The Persistence in Deviations from the Law of One Price

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Abstract

In this paper, we measure the persistence in deviations from the law of one price using data from a number of recent empirical studies. We measure persistence using the sum of the autoregressive coefficients in the AR(*p*) representation of deviations from the law of one price, and we focus on the lower bound of the 90% confidence interval for the sum of the autoregressive coefficients, as this represents the lowest degree of persistence consistent with the data. Our results indicate that deviations from the law of one price are typically quite persistence across locations in different countries, even for putatively traded goods. In contrast, deviations from the law of one price across locations within a country are often transient. Our results thus point to a border effect with respect to the persistence in deviations from the law of one price. We formally test for a border effect by estimating cross-sectional regression models, and we find that crossing an international border significantly increases the persistence in deviations from the law of one price for many types of consumer goods and services. We discuss the implications of our results for recently developed theoretical models in international macroeconomics.

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1. Introduction

Partly stimulated by the earlier findings of, among others, Isard (1977), Richardson (1978), Dornbusch (1987), and Giovannini (1988), the last decade has witnessed the emergence of a substantial empirical literature investigating international deviations from the law of one price (LOOP) and their implications for models of real exchange rate behavior. This literature is typified by two empirical approaches. Following Engel (1993), the first approach measures the volatility in deviations from the LOOP. Interestingly, this approach documents substantial volatility in deviations from the LOOP across countries. For example, Engel (1993) shows that the volatility in deviations from the LOOP for similar goods across countries—even putatively traded goods—is much greater than the volatility in relative prices of different goods within a country. This result suggests that fluctuations in real exchange rates (deviations from purchasing power parity) are not primarily due to changes in relative prices within countries and thus is at odds with the “standard” explanation of real exchange rate fluctuations offered by Balassa (1964) and Samuelson (1964). Other papers measuring the volatility in deviations from the LOOP include the well-known study by Engel and Rogers (1996), who use CPI data for 14 categories of consumer prices for U.S. and Canadian cities; Parsley and Wei (2001a), who use the prices of 27 traded goods for U.S. and Japanese cities; Engel and Rogers (2001a), who use aggregate and disaggregated CPI data for European cities and countries; Parsley and Wei (2001b), who use the prices of 95 very disaggregated goods for 83 cities around the world. In line with Engel (1993), these studies document a large “border effect”: after controlling for distance, the volatility in deviations from the LOOP—even for goods that are typically classified as traded—is much higher between locations that lie across a border.

The second approach followed in the recent empirical literature stems from Engel (1999), who decomposes real exchange rate fluctuations into two parts: the part due to fluctuations in the relative price of traded goods between two countries and that due to fluctuations in the relative price of nontraded to traded goods prices within each country. Perhaps surprisingly, Engel (1999) finds that bilateral real exchange rate fluctuations among the G6 countries are nearly entirely due to fluctuations in the relative price of traded goods between countries. Again, this stands in sharp contrast to the standard Balassa-

Samuelson story and indicates that real exchange rate fluctuations are almost solely the result of deviations from the LOOP across countries. Other studies following Engel (1999) include Parsley (2003), who decomposes bilateral real exchange fluctuations among 21 Asian-Pacific economies, and Betts and Kehoe (2001), who examine 1,326 bilateral real exchange rates among 52 countries from 1980-2000. These studies obtain results that are generally similar to those in Engel (1999), in that fluctuations in the relative price of traded goods between countries account for most of the movements in bilateral real exchange rates. In a similar vein, Engel (2000) shows that changes in nominal exchange rates are usually strongly correlated with movements in the relative price of traded goods across countries, again pointing to significant deviations from the LOOP.

As emphasized by Engel (2002a,b), the recent empirical literature has important implications for theoretical models in international macroeconomics, especially those of the so-called “new open-economy macroeconomics” (NOEM) variety. NOEM models are characterized by an optimization-based dynamic general equilibrium framework and some form of sticky prices and/or wages in some sectors of the economy.[1] In what is generally regarded as the seminal NOEM model, Ostfeld and Rogoff (1995) assume that producers set prices in the domestic currency and that the law of one price prevails at all times for traded goods (so-called “producer-currency pricing”).[2] These assumptions turn out to be important, as they open up an “expenditure-switching” channel whereby a domestic monetary expansion causes a depreciation of the domestic currency that increases the demand for domestically produced goods. Such an expenditure-switching channel also characterizes the traditional Mundell-Fleming-Dornbusch model (Engel, 2000), and it provides a theoretical argument against fixing the nominal exchange rate (Obstfeld and Rogoff, 2002; Engel, 2002a,b). However, given the large violations of the law of one price found in the recent empirical literature, a number of NOEM models assume that international goods markets are highly segmented, with firms setting prices in the currency of the buyer’s country (so-called “local-currency pricing”); see, for example, Betts and Devereaux (1996, 2000) and Bachetta and van Wincoop

[1] See Lane (2001), Lane and Ganelli (2002), and Bowman and Doyle (2003) for useful surveys of the NOEM literature.
[2] Under producer-currency pricing, there is complete nominal exchange rate pass-through.

(2000). Under local-currency pricing, the LOOP no longer holds, and the expenditure-switching channel is eliminated.[3] This has important implications for monetary policy, as local-currency pricing can imply that a degree of nominal exchange rate stability is optimal (Engel, 2002b).

While the recent empirical literature typically investigates international deviations from the LOOP by measuring the volatility of deviations from the LOOP or decomposing real exchange rate fluctuations, we generate measures of the *persistence* in deviations from the LOOP in the present paper. We view measures of the persistence in deviations from the LOOP as a useful complement to the metrics typically used in the extant literature. For example, while deviations from the LOOP have been found to be highly volatile in the recent empirical literature, this does not necessarily imply that they are persistent.[4] Measuring the persistence in deviations from the LOOP is likely to be particularly useful in determining whether the assumption of producer-currency pricing or the assumption of local-currency pricing is more appropriate in NOEM models. Even though the recent empirical literature points to sizable deviations from the LOOP across countries, if deviations from the LOOP are quickly corrected, the assumption of producer-currency pricing may nevertheless be a "safe" working hypothesis in NOEM models. However, if deviations from the LOOP across countries are sizable *and* highly persistent, the assumption of producer-currency pricing in NOEM models could be quite misleading, and the assumption of local-currency pricing would likely be more appropriate. Our measures of the persistence in deviations from the LOOP across international locations also serve as a complement to the empirical literature that measures the persistence in real exchange rates based on overall country-wide CPI data (Cheung and Lai, 2000; Kilian and Zha, 2002; Murray and Papell, 2002).

We measure the persistence in deviations from the LOOP using the monthly data from Engel (1999, 2000) and Engel and Rogers (1996, 2001a). The data employed in these studies include highly disaggregated CPI data for a large number of international locations, and this enables us to generate measures of the persistence in deviations in the LOOP for a variety of consumer goods and services

[3] Under local-currency pricing, there is zero exchange rate pass-through.
[4] In the context of deviations from the LOOP, see the discussion in Engel and Rogers (2001b, p. 9).

across a large number of international locations. We also measure the persistence in deviations from the LOOP using the highly disaggregated CPI data for a large number of U.S. cities in Engel and Rogers (2001b). The U.S. economy is typically viewed as being highly integrated, so that deviations from the LOOP across a large variety of goods and services and U.S. cities can provide us with a benchmark of sorts. The extant study closest to ours in its approach is Rogers and Jenkins (1995), which includes measures of the persistence in deviations from the LOOP using disaggregated country-wide consumer price data for 54 categories of goods and services in the U.S. and Canada. The present paper significantly expands the scope of Rogers and Jenkins (1995) by using data from a number of recent studies that cover a wide range of international locations. We also use a recently developed econometric procedure not available to Rogers and Jenkins (1995).

As a scalar measure of persistence, we focus on the sum of the autoregressive (AR) coefficients in the AR(p) representation of deviations from the LOOP. Andrews and Chen (1994) argue that the sum of the AR coefficients is an informative metric for the persistence in an AR(p) process, as it measures the cumulative impulse response function (the sum of the impulse response function over all time horizons).[5] Andrews and Chen (1994) view the sum of the AR coefficients as a more informative measure of persistence than the largest root of the AR(p) process, as two AR(p) processes with identical largest roots can nonetheless have very different persistence properties.[6] We are interested in constructing a 90% confidence interval for the sum of the AR coefficients, and we pay particular attention to the lower bound of the 90% confidence interval. The lower bound of the 90% confidence interval for the sum of the AR coefficients represents *the lowest degree of persistence in deviations from the LOOP consistent with the data*. Expressed equivalently, it represents an upper bound on how quickly deviations from the LOOP are corrected. If the lower bound of the 90% confidence interval for the sum of the AR coefficients is large, we can conclude that there is no support in the data for deviations from price parity being quickly

[5] Andrews and Chen (1994) also point out that the sum of the AR coefficients is directly related to the spectrum at frequency zero.
[6] Rogers and Jenkins (1995) measure persistence using the largest AR root and the procedure in Stock (1991) to construct confidence intervals for the largest AR root.

corrected. We also calculate the half-life (the number of periods required for a unit shock to dissipate by 0.5) associated with the lower bound of the 90% confidence interval for the sum of the AR coefficients, as the half-life is a popular measure of persistence in the empirical literature on real exchange rate behavior.

