convergence (LSDV Estimates)

	World	OECD	LDC	US
Persistence ($\widehat{\rho}$)				
Mean	0.52	0.53	0.51	0.53
Median	0.53	0.54	0.52	0.54
Standard deviation	0.10	0.13	0.12	0.17
Half-lives (years)				
Mean	1.05	1.26	1.03	1.34
Median	1.07	1.12	1.04	1.12
Standard deviation	0.92	0.92	0.98	0.91
Goods	270	270	270	236
Observations	1431	253	465	78

Note: See notes to Table 4.

Table 9. Persistence of Law-of-One-Price Deviations For Traded and Non-Traded Goods

(LSDV Estimates)

	World		OECD		LDC		US	
	T	NT	T	NT	T	NT	T	NT
Persistence ($\widehat{\rho}$)								
Mean	0.50	0.58	0.51	0.60	0.49	0.58	0.51	0.62
Median	0.51	0.57	0.52	0.61	0.49	0.56	0.53	0.62
Standard deviation	0.09	0.10	0.13	0.13	0.11	0.14	0.16	0.16
Half-lives								
Mean	1.05	1.07	1.15	1.65	1.05	0.97	1.20	1.88
Median	1.02	1.20	1.07	1.40	0.98	1.18	1.08	1.45
Standard deviation	0.29	1.88	0.54	1.63	0.44	1.93	0.73	1.28
Goods	213	60	210	60	210	60	204	54
Observations	1431	1485	253	253	465	545	78	78

Note: See notes to Table 4.

