CONVERGENCE TO THE LAW OF ONE PRICE WITHOUT TRADE BARRIERS OR CURRENCY FLUCTUATIONS*

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Using a panel of 51 prices from 48 cities in the United States, we provide an upper bound estimate of the rate of convergence to purchasing power parity. We find convergence rates substantially higher than typically found in cross-country data. We investigate some potentially serious biases induced by i.i.d. measurement errors in the data, and find our estimates to be robust to these potential biases. We also present evidence that convergence occurs faster for larger price differences. Finally, we find that rates of convergence are slower for cities farther apart. However, our estimates suggest that distance alone can only account for a small portion of the much slower convergence rates across national borders.

I. INTRODUCTION

The aim of this paper is to provide an upper bound estimate of the rate of convergence to purchasing power parity (PPP). The speed at which relative prices move toward parity is important for theories of exchange rate determination and for open-economy macro models, almost all of which employ versions of PPP. Professional wisdom regarding the rate of convergence toward PPP has run the full gamut—from fairly high, to nearly zero, and now, back to positive but slow. In markets for goods and services there is little expectation that price disparities will instantly disappear as they do, for example, in financial markets, due to both explicit and implicit barriers to the flows of goods and services. We examine convergence in a context where many of these barriers are absent in order to quantitatively assess their importance in markets less integrated.

Not long after Frenkel's seminal work [1978] which provided evidence supportive of convergence to PPP during a hyperinflation, many subsequent studies concluded a "collapse of purchasing power parities."[1] In particular, these studies failed to reject the hypothesis that real exchange rates follow a random walk, which implies that any deviation from PPP is permanent. This finding undermined confidence in a wide range of open-economy

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1. See the excellent survey in Froot and Rogoff [1996].

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macro models that assumed some version of PPP, including monetary theories of the exchange rate and Dornbusch's [1976] overshooting model.

Recent research has focused on increasing statistical power by using longer time series [Frankel 1986; Edison 1987; Froot, Kim, and Rogoff 1995; Lothian and Taylor 1996], and on combining cross-sectional and time series features of the data [Abuaf and Jorion 1990; Frankel and Rose 1995; Papell 1996; Wei and Parsley 1995]. These studies have been considerably more successful at rejecting the unit root null hypothesis. While these studies have found mean reversion in real exchange rates, the implied half-lives of between three and seven years have been difficult to interpret.

In this study we focus exclusively on prices within the United States in order to establish a natural benchmark for comparison to international evidence.[2] The use of this data set abstracts from two potentially important influences on the rate of convergence: trade barriers and exchange rate volatility. Additionally, the higher degree of factor market integration further limits departures from price parity and thus facilitates convergence. A second important feature of this study is the use of commodity level price data. Thus, we implicitly control for terms of trade and other aggregation effects that can impact convergence estimates. A further benefit is that we are able to make direct comparisons of how rates of convergence depend on the degree of tradability. Finally, we explicitly examine the effects of taxes and transportation costs on estimated rates of convergence. To our knowledge, this is the first study that looks at the effect of tax rates on convergence.

Section II describes the data and its collection in more detail. Section III begins by providing some summary statistics on the price data and subsequently provides estimates of rates of convergence. After comparing rates of convergence across (and within) tradable and nontradable groupings, we investigate other influences on our findings. A final section summarizes our main conclusions.

2. Earlier studies examining disaggregated prices include Richardson [1978], who finds that Canadian and United States prices are only weakly related, and Rogers and Jenkins [1995], who are able to reject the unit root null in fewer than one-sixth of the 54 disaggregated products they study. While these findings are discouraging, there is reason to suspect that the failures are due to the notoriously low power of common unit root tests. Recent work by Levin and Lin [1992] demonstrates that statistical power increases rapidly in a panel setting.

II. Data

The 51 final goods and services prices in our panel are sampled (quarterly) from 48 cities in the United States over the period 1975.1 through 1992.4. The data set includes prices of both tradable and nontradable goods and services. The price data were assembled from publications of the American Chamber of Commerce Researchers Association, and included in the publication, *Cost of Living Index* (hereinafter, *Index*). Each quarterly issue of the *Index* contains comparative average price data for a sample of urban areas, and a cost of living index computed from these data by the association. In this study we use only the raw price data.

The actual data collection is done by the local Chamber of Commerce staff or volunteers for the Chamber, and is voluntary. Explicit instructions and data forms are provided for each data collector by the association.[3] Some prices are obtained by phone, and usually the respondents do not know it is for a survey. Once collected, the data are sent to one of nine different regional coordinators for checking. Finally, the data are sent to Houston where they are transferred to computer and subjected to both computer and visual checks for outliers. Publication occurs approximately five and one-half months after the original data are collected.

Consequently, the sample of cities included in each issue of the *Index* varies. At the beginning of our sample period, there were 166 cities and 44 items priced. The number of cities steadily increased to 297 in 1992.4; however, each report contains a distinct sample of cities. In an attempt to construct a balanced panel, we choose a sample of 48 cities that appeared in roughly 90 percent of the quarterly surveys.

The goods and services sampled, however, are much less variable, although there have been additions to and subtractions from the list. For this study we selected 51 goods and services (hereinafter, commodities) with three criteria in mind. First, for each commodity we wanted wide coverage in terms of availability across cities and over time. Second, we wanted variation in the degree of tradability of the commodities included in the data set.

3. According to phone conversations with the person now in charge of final data checking for ACCRA, the reported prices were obtained as an average over a small number of sellers in the city (generally > 3, and, since 1982, > 5 and < 10 sellers), on the Thursday, Friday, or Saturday of the first week of each quarter.

Finally, we wanted homogeneity in the definitions of the commodities over time. Some commodities, however, did change during the sample period—typically as a result of a change in manufacturer packaging. This change was accounted for by assigning a missing value to the last quarter prior to the change.

For this study we classify the goods into tradables (41) and nontradables (mostly services) (10), for a total of 51 goods and services. Within the tradable category we make a further distinction between perishable goods (mostly vegetables and dairy products) and nonperishable goods. These categories were designed to facilitate the presentation of our results. While it is true that the groupings necessarily involve some subjective judgment, redesignating certain commodities into a different category would not change the basic conclusions. The Appendix provides a detailed description of all commodities included in this study.[4]

Briefly, our sample of fifteen perishable goods includes prices for bacon, bananas, bread, cheese, eggs, fried chicken, ground beef, lettuce, margarine, McDonald's hamburger, milk, potatoes, pizza, steak, and whole chicken. The prices are for some standard unit, e.g., per pound. The (26) nonperishable goods are aspirin, baby food, beer, cigarettes, coffee, corn flakes, frozen corn, game, jeans, liquor, man's shirt, canned orange juice, canned peaches, shampoo, shortening, soft drink, sugar, canned peas, tennis balls, tissue, canned tomatoes, toothpaste, tuna, underwear, washing powder, and wine. The ten services in the sample are appliance repair, auto maintenance, beauty salon, bowling, dentist, doctor, dry cleaning, hospital room, man's haircut, and the price to attend a first-run movie.