There is a well-known econometric difficulty in constructing confidence intervals for the sum of the AR coefficients: conventional asymptotic or bootstrap confidence intervals are not valid for this measure of persistence when the data are generated by a nearly integrated process. In order to construct confidence intervals for the sum of the AR coefficients that provide correct first-order asymptotic coverage, we employ the recently developed Romano and Wolf (2001) subsampling procedure. Andrews and Chen (1994), Hansen (1999), and Gospodinov (2002) also develop procedures for constructing confidence intervals for the sum of the AR coefficients that achieve correct first-order asymptotic coverage. However, these alternative procedures require the disturbance term in the AR(p) process to be independently and identically distributed (iid),[7] while the Romano and Wolf (2001) subsampling procedure allows for dependencies in the disturbance term. In Monte Carlo simulations, Romano and Wolf (2001) find that their subsampling procedure for constructing asymptotically valid confidence intervals also has good coverage in finite samples. In Section 2 below, we conduct a small Monte Carlo experiment that confirms that the Romano and Wolf (2001) subsampling procedure has reasonably good coverage for sample sizes corresponding to those used in the present paper.

In general, our empirical results indicate that deviations from the LOOP across countries are typically quite persistent. Using the monthly CPI data for 14 categories of consumer goods and services in Canadian and U.S. cities from Engel and Rogers (1996), the mean of the lower bound of the 90% confidence interval for the sum of the AR coefficients exceeds 0.95 (and the mean of the corresponding half-life often exceeds 18 months) for a number of categories for pairs of cities that lie across the Canadian-U.S. border. In contrast, deviations from the LOOP between Canadian city pairs or U.S. city pairs are noticeably less persistent, with the mean of the lower bound of the 90% confidence interval for

[7] The Stock (1991) procedure for constructing confidence intervals for the largest AR root also requires the iid assumption, while the Andrews and Chen (1994) procedure requires the additional assumption that the disturbance term is normally distributed.

the sum of the AR coefficients often less than 0.90 and the mean of the corresponding half-life often less than six months. Analogous to Engel and Rogers (1996), we document a border effect by showing that, after controlling for the distance between cities, crossing the Canadian-U.S. border significantly increases the lower bound of the 90% confidence interval for the sum of the AR coefficients for nearly all of the CPI categories considered, including those usually regarded as corresponding to traded goods. Using the monthly data for the G6 countries from Engel (1999), we find that deviations from the LOOP based on the CPI Food and All goods less food components are typically highly persistent across the G6 countries, with the lower bound of the 90% confidence interval for the sum of the AR coefficients often greater than or equal to 0.95. The lower bound on the persistence in deviations from the LOOP based on these CPI components (which are usually viewed as corresponding to traded goods) is often close to that for deviations from the LOOP based on the Rent and All services less rent components of the CPI (which are usually classified as nontraded). Using the monthly data from Engel (2000), we find that deviations from the LOOP are somewhat less persistent across European countries for a variety of consumer goods and services. The mean of the lower bound of the 90% confidence interval for the sum of the AR coefficients is below 0.94 across European countries for most of the 22 CPI categories considered, with the corresponding mean for the half-life close to or less than a year for most CPI categories. While the Engel (2000) data are consistent with deviations from the LOOP across European country pairs being less persistent than deviations across other country pairs, we still document a border effect within Europe using the aggregate CPI data for a large number of European cities from Engel and Rogers (2001a). That is, after controlling for the distance between European cities, we find a significant increase in the lower bound of the 90% confidence interval for the sum of the AR coefficients for pairs of European cities in different European countries in comparison to city pairs in the same European country. Finally, the highly disaggregated CPI data for U.S. cities in Engel and Rogers (2001b) are consistent with deviations from the LOOP within the U.S. being less persistent than deviations in the LOOP within other countries and much less persistent than deviations from the LOOP across countries.

The rest of the paper is organized as follows: Section 2 presents the econometric methodology; Section 3 reports our empirical results for the various data sets; Section 4 concludes.

2. Econometric Methodology

To fix ideas, consider the following AR(p) process for y_t:

$$y_t = \mu + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + ... + \alpha_p y_{t-p} + e_t , \qquad (1)$$

for $t = 1,2,...,T$. In Section 3 below, y_t will measure deviations from the LOOP between locations. As mentioned in the introduction, Andrews and Chen (1994) argue that the sum of the AR coefficients, $\alpha = \sum_{i=1}^{p} \alpha_i$, is an informative scalar measure of the persistence in the AR process. The variable y_t is stationary, or mean-reverting, if $|\alpha| < 1$, while y_t is a unit-root process if $\alpha = 1$. We can straightforwardly obtain a point estimate of α by rearranging equation (1) and using OLS to estimate a version of the familiar augmented Dickey and Fuller (1981, ADF) and Said and Dickey (1984) regression model,

$$y_t = \mu' + \alpha y_{t-1} + \sum_{j=1}^{p-1} \beta_j \Delta y_{t-j} + e_t , \qquad (2)$$

where $\Delta y_t = y_t - y_{t-1}$. The construction of a confidence interval for α is problematic because the asymptotic distribution of the OLS estimator (as well as its rate of convergence) is different in the stationary and unit-root cases. Strictly speaking, if $\alpha < 1$, a confidence interval for α can be constructed through conventional asymptotic methods based on the standard normal distribution. However, the conventional asymptotic procedure fares quite poorly in practice, especially if α is near unity. If fact, if we formalize the near-unit-root case in a local-to-unity framework, where $\alpha = 1 + c/T$ with c held constant as $T \to \infty$, the conventional t-statistic used to construct asymptotic confidence intervals for α has a non-standard distribution. In this case, the conventional asymptotic confidence interval is not valid asymptotically and will likely perform very poorly in finite samples (see, for example, Hansen, 1999). We cannot circumvent this difficulty by relying instead on a conventional bootstrap procedure, as the conventional bootstrap will also fail to generate confidence intervals with correct first-order asymptotic coverage (Basawa et al., 1991). The problem is that the asymptotic *t*-statistic depends on *c*, and thus *α*, and is therefore non-pivotal, while the conventional bootstrap procedure implicitly assumes that the *t*-statistic is pivotal. The conventional bootstrap procedure therefore does not properly control for a Type I error.

Romano and Wolf (2001) develop a subsampling procedure for constructing a confidence interval for *α* that provides correct first-order asymptotic coverage. This approach recomputes the OLS estimator on smaller blocks, or "subsamples," of the observed data. More specifically, we begin with a block of size *b* and calculate the *t*-statistic, $\tau_b(\hat{\alpha}_{b,t} - \hat{\alpha})/\hat{\sigma}_{b,t}$, for each subsample of size *b* for $t = 1,...,T-b+1$, where $\hat{\alpha}$ is the OLS estimate of *α* in equation (2) based on the full sample of data; $\hat{\alpha}_{b,t}$ is the OLS estimates of *α* for the *t*th block of size *b*; $\hat{\sigma}_{b,t} = b^{1/2}s(\hat{\alpha}_{b,t})$, where $s(\hat{\alpha}_{b,t})$ is the standard error corresponding to $\hat{\alpha}_{b,t}$; $\tau_b = b^{1/2}$. We then generate the empirical approximating distribution for the subsample *t*-statistics,

$$L_b(x) = \frac{1}{T-b+1}\sum_{t=1}^{T-b+1} 1\{\tau_b(\hat{\alpha}_{b,t} - \hat{\alpha})/\hat{\sigma}_{b,t} \le x\}. \tag{3}$$

Let $c_{b,0.05}$ and $c_{b,0.95}$ be the 0.05 and 0.95 quantiles of the subsampling distribution, equation (3). A 90% two-sided equal-tailed confidence interval for *α* is then given by

$$[\hat{\alpha} - (1/\tau_T)s(\hat{\alpha})c_{b,0.95}, \hat{\alpha} - (1/\tau_T)s(\hat{\alpha})c_{b,0.05}], \tag{4}$$

where $\tau_T = T^{1/2}$ and $s(\hat{\alpha})$ is the standard error corresponding to $\hat{\alpha}$. Romano and Wolf (2001) also consider the construction of a two-sided symmetric confidence interval. Instead of equation (3), we generate the empirical approximating distribution,

$$L_{b,|\cdot|}(x) = \frac{1}{T-b+1}\sum_{t=1}^{T-b+1} 1\{\tau_b\left|\hat{\alpha}_{b,t} - \hat{\alpha}\right|/\hat{\sigma}_{b,t} \le x\}. \tag{5}$$

Let $c_{b,|\cdot|,01}$ be the 0.10 quantile for the empirical distribution, equation (5). A 90% two-sided symmetric confidence interval can then be expressed as

$$[\hat{\alpha} - (1/\tau_T)s(\hat{\alpha})c_{b,|\cdot|,0.05}, \hat{\alpha} + (1/\tau_T)s(\hat{\alpha})c_{b,|\cdot|,0.1}]. \tag{6}$$

We follow Algorithm 5.1 (Minimizing Confidence Interval Volatility) in Romano and Wolf (2001, p. 1297) in order to select b. The algorithm proceeds as follows:

1. Compute a subsampling 90% confidence interval for α for each b in $b = b_{small}$ to $b = b_{big}$, yielding the endpoints $I_{b,low}$ and $I_{b,up}$ for each b. Set $b_{small} = c_1 T^{\eta}$ and $b_{big} = c_2 T^{\eta}$ for $0 < c_1 < c_2$ and $0 < \eta < 1$. Romano and Wolf (2001) recommend using $c_1 \in [0.5,1]$, $c_2 \in [2,3]$, and $\eta = 0.5$. (We set $c_1 = 1$, $c_2 = 2$, and $\eta = 0.5$.)
2. For each b, compute a volatility index, VI_b, where the volatility index is the standard deviation of the interval endpoints in a neighborhood of b. That is, for a small integer k, let VI_b equal the standard deviation of $\{I_{b-k,low},...,I_{b+k,low}\}$ plus the standard deviation of $\{I_{b-k,up},...,I_{b+k,up}\}$. Romano and Wolf recommend using $k = 2$ or $k = 3$. (We set $k = 2$.)
3. Select the value for b, b^*, with the smallest volatility index and report $[I_{b^*,low}, I_{b^*,up}]$ as the final 90% subsampling confidence interval.