Figure 1. International and Intranational Price in 2000

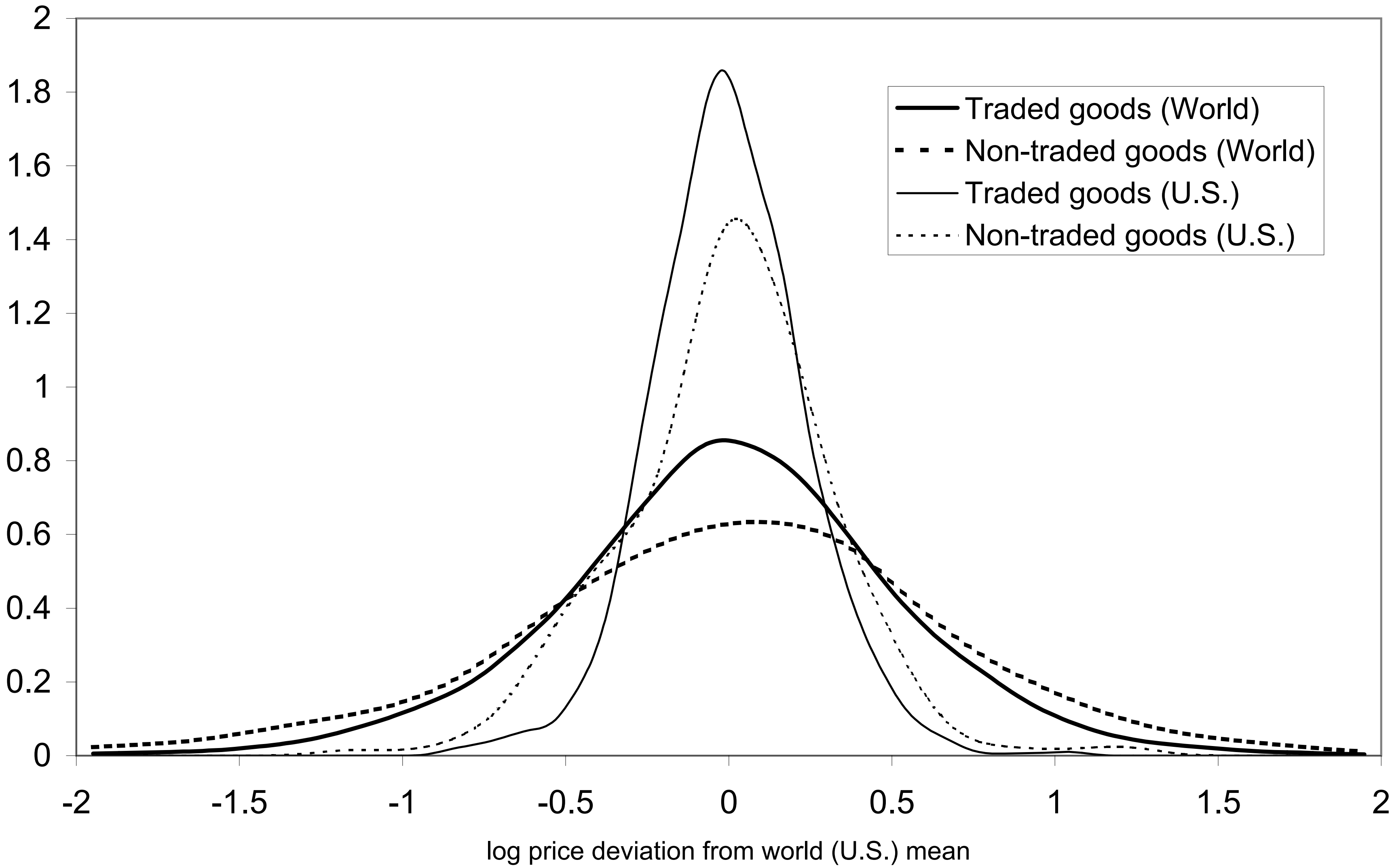

Figure 2. Persistence of All Goods

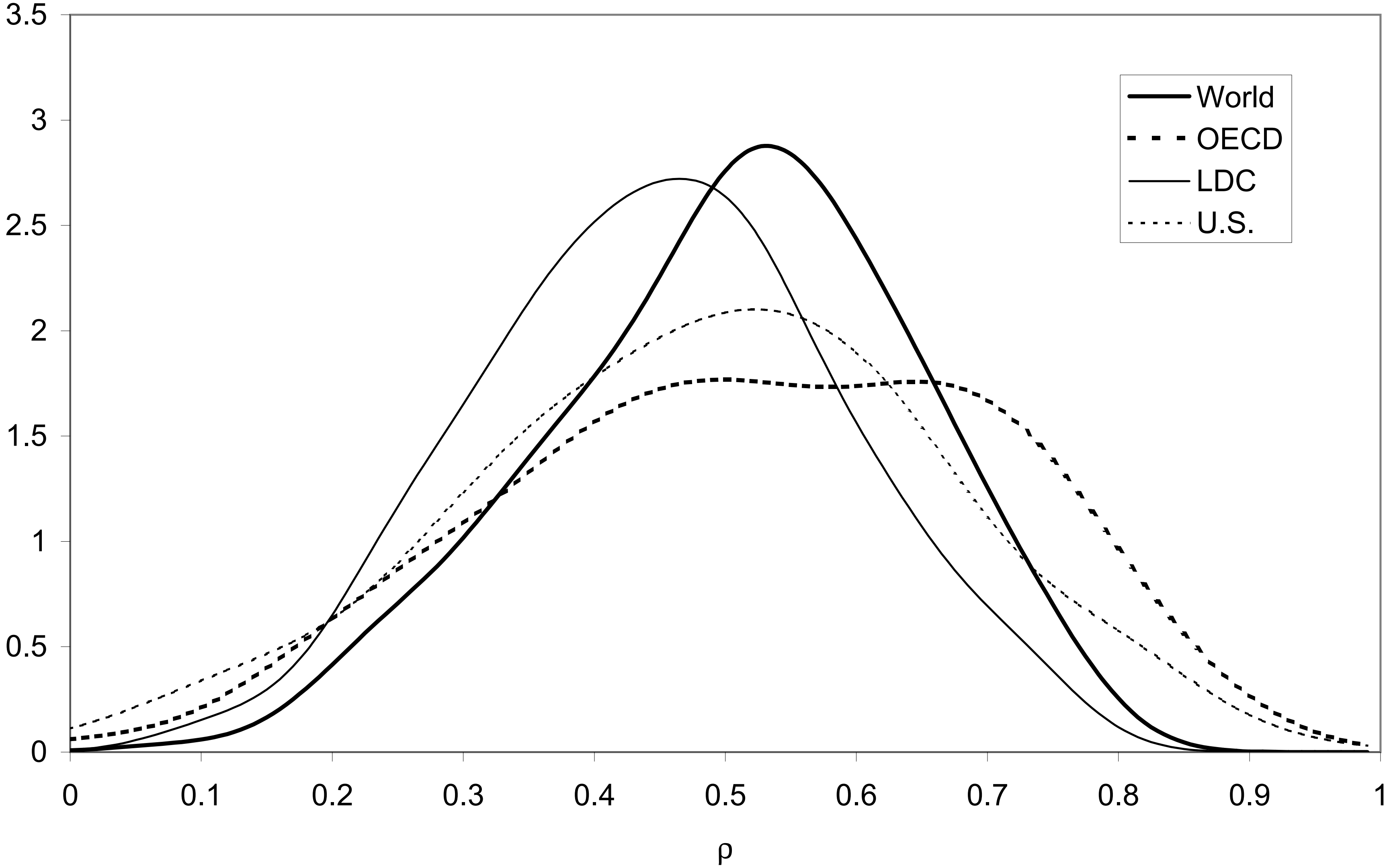

Figure 3. Persistence of Traded and Non-traded Goods: World and U.S.