The tax data are combined (state, county, and local) sales tax rates collected from each local jurisdiction's taxing authority, e.g., the Departments of Revenue. The data were typically obtained by phone, although some jurisdictions provided written histories

4. The cities sampled are Birmingham AL, Mobile AL, Blythe CA, Indio CA, Palm Springs CA, Denver CO, Lakeland FL, Boise ID, Champaign, Urbana IL, Peoria IL, Ft. Wayne IN, Indianapolis IN, Cedar Rapids IA, Lexington KY, Louisville KY, Baton Rouge LA, Lafayette LA, New Orleans LA, Benton Harbor MI, Traverse City MI, Columbus MS, St. Joseph MO, St. Louis MO, Falls City NE, Hastings NE, Omaha NE, Reno, Sparks NV, Newark NJ, New York NY, Hickory NC, Columbus OH, Altoona PA, Rapid City SD, Vermillion SD, Chattanooga TN, Knoxville TN, Abilene TX, El Paso TX, Ft. Worth TX, Houston TX, Lubbock TX, Salt Lake City UT, Charleston WV, Appleton WI, Eau Claire WI, Madison WI, Oshkosh WI, and, Casper WY. Our data set will be available for one year following publication. Requests should include a 3.5 inch IBM formatted (1.44MB) diskette and a self-addressed mailer.

of tax rates and exemptions. For this study it was also necessary to determine whether the good was subject to a differential (including possibly exempt) tax rate, since our sample includes many food and service items and the treatment of these is not uniform across jurisdictions. For our study the primary difference across jurisdictions is in the treatment of grocery items. Thus, we created two tax tables with tax rates for grocery, and one for nongrocery items, for each city. The group we designate as perishables is composed exclusively of grocery items. Our nonperishables group also contains some nongrocery items. Finally, there is generally no sales tax payable explicitly by the customer for the services in our third group. For this reason, we exclude these services from the analysis explicitly incorporating taxes. Summary statistics on the tax data (see Parsley and Wei [1996]) indicate that there is considerable variation in tax rates across cities, although there is less variation over time.

III. CONVERGENCE

A. Basic Statistics

Before discussing our regression results, it is useful to look at some summary statistics on the variability of price differentials and on mean absolute price differentials that are presented in Table I. In the table we compare the three groups on the basis of these two measures of the intercity price differentials over time. Our benchmark city is New Orleans. As a robustness check, we have also used New York as the benchmark city; this change has little effect on the conclusions we draw.

Define the (pretax) price difference $Q_{ij,k,t}$ as the percentage difference in price of commodity k at time t between cities i and j; i.e., $Q_{ij,k,t} = \ln(P_{i,k,t}/P_{j,k,t})$. The natural benchmark for $Q_{ij,k,t}$ is zero. However, given impediments to arbitrage of goods and services, the price difference at any point in time may differ from zero. In models presented in Engel and Rogers [1994] and Wei and Parsley [1995], prices in two locations may differ at any point in time, but these differences are bounded due to the cost of arbitrage between the two cities. The width of this band increases with transportation costs, which can be approximated by distance. This implies that both the variability of $Q_{ij,k,t}$ and the mean absolute deviation, i.e., the mean over time of $|\ln(P_{i,k,t}/P_{j,k,t})|$, are positively related to transportation costs between cities.

TABLE I
SUMMARY STATISTICS

	Mean	Standard deviation	Observations
Variability of price differential[a]			
Perishables	.149	.058	705
Nonperishables	.129	.046	1222
Services	.132	.049	470
Mean absolute price differential[b]			
Perishables	.144	.066	705
Nonperishables	.125	.052	1222
Services	.156	.082	470

a. Price differential variability is defined as the standard deviation over time of the percentage price difference ($Q_{ij,k,t} = \ln(P_{i,k,t}/P_{j,k,t})$), where $P_{i,k,t}$ is the price of good k in city i at time t. For these calculations city i is New Orleans. Since there are 15 perishable goods and 47 city pairs, there are 705 (= 15 × 47) observations over which to take the mean and standard deviation.

b. Mean absolute price differential is defined as the mean absolute deviation of log prices between cities, i.e., the mean over time of $|\ln(P_{i,k,t}/P_{j,k,t})|$.

The three commodity groupings are defined as follows. (1) Perishables: bacon, bananas, bread, cheese, eggs, ground beef, lettuce, margarine, milk, potatoes, steak, whole chicken, fried chicken, McDonald's, pizza. (2) Nonperishables: aspirin, baby food, beer, cigarettes, coffee, corn flakes, frozen corn, game, jeans, liquor, man's shirt, canned orange juice, canned peaches, shampoo, shortening, soft drink, sugar, canned peas, tennis balls, tissue, canned tomatoes, toothpaste, canned tuna, underwear, washing powder, wine. (3) Services: appliance repair, auto maintenance, beauty salon, bowling, dentist, doctor, dry cleaning, hospital room, man's haircut, movie.

From Table I we see that, of the three groups, perishables has on average, the highest variability of the intercity price differential, while services has the highest mean average price differential. The higher variability of perishables price differences could be due to seasonal variation in either the arrival of, or demand for, some of the goods in this group.

It is useful to link these indicators of the magnitude and variability of price differentials with the costs of arbitrage activities, which is what we turn to in Table II. The table presents results by group (i.e., perishables, nonperishables, and services) on the impact of distance on intercity price differentials. Following Engel and Rogers [1994] and Wei and Parsley [1995], we approximate transportation costs by distance as measured by the "greater circle distance" between the cities.[5] The results in Table II overwhelmingly support the implication of these models that transportation costs permit price differences between cities, and the size of such differences increases with arbitrage costs.

From the table the distance between two cities is positively related to the variability of price differences for all three catego-

5. See *The American Practical Navigator* [1977].

TABLE II
SHIPPING COSTS AND INTERCITY PRICE DIFFERENTIALS

Panel A: Variability of price differential

	Perishables		Nonperishables		Services	
Regression number:	1	2	3	4	5	6
ln distance	0.011 (0.002)	−0.087 (0.022)	0.018 (0.001)	0.038 (0.002)	0.004 (0.003)	−0.062 (0.039)
ln distance squared		0.008 (0.002)		−0.003 (0.0003)		0.005 (0.003)
Product dummies	yes	yes	yes	yes	yes	yes
$\bar{R}^2$	.72	.73	.45	.49	.20	.21
Std. error of regression	.0308	.0304	.0341	.0330	.0436	.0435
Number of observations	705	705	1222	1222	470	470

Panel B: Mean absolute price differential

	Perishables		Nonperishables		Services	
Regression number:	1	2	3	4	5	6
ln distance	0.019 (0.0002)	0.030 (0.003)	0.022 (0.0004)	0.019 (0.005)	0.021 (0.006)	−0.336 (0.068)
ln distance squared		−0.002 (0.0004)		0.0004 (0.0007)		0.029 (0.006)
Product dummies	yes	yes	yes	yes	yes	yes
$\bar{R}^2$	−.01	.01	.03	.03	.10	.15
Std. error of regression	.0526	.0523	.0649	.0649	.0771	.0750
Number of observations	705	705	1222	1222	470	470

ln refers to the natural log. In Panel A, columns 1, 3, and 5, the regression run was $s.d.(Q_{ij,k,t}) = \beta \ln(\text{distance}) + \text{dummies}$, and in columns 2,4, and 6, the regression run was $s.d.(Q_{ij,k,t}) = \beta_1 \ln(\text{distance}) + \beta_2 \ln(\text{distance}^2) + \text{dummies}$, where $s.d.(Q_{ij,k,t})$ = the standard deviation over time of $\ln(P_{i,k,t}/P_{j,k,t})$. In Panel B the dependent variable is the mean over time of $|\ln(P_{i,k,t}/P_{j,k,t})|$, i.e., the mean absolute deviation of log prices between cities. Standard errors are in parentheses. New Orleans is defined as the benchmark city.

ries, with the effect being the strongest among tradables. The results for mean absolute price differentials are presented in Panel B. Again, the implication of the models is strongly supported. We explore a possible nonlinearity in this relationship by adding a squared distance term to these specifications: the distance effect shows different convexities for different product groups, but the convexity features depend on whether we examine the variability of price differentials or the mean of their absolute values .