In Monte Carlo simulations, Romano and Wolf (2001) find that the two-sided symmetric subsampling confidence interval has good coverage properties in finite samples and that it performs better overall than the two-sided equal-tailed subsampling confidence interval. As mentioned in the introduction, a potential advantage of the Romano and Wolf (2001) subsampling procedure is that is does not require the assumption that the disturbance term e_t in equation (2) is iid, as it is still valid for dependent processes.

We perform a small Monte Carlo experiment along the lines of Romano and Wolf (2001) in order to examine the performance of the subsampling procedure for the sample sizes we use in Section 3 below. As in Romano and Wolf (2001), we assume that y_t is generated by the process, $y_t = a + \alpha y_{t-1} + \varepsilon_t$, where $a = 0$ and $\varepsilon_t \sim N(0,1)$. Table 1 reports estimated coverage rates and median confidence interval lengths for the equal-tailed and symmetric 90% subsampling confidence intervals, as well as a 90% confidence interval based on standard asymptotic theory, for various sample sizes and values of α. The results are based on 1,000 Monte Carlo replications and are similar to those reported in Romano in Wolf (2001).

Looking at column (4) of Table 1, the symmetric subsampling confidence interval performs well overall, although it appear to undercover slightly for the case of an exact unit root (α = 1) and for the α = 0.99 case and smaller sample sizes. From column (2) of Table 1, we see that the equal-tailed subsampling confidence interval has coverage rates well below 0.90 when $\alpha \leq 0.90$ for all of the sample sizes considered. As can be seen from column (6) of Table 1, the confidence interval based on standard asymptotic theory undercovers severely in the unit-root and near-unit-root cases, as indicated by theory. Overall, the symmetric subsampling confidence interval seems to possess reasonably good coverage properties for a wide range of α values and sample sizes corresponding to the data sets that we use in Section 3 below.

As indicated in the introduction, we concentrate on the lower bound of the symmetric subsampling 90% confidence interval for α. We also report the half-life corresponding to the lower bound of the symmetric subsampling 90% confidence interval for α. The half-life is calculated from the impulse response function and is defined as the number of periods (months) required for a unit shock to dissipate by 0.5: $\sup_{l \in L} \left| \frac{\partial y_{t+l}}{\partial e_t} \right| \geq 0.5$.[8]

3. Empirical Results

3.1. Engel and Rogers (1996) Canadian and U.S. City Data

Engel and Rogers (1996) employ monthly CPI data disaggregated into 14 categories of goods and services for 9 Canadian and 14 U.S. cities covering the period June 1978 to December 1994. They find that the volatility of deviations from the LOOP between U.S. city pairs is generally slightly higher than between Canadian city pairs. Most dramatically, deviations from the LOOP for cross-border city pairs have much higher volatility than deviations between cities within the same country (the border effect).

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[8] The half-life is commonly computed as $\ln(0.5)/\ln(\alpha)$. However, this measure requires the adjustment to be monotonic, which may not be true for the data. In our empirical applications in Section 3 below, we select the lag order (p) in equation (2) using the modified AIC of Ng and Perron (2001).

We use the Engel and Rogers (1996) data for nine Canadian cities (Calgary, Edmonton, Montreal, Ottawa, Quebec, Regina, Toronto, Vancouver, Winnipeg) and the four U.S. cities for which continuous monthly data are available (New York, Chicago, Philadelphia, Los Angeles). Using this data, we investigate the degree of persistence in deviations from the LOOP, where the deviations are measured as the log-level of the ratio of U.S. dollar price of a given consumption category in two different cities.[9] Table 2 reports the mean of the lower bound of the symmetric subsampling 90% confidence interval for α across city pairs for each of the 14 CPI categories, as well as the aggregate CPI. We also report the mean of the half-life corresponding to the lower bound of the confidence interval for α. In columns (2) and (3), we report the mean α lower bound and the mean for the corresponding half-life, respectively, for all combinations of all cities. In columns (4) and (5), we report results for all combinations of Canadian-Canadian cities, in columns (6) and (7) for all combinations of Canadian-U.S. cities, and in columns (8) and (9) for all combinations of U.S.-U.S. cities.

When we consider all city pairs in column (2) of Table 2, we see that the mean α lower bound is at least 0.90 for all categories, with the exceptions of categories 7 (Men’s and boy’s apparel), 8 (Women’s and girl’s apparel), 9 (Footwear), and 11 (Transportation). From column (3), we see that the mean of the corresponding half-life is greater than 9 months for most categories, again with the exceptions of categories 7, 8, 9, and 11, which are all less than 6 months. However, the results in columns (2) and (3) mask important differences between city pairs lying within a given country and pairs lying across the Canadian-U.S. border. When we compare columns (4) and (5) and (8) and (9) with columns (6) and (7) of Table 2, it appears that deviations in the LOOP between cities lying across the border are considerably more persistent than deviations from the LOOP between cities lying within the same country. For Canadian-U.S. city pairs, the mean α lower bound is above 0.90 for all categories and greater than or equal to 0.95 for 10 of the 14 categories. In addition, many of the mean half-life lower bounds are longer

[9] Given that we are working with CPIs, we cannot measure absolute deviations from the LOOP, but only relative deviations. This provides a rationale for including a constant term in equations (1) and (2). A constant term also allows for a permanent wedge between prices due, for example, to various types of transport costs, tax differentials, etc.

than a year for the Canadian-U.S. city pairs. In contrast, for Canadian-Canadian or U.S.-U.S. city pairs, the mean α lower bound is less than or equal to 0.90 for 11 of the 14 categories, and the mean half-life lower bound is less than a year for 13 of the 14 categories.

Figure 1 provides a visual perspective on the differences in persistence between city pairs within Canada or the U.S. and pairs of cities lying across the border. The solid line in each panel portrays the distribution of the α lower bounds for Canadian-Canadian and U.S.-U.S. city pairs, while the dashed line graphs the distribution for Canadian-U.S. city pairs.[10] With the exception of Panel 4 (Shelter), most of the distribution for the Canadian-Canadian and U.S.-U.S. city pairs lies to the left of the distribution for the Canadian-U.S. city pairs (which is typically concentrated just below unity).

In order to examine the border effect more formally, we estimate a regression model for each CPI category that is analogous to the cross-sectional volatility regression model in Engel and Rogers (1996). For each CPI category, Engel and Rogers (1996) regress the volatility in deviations from the LOOP for each city pair on the log-level of the distance between cities, a dummy variable that takes a value of unity if the cities are in different countries and zero otherwise, and a set of city-specific dummy variables. It is important to control for distance when testing for a border effect, as transport costs are likely to be higher for cities that are farther apart.[11] For each cross-sectional regression model, Engel and Rogers (1996) find that the coefficient on the border dummy is positive and highly significant, indicating that, after controlling for distance, crossing the border significantly increases the volatility of deviations from the LOOP (Engel and Rogers, 1996, Table 3). We estimate a similar cross-sectional regression model for each CPI category, but we use the α lower bound for each city pair (or the corresponding half-life lower bound) in place of volatility as the dependent variable in the regression model.[12]

[10] In order to obtain fairly smooth distributions, the distributions were calculated using a nonparametric kernel density estimator.
[11] Distance is measured using the great-circle distance. Engel and Rogers (1996) allow for city-specific dummy variables in order to account for possible idiosyncratic measurement error or seasonalities in some cities.
[12] Following Engel and Rogers (1996), we use the White (1980) procedure to account for heteroskedasticity in the standard errors and *t*-statistics for the coefficient estimates in the cross-sectional regression models.

