Purchasing Power Parity: Three Stakes Through the Heart of the Unit Root Null*

Matthew Higgins Egon Zakrajšek

June 1999

Abstract

A recent influential paper (O'Connell 1998) argues that panel data evidence in favor of purchasing power parity disappears once test procedures are altered to accommodate heterogenous cross-sectional dependence among real exchange rate innovations. We present evidence to the contrary. First, we modify two extant panel unit root panel unit root tests to eliminate the upward size distortion induced by contemporaneous cross-sectional dependence. Second, we exploit recently-introduced test, based on SUR techniques, that also remains valid in the presence of cross-sectional dependence. Using the three new tests, we find overwhelming evidence in favor of real exchange rate stationarity during the post-Bretton Woods era among OECD economies, as well as among a larger group of "open" economies. We also find emphatic evidence of stationarity using O'Connell's GLS test. Bias-corrected parameter estimates indicate that deviations from PPP erode more quickly for real exchange rates defined using wholesale rather than consumer price indices. Monte Carlo experiments indicate that several of the tests discussed here have considerable power against the unit root null.

1 Introduction

Purchasing power parity is a key building block of many models in international macroeconomics. Yet it is by now well-known that the null hypothesis that real

*Both authors are affiliated with the Research Department, Federal Reserve Bank of New York.
We thank Linda Goldberg, Jim Harrigan, Ken Kuttner, Jonathan McCarthy, Gabriel Perez Quiros, Simon Potter, Rob Rich, Eric van Wincoop, and Kei-Mu Yi for their valuable comments. All remaining errors and omissions are our own responsibility.
Please address correspondence to Matthew Higgins, Research Department, Federal Reserve Bank of New York, 33 Liberty Street, New York City, NY 10045, *e-mail:* Matthew.Higgins@ny.frb.org.

exchange rates contain a unit root cannot generally be rejected using univariate tests for data from the post-Bretton Woods era.[1] Frankel (1986, 1990) and Froot and Rogoff (1995) show that failure to reject the unit root null may be driven by the low power of univariate tests against persistent alternatives. Recently, several authors have turned to panel data unit root tests in an attempt to gain statistical power; see, for example, MacDonald (1996), Frankel and Rose (1996a), Oh (1996), Wu (1996), and Papell and Theodoridis (1998). This work uniformly finds evidence of real exchange rate stationarity among developed countries during the recent float.[2]

Recent work by O'Connell (1998) challenges the emerging consensus in favor of real exchange rate stationarity. O'Connell shows that the most widely used panel unit root test, introduced by Levin and Lin (1992), suffers from substantial upward size distortion in the presence of cross-sectional dependence among contemporaneous real exchange rate innovations. He develops develops a new panel unit root test, based on GLS techniques, that eliminates the upward size distortion. Using the new test (OC–GLS hereafter), O'Connell fails to reject the unit root null for several country panels.

We defend the consensus in favor of real exchange rate stationarity. First, we modify the panel unit root test introduced by Im, Pesaran and Shin (1995), as well as a second test introduced by Levin and Lin (1993), to eliminate the upward size distortion induced by contemporaneous cross-sectional dependence. (We call the modified tests $IPS-GLS$ and $LL2-GLS$, respectively.) Second, we exploit a restricted version of the SUR-based panel unit root test recently introduced by Sarno and Taylor (1998) (SUR–GLS hereafter): this test also remains valid in the presence of cross-sectional dependence. Using the three new tests, we find overwhelming evidence in favor of real exchange rate stationarity during the post-Bretton Woods era for three panels of relatively open economies: *i)* 32 countries classified as economically open by Sachs and Warner (1995); *ii)* the 25 countries belonging to the OECD by 1995; and *iii)* 19 European countries. We also find emphatic evidence of stationarity using O'Connell's GLS test.[3]

Bias-corrected parameter estimates indicate that deviations from PPP erode more quickly for real exchange rates defined using wholesale rather than consumer price indices. This result is consistent with the higher share of tradables in the wholesale category. Monte Carlo experiments indicate that the $IPS-GLS$, SUR–GLS and

[1]See, for example, Meese and Rogoff (1988), Mark (1990), and Papell and Theodoridis (1998).

[2]The rapidly growing body of work which applies panel data techniques to real exchange rate behavior includes Wei and Parsley (1996), Flood and Taylor (1996), Frankel and Rose (1996b), Jorian and Sweeney (1996), and Koedijk, Schotman and Dijk (1998). Of these papers, only Koedijk, Schotman and Dijk address the issue of cross-sectional dependence of interest here. The authors' approach, however, differs from our own in treating PPP as the null rather than the alternative hypothesis.

[3]We are unable to explain why O'Connell fails to reject the unit root null for an essentially identical European sample.

$OC–GLS$ tests have considerable power against the unit root null: the exact power ranking depends on the cross-sectional and time-series dimensions of the panel, as well as the degree of serial correlation among real exchange rate innovations. The $LL2-GLS$ test has much lower power against the null, especially in the presence of serial correlation. Notably, though, the $IPS-GLS$ and $LL2-GLS$ tests assume a less restrictive data generating process than the $SUR–GLS$ and $OC–GLS$ tests.

2 PPP and the Unit Root Hypothesis

Purchasing power parity (PPP) is a key building block of many models in international economics. In its simplest and strongest form, purchasing power parity states that the price of similar goods sold in two countries will be equal when expressed in a common currency. This hypothesis, known as absolute purchasing power parity, implies the equality of national price levels, provided that national price indices assign a common set of weights to all goods. Empirical work, on the other hand, has focused on the weaker concept of relative purchasing power parity: a higher rate of domestic inflation—relative to a numeraire country—should be systematically offset by depreciation against the numeraire currency.[4] Relative purchasing power parity implies that real exchange rates—the ratio of a country's nominal exchange rate to its relative price index—should be stationary.

Define the (natural) log of the real exchange rate, q, as:

$$q \equiv (e - e^*) - (p - p^*) \tag{1}$$

where e denotes the log of the nominal (\$US) exchange rate of the domestic country, e^* is the log of the nominal exchange rate of the country used as a numeraire, p is the log of the domestic price level, and p^* is the log of the foreign price level. Note that if p and p^* are measured using consumer price indexes (CPIs), the real exchange rate gives the price of the consumption basket of the numeraire country in terms of the domestic consumption basket. In our analysis, we treat the U.S. as the numeraire country, so that e^* is always equal to 0.

Under the null hypothesis, it is assumed that *each* country's real exchange rate, $q_{i,t}$, contains a unit root, and that the first difference of the real exchange rate, $\Delta q_{i,t}$, is stationary. Under the alternative hypothesis, *all* real exchange rates are assumed to be stationary. Formally, the evolution of the real exchange rate for country i in period t is described by the following data generating process (DGP):

[4] Relative PPP allows for a constant, unobservable differential between different countries' consumption (or production) baskets. As a result, tests of relative PPP can rely on data concerning country price indexes, rather than (generally unavailable) data concerning absolute country price levels.

$$\Delta q_{i,t} = \alpha_i + \rho_i q_{i,t-1} + \eta_{i,t}, \quad i = 1, \ldots, N; \; t = 1, \ldots, T, \tag{2}$$

where α_i denotes a fixed country-specific effect.

Under the null hypothesis that real exchange rates contain a unit root, $\alpha_i = 0$ and $\rho_i = 0$, for all i.[5] Therefore, innovations to the real exchange rate, $\eta_{i,t}$, have a permanent effect on the level of the real exchange rate $q_{i,t}$. Under the alternative hypothesis of stationarity, $\rho_i < 0$, for all i, so that innovations to the real exchange rate decay at the rates ρ_i, $i = 1, \ldots, N$. Moreover, under the alternative, the inclusion of fixed individual effects allows the unconditional mean of $q_{i,t}$ to differ across countries. The long-run equilibrium value of country i's real exchange rate, therefore, is given by $q_i^{LR} = -\alpha_i/\rho_i$.[6]

The simple data generating process described by equation (1) can easily be extended to allow for general ARMA representation of the innovation process under the null hypothesis. For example, one or more lagged real exchange rate changes $(\Delta q_{i,t-1}, \Delta q_{i,t-2}, \ldots)$ can be added as regressors to equation (1) to control for serial correlation, yielding a panel data extension of the standard augmented Dickey-Fuller (ADF) framework. Disturbances that affect all countries equally in a given period t—a pattern of *homogenous* cross-sectional dependence—can easily be accommodated by adding fixed time effects to equation (1), or equivalently, by expressing all variables as deviations from their time-specific means.

3 Panel Data Unit Root Tests

In this section, we review some of the existing panel data unit root tests. A common assumption behind all the tests considered in this paper is that the underlying DGP can be described by a panel data extension of the univariate ADF framework. The

[5] Banerjee et al. (1996, pp. 100-101) describe how common factor restrictions can be used to write the null hypothesis in this composite form. Under the composite null, the fixed effect for each country is absorbed into the initial value $q_{i,0}$, so that $\alpha_i = 0$ for all i.

[6] Unlike some authors, we do not address the possibility that the DGP for real exchange rate changes might contain a linear time trend. That is,

$$\Delta q_{i,t} = \alpha_{1,i} + \alpha_{2,i} t + \rho_i q_{i,t-1} + \eta_{i,t}, \quad i = 1, \ldots, N; \; t = 1, \ldots, T.$$

The null of a unit root in the above equation implies that $\alpha_{1,i} = \alpha_{2,i} = 0$, and $\rho_i = 0$, for all i. Under the stationary alternative, $\rho_i < 0$, and $\alpha_{1,i}$ and $\alpha_{2,i}$ are unrestricted. Under the alternative hypothesis, real exchange rates are stationary around a country-specific deterministic trend. As a result, the real exchange rates for a given country pair i and j can drift apart indefinitely at the rate $\alpha_{2,i} - \alpha_{2,j}$. We view this implication as at odds with the economic content of the relative purchasing power parity hypothesis–that common-currency price levels should not drift apart indefinitely–but are unable to consider the issue further here.

tests can then be classified according to the restrictions imposed on the assumed DGP. For instance, some tests require the speed of convergence to long-run equilibrium under the alternative to be the same across all countries—that is $\rho_i = \rho$, for all i—while others allow the speed of convergence to vary across countries.