B. Testing for Stationarity and Estimating Rates of Convergence

In this section we proceed in two stages. First, we test whether it is possible to reject the unit root hypothesis, and we ask whether the answer varies systematically across products. After rejecting the unit root, we turn to the issue of convergence speed. At this stage the possibility of measurement error must be considered, which leads us to additional estimations prior to reporting rates of convergence. For expositional convenience we discuss each of the three groups separately.

In our test the null hypothesis is a (driftless) random walk. The alternative hypothesis is a zero-mean AR(1) process common to all city-pairs. All regressions reported use New Orleans as the benchmark city; i.e., we examine differences in prices in other cities relative to New Orleans. More precisely, for each commodity (k) the basic regression specification is

$$\Delta Q_{i,k,t} = \beta Q_{i,k,t-1} + \sum_{m=1}^{s(k)} \gamma_m \Delta Q_{i,k,t-m} + \varepsilon_{i,k,t}, \tag{1}$$

where $Q_{i,k,t}$ is the log-difference in the price of product k in city i relative to New Orleans at time t, and Δ is the first difference operator. The lag structure $s(k)$, used to account for possible serial correlation in the error term, is determined on a product-by-product basis as in a univariate augmented Dickey-Fuller test.

Results of panel unit root tests for the first category (i.e., nonperishables) are summarized in Panel A of Table III. The table presents the tests on a commodity-by-commodity basis. Levin and Lin [1992] have shown that panel data can dramatically increase the power of the unit root test, and that in contrast to the univariate case, the test statistic in a panel context is asymptotically normal. In all cases, the point estimate of β is negative. According to Levin and Lin, the critical values for $t = 50$ and $N = 50$ (approximately our panel size) at the 1 percent, 5 percent, and 10 percent levels are -2.38, -1.71, and -1.35. Using these critical values, we reject the unit root for 22 of the 26 products (or 85 percent) at the 10 percent level, of which 20 are rejected at the 5 percent level.

In Panel B of Table III we examine the fifteen perishables,

TABLE III
PANEL UNIT ROOT TESTS

Panel A: Nonperishables							
Good	Beta	# lags	# obs	Good	Beta	# lags	# obs
Aspirin	−0.259* (0.056)	15	503	Shampoo	−0.367* (0.085)	16	465
Baby food	−0.057*** (0.035)	16	474	Shortening	−0.141* (0.046)	16	474
Beer	−0.077* (0.028)	13	585	Soft drink	−0.116* (0.038)	12	639
Cigarettes	−0.045** (0.023)	16	474	Sugar	−0.147* (0.036)	13	583
Coffee	−0.036 (0.071)	14	258	Canned peas	−0.192** (0.109)	15	206
Corn flakes	−0.123** (0.066)	16	463	Tennis balls	−0.207* (0.067)	16	465
Frozen corn	−0.379* (0.096)	16	321	Tissue	−0.063 (0.047)	16	474
Game	−0.067** (0.036)	15	503	Canned tomatoes	−0.141** (0.082)	13	242
Jeans	−0.166* (0.063)	13	585	Toothpaste	−0.037 (0.074)	15	503
Liquor	−0.001 (0.026)	16	163	Canned tuna	−0.192* (0.051)	15	502
Man's shirt	−0.228* (0.055)	15	503	Underwear	−0.058*** (0.039)	16	465
Orange juice	−0.319* (0.058)	14	212	Washing powder	−0.104** (0.060)	16	182
Canned peaches	−0.136* (0.034)	14	233	Wine	−0.100* (0.025)	16	465

Standard errors are in parentheses, and *, **, and *** denote significance at the 1 percent, 5 percent, and 10 percent levels. For each good, the regression run was

$$\Delta Q_{ij,k,t} = \beta Q_{ij,k,t-1} + \sum_{m=1}^{s(k)} \gamma_m \Delta Q_{ij,k,t-m} + \varepsilon_{ij,k,t},$$

where $Q_{ij,k,t}$ is defined as the percentage difference in price of commodity k at time t between cities i and j, i.e., $Q_{ij,k,t} = \ln(P_{i,k,t}/P_{j,k,t})$. $s(k)$ is chosen as the highest significant lag from a preliminary regression including sixteen lags. New Orleans is defined as the benchmark city.

and ten services. For perishables, we can reject the random walk null at the 10 percent level for an overwhelming majority (80 percent, or twelve) of the commodities. In fact, we can reject it at the 1 percent level for ten of the fifteen goods. Even for our final group of mostly services, we can reject the null at the 10 percent level in half of the cases; it can be rejected at the 1 percent level in four of the five cases. This implies that price differences for many of the items that would be called "nontradable" in an inter-

TABLE III
(CONTINUED)
PANEL UNIT ROOT TESTS

Panel B: Perishables and services

Good	Beta	# lags	# obs	Good	Beta	# lags	# obs
Perishables:							
Bacon	−0.207*	16	511	McDonald's	−0.106**	16	465
	(0.040)				(0.047)		
Bananas	−0.427*	16	510	Pizza	−0.166*	15	503
	(0.085)				(0.030)		
Bread	−0.194*	10	1358				
	(0.027)			Services:			
Cheese	−0.064***	14	541	Appliance	−0.045*	10	743
	(0.039)			repair	(0.023)		
Eggs	0.117*	16	474	Auto	−0.015	16	465
	(0.047)			maintenance	(0.056)		
Ground	−0.232*	12	688	Beauty salon	−0.044***	14	543
beef	(0.054)				(0.035)		
Lettuce	−0.251*	15	512	Bowling	−0.082*	15	512
	(0.076)				(0.028)		
Margarine	0.010	16	467	Dentist	−0.015	16	430
	(0.045)				(0.023)		
Milk	−0.109*	13	594	Doctor	−0.093*	16	468
	(0.023)				(0.056)		
Potatoes	−0.050*	15	579	Dry cleaning	0.006	16	474
	(0.061)				(0.035)		
Steak	−0.018*	16	474	Hospital room	−0.003	13	594
	(0.041)				(0.056)		
Whole	−0.175*	10	1732	Man's haircut	−0.017	16	468
chicken	(0.022)				(0.035)		
Fried	−0.157*	16	465	Movie	−0.117*	13	321
chicken	(0.047)				(0.028)		