The cross-sectional regression results are reported in Table 3. From column (3) of Table 3, we see that the border coefficient is positive and highly significant for each category, indicating that crossing the border significantly increases the persistence in deviations from the LOOP between cities (as measured by the lower bound of the 90% confidence interval for α), even after we control for the distance between cities. For a number of categories, the border coefficient in column (3) is near 0.10 indicating that the lower bound of the 90% confidence interval for α increases by approximately 0.10 when we cross the Canadian-U.S. border, so that the border appears quite "wide" for a number of categories. The border coefficient is largest (0.10) in column (3) for Household furnishing and operations, Men's and boy's apparel, and Women's and girl's apparel. Like Engel and Rogers (1996) with respect to volatility, the results in Table 3 document a large border effect with respect to persistence. From column (2) of Table 3, we see that the distance coefficient is only significant for four of the 14 categories, so that the border appears more important than distance itself in generating persistent deviations from the LOOP for most consumer categories.[13]

A border effect is also evident when we measure persistence using the half-life corresponding to the α lower bound, as the border coefficient is positive and highly significant for 13 of the 14 categories in column (6) of Table 3. (The border coefficient for Shelter is "wrongly" signed and significant.) For a number of categories, crossing the border increases the half-life by around a year, so that the border again appears to be very "wide" for a number of categories. The largest border effects are found for Alcoholic beverages and Household furnishings and operations, where crossing the border (controlling for distance) leads to an increase of 20.59 months and 14.59 months, respectively, in the half-life corresponding to the α lower bound.

While we document a border effect with respect to persistence that is analogous to the Engel and Rogers (1996) border effect with respect to volatility, it is not always the case that results pertaining to

[13] Engel and Rogers (1996) obtain a significant border coefficient in their volatility regressions for 10 of the 14 categories. Distance thus appears to be less important in generating persistence than volatility in deviations from the LOOP.

persistence correspond closely to those pertaining to volatility. For example, looking back at column (6) of Table 2, we see that categories 8 (Women's and girl's apparel) and 11 (Public transportation) are the least persistent we when consider Canadian-U.S. city pairs, with each having a mean α lower bound of 0.91. However, Engel and Rogers (1996, Table 2) find that these two categories have the *highest* volatility when considering Canadian-U.S. city pairs. In this instance, the most volatile deviations from the LOOP turn out to be the least persistent. In addition, Engel and Rogers (1996, Table 3) obtain a coefficient on distance that is positive and statistically significant in their volatility regressions for 10 of the 14 categories of goods and services. However, in Table 3 of the present paper, the coefficient on distance in the α lower-bound regression (half-life lower-bound regression) is positive and significant for only 4 (2) of the CPI categories. While a border effect can be documented for all categories with respect to both volatility and persistence, distance appears important for many categories of goods and services with respect to volatility, but only a few categories with respect to persistence.

3.2. Engel (1999) G6 Data

Engel (1999) finds that deviations in the price of traded goods between countries account for almost all of the fluctuations in bilateral real exchange rates in the G6 countries. Engel (1999) uses monthly OECD data from January 1962 to December 1995 for Canada, France, Germany, Italy, Japan, and the United States for nominal exchange rates, overall CPIs, and four CPI categories (All goods less food, Food, All services less rent, Rent). We employ the same data as Engel (1999) and examine the persistence in deviations from the LOOP. We measure deviations from the LOOP as the log-level of the ratio of the U.S. dollar price of a given CPI category between two countries. In Table 4, we report estimates of the lower bound of the symmetric subsampling 90% confidence interval for α in the upper triangle of each matrix and the corresponding half-life in the lower triangle.[14]

[14] Engel (1999) reports that he typically cannot reject the unit root null hypothesis for the deviations from the LOOP.

For the all of the CPI categories, almost all of the lower bounds of the confidence intervals are greater than or equal to 0.95, so that deviations from the LOOP appear quite persistent. It is interesting to observe that the persistence in deviations for the All goods less food and Food categories, which we would typically associate with traded goods, generally display considerable persistence, with many of the lower bounds greater than 0.95 and a number of the corresponding half-lives greater than 2 years. If we compare the measures of persistence in deviations for the categories typically associated with traded goods (All goods less food and Food) to those for typically associated with nontraded goods (All services less rent and Rent), we see that the lower bounds of the confidence intervals for α, as well as the corresponding half-lives, are typically somewhat larger for nontraded goods, as we would expect. Nevertheless, deviations from the LOOP generally seem to be quite persistent when we use the Engel (1999) data, even for CPI categories usually associated with traded goods. Finally, deviations for all of the CPI categories in Table 4 are typically less persistent for European country pairs. For example, the shortest half-life for the Overall, All goods less food, All services less rent, and Rent CPI categories is for the France-Germany country pair; for the Food category, the shortest half-life is for the France-Italy country pair.

3.3. Engel (2000) European Country Data

Engel (1999) finds that the prices of various CPI categories within European countries typically do not fully respond to changes in nominal exchange rates, providing evidence of local currency pricing. Engel (2000) employs monthly CPI data for 22 categories of goods and services and nine European countries (Belgium, Denmark, Germany, Spain, France, Italy, Netherlands, Portugal, United Kingdom). The longest span of data covers the period January 1977 to December 1995, and the shortest covers the period April 1992 to July 1995. Using the Engel (2000) data, Table 5 reports the mean lower bound of the 90% confidence interval for α for deviations from the LOOP across all combinations of country pairs for each of the 22 CPI categories. Table 5 also reports the mean half-life corresponding to the lower bound of the confidence interval for α.

The mean α lower bound is greater than or equal to 0.90 for all categories, with the exception of Fruit. For 8 of the 22 categories, the mean half-life lower bound is less than a year, with the shortest mean half-life lower bounds ranging from approximately 6-8 months for Dairy products, Fruit, Fuel and energy, and Public transport. The longest mean half-life lower bounds are on the order of 19-28 months for Clothing, Clothing and footwear, and Household equipment. Overall, the results in Table 5 confirm a pattern observed in the Table 4 results, in that deviations from the LOOP across European country pairs generally appear to be less persistent than deviations from the LOOP across non-European country pairs.

3.4. Engel and Rogers (2001a) European City Data

Engel and Rogers (2001a) investigate deviations from the LOOP based on overall CPI data for 55 locations across Europe. The city-level data employed by Engel and Rogers (2001a) are only available for the overall CPI, and the data are monthly and span the period from March 1981 to July 1997. The econometric methodology used by Engel and Rogers (2001a) is similar to that of Engel and Rogers (1996), and Engel and Rogers (2001a) also document a border effect.[15] We employ the Engel and Rogers (2001a) data to investigate the degree of persistence in deviations from purchasing power parity across European cities. There are four countries (Germany, Italy, Spain, Switzerland) for which overall CPI data are available for different cities within the country. For seven other countries (France, Austria, Belgium, Denmark, Luxembourg, Netherlands, Portugal), CPI data for the country as a whole are only available, and we follow Engel and Rogers (2001a) and associate the overall CPI with the capital city of the country. Again following Engel and Rogers (2001a), we measure deviations from the LOOP between two given locations as the difference in the log-levels of the CPIs expressed in U.S. dollars.

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[15] Due to the nature of the data used in Engel and Rogers (2001a), they can separate out the border effect into the part due to changes in nominal exchange rates and that due to a "real" border effect. They find the former to be the most important.

Table 6 reports the mean lower bound of the 90% confidence interval for α, as well as the mean half-life corresponding to the lower bound, for various groups of city pairs. From Table 6, we see that the mean α lower bound for city pairs within the same country ranges from 0.92-0.94, while the corresponding mean half-life ranges from 6.78-12.43 months. The deviations appear to be more persistent for city pairs that lie across country borders, with a mean α lower bound of 0.95 and a corresponding mean half-life of 18.21 months for city pairs in different countries. As with the Engel and Rogers (1996) Canadian-U.S. city data, deviations from price parity appear more persistent across countries than within countries when we employ the Engel and Rogers (1996) European city data. Visual evidence of this is given in Figure 2, where we see that most of the distribution for the α lower bounds for city pairs within the same European country lies to the left of the distribution for city pairs in different European countries. As we did in Section 3.1, we formally test for a border effect by estimating a cross-sectional regression model. That is, we regress the α lower bound for each city pair (or the corresponding half-life) on the log-level of the distance between cities, a dummy variable that takes the value of unity if the cities are in the same country and zero otherwise, and a set of city-specific dummy variables. The results are reported in Table 7. From column (2) of Table 7, we see that crossing a border increases the α lower bound by 0.03, which is significant at any reasonable level. A border effect is also evident for the half-life regression, as crossing a border increases the half-life by 7.12 months, which again is easily significant (see column (5) of Table 7). While crossing the border significantly increases the persistence in deviations from price parity, it is interesting to note that distance does not have a significant influence on persistence (see columns (1) and (4) of Table 7).

3.5. Engel and Rogers (2001b) U.S. City Data

Engel and Rogers (2001b) use disaggregated CPI data to examine the variability in relative prices of a wide variety of goods and services across U.S. cities. We employ their monthly data for 29 U.S. cities and 41 CPI categories (in addition to the overall CPI), which begin in December 1986 and run through June

1996. We measure deviations from the LOOP as the log-level of the ratio of the value of a given CPI category between two cities. Table 8 reports the mean α lower bound and corresponding mean half-life lower bound across all city pairs for the 41 CPI categories and the overall CPI.