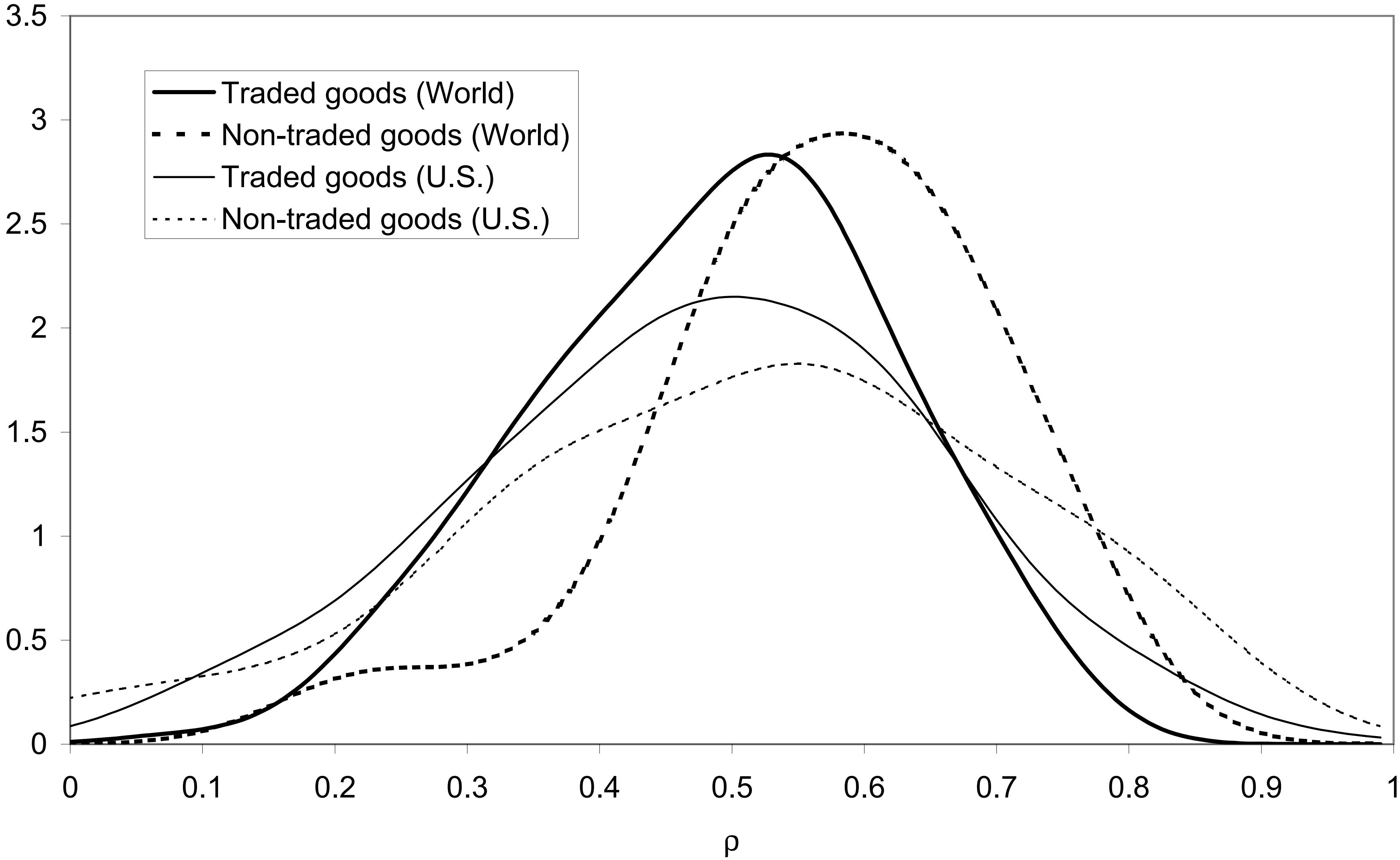

Figure 4. Persistence of Traded and Non-traded Goods: OECD and LDCs

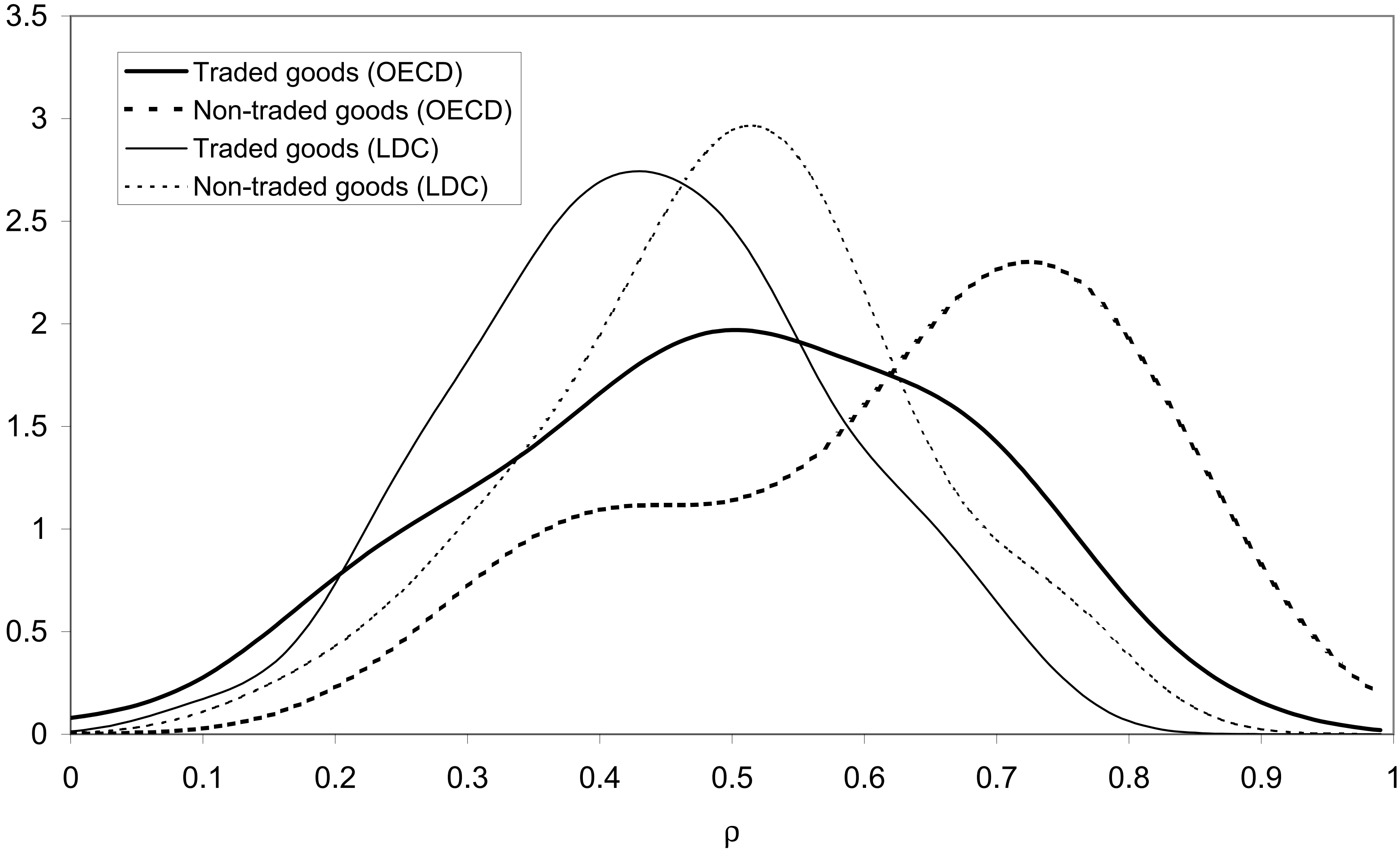

Table A1. List of Individual Goods

Goods-name	ρ	Goods-name	ρ
[T] White bread (1 kg) *	0.67	[T] Fresh fish (1 kg) *	0.63
[T] Butter (500 g) *	0.38	[T] Instant coffee (125 g) *	0.50
[T] Margarine (500g) *	0.45	[T] Ground coffee (500 g) *	0.30
[T] White rice (1 kg) *	0.52	[T] Tea bags (25 bags) *	0.48
[T] Spaghetti (1 kg) *	0.47	[T] Cocoa (250 g) *	0.51
[T] Flour, white (1 kg) *	0.52	[T] Drinking chocolate (500 g) *	0.52
[T] Sugar, white (1 kg) *	0.42	[T] Coca-Cola (1 ℓ) *	0.41
[T] Cheese, imported (500 g) *	0.53	[T] Tonic water (200 mℓ) *	0.31
[T] Cornflakes (375 g) *	0.42	[T] Mineral water (1 ℓ) *	0.54
[T] Milk, pasteurized (1 ℓ) *	0.54	[T] Orange juice (1 ℓ) *	0.50
[T] Olive oil (1 ℓ) *	0.49	[T] Wine, superior quality (700 mℓ) *	0.56
[T] Peanut or corn oil (1 ℓ) *	0.37	[T] Wine, fine quality (700 mℓ) *	0.66
[T] Potatoes (2 kg) *	0.35	[T] Beer, local brand (1 ℓ) *	0.59
[T] Onions (1 kg) *	0.37	[T] Beer, top quality (330 mℓ) *	0.59