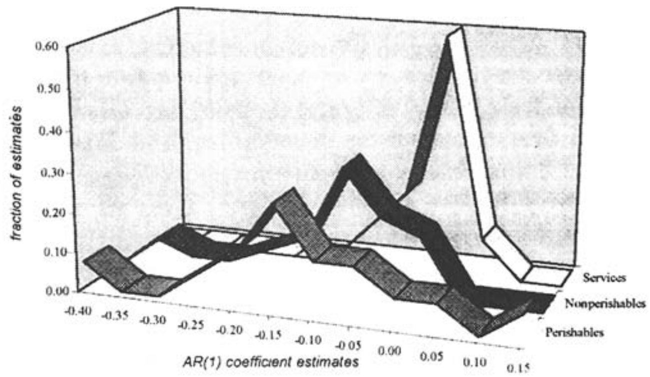
Standard errors are in parentheses, and *, **, and *** denote significance at the 1 percent, 5 percent, and 10 percent levels. For each good, the regression run was

$$\Delta Q_{ij,k,t} = \beta Q_{ij,k,t-1} + \sum_{m=1}^{s(k)} \gamma_m \Delta Q_{ij,k,t-m} + \varepsilon_{ij,k,t},$$

where $Q_{ij,k,t}$ is defined as the percentage difference in price of commodity k at time t between cities i and j, i.e., $Q_{ij,k,t} = \ln(P_{i,k,t}/P_{j,k,t})$. $s(k)$ is chosen as the highest significant lag from a preliminary regression including sixteen lags. New Orleans is defined as the benchmark city.

national context are disciplined to not wander away from zero indefinitely.

Thus, the bulk of the evidence rejects the random walk null hypothesis in favor of a zero-mean stationary process for all three categories. Does this imply that the distinction between tradables and nontradables is unimportant within a given country? Not necessarily, since so far we have not addressed the issue of the



	<-.40	(-.40,-.35)	(-.35,-.30)	(-.30,-.25)	(-.25,-.20)	(-.20,-.15)	(-.15,-.10)	(-.10,-.05)	(-.05,0.0)	> 0.0
Perishables	0.07	0.00	0.00	0.07	0.13	0.27	0.13	0.13	0.07	0.14
Nonperishables	0.00	0.08	0.04	0.04	0.08	0.12	0.31	0.19	0.15	0.00
Services	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.20	0.60	0.10

FIGURE I
Empirical Density Functions of Coefficient Estimates
Based on Panel Unit Root Test Regressions without City Dummies

speed of convergence. Under the assumption that the $Q_{i,k,t}$ process is a zero-mean AR(1) process, the rate of convergence is positively related to the absolute size of the estimated coefficient β.[6] In Figure I we plot the empirical density functions of the estimated AR(1) coefficients for the three categories based on the estimates in Table III. As can be seen, the estimated coefficients for the service items tend to be smaller in absolute magnitude than both the perishables and the nonperishable groups. That is, on average, the deviation from price parity tends to last longer for services.

A further way to examine differences among the three groups is to focus on the median convergence rate for each group. That is, for each group we calculate the implied half-life for the product whose AR(1) coefficient is the median value in the group.[7] The

6. The interpretation that follows is complicated by the possible presence of measurement errors. We return to this issue in more detail below. For now, we assume that there is no measurement error in order to obtain a suggestive characterization of convergence rates across groups.
7. In the case of two medians, we pick the one with a smaller coefficient in absolute value.

medians are corn flakes (−0.123), fried chicken (−0.157), and beauty salon visit (−0.044), for nonperishables, perishables, and services, respectively. These coefficient estimates imply half-lives for deviations from parity of approximately five quarters for nonperishables, four quarters for perishables, and fifteen quarters for services.[8] Thus, in fact, the median convergence rate is substantially lower for the services category than for either of the tradable counterparts. In a broader context both tradable categories converge substantially faster than rates estimated in an international context (typically with a half-life of three to five years, see Frankel and Rose, [1995], for CPI-based real exchange rates, and Wei and Parsley [1995], for tradable sector price indices).

C. City-Specific Effects

So far, the only alternative to a random walk null that we have entertained is a mean-zero AR(1) process. We may also want to consider nonzero city-specific means. This is to allow the sale prices of the products to reflect the cost of local nontraded components (e.g., extra store security guards in a more crime-prone city). Additionally, we may want to control for possible seasonal effects. Specifically, we augment the basic specification in Table III by allowing city and quarter dummies; i.e.,

$$\Delta Q_{i,k,t} = \beta Q_{i,k,t-1} + \sum_{m=1}^{s(k)} \gamma_m \Delta Q_{i,k,t-1} + \Sigma \textit{ city and quarter dummies} + \varepsilon_{i,k,t}.$$

The results are reported in Table IV. We also perform an F-test to see whether the city dummies are jointly significant. It turns out that for about 60 percent of the time, the city dummies are jointly significant if we use a 10 percent critical value. As demonstrated by Levin and Lin [1992], the critical values to reject the unit root null increase dramatically in a fixed effects regression relative to a uniform intercept case, and a comparison of their Figures 4 and 9 indicates that the power to reject the null also declines. According to their Table V, the critical values at the 1 percent, 5 percent, and 10 percent levels for $T = 50$ and $N = 25$ (approximately our panel size after allowing for lagged dependent variables) are −8.25, −7.71 and −7.39, respectively. Based on

8. The implied half-life = $\ln(0.5)/\ln(\beta)$.

TABLE IV
PANEL UNIT ROOT TESTS WITH SEASONAL AND INDIVIDUAL SPECIFIC FIXED EFFECTS

Panel A: Nonperishables							
Good	Beta	F-test	signif.	Good	Beta	F-test	signif.
Aspirin	−0.661 (0.101)	0.93	0.599	Shampoo	−1.595*** (0.214)	1.30	0.101
Baby food	−1.142* (0.119)	2.86	0.001	Shortening	−0.677 (0.120)	1.62	0.009
Beer	−0.713*** (0.095)	1.57	0.012	Soft drink	−0.458 (0.102)	1.51	0.019
Cigarettes	−0.831** (0.104)	1.89	0.001	Sugar	−0.488*** (0.064)	1.52	0.017
Coffee	−0.301 (0.224)	0.46	0.999	Canned peas	−0.939 (0.424)	1.33	0.102
Corn flakes	−0.457 (0.151)	0.96	0.544	Tennis balls	−1.107* (0.133)	1.77	0.002
Frozen corn	−1.684 (0.264)	1.26	0.131	Tissue	−1.030** (0.127)	1.99	0.001
Game	−0.568 (0.145)	1.03	0.417	Canned tomatoes	−2.047 (0.370)	1.31	0.105
Jeans	−0.641 (0.131)	1.17	0.215	Toothpaste	−0.270 (0.131)	0.93	0.604
Liquor	−1.577 (0.470)	0.93	0.599	Canned tuna	−1.103** (0.137)	1.65	0.006
Man's shirt	−0.827 (0.112)	1.19	0.191	Underwear	−0.780 (0.119)	1.72	0.003
Orange juice	−1.084 (0.207)	1.66	0.011	Washing powder	−2.907 (0.490)	1.80	0.005
Canned peaches	−1.024 (0.183)	1.03	0.433	Wine	−0.746 (0.127)	1.56	0.014

Standard errors are in parentheses, and *, **, and *** denote significance at the 1 percent, 5 percent, and 10 percent levels. For each good, the regression run was

$$\Delta Q_{ij,,t} = \beta Q_{ij,k,t-1} + \sum_{m=1}^{s(k)} \gamma_m \Delta Q_{ij,k,t-m} + dummies + \varepsilon_{ij,k,t},$$

where, $Q_{ij,k,t}$ is defined as the percentage difference in price of commodity k at time t between cities i and j, i.e., $Q_{ij,k,t} = \ln(P_{i,k,t}/P_{j,k,t})$. $s(k)$ is chosen as the highest significant lag from a preliminary regression including sixteen lags. The F-test is a test of the joint significance of city-pair dummies. New Orleans is defined as the benchmark city.

these critical values, we can reject the unit root null far less frequently than for the case of a zero-mean AR(1) process as the alternative: 53 percent for perishables, 31 percent for nonperishables, and only 10 percent for services. This result echoes that in Frankel and Rose [1995], who, using a panel of real exchange rates from IMF member countries, also find it hard to reject the unit root null when fixed effects are allowed.