Similarly, some tests impose a common autoregressive error structure on the real exchange rate innovations, while others allow it to differ across countries. Some of the tests are designed to accommodate only a homogenous pattern of cross-sectional correlation among real exchange rate innovations, while others are designed to accommodate an arbitrary pattern of contemporaneous cross-sectional dependence. We show below, however, that simple Generalized Least Squares (GLS) transformation techniques can be used to render the first class of tests suitable for panels characterized by heterogenous cross-sectional dependence.

3.1 Levin and Lin (1992)

The first widely used panel data unit root test, developed by Levin and Lin (1992), is a direct extension of a univariate ADF test to the panel data setting. This test ($LL1$ hereafter) restricts the speed of convergence to long-run equilibrium under the alternative of stationarity to be the same for all countries. As in the standard ADF test, serial correlation among real exchange rate innovations is accommodated by adding one or more lags of the change in the real exchange rate as explanatory variables to the regression; autoregressive parameters at each lag and the lag length itself are restricted to be the same for all countries. The estimated model is given by the standard Least Squares with Dummy Variables ($LSDV$) representation:

$$\Delta q_{i,t} = \alpha_i + \rho q_{i,t-1} + \sum_{k=1}^{m} \lambda_k \Delta q_{i,t-k} + \eta_{i,t}; \quad i = 1, \ldots, N; \quad t = 1, \ldots, T. \qquad (3)$$

Levin and Lin (1992) show that under the null hypothesis the t-statistic for $\widehat{\rho}$, $t_{\widehat{\rho}}$, diverges to $-\infty$ at the rate $\sqrt{N}$.[7] A simple transformation of $t_{\widehat{\rho}}$, however, converges to a standard normal variate as $\frac{\sqrt{N}}{T} \rightarrow 0$. For given N and T, appropriate critical values can be derived using Monte Carlo techniques, and critical values for various sample sizes are reported by the authors.

[7] Intuitively, the divergence occurs because the presence of country-specific fixed effects induces a downward bias, for finite T, on the least squares estimator of ρ; see, for example, Nickell (1981). Thus the estimation of fixed individual effects shifts the asymptotic mean and variance of the regression estimator of ρ. In the case of panel data, averaging across N preserves the shift in the mean, so that $\widehat{\rho}$ converges to a non-central normal distribution. Because an increase in the cross-sectional dimension N reduces the sample variance—but for fixed T has no effect on the downward bias of $\widehat{\rho}$—the t-statistic, $t_{\widehat{\rho}}$, approaches $-\infty$ at the rate $\sqrt{N}$.

The $LL1$ test is implemented by estimating equation (2) jointly for all countries. The test can be extended to accommodate an arbitrary pattern of homogenous cross-sectional dependence by adding fixed time effects to equation (2), or equivalently, by expressing all variables as deviations from their time-specific means. Such a transformation has no effect on the limiting distribution of $t_{\widehat{\rho}}$, although in finite samples, there is some loss in statistical power for given N and T.

3.2 Heterogeneous cross-sectional dependence

In a recent paper, O'Connell (1998) shows that the $LL1$ test suffers from significant size distortion in the presence of heterogeneous correlation among contemporaneous real exchange rate innovations. The inclusion of fixed time effects is, at best, only a partial solution to the problem of heterogeneous cross-sectional dependence. For example, if the true covariance matrix of the real exchange rate innovations exhibits substantial heterogeneity in its off-diagonal elements, the removal of the time-mean from each individual series will do little to reduce the amount of cross-sectional dependence present in the data.

Because the data strongly favor the presence of heterogenous cross-sectional correlation, the failure to control properly for this feature of the data has dramatic consequences for the size and power of the $LL1$ test. To address this problem, O'Connell proposes a GLS extension of the $LL1$ unit root test (*OC–GLS* hereafter). The use of GLS techniques produces an estimator with critical values invariant to the actual pattern of contemporaneous cross-sectional correlation among real exchange rate innovations. Like the $LL1$ test, the *OC–GLS* test requires the speed of convergence to long run equilibrium under the alternative to be the same for all countries and imposes a common autoregressive structure on the real exchange rate innovations.

The *OC–GLS* test relies on the first differences of raw data to estimate the covariance matrix of real exchange rate innovations. In particular, the covariance of exchange rate innovations between countries i and j is estimated as:

$$\widehat{\omega}_{ij} = \left(\frac{1}{T-1}\right)\sum_{t=2}^{T}\left(\Delta q_{i,t} - \overline{\Delta q}_i\right)\left(\Delta q_{j,t} - \overline{\Delta q}_j\right), \tag{4}$$

where $\overline{\Delta q}_i = \frac{1}{T-1}\sum_{t=2}^{T}\Delta q_{i,t}$. Under the null hypothesis of a unit root, the first difference of the real exchange rate and its innovation are equivalent (i,e., $\Delta q_{i,t} = \eta_{i,t}$), and the procedure yields consistent estimates of the innovation covariances; the $N\times N$ contemporaneous covariance matrix of real exchange rate innovations, $\widehat{\Omega}$, is defined as $\widehat{\Omega} \equiv [\widehat{\omega}_{ij}]$, $i, j = 1, \ldots, N$.

To implement the *OC–GLS* test, the data matrices corresponding to equation (1) are transformed using the estimated covariance matrix $\widehat{\Omega}$, rendering the error term $\eta_{i,t}$ cross-sectionally homoskedastic. Formally, equation (1) is pre-multiplied by the $NT \times NT$ GLS-transformation matrix $\Gamma \equiv P \otimes I_T$, where P is the lower triangular matrix from the Cholesky decomposition of $\widehat{\Omega}^{-1}$, I_T is an identity matrix of dimension T, and $\otimes$ denotes the Kronecker product. Critical values for the *OC–GLS* estimator are derived via Monte Carlo simulations: artificial data consistent with the null hypothesis are generated, and the lower 1-, 5- and 10-percent tails for $t_{\widehat{\rho}}$ are recorded.

To accommodate serial correlation among real exchange rate innovations, the *OC–GLS* test relies on a two-step procedure. In the first "pre-whitening" stage, differences of the real exchange rate are regressed on one or more lags of itself:

$$\Delta q_{i,t} = \sum_{k=1}^{m} \lambda_k \Delta q_{i,t-k} + u_{i,t} \tag{5}$$

To ensure consistency with the assumptions of the *LL*1 test and achieve a parsimonious specification, equation (4) is estimated jointly for all countries, imposing a common maximum lag length, m, and a common serial correlation pattern, determined by the autoregressive parameters λ_k, $k = 1, \ldots, m$.

Under the null hypothesis of a unit root, $\Delta q_{i,t} = \eta_{i,t}$, and the autoregressive parameters are estimated consistently. In the second stage, the estimated residuals from the first-stage regression, $\widehat{u}_{i,t}$, are used in place of $\Delta q_{i,t}$ and $\Delta q_{j,t}$ in equation (3) to obtain a consistent estimate of Ω. To implement the *OC-GLS* test, the data corresponding to equation (2) are first quasi-differenced to eliminate serial correlation, using the estimated autoregressive parameters $\widehat{\lambda}_k$, $k = 1, \ldots, m$.[8] Finally, a GLS transformation is performed on the quasi-differenced data, ρ is estimated by OLS, and $t_{\widehat{\rho}}$ is compared with the appropriate critical values.

A potential problem with the *OC–GLS* test is that it yields inconsistent estimates of the autoregressive parameters of the ADF regression under the alternative. This point is easiest to illustrate in the case of first-order serial correlation. Note that, under the alternative, a regression of $\Delta q_{i,t}$ on its own lag involves the following term in the numerator of the OLS estimator of λ:

$$\left(\frac{1}{T-1}\right) \sum_{t=2}^{T} \left(\alpha_i + \rho q_{i,t-1} + \eta_{i,t}\right) \left(\alpha_i + \rho q_{i,t-2} + \eta_{i,t-1}\right) \tag{6}$$

Note that $q_{i,t-1}$directly contains $\eta_{i,t-1}$, while $q_{i,t-1}$and $q_{i,t-2}$ share the innovation terms $\eta_{i,t-2}, \eta_{i,t-3}, \ldots$. In a case when there is no serial correlation ($\lambda = 0$), it can be shown that the estimated autoregressive parameter $\widehat{\lambda}$ converges to $\rho/2$ (instead of zero) as $T \to \infty$. This inconsistency also applies to all the parameters estimated for higher-

[8] For example, if first-order serial correlation is assumed, the quasi-differenced model is given by $\left(\Delta q_{i,t} - \widehat{\lambda}\Delta q_{i,t-1}\right) = \alpha_i \left(1 - \widehat{\lambda}\right) + \rho \left(q_{i,t-1} - \widehat{\lambda} q_{i,t-2}\right) + (\eta_{i,t} - \widehat{\lambda}\eta_{i,t-1})$. Under the null hypothesis of a unit root, the transformed error term, $(\eta_{i,t} - \widehat{\lambda}\eta_{i,t-1})$, is serially uncorrelated.

order processes.[9,10] Using Monte Carlo experiments, we show that the inconsistency of the estimated autoregressive parameters can lead to a sizeable loss in statistical power.