[T] Tomatoes (1 kg) *	0.12	[T] Scotch whisky, six years old (700 mℓ) *	0.35
[T] Carrots (1 kg) *	0.38	[T] Gin, Gilbey's or equivalent (700 mℓ) *	0.60
[T] Oranges (1 kg) *	0.45	[T] Vermouth, Martini & Rossi (1 ℓ) *	0.62
[T] Apples (1 kg) *	0.46	[T] Cognac, French VSOP (700 mℓ) *	0.54
[T] Lemons (1 kg) *	0.31	[T] Liqueur, Cointreau (700 mℓ) *	0.58
[T] Bananas (1 kg) *	0.25	[T] Soap (100 g) *	0.46
[T] Lettuce (one) *	0.29	[T] Laundry detergent (3 ℓ) *	0.42
[T] Eggs (12) *	0.39	[T] Toilet tissue (two rolls) *	0.54
[T] Peas, canned (250 g) *	0.39	[T] Dishwashing liquid (750 mℓ) *	0.60
[T] Tomatoes, canned (250 g) *	0.30	[T] Insect-killer spray (330 g) *	0.51
[T] Peaches, canned (500 g) *	0.27	[T] Light bulbs (two, 60 watts) *	0.39
[T] Sliced pineapples, canned (500 g) *	0.51	[T] Batteries (two, size D/LR20) *	0.56
[T] Beef: filet mignon (1 kg) *	0.52	[T] Frying pan (Teflon or good equivalent) *	0.45
[T] Beef: steak, entrecote (1 kg) *	0.33	[T] Electric toaster (for two slices) *	0.32
[T] Beef: stewing, shoulder (1 kg) *	0.41	[NT] Laundry (one shirt) *	0.44