In an effort to increase the power of the statistical tests, we

TABLE IV
(CONTINUED)
PANEL UNIT ROOT TESTS WITH SEASONAL AND INDIVIDUAL SPECIFIC FIXED EFFECTS

Panel B: Perishables and services							
Good	Beta	F-test	signif.	Good	Beta	F-test	signif.
Perishables:							
Bacon	−0.933	0.79	0.836	McDonald's	−1.184**	1.96	0.001
	(0.040)				(0.148)		
Bananas	−1.601**	1.47	0.028	Pizza	−0.569	1.22	0.159
	(0.085)				(0.097)		
Bread	−0.594**	1.58	0.009				
	(0.027)			Services:			
Cheese	−0.608	1.46	0.029	Appliance repair	−0.237**	2.08	0.001
	(0.039)				(0.029)		
Eggs	−0.546	1.23	0.153	Auto maintenance	−0.491	1.45	0.033
	(0.047)				(0.118)		
Ground beef	−1.508*	2.39	0.001	Beauty salon	−0.235	1.03	0.420
	(0.054)				(0.057)		
Lettuce	−1.799*	1.71	0.004	Bowling	−0.418	2.72	0.001
	(0.076)				(0.072)		
Margarine	−1.173	2.06	0.001	Dentist	−0.360	1.13	0.266
	(0.045)				(0.060)		
Milk	−0.360*	1.27	0.116	Doctor	−0.535	2.08	0.001
	(0.023)				(0.087)		
Potatoes	−1.569***	2.68	0.001	Dry cleaning	−0.403	2.06	0.001
	(0.061)				(0.073)		
Steak	−0.740**	0.19	1.000	Hospital room	−0.060	1.69	0.004
	(0.041)				(0.053)		
Whole chicken	−0.705	7.87	0.001	Man's haircut	−0.449	1.84	0.001
	0.022				(0.065)		
Fried chicken	−1.677**	1.36	0.067	Movie	−0.466	0.84	0.750
	(0.047)				(0.160)		

Standard errors are in parentheses, and *, **, and *** denote significance at the 1 percent, 5 percent, and 10 percent levels. For each good, the regression run was

$$\Delta Q_{ij,k,t} = \beta Q_{ij,k,t-1} + \sum_{m=1}^{s(k)} \gamma_m \Delta Q_{ij,k,t-m} + dummies + \varepsilon_{ij,k,t},$$

where, $Q_{ij,k,t}$ is defined as the percentage difference in price of commodity k at time t between cities i and j, i.e., $Q_{ij,k,t} = \ln(P_{i,k,t}/P_{j,k,t})$. $s(k)$ is chosen as the highest significant lag from a preliminary regression including sixteen lags. The F-test is a test of the joint significance of city-pair dummies. New Orleans is defined as the benchmark city.

pooled the data and repeated the estimation. Though not reported here (see Parsley and Wei [1996]), we find that even after imposing the constraint that decay rates are the same within each group we can reject the unit root in regressions with individual specific intercepts only for perishables. Thus, the inclusion of individual specific fixed effects greatly diminishes our ability to reject the unit root hypothesis.[9]

In an international context various authors have found results sensitive to the choice of benchmark currency, e.g., Frenkel [1981] and Fisher and Park [1991]. We repeated the panel augmented Dickey-Fuller tests using New York as an alternative benchmark city. These results are described more fully in Parsley and Wei [1996]. Briefly, our ability to reject the null is virtually unaffected by the choice of benchmark city. Thus, in what follows, we use the New Orleans benchmark exclusively.

D. Tax Adjustment

As noted in Caves, Frankel, and Jones [1993], tariffs and transportation costs create a band within which the real exchange rate can fluctuate. Moreover, time variation in taxes or transportation costs suggests the band itself would shift. There is little guidance in the literature however, concerning whether PPP should hold on a pretax, or tax-adjusted, basis. One might conjecture that consumers care about posttax prices while producers respond to pretax prices. That is, a sufficiently large postsales-tax price differential between two cities would induce consumers to arbitrage the difference. Alternatively, if presales-tax prices between two cities diverge too far, producers would respond and arbitrage this difference.

Define $R_{i,k,t}$ to be the tax-adjusted price difference for product k at time t between city i and New Orleans, i.e., $R_{i,k,t} = \log[P_{i,k,t}(1 + t_{i,k,t})] - \log[P_{j,k,t}(1 + t_{j,k,t})]$, where t is the tax rate and j = New Orleans. Also, define $Z_{i,k,t}$ to be either $Q_{i,k,t}$ or $R_{i,k,t}$, depending on which one is smaller in absolute value. Thus, $Z_{i,k,t}$ is the minimum price difference at each point in time.

Since sales taxes generally do not apply to the services in our study, we repeated the tests for these (minimum) price differences (a more detailed discussion is presented in Parsley and Wei [1996]) for both tradable categories. Results for these tax-adjusted price differentials are virtually identical to those presented in Tables III and IV, both in the magnitude of the esti-

9. Despite the fact that the data reject the restriction that the AR(1) coefficient is the same across products within a group, we find that for nonperishables and services, the point estimates obtained from the pooled estimation are broadly similar to those reported in Table III, though for perishables the estimate of convergence is somewhat faster.

mates, and in our ability to reject the null hypothesis. This suggests that explicit sales taxes have a minimal influence on the time series properties of deviations from price parity. Thus, in the remaining analysis we focus on the nontax-adjusted price differentials.

E. Measurement Errors

The convergence rates reported earlier assume no measurement error in the data. However, if the price data are collected with measurement error, the estimates could be affected. To see this, suppose that the true process is given by

$$Q_t^* = \beta Q_{t-1}^* + \varepsilon_t, \tag{2}$$

where Q_t^*, the true price, is unobservable. We actually observe $Q_t = Q_t^* + u_t$, where u_t is a zero-mean, serially uncorrelated measurement error. This implies that $Q_t = \beta Q_{t-1} + \varepsilon_t + u_t - \beta u_{t-1}$, which is almost an ARMA(1,1) process.