3.3 The SUR approach to cross-sectional dependence

When testing for the presence of unit roots in a panel data setting, the time series dimension T typically exceeds the cross-sectional dimension N. This feature of the data can be exploited in a Seemingly Unrelated Regression (SUR) framework to accommodate an arbitrary pattern of contemporaneous cross-sectional correlation. In this section, we describe a SUR-based feasible GLS unit root test (SUR–GLS) as an alternative to the OC–GLS test, which controls for heterogeneous cross-sectional dependence, is simple to compute, and avoids the aforementioned problems with the OC–GLS test.

In spirit, our SUR–GLS test is similar to the OC–GLS test. The fact that $T > N$ allows us to replace the $LSDV$ specification of the OC–GLS tests given in equation (2) with a SUR system of N ADF regressions with country-specific intercepts.[11] The key difference between the OC–GLS test and the SUR-based test is that is that all parameters in the system of N equations are estimated simultaneously, including of course the parameters contained in the contemporaneous cross-sectional covariance matrix Ω, and the parameters λ_k, $k = 1, \ldots, m$, determining temporal dependence among real exchange rate innovations. In particular, we rely on an iterative GLS procedure, with the residuals at each stage used to generate $\widehat{\Omega}$ and the $\widehat{\lambda_k}$ for the subsequent round of estiamation.[12] In contrast with the GLS–OC test, estimates of the serial correlation paramters are consistent under both the null and alternative hypotheses. (Under our approach, the estimates are in fact biased in finite samples under both the null and alternative hypotheses, but Monte Carlo experiments indicate that the degree of finite-sample bias is small.) Also in contrast to the OC–GLS test, Monte Carlo experiments also indicate that extending the test to allow for serial correlation results in a relatively small loss in statistical power.

[9] Suppose, for example, that an AR(2) model is estimated when in fact there is no serial correlation among real exchange rate innovations. It can be shown that the AR(1) parameter $\widehat{\lambda}_1$ converges in probability to $\frac{1-\rho}{2-\rho}\rho$, while the AR(2) parameter $\widehat{\lambda}_2$ converges to $\frac{\rho}{2-p}$. Note that, with $\rho < 0$, the asymptotic bias of $\widehat{\lambda}_1$ increases as additional lags of $\Delta q_{i,t}$ are added to the ADF regression.

[10] The inconsistency of the estimated autoregressive parameters under the alternative implies that the contemporaneous covariance matrix, Ω, is also estimated inconsistently. However, it can be shown through direct calculation or Monte Carlo techniques that $E(\widehat{\Omega_{i,j}} - \Omega_{i,j})$ remains negligible for plausible values of ρ, for $\forall i, j$.

[11] Like the OC–GLS test, our test imposes a common decay parameter ρ on all countries and restricts the temporal process of real exchange rate innovations to be the same across countries.

[12] The iteration terminates when the covariance matrix of equation errors changes less than the specified convergence criterion; see Davidson and MacKinnon (1993) for discussion.

The SUR test described above differs from the test recently introduced by Sarno and Taylor (1998) only in minor respects. Monte Carlo exploitation of the SUR procedure is computationally expensive because the slope and covariance parameters for the system of N equations must be estimated simultaneously. Sarno and Taylor achieve computational feasibilty by limiting the panel to four countries. In contrast, we achieve computational feasibility by restricting the speed of convergence to long-run equilibrium and the paramaters determining serial correlation among innovations to be the same for all countries. As a result, we are able to consider much larger panels. Second, as noted earlier, we rely on an interative SUR procedure, whereas Sarno and Taylor rely on a two-step procedure. The choice of an interative rather than two-step procedure affects the finite-sample but not the asymptotic properties of the tests.

3.4 Levin and Lin (1993)

The strong identifying assumptions of the $LL1$ test have led those authors to develop a panel unit root test that places fewer restrictions on the DGP than their original test. The second test developed by Levin and Lin (1993), allows the speed of convergence to long-run equilibrium under the alternative to vary across countries; and for autoregressive parameters at all lags—as well as the lag-length m itself—to vary across individual countries. The empirical model, then, corresponds to an unrestricted ADF specification:

$$\Delta q_{i,t} = \alpha_i + \rho_i q_{i,t-1} + \sum_{k=1}^{m_i} \lambda_{i,k} \Delta q_{i,t-k} + \eta_{i,t}; \quad i = 1, \ldots, N; \quad t = 1, \ldots, T \qquad (7)$$

As with the $LL1$ test, a homogenous pattern of contemporaneous cross-sectional dependence can be accommodated by expressing all variables as deviations from their time-specific means.

The procedure for the $LL2$ test is elaborate, requiring the calculation of various statistics for each country. The ultimate test statistic has a limiting N(0,1) distribution as $N \to \infty$, $T \to \infty$, and $\frac{N}{T} \to 0$. In finite samples, Monte Carlo techniques are required to estimate mean and variance adjustment factors which preserve a standard normal distribution under the unit root null. The test procedure is described in detail in the Appendix.

3.5 Im, Pesaran and Shin (1995)

Im, Pesaran and Shin (1995) propose a unit root test for heterogeneous dynamic panels based on the mean-group approach recently advanced in Pesaran and Smith (1995) and Pesaran, Smith, and Im (1996). The IPS unit root test is equivalent to the $LL2$ test, in the sense that it is valid in the presence of heterogeneity across cross-sectional units, as well as of residual serial correlation across time periods. As with the $LL2$ test, homogenous cross-sectional dependence can be accommodated by expressing all variables as deviations from their time-specific means.

The IPS test statistic is a simple function of the average t-statistic for $\widehat{\rho}_i$ from the N individual ADF regressions. The authors show that this simple function converges to a standard normal variate as $N \rightarrow \infty$, $T \rightarrow \infty$, and $\frac{N}{T} \rightarrow 0$. As with the LL2 test, Monte Carlo techniques are required to estimate mean and variance adjustment factors which preserve an $N(0,1)$ distribution in finite samples. The test procedure is described in detail in the Appendix.

3.6 Cross-sectional dependence and the LL2 and IPS tests

As noted above, the $LL2$ and IPS tests assume that contemporaneous innovations in different cross-sectional units are uncorrelated: $E(\eta_{i,t}\eta_{j,t}) = 0, \forall i, j$. Homogenous cross-sectional dependence can be accommodated by expressing all variables as deviations from time specific means, but the tests remain invalid in the presence of heterogenous correlation. This section describes a simple GLS procedure which allows the $LL2$ and IPS tests to be implemented when contemporaneous innovations display heterogenous cross-sectional correlation. In spirit, our procedure is similar to O'Connell's (1998). We first take raw real exchange rate differences, and "pre-whiten" them to eliminate serial correlation, as in equation (4). The residuals from the pre-whitening regression, $\widehat{u}_{i,t}$, are used to obtain an estimate of Ω. We then pre-multiply the entire system of NT equations (corresponding to equation (5)) by the $NT \times NT$ GLS-transformation matrix $\Gamma \equiv P \otimes I_T$, where P is the lower triangular matrix from the Cholesky decomposition of $\widehat{\Omega}^{-1}$. The result is to restore independence among contemporaneous real exchange rate innovations. The $LL2$ and IPS tests are then applied to the transformed data in the usual manner; we refer to the modified tests as $LL2$–GLS and IPS–GLS, respectively.

Note that the pre-whitening regression (raw real exchange rate changes on one or more lags) is used only to derive temporally independent residuals, $\widehat{u}_{i,t}$, for estimating the contemporaneous covariance matrix, Ω. The estimated serial correlation parameters are then discarded, and the possibility of serial dependence among innovations is accomodated by including one or more ADF lags in the estimating equation, as in equation (5).

4 Implementing the Panel Unit Root Tests

Implementing the OC–GLS and SUR–GLS tests requires calculation of appropriate critical values using Monte Carlo techniques. The process is straightforward. We first generate 10,000 artificial real exchange rate panels that match the time-series and cross-sectional dimensions of the relevant samples.[13] The artificial panels are consistent with the null hypothesis of a unit root, so that $q_{i,t} = \sum_{s=1}^{t} \eta_{i,s}$ and $\Delta q_{i,t} = \eta_{i,t}$. For each of the two tests, we calculate $\widehat{t}_\rho$ as described above and record the 1-, 5- and 10-percent critical values. For the OC–GLS test, we calculate different critical values corresponding to the number of lags included in the first-stage, "pre-whitening" regression. For the SUR–GLS test, we calculate critical values corresponding to the number of lags in the ADF regression. For both tests, however, autoregressive lag length has only an negligible effect on estimated critical values (see Tables A.5 - A.8).

Implementing the $LL2$–GLS and IPS–GLS tests requires calculation of appropriate mean and variance adjustment factors using Monte Carlo techniques. As above, we generate 10,000 artificial real exchange rate panels, consistent with the unit root null, matching the time-series and cross-sectional dimensions of the relevant samples. We then calculate the mean and variance of the relevant test statistics absent adjustment (see equations (6) and (9)), and, to derive the adjustment factors needed to leave those test statistics with a $N(0, 1)$ distribution. Also as above, we allow the adjustment factors to vary with the number of lags included in the ADF regression.[14]

The DGP used to generate artificial data for calculation of critical values assumes that there is in fact no cross-sectional dependence among contemporaneous real exchange rate innovations, and that such innovations also display no temporal dependence. These assumptions are innocuous. Monte Carlo experiments (not reported) show that, within the range of experimental error, estimated critical values do not depend on the actual contemporaneous covariance matrix, Ω, or on the actual serial correlation parameters λ_k, $k = 1, \ldots, m$.[15] The same holds true for calculation of adjustment factors.

5 Empirical Results

[13] For each "country," the first 25 observations are discarded to avoid initial-value bias. After these initial observations are discarded, the time series dimension of the artificial real exchange rate panel matches that of the panel of interest.