[T] Beef: roast (1 kg) *	0.54	[NT] Dry cleaning, man's suit *	0.52
[T] Beef: ground or minced (1 kg) *	0.46	[NT] Dry cleaning, woman's dress *	0.44
[T] Veal: chops (1 kg) *	0.45	[NT] Dry cleaning, trousers *	0.62
[T] Veal: fillet (1 kg) *	0.35	[T] Aspirins (100 tablets) *	0.32
[T] Veal: roast (1 kg) *	0.50	[T] Razor blades (five pieces) *	0.39
[T] Lamb: leg (1 kg) *	0.47	[T] Toothpaste with fluoride (120 g) *	0.55
[T] Lamb: chops (1 kg) *	0.47	[T] Facial tissues (box of 100) *	0.52
[T] Lamb: Stewing (1 kg) *	0.45	[T] Hand lotion (125 mℓ) *	0.54
[T] Pork: chops (1 kg) *	0.46	[T] Lipstick (deluxe type) *	0.40
[T] Pork: loin (1 kg) *	0.49	[NT] Man's haircut (tips included)	0.50
[T] Ham: whole (1 kg) *	0.57	[NT] Woman's cut & blow dry (tips included)	0.52
[T] Bacon (1 kg) *	0.59	[T] Cigarettes, Marlboro (pack of 20) *	0.55
[T] Chicken: frozen (1 kg) *	0.57	[T] Cigarettes, local brand (pack of 20) *	0.26
[T] Chicken: fresh (1 kg) *	0.59	[T] Pipe tobacco (50 g)	0.51
[T] Frozen fish fingers (1 kg) *	0.58	[NT] Telephone and line, monthly rental	0.73