We attempt to gauge the impact of the possible measurement errors using two approaches: (1) a restricted ARMA(1,1) specification, and (2), an instrumental variable approach. In both approaches, we reduce the dimensionality of the problem by choosing the three products that bracket the median from each of the three categories.[10] We also restrict our sample to the ten cities (in addition to New Orleans) with the fewest missing observations.[11]

The first column of Table V reports a simple AR(1) estimation. In the second column we estimate an ARMA(1,1), in which the moving average coefficient is restricted to be the minus of the autoregressive coefficient ($\theta = -\beta$). This restriction approximates that implied by the assumption of an i.i.d. measurement error. As one can see, the autoregressive coefficients in the restricted ARMA(1,1) are almost always larger than those in the straight AR(1) regressions. Hence a straightforward AR(1) regression, ignoring possible measurement error, exaggerates rates of convergence. Column 3 of Table V presents the results of unrestricted

10. That is, in the case of a single median, we choose the median, and one product above and below the median, in terms of their rate of convergence as in Table III. When there are two medians, we choose the product with the next smallest coefficient estimate in absolute value as the third product.

11. Missing values were interpolated that these are the average of the values just prior and following the missing observations. Some experiments with other interpolation methods, e.g., by choosing the value just prior to the missing observation, did not affect our conclusions. See Table VII for a list of the ten cities included in the estimations.

ARMA(1,1) regressions. Comparing unrestricted and restricted ARMA(1,1) regressions, the coefficient restrictions are rejected in all cases.[12]

Our second method of accounting for possible measurement errors is to employ an instrumental variables approach. Specifically, we use Q_{t-3} as an instrument for Q_{t-1}. According to our assumptions, Q_{t-3} is clearly correlated with Q_{t-1}, yet uncorrelated with the error terms in the basic AR(1) regressions. The IV-estimation results are reported as the last column of Table V. There are two noteworthy features in this column. First, the coefficient estimates on Q_{t-1} are higher than the corresponding AR(1) estimates, implying that the rates of convergence for all products are somewhat slower after accounting for possible measurement errors. And second, consistent with our earlier results, tradable goods converge to the law of one price faster than services. Using the IV estimates in column 4, the half-lives for the median products become 4.5 for nonperishables (corn flakes), 3.5 quarters for perishables (fried chicken), and 10.5 for services (beauty salon visit). These half-lives correspond very closely to those reported earlier (5, 4, and 15, respectively), suggesting that our estimates derived from augmented Dickey-Fuller specifications also approximately address the measurement errors issue.

F. Nonlinearities in the Rate of Convergence

We wish to know whether convergence is nonlinear in the initial price difference, as found by e.g., Wei and Parsley [1995]. In particular, convergence may occur faster if the initial price difference is wider. For ease of exposition, we pool the data, and report results for each of our three groups. To examine formally whether there is a nonlinear pattern in the rate of convergence, we add an interaction term of the lagged price difference and its absolute value, and include product dummies. To be precise, the specification for each group is

$$\Delta Q_{ij,k,t} = \beta_0 Q_{ij,k,t-1} + \gamma Q_{ij,k,t-1} \cdot \left| Q_{ij,k,t-1} \right| + \sum_{m=1}^{s(k)} \beta_m \Delta Q_{ij,k,t-m} + dummies + \varepsilon_{ij,k,t}. \tag{3}$$

12. Let L_u and L_r be the log likelihood values for the unrestricted and restricted ARMA regressions, respectively. Then, $2(L_u - L_r)$ has a χ^2 distribution with a degree of freedom of $N - 1$, where N is the number of observations. The 5 percent critical value is approximately 101.9 for all products.

TABLE V
THE IMPACT OF MEASUREMENT ERRORS ON ESTIMATED RATES OF CONVERGENCE

	AR(1)		ARMA(1,1)*		ARMA(1,1)		IV
Corn flakes	0.643	σ^2 = .0067	0.903	σ^2 = .0107	0.836	σ^2 = .0063	0.856
	(0.035)	l = 1083	(0.036)	l = 954	(0.034)	l = 1097	(0.023)
					$\theta = -0.347$		
					(0.058)		
Canned peaches	0.694	σ^2 = .0103	0.579	σ^2 = .0201	0.853	σ^2 = .0099	0.924
	(0.026)	l = 1268	(0.090)	l = 1031	(0.028)	l = 1284	(0.014)
					$\theta = -0.340$		
					(0.054)		
Shortening	0.698	σ^2 = .0087	0.973	σ^2 = .0149	0.952	σ^2 = .0073	0.899
	(0.027)	l = 1328	(0.003)	l = 1137	(0.014)	l = 1393	(0.017)
					$\theta = -0.592$		
					(0.037)		
Milk	0.890	σ^2 = .0051	0.707	σ^2 = .0244	0.967	σ^2 = .0045	0.973
	(0.017)	l = 1501	(0.094)	l = 950	(0.012)	l = 1538	(0.009)
					$\theta = -0.430$		
					(0.048)		
Fried chicken	0.564	σ^2 = .0423	0.755	σ^2 = .0468	0.909	σ^2 = .0341	0.821
	(0.039)	l = 443	(0.042)	l = 380	(0.024)	l = 488	(0.028)
					$\theta = -0.586$		
					(0.054)		

Pizza	0.762	σ^2 = .0036	0.639	σ^2 = .0084	0.750	σ^2 = .0036	0.902
	(0.030)	l = 949	(0.049)	l = 776	(0.038)	l = 949	(0.022)
					θ = 0.034		
					(0.065)		
Appliance repair	0.879	σ^2 = .0080	0.950	σ^2 = .0303	0.928	σ^2 = .0078	0.921
	(0.017)	l = 1357	(0.006)	l = 886	(0.016)	l = 1369	(0.015)
					θ = −0.238		
					(0.046)		
Beauty salon	0.886	σ^2 = .0072	0.909	σ^2 = .0261	0.976	σ^2 = .0064	0.936
	(0.024)	l = 806	(0.013)	l = 543	(0.015)	l = 832	(0.020)
					θ = −0.439		
					(0.047)		
Man's haircut	0.804	σ^2 = .0075	0.825	σ^2 = .0187	0.859	σ^2 = .0074	0.927
	(0.022)	l = 1383	(0.039)	l = 1021	(0.024)	l = 1388	(0.014)
					θ = −0.161		
					(0.050)		

Standard errors are in parentheses, l = the value of the log likelihood function, and σ^2 = the estimate of the sample variance. Columns 1–3 report maximum likelihood estimates pooling data from ten cities. *Column 2 imposes the restriction that the MA(1) coefficient (θ) = −1* the AR(1) coefficient. The estimates in column 4 were obtained instrumenting $Q_{ij,k,t-1}$ with $Q_{ij,k,t-3}$. The ten cities used are Mobile, AL; Blythe, CA; Denver, CO; Indianapolis, IN; Lexington, KY; Louisville, KY; St. Louis, MO; Hastings, NE; Rapid City, SD; and Houston, TX.