[14] Im, Pesaran and Shin's (1995) original test also tailor mean and variance adjustment factors to the number of ADF lags. Levin and Lin (1993) do not allow adjustment factors to vary with the number of ADF lags, but our Monte Carlo results indicate that doing so is necessary in order to leave the $LL2$ or $LL2$–GLS test statistics with the desired $N(0, 1)$ distribution.

[15] This result should not be surprising. The covariance matrix, Ω, is estimiated in order to transform the data, restoring a homoskedastic relationship among contemporaneous innovations. The estimation error separating Ω and $\widehat{\Omega}$ does not depend on the actual degree of cross-sectional dependence. Similarly, the λ_k are estimated in order to render the equation innovations serially uncorrelated. The estimation error separating the λ_k and $\widehat{\lambda_k}$ does not depend on the actual parameter values.

We study the behavior of real exchange rates during the post-Bretton Woods era, applying the four panel data unit root tests described above to three different data sets. The three samples consist of three, partly overlapping groups of countries: *i)* 32 countries classified as economically open by Sachs and Warner (1995); *ii)* the 25 countries belonging to the OECD as of the end of 1995; and *iii)* 19 European countries. We rely on quarterly, seasonally unadjusted data, and define real exchange rates using consumer price indices (CPIs). As a check on the robustness of our results, we also study the behavior of real exchange rates defined using wholesale price indices (WPIs) with minor changes in the sample composition and length. Details concerning sample selection and variable construction are reported in the tables A.1 and A.3.

5.1 Results using consumer price indices

We being by estimating univariate ADF tests for the 36 countries included in our various samples (Table A.2). In line with most previous research, the U.S. is treated as the numeraire country. To choose lag lengths for the ADF regressions, we rely on the Akaike information criterion, while assuming a minimum lage length of four.[16] For 34 of the 36 countries, a four-lag ADF specification appears adequate to capture any serial dependence among real exchange rate innovations; for two countries (Barbados and Maritius) the Akaike information criterion points to a five-lag specification.

The univariate ADF results provide essentially no support for real exchange rate stationarity. We are able to reject the unit root null at the 10-percent significance level for only five of the 36 countries–little better than would be expected to happen by chance. We are unable to reject the unit root null at the five-percent level for even a single country. These unsupportive results come as no surprise: numerous studies, including most recently (**?**), fail to reject the unit root null for the recent float using univariate ADF tests. Does this lack of support for (relative) purchasing power parity stem from low statistical power, or does it reveal that real exchange rates during the post-Bretton Woods era are, in fact, nonstationary?

To anwer this question, we apply the panel unit root tests desribed above to the Open, OECD and Europe samples. We rely on a four-lag ADF specification, corresponding to the univariate evidence from the Akaike information criterion. The results indicate that low power statistical power stands behind the lack of support from univariate ADF tests for real exchange rate stationarity (Table 1). The evidence is strongest using the $IPS–GLS$ and $SUR–GLS$ tests: the unit-root null is easily

[16] For each sample of interest, we also estimate the LSDV specification of the ADF regression, so that $\rho_i = \rho$ and $\lambda_{i,k} = \lambda_k$, for all i. We allow the covariance matrix of the regression errors to exhibit unrestricted contemporaneous cross-sectional dependence and estimate the resulting specification with restricted maximum likelihood (REML); see, for instance, Diggle, Liang, and Zeger (1995). Using the AIC, the results indicate that for all three samples four lags are sufficient to capture the serial correlation pattern of real exchange rate innovations.

rejected at the one-percent level for all three samples. Support for the stationarity of real exchange rates also comes from the *OC–GLS* test: the unit root null is rejected at the one-percent level for the Europe and OECD samples, although it is not rejected at conventional significance levels for the larger Open sample.[17] The *LL2–GLS* test also supports mean reversion: the unit-root null is rejected at the five-percent level for the Europe and OECD samples, and at the 10-percent level for the Open sample.

Taken together, the five tests provide overwhelming support for real exchange rate stationarity for the Europe and OECD samples, and strong support for the Open sample. We think of the results using the $IPS - GLS$ and $SUR - GLS$ tests as two stakes through the heart of the unit root null; the somewhat less emphastic results from the *OC–GLS* and $LL2 - GLS$ tests together comprise a third stake.

To ensure that the results are not driven by failure to accommodate higher-order serial correlation, we derive a second set of results with $K = 6$ (Table 1). The results are largely unchanged, except that the $LL2 - GLS$ test now fails to reject the null for any sample.

5.2 Results using wholesale price indices

As a check on the robustness of our results, we conduct tests for the stationarity of real exchange rates defined using wholesale rather than consumer prices indices. The new tests also allow us to ask whether the higher weight of tradable goods in wholesale price indices brings faster reversion to purchasing power parity (section 5.4).

As before, we begin by conducting univariate *ADF* tests, with individual country lag lengths chosen using the Akaike information criterion, while assuming a minimum lag length of four (Table A.4). For 27 of the 28 countries with complete wholesale price data, a lag length of four appears sufficient to capture any temporal dependence among real exchange rate innovations; for one country (Taiwan), a five-lag specification appears necessary.

Again, the univariate *ADF* tests provide essentially no support for the (relative) puchasing power parity hypothesis. We are able to reject the unit root null at the 10-percent level for only two of the 28 countries, less often than would be expected to happen by chance.

The picture changes dramatically when we turn to more powerful panel unit root techniques (Table 2): *all* of the test reject the unit root null at the one-percent level, for *every* sample. (Note that the number of countries included in each sample is smaller than for the CPI-based panel unit root tests, due to more limited availability of wholesale price data.)

As before, to ensure that the results are not driven by failure to accommodate higher-order serial correlation, we derive a second set of results with $K = 6$ (Table

[17] As noted earlier, we cannot explain O'Connell's failure to reject the unit-root null for a Europe sample essentially identical to our own.

2). The main change is that the $LL2$–GLS test is now unable to reject the unit root null at conventional significance levels for any sample.

5.3 Test power

The empirical results described above build a strong case that real exchange rates have in fact followed a stationary process during the recent float. However, the results differ across the five tests. For example, with CPI-based real exchange rates, the IPS–GLS test rejects the unit root null at the one-perent level for all three panels; the LL2–GLS test is able to reject only at the five- or ten-percent level. Do these differing results reflect differences in the power properties of the various panel unit root tests?

To address this question, we conduct additional Monte Carlo experiments, with the data generated under the alternative hypothesis of real exchange rate stationarity. The design of the experiments is as follows.

1. For each of 5,000 Monte Carlo replications, we then generate an $N \times T$ matrix of independently and identically distributed real exchange rate innovations. We then premultiply this innovation matrix by the Cholesky decomposition of $\widehat{\Omega}$, estimated as described in Section 4, and vectorize the resulting $N \times T$ matrix. For each of the 5,000 replications, this procedure yields an artificial panel of real exchange rate innovations characterized by the pattern of contemporaneous cross-sectional correlation estimated to be present in the actual data. Our experiments assume that real exchange rate innovations decay at the rate $\rho = -.04$, so that the level of the real exchange rate is given by $q_{i,t} = \sum_{s=0}^{t-1}(1+\rho)^s \eta_{i,t-s}$.[18]

2. We then apply the OC–GLS, SUR–GLS, $LL2$–GLS, and IPS–GLS tests in the usual manner to the artificial panels to test for real exchange rate mean reversion, relying on the critical values calculated as described in Section 4.

3. To assess the effects of the number of estimated ADF lags on test power (or, in the case of the OC–GLS estimator, the number of lags included in the pre-whitening regression), we conduct Monte Carlo experiments for zero-, four- and eight-lag specifications.

The effect of lag length on test power is of interest for two reasons. First, as noted earlier, the OC–GLS test yields inconsistent estimates of the autoregressive parameters under the alternative hypothesis of stationarity. The test might therefore suffer a relatively large loss in power as the number of lags included in the estimating

[18] As customary in power calculations, we set the nuisance parameters, α_i, equal to zero for all panel members.

equation increases. Second, as noted earlier, two of the tests (IPS–GLS and $LL2$–GLS) allow the autoregressive parameters to vary across panel members, while the others impose parameter homogeneity. The cost of this greater generality may be a greater loss in test power as lag length increases. In particular, adding an additional lag involves estimating only a single additional parameter for the SUR–GLS and OC–GLS tests, but N additional parameters for the $LL2$–GLS and IPS–GLS tests.

Our Monte Carlo experiments indicate that the OC–GLS, SUR–GLS and IPS–GLS tests have very high power against the unit root null. Consider the Europe panel (Table 3A). In the zero-lag case, for example, the OC–GLS test has power of 59 percent for a one-percent test size, and 94 percent for a ten-percent test. The power of the SUR-GLS is slightly lower, with the IPS–GLS test close behind. The power of the $LL2$–GLS is far lower, however, at only six percent for a one-percent test size, and 45 percent for a 10 percent test.

However, the power of the OC–GLS test fades relatively rapidly with the assumed autoregressive lag length. Consider moving from a zero-lag to an eight-lag ADF specification (while remaining with the Europe panel). At the five-percent significance level, the power of the OC–GLS test falls by half, from 86 to 45 percent.. The power of the SUR–GLS test falls much less sharply, from 80 to 62 percent. Evidently, the power of the SUR–GLS test suffers only from the number of additional parameters estimated; the power of the OC–GLS test suffers from the number of additional parameters estimated, and also from the fact that the additional parameters are estimated inconsistently. The IPS–GLS test also suffers only a moderate reduction in test power, from 77 to 53 percent at the five-percent level. The power of the $LL2$–GLS test, however, essentially disappears, falling from 28 to zero percent.