The first thing to notice from Table 8 is that the Engel and Rogers (2001b) U.S. city data are consistent with quite rapid adjustment to price parity when compared to the other data sets we have analyzed in Sections 3.1-3.4 above. If one views the U.S. economy as a highly integrated economy, the results in Table 8 provide a benchmark for the fastest speed of adjustment that can be expected in areas that become as integrated as the U.S. economy. Categories that have the lowest values for the mean α lower bound, ranging from 0.60 to 0.70, are Meats, Fresh fruits and vegetables, Fuels, Men and boy's apparel, Women and girl's apparel, Poultry, Fish and seafood, and Eggs. A large number of other categories have values ranging from 0.71 to 0.80. Note that the mean α lower bound is greater than 0.90 for only one category, Used cars (0.97). In terms of the mean half-life lower bound, 31 of the 42 categories (including the overall CPI) have a mean half-life lower bound of less than 5 months, and 10 other categories have a mean half-life lower bound ranging from 5-10 months. The only category with a mean half-life lower bound greater than 10 months is Used cars (32.65 months).[16]

We also estimate cross-sectional regression models that are similar to those in Engel and Rogers (2001b), who regress the volatility in deviations from the LOOP between city pairs on the distance between cities. They find that distance has a statistically significant effect on volatility for most of the CPI categories. Similar to our cross-sectional regressions in Section 3.1 and 3.4 above, we regress the α lower bound (or the corresponding half-life) on the log-level of the distance between cities and a set of city-

[16] It is somewhat difficult to compare our results with those of some extant studies that also contain measures of the persistence in deviations from the LOOP across U.S. cities, as these other studies typically rely on panel-data methods that involve homogeneity assumptions. Nevertheless, the mean α lower bounds reported in Table 8 appear to be consistent with the fairly rapid adjustments to price parity reported in Parsley and Wei (1996). Cecchetti, Mark, and Sonora (2002) report a half-life point estimate of approximately 9 years for deviations from price parity across U.S. cities (based on the overall CPI). This estimate seems too high, given that the mean half-life lower bound for the overall CPI in Table 8 is 3.30 months. We surmise that the long half-life estimate in Cecchetti, Mark, and Sonora (2002) may be due to the type of temporal aggregation bias analyzed by Taylor (2001). Taylor (2001) shows that the half-life can be seriously over-estimated if the adjustment to parity takes place during a period that is shorter than the sampling frequency of the data. Given that Cecchetti, Mark, and Sonora (2002) use annual data, it will be difficult to detect an adjustment process that takes place within months.

specific dummy variables. The results are reported in Table 9. In general, distance is not very important in explaining measures of persistence. For the α lower-bound regression, the coefficient on distance is positive and significant only for the Poultry and Alcoholic beverage categories. It takes on a significant negative value (opposite from what theory suggests) for the Fresh fruits and vegetable category. In the half-life lower-bound regression, the coefficient on distance is positive and significant for Entertainment commodities, Alcoholic beverages, and Hospital and related services (and negative and significant for Tobacco and smoking products). Although Engel and Rogers (2001b) find distance to be a significant determinant of the volatility in deviations from the LOOP for most CPI categories, we almost always find that distance has an insignificant effect on the persistence in deviations from the LOOP across U.S. cities.

4. Conclusion

In the present paper, we measure the persistence in deviations from the LOOP across a large number of international locations using monthly data from a number of recent empirical studies. We focus on the lower bound of the 90% confidence interval for α, as this represents the lowest degree of persistence in deviations from the LOOP consistent with the data. In computing confidence intervals, we employ the recently developed subsampling procedure of Romano and Wolf (2001). We find that deviations from the LOOP across countries are often very persistent, with the lower bound of the 90% confidence interval for α often greater than or equal to 0.95. In contrast, the data are consistent with deviations from the LOOP across locations within a given country being quite transient. This is especially true for deviations from the LOOP across U.S. cities. The contrast in the persistence of deviations from the LOOP for locations across countries and locations within a country indicates the existence of a border effect with respect to persistence. Using cross-sectional regressions, we show that crossing an international border significantly increases the persistence in deviations from the LOOP.

The recent empirical literature shows that deviations from the LOOP across countries are highly volatile. We add value to the recent empirical literature by showing that deviations from the LOOP across countries are also highly persistent. With respect to theoretical models in international macroeconomics, the highly volatile and highly persistent nature of deviations from the LOOP across countries provides support for the assumption of local-currency pricing—which allows for deviations from the LOOP—in theoretical models. Theoretical models that rely on producer-currency pricing—which assumes away deviations from the LOOP—fail to take account of important features of international consumer price data. While our results, along with those from the extant literature, provide support for the assumption of local-currency pricing with respect to consumer goods, Obstfeld and Rogoff (2000) and Obstfeld (2002) argue that the assumption of producer-currency pricing is more appropriate at earlier points in the production process. For example, a depreciation in the domestic currency may fail to significantly lower the price of domestically produced consumer goods relative to consumer goods produced abroad because of local-currency pricing behavior with respect to consumer goods. Nevertheless, multinational firms may find that domestic labor and other inputs become relatively cheaper, so that they shift some of their production from foreign to domestic plants. This can reopen the expenditure-switching channel closed off by local-currency pricing. We view measuring the volatility and persistent in deviations from the LOOP at earlier points in the production process as an important area for future research.

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Table 1: Estimated coverage rates and median lengths for confidence intervals calculated using subsampling procedures and standard asymptotic theory

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Subsampling, equal-tailed		Subsampling, symmetric		Standard asymptotic	
True α	Coverage rate	Median length	Coverage rate	Median length	Coverage rate	Median length
A. 115 observations						
1.00	0.85	0.08	0.83	0.12	0.55	0.08
0.99	0.85	0.09	0.85	0.14	0.66	0.09
0.95	0.80	0.11	0.89	0.17	0.82	0.12
0.90	0.76	0.13	0.90	0.19	0.85	0.15
0.80	0.77	0.17	0.91	0.23	0.88	0.20
0.60	0.78	0.22	0.88	0.26	0.88	0.25
B. 197 observations						
1.00	0.87	0.04	0.84	0.07	0.55	0.05
0.99	0.84	0.06	0.88	0.09	0.69	0.06
0.95	0.77	0.08	0.92	0.12	0.84	0.09
0.90	0.77	0.10	0.92	0.14	0.86	0.11
0.80	0.75	0.13	0.90	0.17	0.87	0.15
0.60	0.79	0.17	0.89	0.20	0.89	0.19
C. 228 observations						
1.00	0.86	0.04	0.84	0.06	0.56	0.04
0.99	0.87	0.05	0.91	0.08	0.72	0.05
0.95	0.76	0.07	0.92	0.10	0.84	0.08
0.90	0.78	0.09	0.95	0.13	0.89	0.10
0.80	0.78	0.12	0.92	0.15	0.90	0.14
0.60	0.79	0.16	0.88	0.18	0.89	0.18
D. 408 observations						
1.00	0.87	0.02	0.84	0.04	0.54	0.02
0.99	0.84	0.03	0.92	0.05	0.76	0.03
0.95	0.77	0.05	0.94	0.07	0.87	0.06
0.90	0.75	0.07	0.93	0.09	0.89	0.07
0.80	0.78	0.09	0.91	0.11	0.89	0.10
0.60	0.81	0.12	0.88	0.14	0.88	0.13

Notes: data-generating process is $y_t = a + \alpha y_{t-1} + \varepsilon_t$, where $a = 0$ and $\varepsilon_t \sim N(0,1)$; results are based on 1,000 Monte Carlo replications; columns (2), (4), and (6) report the proportion of the 90% confidence intervals that contain the true value of α; columns (3), (5), and (7) report the median length of the 90% confidence intervals.

Table 2: Lower bounds of symmetric subsampling 90% confidence intervals for α and corresponding half-lives, Engel and Rogers (1996) Canadian and U.S. city data