TABLE VI

NONLINEARITY IN RATES OF CONVERGENCE TOWARD THE LAW OF ONE PRICE

	Regression 1	Regression 2	Regression 3	Regression 4
Perishables				
$Q_{ij,k,t-1}$	−0.434	−0.517	−0.646	−0.676
	(0.008)	(0.008)	(0.014)	(0.014)
$Q_{ij,k,t-1} \cdot \lvert Q_{ij,k,t-1} \rvert$	−0.099	−0.084	−0.076	−0.067
	(0.020)	(0.020)	(0.032)	(0.032)
Nonperishables				
$Q_{ij,k,t-1}$	−0.298	−0.367	−0.580	−0.585
	(0.008)	(0.008)	(0.015)	(0.015)
$Q_{ij,k,t-1} \cdot \lvert Q_{ij,k,t-1} \rvert$	−0.189	−0.118	0.034	0.047
	(0.024)	(0.024)	(0.045)	(0.045)
Services				
$Q_{ij,k,t-1}$	−0.131	−0.114	−0.480	−0.468
	(0.010)	(0.009)	(0.019)	(0.019)
$Q_{ij,k,t-1} \cdot \lvert Q_{ij,k,t-1} \rvert$	0.005	0.015	−0.039	−0.019
	(0.023)	(0.023)	(0.048)	(0.048)
Std. error of regression	.1347	.1322	.1218	.1211
Number of observations	106,910	106,910	36,180	36,180
Product dummies	no	yes	no	yes
City dummies	no	no	no	yes
Lagged dependent variable	no	no	yes	yes

Standard errors are in parentheses. For columns 1 and 2, the regression run was

$$\Delta Q_{ij,k,t} \sum_{n=1}^{3} \beta_n Q_{ij,k,t-1} + \sum_{n=1}^{3} \gamma_n Q_{ij,k,t-1} \cdot \lvert Q_{ij,k,t-1} \rvert + dummies + \varepsilon_{ij,k,t}.$$

For columns 3 and 4, the regression run was

$$\Delta Q_{ij,k,t} = \sum_{n=1}^{3} \beta_n Q_{ij,k,t-1} + \sum_{n=1}^{3} \gamma'_n Q_{ij,k,t-1} \cdot \lvert Q_{ij,k,t-1} \rvert + \sum_{m=2}^{s(k)} \delta_m Q_{ij,k,t-m} + \sum_{m=2}^{s(k)} \lambda_m Q_{ij,k,t-1} \cdot \lvert Q_{ij,k,t-1} \rvert + dummies + \varepsilon_{ij,k,t},$$

where $n = 1$ if k is perishable, $n = 2$ if k is nonperishable, and $n = 3$ if k is a service. $s(k)$ is chosen as the highest significant lag from a preliminary regression including sixteen lags of each independent variable; for regression 3 and 4, $s(k) = 10$. $Q_{ij,k,t}$ is defined as the percentage difference in price of commodity k at time t between cities i and j, i.e., $Q_{ij,k,t} = \ln(P_{i,k,t}/P_{j,k,t})$. New Orleans is defined as the benchmark city.

The quarterly decay rate now becomes $\beta_0 + 2\gamma \lvert Q_{ij,k,t-1} \rvert$. The estimation results are reported in Table VI. In the table we report four specifications depending on the structure of lagged dependent variables and additional fixed effects. The evidence in the table suggests that nonlinearities are present, especially for tradables. In particular, the interaction term is negative and statistically significant for perishables and for nonperishables in the first two regressions. The results for services are not statistically significant. Thus, at least for tradables, the evidence indicates that convergence occurs faster for larger price differences.

Results in Table II imply that distance is a factor in ex-

TABLE VII
THE IMPACT OF DISTANCE ON CONVERGENCE

	Regression 1	Regression 2	Regression 3	Regression 4
Perishables				
$Q_{ij,k,t-1}$	−1.174	−1.150	−0.691	−0.622
	(0.042)	(0.042)	(0.074)	(0.075)
$Q_{ij,k,t-1}$ *ldist	0.104	0.090	0.073	0.054
	(0.006)	(0.006)	(0.011)	(0.011)
Nonperishables				
$Q_{ij,k,t-1}$	−0.570	−0.609	−0.265	−0.283
	(0.040)	(0.039)	(0.075)	(0.076)
$Q_{ij,k,t-1}$ *ldist	0.031	0.031	0.025	0.024
	(0.006)	(0.006)	(0.011)	(0.011)
Services				
$Q_{ij,k,t-1}$	−0.274	−0.303	−0.070	−0.103
	(0.045)	(0.046)	(0.078)	(0.080)
$Q_{ij,k,t-1}$ *ldist	0.021	0.025	0.007	0.008
	(0.007)	(0.007)	(0.012)	(0.012)
ln distance	−.0012	−.0004	−.0005	.0004
	(.0001)	(.0003)	(.0001)	(.0007)
Std. error of regression	.1343	.1321	.1224	.1212
Number of observations	106910	106910	26989	26989
Product dummies	no	yes	no	yes
City dummies	no	no	no	yes
Lagged dependent variable	no	no	yes	yes

ln refers to the natural log; standard errors are in parentheses. For columns 1 and 2, the regression run was

$$\Delta Q_{ij,k,t} = \theta \ln distance + \sum_{n=1}^{3} \beta_n Q_{ij,k,t-1} + \sum_{n=1}^{3} \gamma_n Q_{ij,k,t-1} \ln distance + dummies + \varepsilon_{ij,k,t}.$$

For columns 3 and 4, the regression was

$$\Delta Q_{ij,k,t} = \theta \ln distance + \sum_{n=1}^{3} \beta_n Q_{ij,k,t-1} + \sum_{n=1}^{3} \gamma_n Q_{ij,k,t-1} \ln distance + \sum_{m=1}^{16} \delta_m \Delta Q_{ij,k,t-m} + dummies + \varepsilon_{ij,k,t},$$

where $n = 1$ if k is perishable, $n = 2$ if k is nonperishable, and $n = 3$ if k is a service, and $Q_{ij,k,t}$ is defined as the percentage difference in price of commodity k at time t between cities i and j, i.e., $Q_{ij,k,t} = (P_{i,k,t}/P_{j,k,t})$. New Orleans is defined as the benchmark city.

plaining intercity price differential variability; i.e., price differentials are more variable for cities farther apart. We now ask whether an effect exists on rates of convergence. In Table VII we augment the basic specification (equation (1)) with two more terms. The first is log distance, and the second is an interaction term between log distance and the initial price differential:

$$\Delta Q_{ij,k,t} = \theta \ln(distance) + \beta_0 Q_{ij,k,t-1} + \gamma Q_{ij,k,t-1} \ln(distance) + \sum_{m=1}^{16} \beta_m \Delta Q_{ij,k,t-m} + dummies + \varepsilon_{ij,k,t}. \tag{4}$$

Results in the table provide evidence that convergence rates are slower for cities farther apart. The implied half-life now depends on the distance between the cities in question and on the initial price difference. An approximation, however, can be obtained by using the average distance between cities within the United States (856 miles using New Orleans as the benchmark city) and the estimates obtained from Tables III. Using the results in column 4, the (approximate) half-lives for nonperishables, perishables, and services are six, three, and fourteen quarters.[13]

We are now in a position to ask how the convergence rates estimated in this paper compare with existing estimates obtained from cross-country data. That is, our lower estimated convergence rates may simply reflect the fact that cities within the United States are closer to one another than are "typical" international city-pairs. Indeed, the average distance between the OECD sample in Wei and Parsley [1995] is 3285 miles (using the United States as a benchmark) as compared with 856 miles for this sample. According to the estimates in column 4 of Table VII, if distance were the only factor differentiating cities within the United States and OECD cities, the average half-lives among OECD countries would be (approximately) four to seven quarters for tradables. However, estimates in Wei and Parsley [1995] for tradable sector price indices are closer to four years![14] Similarly, if distance were the only factor, then price differences for services that would be classified "nontradable" internationally, would have a half-life of about eighteen quarters. Thus, we conclude that distance explains only a small part of the difference between domestic and international estimates of convergence.