The potential power loss arising from estimating additional AR parameters becomes more pressing if the method for choosing maximum lag length tends to select a high-order AR process. For example, O'Connell's (1998) procedure is to regress raw real exchange rate changes on lagged changes, beginning with a maximum lag length of 12. If the deepest lag is significant, according to a likelihood ratio test, that lag length is selected; if not, the number of lags is reduced by one, and the likelihood ratio test is reapplied. Recall here that autoregressive regressions involving raw real exchange rate changes yield inconsistent estimates under the alternative of stationarity. As a result, the method just described tends to point to "significant" temporal dependence where none exists. For example, with $T = 95$ and $N = 19$ (as in the Europe sample), and $\rho = -.04$, a specification containing eight or more lags will be chosen 68 percent of the time, in the absence of any true temporal dependence, and using a ten-percent test to assess statistical significance.[19] The OC–GLS procedure not only loses power quickly as the number of estimated AR parameters increases,

[19] This conclusion is based on a Monte Carlo experiment involving 5,000 replications. If statistical significance is assessed using a five-percent test, a specification containing eight or more lags will be chosen 39 percent of the time.

but tends to choose a high-order parameterization.

The power of the various tests also depends on N, the cross-sectional dimension of the panel. Note that the power of the OC–GLS test, relative to SUR–GLS, improves as the cross-sectional dimension of the panel grows. Indeed, for a panel corresponding to our Open sample (with CPI-based real exchange rates), the power of the OC–GLS test exceeds the power of SUR–GLS, even under an eight-lag specification. This result is not surprising. As the cross-sectional dimension of the panel rises, the the number of elements in Ω to be estimated rises with it. This places a premium on the small sample efficiency of the OC–GLS estimator, outweighing the large-sample inconsistency of the estimated autoregressive parameters. The lesson is that the OC–GLS grows increasingly attractive relative to SUR–GLS as (T/N) declines. However, we are unable to provide a firm metric for choosing between the two tests. The power of the IPS–GLS test also rises relative to that of SUR–GLS as the cross-sectional dimension of the panel rises, but only slightly.

As noted earlier, the power comparisons above do not impose a level playing field. In particular, the OC–GLS and SUR–GLS tests impose homogeneity in the speed of convergence to long-run equilibrium, and in the autoregressive process describing real exchange rate innovations; the IPS–GLS and $LL2$–GLS tests allow heterogeneity along both dimensions. For reasons of computational feasibility, we have not attempted to assess the power performance of an unrestricted SUR-based estimator for panels of the relatively large cross-sectional dimensions considered here. However, initial experiments with $N = 4$ suggest that relaxing our parameter restrictions results in a moderate loss in test power.

One should also note that we report lower test power using the SUR–GLS test than do Sarno and Taylor (1998) using a similar test. The lower test power reported here stems from an important difference in test implementation. Sarno and Taylor estimate the country-specific drift terms–the α_i in equation (2)–using univariate regressions. The authors then include the estimated parameters in the DGP used to generate artificial data consistent with the null hypothesis,[20] and rely on the artificial data for estimating test critical values. The estimated critical values are valid only if the estimated α_i match those present in the true DGP. Monte Carlo experiments (results available on request) show that that the initial estimates of the country-specific drift terms are biased both under the null hypothesis and local alternatives: in particular, the α_i are typically overestimated in absolute value. Moreover, the estimates are subject to very wide dispersion under either the null or local alternatives. The experiments also show that the distribution of test statistics under the null hypothesis is very sensitive to the values of the drift terms included in the process used to generate artificial data. In particular, small increases (in absolute value) in the α_i bring sizeable reductions in estimated critical values. As a result, including

[20] As noted earlier, some interpretations of the null hypothesis require that $\alpha_i = 0, \forall i$. See Banerjee et al. (1996)

estimated drift terms in the process used to generate artificial data will generally leave nominal test size well above true test size, boosting apparent test power.[21] Because the true α_i are unknown and cannot be estimated accurately, we follow the more conservative procedure of setting such nuisance parameters to zero under the null DGP. The points made here are not specific to SUR-based panel unit root tests. For example, adding a drift term of -.01 to a univariate unit root process with an innovation standard deviation of .05 changes the estimated five-percent critical value for the ADF test from -2.89 to -2.52. With $\rho = -.04$ and $T = 100$, the power of the univariate test would appear to rise from 9.8 to 20.8 percent.

Our discussion thus far has side-stepped the important issue of the performance of panel unit root tests in the face of structural breaks. Perron (1988) has shown that a series which is stationary around a changing mean may appear to contain a unit root, and several authors have argued that the unit root null can be rejected using univariate tests once such breaks are accommodated (Perron and Vogelsang 1992, Culver and Pappell 1995, Hegwood and Pappel 1996).[22] We do not know whether panel data unit root are more sensitive to structural breaks than univariate tests (because several panel members may experience a structural break) or less sensitive (because the typical panel member may not experience a structural break).

5.4 The speed of convergence

Although the results presented above provide strong evidence of real exchange rate stationarity during the post-Bretton Woods era, they do not provide direct evidence as to the speed of convergence to long-run equilibrium. True, the point estimates from the various tests imply fairly rapid mean reversion. For example, applying the SUR–GLS test to CPI-based real exchange rates, the estimated speed of convergence is more than six percent per quarter, or 25 percent per annum, for the Europe and OECD samples, and at almost five percent per quarter for the Open sample (Table 4A). However, as noted earlier, the point estimates are biased downward under both the null and alternative hypotheses: the tranformed RHS variable $(q_{i,t} - \overline{q}_{i,-1})$, and the transformed disburbance, $(\varepsilon_{i,t} - \overline{\varepsilon}_i)$, are correlated through their mean components. Indeed, under the null hypothesis that $\rho = 0$, the expected value of $\widehat{\rho}$ comes to about -0.04 for each of the three samples. (Recall that the bias goes to zero as the time-series dimension of the sample increases.) The degree of bias is somewhat smaller under the alternative, because shocks to the real exchange rate erode at the rate ρ, reducing the covariance between $\overline{\varepsilon}_i$ and $\overline{q}_{i,-1}$.

[21] It is worth emphasizing that the authors' empirical results imply rejection of the unit root null for the G-5 countries even using the critical values that would be calcuated setting the $\alpha_i = 0$.

[22] The null hypothesis must be stated carefully for models which allow structural breaks. In particular, if the structuaral breaks themselves follow an i.i.d. random process, the real exchange rate remains nonstationary.

We rely on Monte Carlo techniques to calculate the speed of convergence implied by our emprical results.[23] In particular, for each sample, we find the *estimated* speed of convergence corresponding to various assumed values for ρ: $\rho = -.05, -.04, -.03$, etc. Our earlier empirical results then imply that the true ρ lies between two assumed values; say, between $-.04$ and $-.03$. We then rely on linear interpolation to derive a bias-corrected estimate of ρ.

Our bias-corrected estimates imply that real-exchange rates return to their long-run equilibrium values rather slowly. Consider the results for the *SUR–GLS* test with CPI-based real exchange rates. For the Europe sample, the bias-corrected estimated speed of convergence comes to 3.2 percent quarter, or 12.2 percent per annum, implying a half-life for real exchange rate equilibrium deviations of just over five years. The estimated speed of convergence is somewhat lower for the OECD sample. For the larger Open sample, convergence apparently occurs at a snail's pace: only 0.2 percent per quarter, implying a half-life for equilibrium deviations of more than 85 years! One could well interpret this result as supporting the absence of mean reversion in any economically relevant sense.

Our estimates point to substantially faster convergence to long-run equilibrium for WPI-based real exchange rates, which assign a greater weight to tradable goods. For the Europe sample, the bias-corrected speed of convergence 5.7 percent for quarter, or 21 percent per year, implying a half-life for equilibrium deviations of just under three years. The estimated speed of convergence for the OECD sample is about the same. The sharpest contrast is found for the larger, Open sample: the estimated speed of convergence is 7.0 percent per quarter, as against only 0.2 percent earlier, implying a half life of less than 2.5 years. The much faster estimated speed of convergence for the Open, WPI-based real exchange rates is not due to the fact that fewer countries report wholesale price data (26, as against 32 for consumer prices). If we remove countries that do not report wholesale price data from the Open sample, the bias-corrected speed of convergence for CPI-based real exchange rates remains very low, at about 0.4 percent per quarter.

We also generate biased-corrected estimates of the speed of convergence to PPP using the *IPS–GLS* test (Table 4B). This alternative test implies somewhat faster mean reversion for CPI-based real exchange rates. The contrast is sharpest for the Open sample: the estimated speed of convergence is now a slow but economically meaningful 1.5 percent per quarter, implying a half life for equilibrium deviations of about 11.5 years. The *IPS–GLS* test also finds that WPI-based real exchange rates display faster mean reversion, although the contrast is less stark than with the *SUR–GLS* test.

---

[23] An analytical solution can be found for the expected bias as a function of ρ and T, when ρ is estimated via OLS. However, the Monte Carlo experiments indicate that the *FGLS* estimator exhibits somewhat different (and slightly smaller) finite sample bias.

6 Conclusion

We have found strong support for real exchange rate stationarity using several panel unit root tests: OC–GLS, SUR–GLS, $LL2$–GLS and IPS–GLS remain valid in the presence of heterogenous cross-sectional correlation. Because our results using the $LL2$–GLStest are less than emphatic, we think of the paper as placing three stakes through the heart of the unit root null. Our results support other recent work. Cheung and Lai (1998) apply two efficient univariate tests to post-Bretton Woods real exchange rates for the G-5 countries (the U.S., Japan, Germany, France and the UK). The authors are able to reject the unit root null for most country pairs. Sarno and Taylor (1998), relying on the less restrictive version of our SUR–GLS test, find strong evidence of real exchange rate stationarity for the G-5 countries. The Sarno-Tarylor bottom line is the same as our own: controlling for cross-sectional dependence does not in fact undermine panel data evidence in favor of real exchange rate stationarity among relatively open economies.