Table A1. (continued)

Goods-name	ρ	Goods-name	ρ
[NT] Telephone, charge per local call (3 min)	0.59	[NT] Visit of four people to a nightclub	0.61
[NT] Electricity, monthly bill	0.56	[NT] Four best seats at theatre or concert	0.54
[NT] Gas, monthly bill	0.73	[NT] Four best seats at cinema	0.63
[NT] Water, monthly bill	0.78	[T] Low priced car (900-1299 cc) *	0.33
[NT] Heating oil (100 ℓ)	0.50	[T] Compact car (1300-1799 cc) *	0.42
[T] Business suit, two piece, medium weight *	0.73	[T] Family car (1800-2499 cc) *	0.54
[T] Business shirt, white *	0.65	[T] Deluxe car (2500 cc upwards) *	0.32
[T] Men's shoes, business wear *	0.70	[NT] Yearly road tax or registration fee *	0.44
[T] Mens raincoat, Burberry type *	0.63	[NT] Cost of a tune up (but no major repairs) *	0.73
[T] Socks, wool mixture *	0.64	[NT] Annual premium for car insurance *	0.62
[T] Dress, ready to wear, daytime *	0.64	[T] Regular unleaded petrol (1 ℓ)	0.41
[T] Women's shoes, town *	0.65	[NT] Taxi: initial meter charge	0.22
[T] Women's cardigan sweater *	0.68	[NT] Taxi rate per additional kilometre	0.48
[T] Women's raincoat, Burberry type *	0.69	[NT] Taxi: airport to city centre	0.19
[T] Tights, panty hose *	0.50	[NT] Furnished residential apartment: 1 bedroom *	0.74
[T] Child's jeans *	0.58	[NT] Furnished residential apartment: 2 bedroom *	0.64
[T] Child's shoes, dresswear *	0.54	[NT] Unfurnished residential apartment: 2 bedrooms *	0.64
[T] Child's shoes, sportswear *	0.59	[NT] Unfurnished residential apartment: 3 bedrooms *	0.67
[T] Girl's dress *	0.52	[NT] Unfurnished residential apartment: 4 bedrooms *	0.60
[T] Boy's jacket, smart *	0.71	[NT] Furnished residential house: 3 bedrooms *	0.53
[T] Boy's dress trousers *	0.63	[NT] Unfurnished residential house: 3 bedrooms *	0.49
[NT] Hourly rate for domestic cleaning help	0.65	[NT] Unfurnished residential house: 4 bedrooms *	0.50
[NT] Maid's monthly wages (full time)	0.25	[NT] Business trip, typical daily cost	0.64
[NT] Babysitter's rate per hour	0.76	[NT] Hilton-type hotel, single room, 1 night	0.55
[T] Compact disc album	0.55	[NT] Moderate hotel, single room, 1 night	0.60
[T] Television, colour (66 cm)	0.43	[NT] One drink at bar of first class hotel	0.50
[T] Kodak colour film (36 exposures)	0.41	[NT] Two-course meal for two people	0.56
[NT] Cost of developing 36 colour pictures	0.67	[NT] Simple meal for one person	0.66
[T] International foreign daily newspaper	0.21	[NT] Hire car, weekly rate for lowest classification	0.31
[NT] Daily local newspaper	0.55	[NT] Hire car, weekly rate for moderate classification	0.46
[T] International weekly news magazine (Time)	0.49	[NT] One good seat at cinema	0.63
[T] Paperback novel (at bookstore)	0.65	[NT] Average cost of labor per hour	0.72
[NT] Three course dinner for four people	0.61		

Notes: Traded and non-traded goods are indicated by T and NT in brackets, respectively. * indicates the good with multiple price observations. GMM estimates of ρ are obtained using all the available countries. Estimates for goods with multiple price observations are averages.