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All city pairs		Canadian-Canadian city pairs		Canadian-U.S. city pairs		U.S.-U.S. city pairs	
CPI Category	Mean α Lower Bound	Mean half-life lower bound	Mean α Lower bound	Mean half-life lower bound	Mean α lower bound	Mean half-life lower bound	Mean α lower bound	Mean half-life lower bound
0	0.94	15.99	0.93	10.83	0.96	22.93	0.86	5.33
	(0.05)	(14.58)	(0.03)	(5.86)	(0.004)	(18.33)	(0.11)	(2.56)
1	0.90	9.42	0.86	4.90	0.95	14.89	0.87	3.71
	(0.06)	(6.03)	(0.06)	(2.03)	(0.01)	(4.29)	(0.03)	(1.08)
2	0.94	17.64	0.92	10.77	0.97	24.73	0.95	16.35
	(0.04)	(12.79)	(0.04)	(6.71)	(0.01)	(14.21)	(0.03)	(9.49)
3	0.93	15.82	0.90	6.90	0.97	26.52	0.89	5.09
	(0.04)	(10.65)	(0.04)	(3.84)	(0.003)	(3.88)	(0.03)	(2.07)
4	0.96	23.08	0.97	32.07	0.95	16.95	0.90	5.85
	(0.03)	(14.75)	(0.02)	(16.04)	(0.02)	(6.79)	(0.03)	(4.35)
5	0.92	10.43	0.89	5.27	0.95	16.56	0.86	4.61
	(0.05)	(8.16)	(0.03)	(1.98)	(0.03)	(8.29)	(0.12)	(3.83)
6	0.91	9.93	0.87	3.80	0.96	17.42	0.84	1.75
	(0.07)	(7.80)	(0.06)	(1.92)	(0.006)	(4.73)	(0.10)	(0.84)
7	0.87	3.75	0.81	1.61	0.93	6.24	0.85	1.58
	(0.08)	(3.51)	(0.09)	(1.22)	(0.02)	(3.69)	(0.04)	(0.07)
8	0.87	2.75	0.85	2.07	0.91	3.59	0.77	1.81
	(0.08)	(1.76)	(0.08)	(1.44)	(0.03)	(1.84)	(0.15)	(0.27)
9	0.86	3.23	0.82	1.39	0.94	5.30	0.81	1.85
	(0.13)	(2.41)	(0.16)	(0.64)	(0.03)	(1.99)	(0.13)	(0.98)
10	0.90	10.76	0.85	3.85	0.96	17.88	0.91	9.53
	(0.08)	(8.48)	(0.10)	(3.63)	(0.01)	(6.39)	(0.05)	(4.32)
11	0.89	5.41	0.87	4.52	0.91	6.40	0.88	4.73
	(0.04)	(1.84)	(0.04)	(1.61)	(0.02)	(1.57)	(0.02)	(1.83)
12	0.93	13.59	0.92	9.91	0.96	18.81	0.87	4.30
	(0.04)	(7.64)	(0.05)	(4.97)	(0.03)	(6.82)	(0.03)	(1.92)
13	0.91	7.19	0.90	4.98	0.93	10.06	0.91	3.21
	(0.04)	(4.16)	(0.04)	(2.67)	(0.02)	(3.79)	(0.05)	(1.64)
14	0.92	9.07	0.90	5.76	0.95	12.75	0.90	6.85
	(0.05)	(5.34)	(0.05)	(4.25)	(0.01)	(4.00)	(0.05)	(4.32)

Notes: columns (2), (4), (6), and (8) report the mean of the lower bounds of the symmetric subsampling 90% confidence intervals for α for the indicated city pairs (standard deviations are given in parentheses); columns (3), (5), (7), and (9) report the mean of the half-lives corresponding to the lower bounds of the symmetric subsampling 90% confidence intervals for α for the indicated city pairs (standard deviations are given in parentheses); the CPI categories are the following: 0. All items; 1. Food at home; 2. Food away from home; 3. Alcoholic beverages; 4. Shelter; 5. Fuel and other utilities; 6. Household furnishings and operations; 7. Men's and boy's apparel; 8. Women's and girl's apparel; 9. Footwear; 10. Private transportation; 11. Public transportation; 12. Medical care; 13. Personal care; 14. Entertainment.

Table 3: Cross-sectional regression results, Engel and Rogers (1996) Canadian and U.S. city data

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	α lower-bound regression			Half-life lower-bound regression		
CPI category	Distance coefficient	Border coefficient	R^2	Distance coefficient	Border coefficient	R^2
All items	0.009 (1.47)	0.07** (3.63)	0.52	-0.86 (-0.34)	15.04** (4.46)	0.37
Food at home	-0.001 (-0.08)	0.08** (10.73)	0.57	0.25 (0.69)	10.53** (17.46)	0.80
Food away from home	0.015** (3.26)	0.03** (3.59)	0.56	2.50* (1.70)	10.59** (4.09)	0.39
Alcoholic beverages	-0.003 (-0.73)	0.07** (12.63)	0.78	-0.29 (-0.70)	20.59** (33.6)	0.93
Shelter	0.017** (6.92)	0.01** (4.04)	0.77	9.69** (7.40)	-4.23** (-2.34)	0.76
Fuel and other utilities	-0.003 (-0.63)	0.08** (3.40)	0.49	0.90 (1.49)	11.41** (9.60)	0.87
Household furnishing and operations	0.008 (0.99)	0.10** (5.40)	0.61	0.23 (0.64)	14.59** (19.81)	0.88
Men’s and boy’s apparel	0.005 (0.55)	0.10** (9.84)	0.61	-0.43 (-1.58)	4.74** (7.33)	0.82
Women’s and girl’s apparel	0.007 (0.64)	0.10** (4.68)	0.51	0.25 (1.36)	1.59** (5.12)	0.61
Footwear	0.046* (1.78)	0.09** (3.24)	0.29	0.19 (1.32)	3.64** (7.51)	0.84
Private transportation	0.012 (1.31)	0.07** (6.12)	0.70	0.006 (0.01)	11.20** (11.80)	0.85
Public transportation	-0.006 (-1.25)	0.04** (5.68)	0.46	-0.64** (-3.36)	1.92** (4.97)	0.47
Medical care	0.007 (1.01)	0.06** (9.94)	0.54	0.52 (0.76)	11.61** (15.38)	0.72
Personal care	0.016** (3.09)	0.03** (2.51)	0.44	1.62** (5.00)	5.59** (7.56)	0.64
Entertainment	-0.007 (-1.49)	0.05** (5.87)	0.53	-1.65** (-4.60)	6.83** (9.14)	0.72

Notes: heteroskedasticy-consistent t-statistics are given in parentheses; * (**) indicates significance at the 10% (5%) level.

Table 4: Lower bounds of symmetric subsampling 90% confidence intervals for α and corresponding half-lives, Engel (1999) G6 data

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	CPI, Overall							CPI, All goods less food					
	CAN	FRA	GER	ITA	JPN	USA		CAN	FRA	GER	ITA	JPN	USA
CAN		0.95	0.96	0.96	0.98	0.96	CAN		0.95	0.96	0.95	0.97	0.96
FRA	16.59		0.93	0.95	0.97	0.96	FRA	15.74		0.92	0.96	0.97	0.96
GER	18.87	9.71		0.96	0.97	0.96	GER	17.40	8.81		0.96	0.96	0.96
ITA	16.67	14.72	18.03		0.96	0.96	ITA	15.59	18.47	18.76		0.96	0.97
JAP	30.23	25.10	26.93	19.51		0.97	JAP	26.89	22.17	20.07	17.61		0.98
USA	29.45	17.28	17.18	16.27	26.20		USA	28.29	17.23	17.33	22.08	29.32	
	CPI, Food							CPI, All services less rent					
	CAN	FRA	GER	ITA	JPN	USA		CAN	FRA	GER	ITA	JPN	USA
CAN		0.96	0.95	0.95	0.98	0.95	CAN		0.95	0.96	0.97	0.98	0.98
FRA	17.71		0.95	0.93	0.96	0.96	FRA	16.34		0.91	0.97	0.98	0.96
GER	14.76	14.88		0.95	0.97	0.95	GER	17.73	8.54		0.97	0.98	0.96
ITA	13.52	9.79	14.16		0.97	0.95	ITA	22.33	22.15	20.95		0.96	0.96
JAP	30.93	19.76	27.66	24.59		0.98	JAP	36.00	31.04	30.20	19.73		0.97
USA	12.46	16.86	13.81	14.68	29.44		USA	39.70	20.46	19.88	16.65	26.90	
	CPI, Rent												
	CAN	FRA	GER	ITA	JPN	USA							
CAN		0.97	0.97	0.97	0.99	0.98							
FRA	29.16		0.94	0.96	0.97	0.97							
GER	28.45	12.25		0.96	0.97	0.96							
ITA	24.89	17.08	22.99		0.95	0.95							
JAP	48.59	22.39	28.15	18.15		0.98							
USA	48.76	21.28	17.40	13.89	34.24								

Notes: entries above the main diagonal report lower bounds of the symmetric subsampling 90% confidence intervals for α for the country pairs; entries below the main diagonal report half-lives corresponding to the lower bounds of the symmetric subsampling 90% confidence intervals for α for the country pairs.

Table 5: Lower bounds of symmetric subsampling 90% confidence intervals for α and corresponding half-lives, Engel (2000) European country data

(1) Category	(4) Mean α lower bound	(5) Mean half-life lower bound	(6) Category	(9) Mean α lower bound	(10) Mean half-life lower bound
Food	0.94 (0.02)	12.36 (3.63)	Household equipment	0.96 (0.02)	19.36 (7.09)
Bread and cereals	0.92 (0.03)	11.15 (4.52)	Furniture	0.94 (0.03)	15.39 (6.49)
Meat	0.91 (0.04)	8.75 (3.14%)	Domestic appliances	0.94 (0.02)	12.75 (4.15)
Dairy products	0.90 (0.03)	8.19 (2.74)	Transport and Communications	0.94 (0.01)	12.79 (4.16)
Fruit	0.84 (0.08)	6.64 (4.83)	Vehicles	0.92 (0.04)	10.73 (4.01)
Alcoholic and non-alcoholic drinks	0.92 (0.05)	13.26 (6.52)	Public transport	0.90 (0.04)	8.30 (3.78)
Clothing and footwear	0.95 (0.03)	28.68 (23.02)	Recreation	0.95 (0.02)	16.25 (5.05)
Clothing	0.95 (0.02)	25.74 (19.52)	Sound and photo-graphic equipment	0.93 (0.02)	12.79 (7.29)
Footwear	0.93 (0.04)	16.77 (11.04)	Leisure	0.92 (0.05)	11.09 (4.52)
Rents	0.94 (0.03)	12.16 (3.48)	Books	0.94 (0.03)	13.21 (4.51)
Fuel and energy	0.90 (0.04)	6.89 (3.22)	Hotels	0.94 (0.02)	14.90 (5.72)

Notes: columns (2) and (5) report the mean of the lower bounds of the symmetric subsampling 90% confidence intervals for α for all country pairs (standard deviations are given in parentheses); columns (3) and (6) report the mean of the half-lives corresponding to the lower bounds of the symmetric subsampling 90% confidence intervals for α for all country pairs (standard deviations are given in parentheses).