We suggest that research attention should now move beyond the purely statistical issue of whether real exchange rates contain a unit root, to examine the economic sources persistent—but not indefinite—departures from relative purchasing power parity.

References

Andrews, Donald W. K., "Heteroscedasticity and Autocorrelation Consistent Covariance Matrix Estimation," *Econometrica*, 1991, *59*, 817–58.

Banerjee, Anindya, Juan Dolado, John Galbraith, and David Hendry, *Cointegration, Error Correction and the Econometric Analysis of Non-Stationary Data*, New York: Oxford University Press, 1996.

Davidson, Russell and James MacKinnon, *Estimation and Inference in Econometrics*, New York: Oxford University Press, 1993.

Diggle, Peter J., Kung-Yee Liang, and Scott L. Zeger, *Analysis of Longitudinal Data*, Oxford, United Kingdom: Clarendon Press, 1995.

Flood, Robert P. and Mark P. Taylor, "Exchange Rate Economics: What's Wrong with the Conventional Macro Approach?," in J. Frankel, G. Galli, and A. Giovannini, eds., *The Microstructure of Foreign Exchange Markets*, Chicago, IL: Chicago University press, 1996, p. ?

Frankel, Jeffrey, "International Capital Mobility and Crowding Out in the U.S. Economy: Imperfect Integration of Financial Markets or of Goods Markets," in R. Hafer, ed., *How Open is the U.S. Economy?*, Lexington, MA: Lexington Books, 1986, p. ?

____ , "Zen and the Art of Modern Macroeconomics: The Search for Perfect Nothingness," in W. Haraf and T. Willett, eds., *Monetary Policy for a Volatile Global Economy*, Washington DC: American Enterprise Institute, 1990, p. ?

____ **and Andrew Rose**, "A Panel Project on Purchasing Power Parity: Mean Reversion within and between Countries," *Journal of International Economics*, 1996, *40* (1), 209–224.

____ **and** ____ , "A Panel Project on Purchasing Power Parity: Mean Reversion within and between Countries," *Journal of International Economics*, 1996, *40*, 209–224.

Froot, Kenneth A. and Kenneth Rogoff, "Perspectives on PPP and Long-Run Real Exchange Rates," in G. Grossman and K. Rogoff, eds., *Handbook of International Economics, Vol III*, Amsterdam: Elsevier Science, 1995, pp. 1647–1688.

Im, Kyong So, M. Hashem Pesaran, and Yongcheol Shin, "Testing for Unit Roots in Heterogeneous Panels," 1995. Unpublished paper, Dept. of Applied Economics, University of Cambridge.

Jorian, P. and R. Sweeney, "Mean Reversion in Real Exchange Rates: Evidence and Implications for Forecasting," *Journal of International Money and Finance*, 1996, *15*, 535–550.

Koedijk, Kees, Peter Schotman, and Mathijs Dijk, "The Re-Emergence of PPP in the 1990s," *Journal of International Money and Finance*, 1998, *17*, 51–61.

Levin, Andrew and Chien-Fu Lin, "Unit Root Tests in Panel Data: Asymptotic and Finite Sample Properties," 1992. Unpublished paper, Dept. of Economics, University of California, San Diego.

___ and ___ , "Unit Root Tests in Panel Data: New Results," 1993. Unpublished paper, Dept. of Economics, University of California, San Diego.

MacDonald, Ronald, "Panel Unit Root Tests and Real Exchange Rates," *Economic Letters*, 1996, *50*, 7–11.

Mark, Nelson, "Real Exchange Rates in the Long-Run: An Empirical Investigation," *Journal of International Economics*, 1990, *28*, 115–136.

Meese, Richard and Kenneth Rogoff, "Was It Real? The Exchange Rate Interest Differential Relation over the Modern Floating Exchange Rate Period," *Journal of Finance*, 1988, *43*, 933–948.

Newey, Whitney K. and Ken D. West, "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 1987, *55*, 703–08.

Nickell, Stephen, "Biases in Dynamic Models with Fixed Effects," *Econometrica*, 1981, *49*, 1417–26.

O'Connell, Paul G.J., "The Overvaluation of Purchasing Power Parity," *Journal of International Economics*, 1998, *44* (1), 1–20.

Oh, Keun-Yeob, "Purchasing Power Parity and Unit Root Tests Using Panel Data," *Journal of International Money and Finance*, 1996, *15*, 405–418.

Papell, David H. and Hristos Theodoridis, "Increasing Evidence of Purchasing Power Parity Over the Current Float," *Journal of International Money and Finance*, 1998, *17*, 41–50.

Parsley, David and Shang-Jin Wei, "Convergence to the Law of One Price Without Trade Barriers or Currency Fluctuations," *Quarterly Journal of Economics*, 1996, *111* (4), 1211–36.

Pesaran, M. Hashem and Ron Smith, "Estimating Long-Run Relationships from Dynamic Heterogeneous Panels," *Journal of Econometrics*, 1995, *68*, 79–113.

——, ——, and Kyung So Im, "Dynamic Linear Models for Heterogeneous Panels," in L. Matyas and P. Sevestre, eds., *The Econometrics of Panel Data: A Handbook of the Theory with Applications*, Norwell, MA: Kluwer Academic Publishers, 1996, pp. 145–95.

Sachs, Jeffrey and Andrew Warner, "Economic Reform and the Process of Global Integration," *Brookings Papers on Economic Activity*, 1995, (1), 1–95.

Sarno, Lucio and Mark P. Taylor, "The Behavior of the Real Exchange Rates During the Post-Bretton Woods Period," *Journal of International Economics*, 1998, *46*, 281–312.

Wu, Yangru, "Are Real Exchange Rates Nonstationary? Evidence from a Panel Data Test," *Journal of Money, Credit, and Banking*, 1996, *28* (1), 54–63.

TABLE 1

Panel Data Unit Root Tests of PPP
CPI Based Exchange Real Rates
Empirical Size Properties

Four-Lag ADF Specification ($m = 4$)

Unit Root Test	SAMPLE EUROPE	OECD	OPEN
OC–GLS	0.01	0.01	nr
SUR–GLS	0.01	0.01	0.01
LL2–GLS	0.05	0.05	0.10
IPS–GLS	0.01	0.01	0.01
N	19	25	32
$\min T_i$	-	-	71
$\max T_i$	-	-	95
$\bar{T}$	95	93	93
Obs.	1,805	2,375	2,975

Six-Lag ADF Specification ($m = 6$)

Unit Root Test	SAMPLE EUROPE	OECD	OPEN
OC–GLS	0.01	0.01	nr
SUR–GLS	0.05	0.05	0.05
LL2–GLS	nr	nr	nr
IPS–GLS	0.01	0.01	0.01
N	19	25	32
$\min T_i$	-	-	69
$\max T_i$	-	-	93
$\bar{T}$	93	93	91
Obs.	1,767	2,325	2,911

Notes: The entries in the table correspond to the significance level (%) at which the null hypothesis of a unit root can be rejected; nr indicates that the null hypothesis cannot be rejected at the 10 percent (or better) significance level. All empirical significance levels are based on 10,000 Monte Carlo replications of a panel with the cross-sectional dimension N and time series dimension $\bar{T}$.

TABLE 2

Panel Data Unit Root Tests of PPP
WPI Based Exchange Real Rates
Empirical Size Properties

Four-Lag ADF Specification ($m = 4$)

Unit Root Test	SAMPLE EUROPE	SAMPLE OECD	SAMPLE OPEN
OC–GLS	0.01	0.01	0.01
SUR–GLS	0.01	0.01	0.01
LL2–GLS	0.01	0.01	0.01
IPS–GLS	0.01	0.01	0.01
N	16	22	26
$\min T_i$	67	67	49
$\max T_i$	95	95	95
$\bar{T}$	90.8	92	90
Obs.	1,453	2,023	2,340

Six-Lag ADF Specification ($m = 6$)

Unit Root Test	SAMPLE EUROPE	SAMPLE OECD	SAMPLE OPEN
OC–GLS	0.01	0.01	0.01
SUR–GLS	0.01	0.01	0.01
LL2–GLS	nr	nr	nr
IPS–GLS	0.05	0.01	0.01
N	16	22	26
$\min T_i$	65	65	47
$\max T_i$	93	93	93
$\bar{T}$	88.8	90	88
Obs.	1,421	1,979	2,288

Notes: The entries in the table correspond to the significance level (%) at which the null hypothesis of a unit root can be rejected; nr indicates that the null hypothesis cannot be rejected at the 10 percent (or better) significance level. All empirical significance levels are based on 10,000 Monte Carlo replications of a panel with the cross-sectional dimension N and time series dimension $\bar{T}$.