IV. Conclusion

To summarize, there are a few noteworthy observations. First, tradable goods (perishable and nonperishable categories) converge very fast to price parity. The half-life of the price gap for

13. The half-life was calculated as $\ln(0.5)/\ln(1 + \beta + \gamma \ln(distance))$. This approximation ignores a possible drift term in the time series representation of the price differential. The approximation yields an estimate of the rate of convergence that is slightly slower than the true one when the drift term is small.

14. The estimates in Wei and Parsley [1995] are in line with other cross-country evidence. See, e.g., Frankel [1986], and Edison [1987], who obtain estimates using extremely long time-series, or more recently Frankel and Rose [1995]. The estimates in Papell [1996] imply somewhat faster convergence.

tradable goods is roughly four to five quarters (fried chicken and corn flakes), and fifteen quarters for services (beauty salon visit). Convergence rates for both tradable categories (perishables and nonperishables) are much faster than those found in cross-country data; indeed, the convergence rate for our least tradable category is on a par with convergence rates found in studies examining international tradable goods. These conclusions are not affected by the presence of tax differentials or by possible measurement errors in the data. Additionally, we present evidence of nonlinearities in the rate of convergence. In particular, convergence occurs faster for larger initial price differences, and far away locations exhibit slower convergence. However, using these estimates, we find that transport costs account for only a small portion of the much slower convergence rates found in cross-country data.

APPENDIX: DESCRIPTIONS OF COMMODITIES INCLUDED

Item	Date added	Description
Appliance repair	75.1	Service call excluding parts color TV (75.1–79.1); Washing machine (79.2–92.4)
Aspirin	82.2	Bayer brand, 100 tablets, bottle 325 mg tablets (82.2–92.4)
Auto maintenance	79.2	Average price to balance two front wheels (79.2–84.1); average price to balance one front wheel (84.2–88.3); average price to computer or spin balance one front wheel (88.4–92.4)
Baby food	75.1	Jar 4½ oz. strained vegetables
Bacon	75.1	Pound of national brands
Bananas	75.1	Pound
Beauty salon	82.2	Woman's visit, shampoo, trim, and blow-dry
Beer	82.2	6 pack, 12 oz. containers, excluding deposit, Miller Lite or Budweiser
Bowling	75.1	Price per line evening price
Bread	75.1	24 oz. (75.1–80.2); 20 oz. (80.3–92.4)
Cheese	82.2	Parmesan, grated 8 oz. canister, Kraft
Cigarettes	75.1	Carton Winston king-size
Coffee	75.1	2 lbs. (75.1–80.2); 1 lb. (80.3–88.3); 13 oz. (88.4–92.4); Maxwell House, Hills Brothers, or Folgers
Corn flakes	79.2	12 oz. Kellogg's or Post Toasties (79.2–80.3); 18 oz. (80.4–92.4)
Dentist	75.1	Office visit, teeth cleaning and inspection, no X-ray or fluoride treatment

APPENDIX: DESCRIPTIONS OF COMMODITIES INCLUDED

Item	Date added	Description
Doctor	75.1	Office visit, general practitioner routine exam of existing patient
Dry cleaning	75.1	Man's two-piece suit
Eggs	75.1	One dozen large grade A
Fried chicken	82.2	Breast and drumstick (82.2–83.4), thigh and drumstick (84.1–92.4), Church's, or Kentucky Fried Chicken if available
Frozen corn	84.1	Frozen, whole kernel, 10 oz. package
Game	82.2	Monopoly, standard (No. 9) edition
Ground beef	75.1	lb.; or hamburger
Hospital room	75.1	Semiprivate cost per day
Jeans	82.2	Levi's straight leg, sizes 28/30 to 34/36 (82.2–87.4), Levi's 501 (88.1–91.3); Levi's 505s or 501s (91.4–92.4)
Lettuce	75.1	Each
Liquor	75.1	750 ml. bottle Seagram's 7 Crown (75.1–88.3); J&B scotch (88.4–92.4)
Man's haircut	75.1	No styling
Man's shirt	82.2	Arrow or Van Heusen, white, long sleeve, cotton/polyester blend (82.2–83.4); sizes 15/32 to 16/34 (89.1–89.3); Arrow, Enro, Van Heusen, J. C. Penney, cotton/polyester (at least 55% cotton) long sleeves (89.4–92.4)
Margarine	75.1	Pound
McDonald's	82.2	½ lb. patty (82.2–83.2); ¼ lb. patty with cheese, pickle, onion, mustard, catsup (83.3–92.4)
Milk	75.1	½ gal. carton
Movie	75.1	First-run indoor evening price
Canned orange juice	75.1	6 oz. can (75.1–85.4); 12 oz. can (86.1–92.4)
Canned peaches	75.1	#2 ½ can approx 29 oz. (75.1–85.4); 29 oz. (86.1–92.4); Del Monte or Libby's halves or slices
Pizza	82.2	12″–13″ thin crust, regular cheese, Pizza Hut or Pizza Inn, where available
Potatoes	75.1	10 lbs. white or red
Shampoo	82.2	11 oz. container Johnson's (82.2–88.3); 15 oz. bottle (88.4–89.3); 11 oz. (89.4–90.4); 15 oz. bottle (91.1); 11 oz. bottle (91.2); 15 oz. bottle Alberto VO5 (91.3–92.4)
Shortening	75.1	3 lb. can all vegetable, Crisco brand
Soft drink	75.1	1 qt. Coca-Cola (75.1–79.2); 2 liter (79.3–92.4)
Steak	75.1	lb.; round steak (75.1–80.3); T-bone steak (80.4–92.4) USDA Choice
Sugar	79.2	5 lbs. cane or beet (79.2–92.3); 4 lbs. cane or beet. 92.4
Canned peas	75.1	#303 can 15–17 oz. (75.1–85.4); 17 oz. (86.1–92.4); Del Monte or Green Giant

APPENDIX: DESCRIPTIONS OF COMMODITIES INCLUDED

Item	Date added	Description
Tennis balls	82.2	Wilson or Penn brands, yellow, can of 3 heavy duty
Tissue	75.1	1 roll (75.1–79.1); 4 rolls (79.2–80.2); Kleenex brand 175 count box (80.3–92.4)
Canned tomatoes	75.1	#303 can 15–17 oz. (75.1–85.4); 14.5 oz. (86.1–92.4); Del Monte or Green Giant
Toothpaste	82.2	6 to 7 oz. tube Crest, or Colgate
Canned tuna	82.2	6.5 oz., Starkist or Chicken of the Sea, packed in oil (82.2–91.3); 6.125–6.5 oz (92.4)
Underwear	82.2	Package of 3 briefs, sizes 28/30–34/36 (82.2–90.3); sizes 10–14 (90.4–92.4)
Washing powder	75.1	49 oz. (75.1–88.4); 42 oz. (89.1–92.4); Giant Tide, Bold, or Cheer
Whole chicken	75.1	lb.; Grade A frying
Wine	82.2	Paul Masson Chablis 750 milliliter bottle (82.2–83.4), Paul Masson Chablis 1.5 liter (84.1–90.3) Gallo Sauvignon Blanc 1.5 liter (90.4–91.3); Gallo Chablis Blanc 1.5 liter (91.3–92.4)

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