Table 6: Lower bounds of symmetric subsampling 90% confidence intervals for α and corresponding half-lives, Engel and Rogers (2001a) European city data

(1) Group	(2) Mean α lower bound	(3) Mean half-life lower bound
All city pairs	0.95 (0.03)	16.19 (7.57)
German-German city pairs	0.94 (0.03)	11.75 (3.68)
Italian-Italian city pairs	0.93 (0.04)	12.43 (8.14)
Spanish-Spanish city pairs	0.92 (0.05)	6.78 (5.29)
Swiss-Swiss city pairs	0.93 (0.03)	7.82 (4.91)
City pairs across borders	0.95 (0.02)	18.21 (6.43)

Notes: column (2) reports the mean of the lower bounds of the symmetric subsampling 90% confidence intervals for α for the indicated city pairs (standard deviations are given in parentheses); column (3) reports the mean of the half-lives corresponding to the lower bounds of the symmetric subsampling 90% confidence intervals for α for the indicated city pairs (standard deviations are given in parentheses).

Table 7: Cross-sectional regression results, Engel and Rogers (2001a) European city data

(1)	(2)	(3)	(4)	(5)	(6)
α lower-bound regression			Half-life lower-bound regression		
Distance Coefficient	Border coefficient	R^2	Distance coefficient	Border coefficient	R^2
0.0004 (0.37)	0.03** (9.34)	0.19	-0.09 (-0.41)	7.12** (11.02)	0.40

Notes: heteroskedasticy-consistent t-statistics are given in parentheses; * (**) indicates significance at the 10% (5%) level.

Table 8: Lower bounds of symmetric subsampling 90% confidence intervals for α and corresponding half-lives, Engel and Rogers (2001b) U.S. city data

(1) Category	(2) Mean α lower bound	(3) Mean half-life lower bound	(4) Category	(5) Mean α lower bound	(6) Mean half-life lower bound
All items	0.81 (0.11)	3.30 (2.44)	Alcoholic beverages	0.83 (0.10)	4.24 (3.12)
Cereals and bakery products	0.71 (0.14)	1.25 (0.74)	Rent, residential	0.89 (0.07)	9.35 (13.83)
Meats	0.69 (0.14)	1.18 (0.60)	Homeowners’ costs	0.86 (0.09)	6.56 (9.54)
Fresh fruits and vegetables	0.63 (0.16)	1.35 (0.48)	Other utilities and public services	0.72 (0.25)	3.07 (3.50)
Processed fruits and vegetables	0.75 (0.15)	1.59 (1.39)	Textile house-furnishings	0.75 (0.14)	2.28 (1.78)
Other food at home	0.75 (0.15)	1.62 (1.83)	Furniture and bedding	0.82 (0.09)	3.37 (2.49)
Other renters’ costs	0.73 (0.15)	2.47 (1.73)	Other house-furnishings	0.80 (0.10)	2.79 (1.86)
Household maintenance and repairs	0.84 (0.08)	4.86 (3.29)	Housekeeping supplies	0.82 (0.10)	3.48 (2.37)
Fuels	0.63 (0.26)	8.72 (20.90)	Housekeeping services	0.86 (0.09)	5.98 (4.81)
Appliances, incl. electronic equipment	0.81 (0.11)	4.26 (6.52)	Footwear	0.76 (0.11)	2.51 (1.32)
Mean’s and boy’s apparel	0.70 (0.12)	1.87 (0.91)	Infants’ and toddlers’ apparel	0.76 (0.13)	3.15 (1.72)
Women’s and girl’s apparel	0.65 (0.17)	2.55 (2.95)	Apparel services	0.87 (0.07)	6.12 (3.34)
Other apparel commodities	0.78 (0.14)	3.24(8.44)	New vehicles	0.78 (0.10)	2.85 (1.69)
Medical care commodities	0.84 (0.07)	4.69 (3.84)	Used cars	0.97 (0.02)	32.65 (24.59)
Entertainment commodities	0.83 (0.09)	4.02 (2.64)	Motor fuel	0.71 (0.16)	2.75 (1.36)
Personal care	0.85 (0.08)	4.93 (4.62)	Automobile maintenance and repairs	0.86 (0.08)	5.97 (4.20)
Personal and educational expenses	0.88 (0.08)	7.24 (6.33)	Public transportation	0.79 (0.11)	3.02 (1.93)
Poultry	0.66 (0.16)	1.02 (0.11)	Professional medical services	0.86 (0.08)	6.70 (4.44)
Fish and seafood	0.69 (0.15)	1.29 (0.56)	Hospital and related services	0.85 (0.08)	5.12 (3.91)
Eggs	0.65 (0.21)	1.26 (0.66)	Entertainment services	0.80 (0.12)	4.42 (3.98)
Food away from home	0.86 (0.07)	6.03 (3.49)	Tobacco and smoking products	0.83 (0.09)	3.94 (2.97)

Notes: columns (2) and (5) report the mean of the lower bounds of the symmetric subsampling 90% confidence intervals for α for all city pairs (standard deviations are given in parentheses); columns (3) and (6) report the mean of the half-lives corresponding to the lower bounds of the symmetric subsampling 90% confidence intervals for α for all city pairs (standard deviations are given in parentheses).

Table 9: Cross-sectional regression results, Engel and Rogers (2001b) U.S. city data

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	α lower-bound regression		half-life lower-bound regression			α lower-bound regression		half-life lower-bound regression	
Category	Distance Coeff.	R^2	Distance Coeff.	R^2	Category	Distance Coeff.	R^2	Distance Coeff.	R^2
All items	0.001 (0.21)	0.38	-0.01 (-0.07)	0.45	Alcoholic beverages	0.02** (2.63)	0.39	0.33** (2.23)	0.55
Cereals and bakery products	-0.004 (-0.52)	0.46	0.03 (0.60)	0.36	Rent, residential	-0.001 (-0.26)	0.28	-0.52 (-0.75)	0.34
Meats	-0.006 (-0.76)	0.41	0.02 (0.63)	0.21	Homeowners' costs	0.002 (0.44)	0.20	-0.64 (-1.10)	0.40
Fresh fruits and Vegetables	-0.02** (-2.21)	0.27	-0.02 (-0.64)	0.35	Other utilities and public services	0.02 (1.45)	0.60	0.03 (0.21)	0.60
Processed fruits and vegetables	-0.002 (-0.26)	0.57	-0.001 (-0.02)	0.26	Textile house-furnishings	-0.005 (-0.71)	0.40	0.12 (0.89)	0.33
Other food at home	0.000 (0.01)	0.32	0.03 (0.28)	0.30	Furniture and bedding	0.002 (0.21)	0.33	-0.05 (-0.31)	0.37
Other renters' costs	-0.003 (-0.30)	0.24	-0.08 (-0.71)	0.25	Other house-furnishings	-0.001 (-0.15)	0.28	0.08 (0.62)	0.29
Household maintenance and repairs	-1.167e-006 (-0.0003)	0.47	-0.08 (-0.61)	0.66	Housekeeping supplies	0.003 (0.67)	0.43	-0.11 (-0.85)	0.39
Fuels	0.02 (1.29)	0.49	-1.31 (-1.12)	0.38	Housekeeping Services	0.003 (0.80)	0.60	-0.08 (-0.33)	0.39
Appliances, incl. electronic equipment	-0.008 (-1.27)	0.34	-0.03 (-0.12)	0.15	Footwear	0.007 (0.94)	0.23	0.04 (0.63)	0.28
Mean's and boy's Apparel	-0.0002 (-0.03)	0.41	0.001 (0.01)	0.18	Infants' and toddlers' apparel	-0.001 (-0.12)	0.49	0.07 (1.02)	0.60
Women's and girl's Apparel	0.005 (0.55)	0.51	0.09 (0.71)	0.69	Apparel services	0.005 (1.06)	0.40	0.17 (1.10)	0.53
Other apparel Commodities	-0.01 (-0.83)	0.57	0.19 (0.62)	0.12	New vehicles	0.005 (0.98)	0.43	0.14 (1.46)	0.39
Medical care Commodities	-0.001 (-0.17)	0.31	-0.08 (-0.47)	0.26	Used cars	5.412e-005 (0.04)	0.26	0.38 (0.30)	0.27
Entertainment Commodities	0.008 (1.39)	0.22	0.27* (1.96)	0.41	Motor fuel	-0.005 (-0.57)	0.49	-0.006 (-0.12)	0.69
Personal care	0.004 (0.87)	0.41	0.30 (1.31)	0.58	Automobile main-tenance and repairs	0.001 (0.12)	0.27	0.05 (0.19)	0.42
Personal and educational expenses	9.384e-005 (0.02)	0.26	-0.07 (-0.22)	0.61	Public transportation	-0.002 (-0.29)	0.35	0.08 (0.73)	0.38
Poultry	0.02** (2.52)	0.36	0.002 (0.49)	0.11	Professional medical services	0.007 (1.54)	0.46	0.31 (1.84)	0.51
Fish and seafood	-0.001 (-0.13)	0.36	0.03 (0.94)	0.51	Hospital and related services	0.004 (0.79)	0.28	0.38* (1.72)	0.42
Eggs	-0.01 (-0.93)	0.44	-0.03 (-0.83)	0.34	Entertainment services	-0.003 (-0.60)	0.43	-0.15 (-0.78)	0.50
Food away from home	-0.0006 (-0.14)	0.25	0.04 (0.19)	0.42	Tobacco and smoking products	-0.003 (-0.64)	0.41	-0.33** (-2.44)	0.53

Notes: heteroskedasticy-consistent *t*-statistics are given in parentheses; * (**) indicates significance at the 10% (5%) level.