TABLE 3A

Panel Data Unit Root Tests of PPP
CPI Based Real Exchange Rates
Empirical Power Properties

	Zero Lag ADF Specification ($m = 0$)								
	EUROPE			OECD			OPEN		
	Test Size			Test Size			Test Size		
Unit Root Test	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%
OC–GLS	0.59	0.86	0.94	0.74	0.93	0.97	0.82	0.95	0.98
SUR–GLS	0.51	0.80	0.91	0.55	0.85	0.94	0.48	0.84	0.94
LL2–GLS	0.06	0.28	0.45	0.07	0.31	0.51	0.10	0.31	0.51
IPS–GLS	0.46	0.77	0.88	0.59	0.85	0.93	0.67	0.87	0.94

	Four Lag ADF Specification ($m = 4$)								
	EUROPE			OECD			OPEN		
	Test Size			Test Size			Test Size		
Unit Root Test	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%
OC–GLS	0.34	0.70	0.83	0.50	0.79	0.89	0.64	0.86	0.94
SUR–GLS	0.37	0.72	0.86	0.46	0.79	0.90	0.43	0.76	0.89
LL2–GLS	0.00	0.03	0.08	0.00	0.03	0.09	0.00	0.03	0.07
IPS–GLS	0.35	0.65	0.80	0.48	0.76	0.86	0.52	0.79	0.89

	Eight Lag ADF Specification ($m = 8$)								
	EUROPE			OECD			OPEN		
	Test Size			Test Size			Test Size		
Unit Root Test	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%
OC–GLS	0.16	0.45	0.63	0.22	0.58	0.74	0.36	0.68	0.82
SUR–GLS	0.27	0.62	0.77	0.33	0.67	0.83	0.25	0.63	0.81
LL2–GLS	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.01	0.02
IPS–GLS	0.22	0.53	0.68	0.31	0.61	0.76	0.37	0.67	0.80

Notes: All power calculations are based on 5,000 Monte Carlo replications. The data for each panel dimension are generated under the alternative hypothesis of stationarity: $q_{it} = 0.96q_{it-1} + \epsilon_{it}$, where $\epsilon_{it} \sim N(0, 1)$.

TABLE 3B

Panel Data Unit Root Tests of PPP
WPI Based Real Exchange Rates
Empirical Power Properties

	Zero Lag ADF Specification ($m = 0$)								
	EUROPE			OECD			OPEN		
	Test Size			Test Size			Test Size		
Unit Root Test	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%
OC–GLS	0.47	0.75	0.87	0.63	0.87	0.95	0.69	0.90	0.95
SUR–GLS	0.40	0.74	0.86	0.47	0.82	0.92	0.49	0.81	0.92
LL2–GLS	0.04	0.21	0.37	0.06	0.23	0.41	0.07	0.28	0.46
IPS–GLS	0.37	0.67	0.80	0.48	0.78	0.89	0.51	0.81	0.95

	Four Lag ADF Specification ($m = 4$)								
	EUROPE			OECD			OPEN		
	Test Size			Test Size			Test Size		
Unit Root Test	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%
OC–GLS	0.25	0.55	0.71	0.37	0.70	0.84	0.44	0.75	0.87
SUR–GLS	0.27	0.63	0.78	0.41	0.73	0.86	0.41	0.75	0.87
LL2–GLS	0.00	0.02	0.06	0.00	0.03	0.08	0.00	0.02	0.07
IPS–GLS	0.27	0.58	0.73	0.37	0.67	0.80	0.39	0.68	0.82

	Eight Lag ADF Specification ($m = 8$)								
	EUROPE			OECD			OPEN		
	Test Size			Test Size			Test Size		
Unit Root Test	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%
OC–GLS	0.10	0.35	0.54	0.19	0.48	0.66	0.22	0.53	0.70
SUR–GLS	0.18	0.53	0.70	0.27	0.61	0.78	0.26	0.60	0.76
LL2–GLS	0.00	0.00	0.02	0.00	0.01	0.02	0.00	0.01	0.01
IPS–GLS	0.17	0.46	0.62	0.25	0.55	0.70	0.28	0.59	0.74

Notes: All power calculations are based on 5,000 Monte Carlo replications. The data for each panel dimension are generated under the alternative hypothesis of stationarity: $q_{it} = 0.96 q_{it-1} + \epsilon_{it}$, where $\epsilon_{it} \sim N(0,1)$.

TABLE 4A

Speed of Convergence to PPP
Actual and Bias-Corrected *SUR–GLS* Estimates of ρ
Four-Lag ADF Specification

CPI Based Real Exchange Rates					
EUROPE		OECD		OPEN	
Actual $\widehat{\rho}$	B-C $\widehat{\rho}$	Actual $\widehat{\rho}$	B-C $\widehat{\rho}$	Actual $\widehat{\rho}$	B-C $\widehat{\rho}$
-0.064	-0.032	-0.061	-0.020	-0.047	-0.002

WPI Based Real Exchange Rates					
EUROPE		OECD		OPEN	
Actual $\widehat{\rho}$	B-C $\widehat{\rho}$	Actual $\widehat{\rho}$	B-C $\widehat{\rho}$	Actual $\widehat{\rho}$	B-C $\widehat{\rho}$
-0.087	-0.057	-0.086	-0.056	-0.095	-0.070

Notes: Bias-corrected estimates of the decay parameter ρ are computed by matching the actual empirical estimates of ρ with Monte Carlo estimates generated using various assumed values for ρ. For each replication, N stationary processes of length $T+30$ are generated as $q_{i,t} = (1+\rho)\, q_{i,t-1} + \epsilon_{i,t}$, where $\epsilon_{i,t} \sim N(0,1)$ and $\rho = -.04, -.03, -.025, -.02, -.015, -.01, -.005$. The first 25 observations are discarded to minimize the effect of the initial value bias. The following N-equation system of ADF regressions is estimated in a SUR framework with iterative GLS: $\Delta q_{i,t} = \alpha_i + \rho q_{i,t-1} + \sum_{k=1}^{4} \lambda_k \Delta q_{i,t-k} + \eta_{i,t}$, $t = 1, \ldots, T$. There were 5,000 Monte Carlo replications for each assumed value of ρ.

TABLE 4B

Speed of Convergence to PPP
Actual and Bias-Corrected *IPS–GLS* Estimates of ρ
Four-Lag ADF Specification

CPI Based Real Exchange Rates					
EUROPE		OECD		OPEN	
Actual $\widehat{\rho}$	B-C $\widehat{\rho}$	Actual $\widehat{\rho}$	B-C $\widehat{\rho}$	Actual $\widehat{\rho}_{MG}$	B-C $\widehat{\rho}$
-0.071	-0.035	-0.070	-0.035	-0.059	-0.015

WPI Based Real Exchange Rates					
EUROPE		OECD		OPEN	
Actual $\widehat{\rho}$	B-C $\widehat{\rho}$	Actual $\widehat{\rho}$	B-C $\widehat{\rho}$	Actual $\widehat{\rho}$	B-C $\widehat{\rho}$
-0.077	-0.035	-0.082	-0.045	-0.083	-0.045

Notes: Bias-corrected estimates of the decay parameter ρ are computed by matching the actual empirical estimates of ρ with Monte Carlo estimates generated using various assumed values for ρ. For each replication, N stationary processes of length $T+30$ are generated as $q_{i,t} = (1+\rho)\, q_{i,t-1} + \epsilon_{i,t}$, where $\epsilon_{i,t} \sim N(0,1)$ and $\rho = -.04, -.03, -.025, -.02, -.015, -.01, -.005$. The first 25 observations are discarded to minimize the effect of the initial value bias. A GLS transformation, rendering the error term cross-sectionally homoscedastic, is performed on the data, and for each of the N countries, the following ADF regressions is estimated by OLS: $\Delta q_{i,t} = \alpha_i + \rho_i q_{i,t-1} + \sum_{k=1}^{4} \lambda_{i,k} \Delta q_{i,t-k} + \eta_{i,t}$, $t = 1, \ldots, T$. The mean-group (MG) estimate of ρ is computed as $\widehat{\rho} = \frac{1}{N} \sum_{i=1}^{N} \widehat{\rho}_i$ There were 5,000 Monte Carlo replications for each assumed value of ρ.

Appendix: The LL2 and IPS Tests

A.1. Levin and Lin (1993)

The LL2 test can be summarized in four steps. First, two country-specific auxilliary regressions are estimated using OLS to obtain orthogonalized residuals $\widehat{e}_{i,t}$ and $\widehat{\nu}_{i,t-1}$, defined as

$$\begin{aligned} \widehat{e}_{i,t} &= \Delta q_{i,t} - \widehat{\alpha}_i - \sum_{k=1}^{m_i} \widehat{\gamma}_{i,k} \Delta q_{i,t-k}; \\ \widehat{\nu}_{i,t-1} &= q_{i,t-1} - \widehat{\alpha}_i - \sum_{k=1}^{m_i} \widehat{\theta}_{i,k} \Delta q_{i,t-k}. \end{aligned} \quad \text{(A.1)}$$

To control for heterogeneity across countries, the residuals $\widehat{e}_{i,t}$ and $\widehat{\nu}_{i,t-1}$ are normalized, where the normalization factor is equal to the standard error of the country-specific regression of $\widehat{e}_{i,t}$ on $\widehat{v}_{i,t-1}$. That is, the heterogeneity-corrected orthogonalized residuals $\tilde{e}_{i,t}$ and $\tilde{v}_{i,t-1}$ are defined as

$$\tilde{e}_{i,t} = \frac{\widehat{e}_{i,t}}{\widehat{\sigma}_{i,T}} \quad \text{and} \quad \tilde{v}_{i,t-1} = \frac{\widehat{v}_{i,t-1}}{\widehat{\sigma}_{i,T}} \quad \text{(A.2)}$$

where

$$\widehat{\sigma}_{i,T}^2 = \left(\frac{1}{T - m_i - 1}\right) \sum_{t=m_i+2}^{T} (\widehat{e}_{i,t} - \widehat{\delta}_i \widehat{v}_{i,t-1})^2 \quad \text{(A.3)}$$

and $\widehat{\delta}_i$ is the OLS estimator of δ_i in the country-specific regression of $\widehat{e}_{i,t}$ on $\widehat{v}_{i,t-1}$.