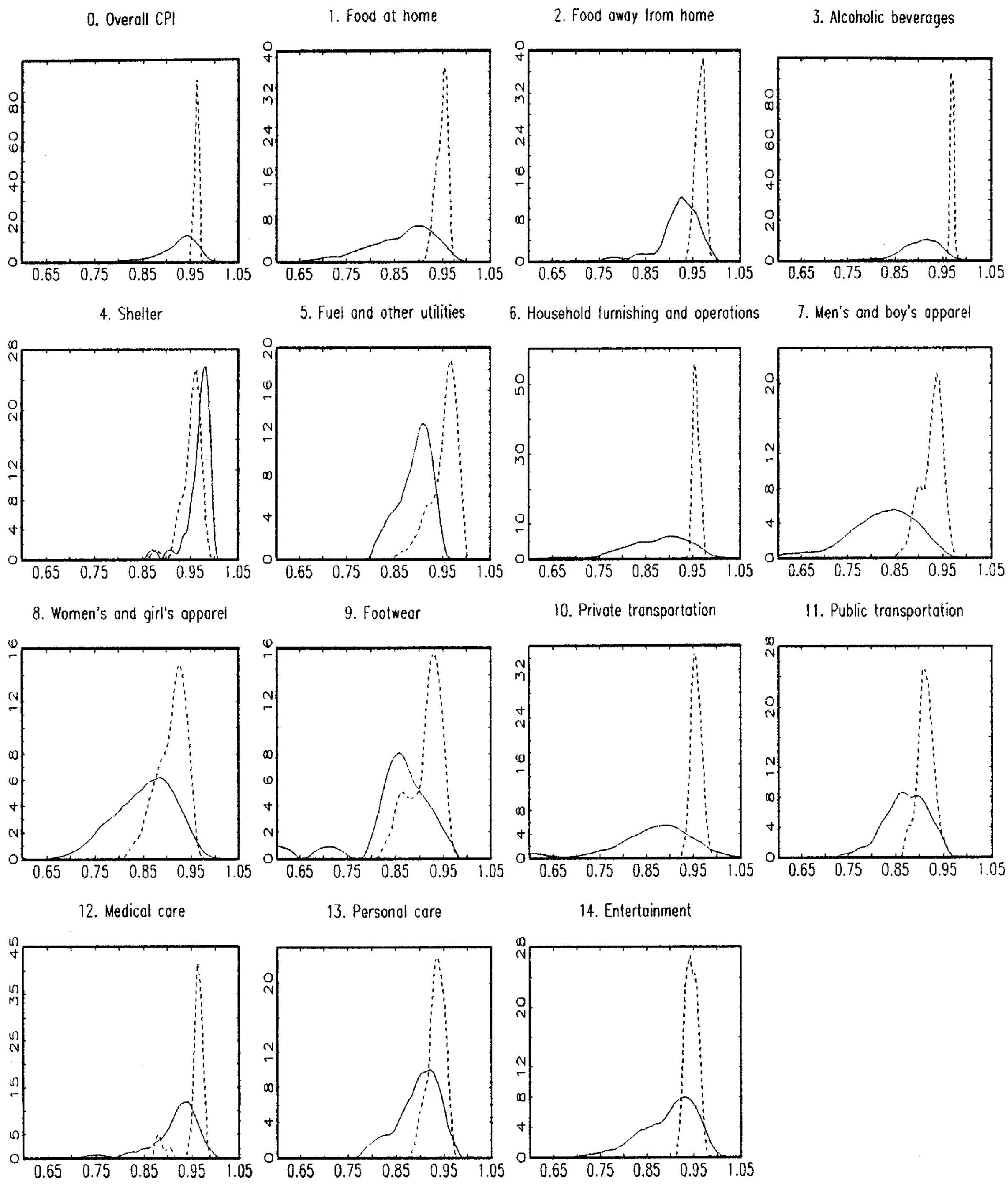

Figure 1: Distribution of the α lower bounds for Canadian-Canadian and U.S.-U.S. city pairs (solid line) and Canadian-U.S. city pairs (dashed lines), Engel and Rogers (1996) Canadian and U.S. city data.

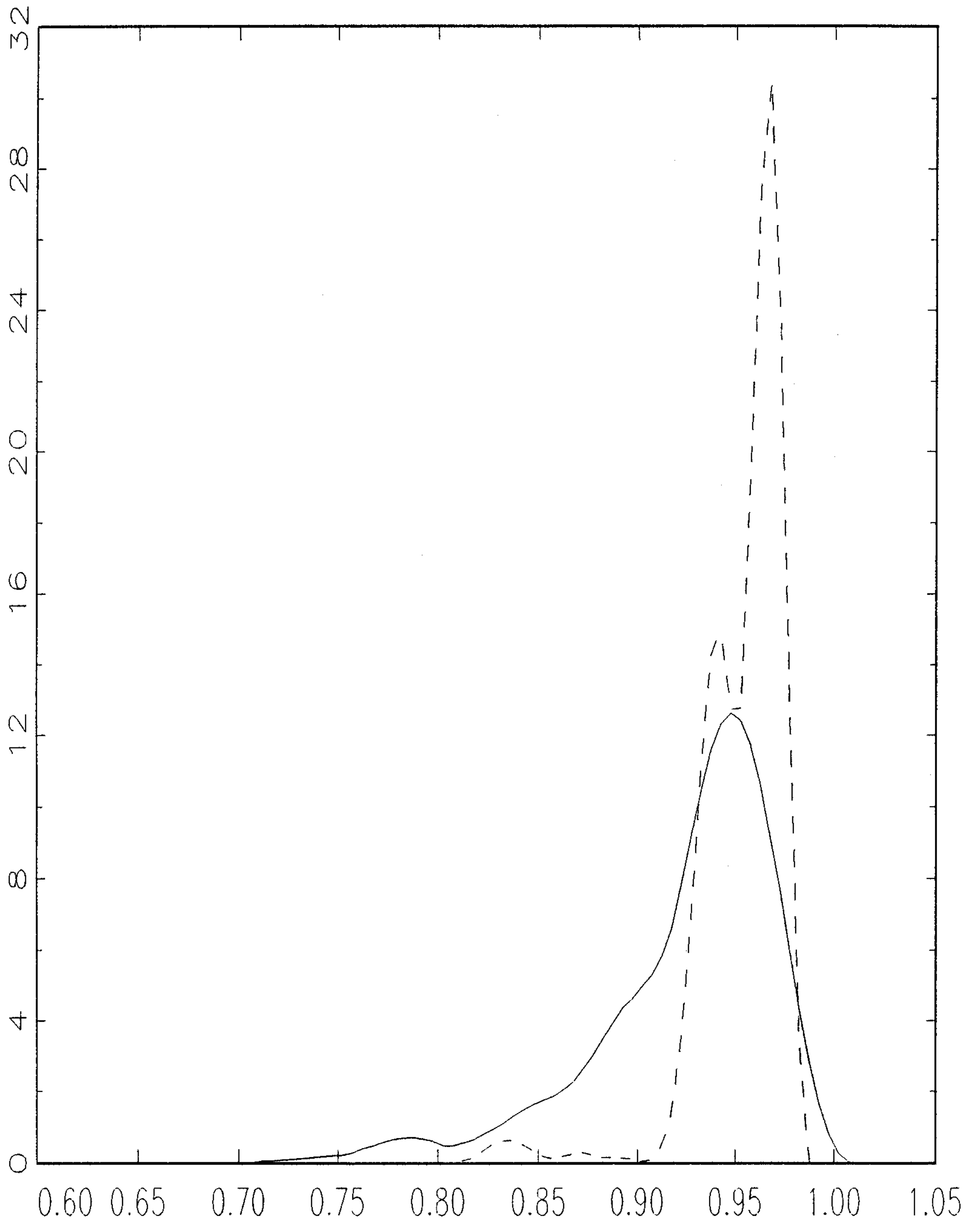

Figure 2: Distribution of the α lower bounds for city pairs within the same European country (solid line) and city pairs in different European countries (dashed line), Engel and Rogers (2001a) European city data.