Second, Levin and Lin estimate the ratio of long-run to short-run (innovation) standard deviation for each country-specific ADF regression and calculate the average of this ratio for the entire panel as:

$$\widehat{S}_{NT} = \frac{1}{N} \sum_{i=1}^{N} \frac{\widehat{\sigma}_{\eta_i,T}}{\widehat{\sigma}_{i,T}} \quad \text{(A.4)}$$

where $\widehat{\sigma}_{\eta_i,T}^2$ is the estimator of the long-run variance $\sigma_{\eta_i,T}^2$, obtained as

$$\widehat{\sigma}_{\eta_i,T}^2 = \frac{1}{T-1} \sum_{t=2}^{T} (\Delta q_{i,t})^2 + 2 \sum_{j=1}^{L} w(j,L) \left(\frac{1}{T-1} \sum_{t=2+j}^{T} \Delta q_{i,t} \Delta q_{i,t-j} \right) \quad \text{(A.5)}$$

where $w(j, L)$ are the sample covariance weights to ensure a non-negative value of $\widehat{\sigma}^2_{\eta_i,T}$.[24]

Third, the authors consider the following pooled regression:

$$\tilde{e}_{i,t} = \beta\tilde{v}_{i,t-1} + error, \quad i = 1, \ldots, N; \quad t = m_i + 2, \ldots, T \tag{A.6}$$

where $\tilde{e}_{i,t}$ and $\tilde{v}_{i,t-1}$ denote the heterogeneity-corrected normalized residuals from step one. The null hypothesis of a unit root is tested against the alternative of stationarity by considering the t-statistic for testing $\beta = 0$:

$$t_{\widehat{\beta}_{NT}} = \frac{\widehat{\beta}_{NT}}{RSE(\widehat{\beta}_{NT})} \tag{A.7}$$

where $\widehat{\beta}_{NT}$ is the pooled OLS estimator of β,

$$RSE(\widehat{\beta}_{NT}) = \widehat{\sigma}_{NT}\left[\sum_{i=1}^{N}\sum_{t=2+m_i}^{T}\tilde{v}^2_{i,t-1}\right]^{-\frac{1}{2}} \tag{A.8}$$

is the standard error of $\widehat{\beta}_{NT}$, and $\widehat{\sigma}_{NT}$ is the standard error of the regression, computed as the square root of

$$\widehat{\sigma}^2_{NT} = \frac{1}{N\widetilde{T}}\sum_{i=1}^{N}\sum_{t=2+m_i}^{T}(\tilde{e}_{i,t} - \widehat{\beta}_{NT}\tilde{v}_{i,t-1})^2 \tag{A.9}$$

where $\widetilde{T} = T - \overline{m} - 1$, and $\overline{m} = \frac{1}{N}\sum_{i=1}^{N} m_i$.

Finally, the authors show that as $N \to \infty$, $T \to \infty$, and $\frac{N}{T} \to 0$, a function of the t-statistic $t_{\widehat{\beta}_{NT}}$ converges to a standard normal variate. In particular, the specific functional form for the Levin and Lin (1993) test statistic is

$$LL2 = \frac{t_{\widehat{\beta}_{NT}} - N\widetilde{T}\widehat{S}_{NT}\widehat{\sigma}^{-2}_{NT}RSE(\widehat{\beta}_{NT})\mu^*_{\widetilde{T}}}{\sigma^*_{\widetilde{T}}} \overset{a}{\sim} N(0, 1) \tag{A.10}$$

where $\mu^*_{\widetilde{T}}$ and $\sigma^*_{\widetilde{T}}$ are the mean and the standard deviation adjustment factors, obtained by the authors via stochastic simulations, so that the test statistic retains a $N(0, 1)$ distribution.

The adjustment factors are tabulated for $N = 250$ and different values of $\widetilde{T}$. In particular, at each Monte Carlo replication, Gaussian random numbers with unit variance are used to generate 250 independent unit root processes of time series dimension $\widetilde{T} + 1$. The panel is then used to compute the sample statistics $\widehat{\beta}_{NT}$,

[24] Levin and Lin (1993) advocate the use of Bartlett weights, $w(j, L) = j/(L + 1)$, proposed by Newey and West (1987); in this case, the estimator $\widehat{\sigma}^2_{\eta_i,T}$ is consistent if the lag truncation parameter L grows exponentially at a rate less than T.

$t_{\widehat{\beta}_{NT}}$, $\widehat{S}_{NT}$, $\widehat{\sigma}_{NT}$, and $RSE(\widehat{\beta}_{NT})$, using the lag truncation parameter $L = 3.21T^{\frac{1}{3}}$ (see Andrews (1991)) and $m_i = 0$ for all i. Finally, based on 25,000 replications, $\mu^*_{\widetilde{T}}$ is computed as the mean of $t_{\widehat{\beta}_{NT}}/N\widetilde{T}\widehat{S}_{NT}\widehat{\sigma}^{-2}_{NT}RSE(\widehat{\beta}_{NT})$, and $\sigma^*_{\widetilde{T}}$ is computed as the standard deviation of $t_{\widehat{\beta}_{NT}} - N\widetilde{T}\widehat{S}_{NT}\widehat{\sigma}^{-2}_{NT}RSE(\widehat{\beta}_{NT})\mu^*_{\widetilde{T}}$.

A.2. Im, Pesaran and Shin (1995)

The IPS t-bar statistic, $\bar{t}_{NT}$, is based on the average of the t-statistics for $\widehat{\rho}_i$, obtained from country-specific estimation of the standard ADF regression. The t-bar statistic is defined as:

$$\bar{t}_{NT} = \frac{1}{N}\sum_{i=1}^{N} t_i(T_i, m_i, \widehat{\rho}_i), \tag{A.11}$$

where $t_i(T_i, m_i, \widehat{\rho}_i)$ denotes the t-statistic of the OLS estimator of ρ_i, based on the sample of length T_i and with m_i lags in the ADF regression. Im, Pesaran and Shin (1995) show that as $N \to \infty$, $T \to \infty$, and $\frac{N}{T} \to 0$, the standardized $\bar{t}_{NT}$ statistic converges to the $N(0,1)$ distribution. That is, the IPS test statistic is given by:

$$IPS = \frac{\sqrt{N}(\bar{t}_{NT} - a_{NT})}{\sqrt{b_{NT}}} \overset{a}{\sim} N(0,1), \tag{A.12}$$

where a_{NT} and b_{NT} are the mean and the variance adjustment factors for the t-bar statistic $\bar{t}_{NT}$, obtained via stochastic simulations.

Im, Pesaran and Shin tabulate the adjustment factors a_{NT} and b_{NT} for $N = 1$ and different values of T and m. In particular, at each Monte Carlo replication, Gaussian random numbers with unit variance are used to generate a random walk of dimension $T+m+1$. Next, the authors estimate the standard ADF regression given in equation (7) to obtain the t-statistic for testing $\rho = 0$, denoted by $t^j(T, m, 0)$, where j stands for the j-th Monte Carlo replication. This procedure is repeated R times, and the mean:

$$a_{NT} = E_R[t(T, m, 0)] = \frac{1}{R}\sum_{j=1}^{R} t^j(T, m, 0) \tag{A.13}$$

and the variance:

$$b_{NT} = V_R[t(T, m, 0)] = \frac{1}{R}\sum_{j=1}^{R} \left[t^j(T, m, 0) - E_R[t(T, m, 0)]\right]^2 \tag{A.14}$$

are computed.[25]

[25] The adjustment factors reported by Im, Pesaran, and Shin (1995) are based on 50,000 replications.

TABLE A.1

Sample Membership
CPI Based Real Exchange Rates

Country	Sample			Start	End	T
	EUROPE	OECD	OPEN			
Australia		√	√	73Q1	97Q4	100
Austria	√	√	√	73Q1	97Q4	100
Barbados			√	73Q1	97Q4	100
Belgium	√	√	√	73Q1	97Q4	100
Botswana			√	79Q1	97Q4	76
Canada		√	√	73Q1	97Q4	100
Chile			√	76Q1	97Q4	88
Cyprus	√		√	73Q1	97Q4	100
Denmark	√	√	√	73Q1	97Q4	100
Finland	√	√	√	73Q1	97Q4	100
France	√	√	√	73Q1	97Q4	100
Germany	√	√	√	73Q1	97Q4	100
Greece	√	√	√	73Q1	97Q4	100
Hong Kong			√	76Q1	97Q4	88
Iceland	√	√		73Q1	97Q4	100
Indonesia			√	73Q1	97Q4	100
Ireland	√	√	√	73Q1	97Q4	100
Italy	√	√	√	73Q1	97Q4	100

TABLE A.1 (Continued)

Country	Sample: EUROPE	OECD	OPEN	Start	End	T
Japan		$\surd$	$\surd$	73Q1	97Q4	100
Jordan			$\surd$	76Q1	97Q3	87
Korea		$\surd$	$\surd$	73Q1	97Q4	100
Luxemburg	$\surd$	$\surd$	$\surd$	73Q1	97Q4	100
Malaysia			$\surd$	73Q1	97Q4	100
Mauritius			$\surd$	73Q1	97Q4	100
Mexico		$\surd$	$\surd$	73Q1	97Q4	100
Netherlands	$\surd$	$\surd$	$\surd$	73Q1	97Q4	100
New Zealand		$\surd$		73Q1	97Q4	100
Norway	$\surd$	$\surd$	$\surd$	73Q1	97Q4	100
Portugal	$\surd$	$\surd$	$\surd$	73Q1	97Q4	100
Singapore			$\surd$	73Q1	97Q4	100
Spain	$\surd$	$\surd$	$\surd$	73Q1	97Q4	100
Sweden	$\surd$	$\surd$	$\surd$	73Q1	97Q4	100
Switzerland	$\surd$	$\surd$	$\surd$	73Q1	97Q4	100
Thailand			$\surd$	73Q1	97Q3	99
Turkey		$\surd$		73Q1	97Q4	100
United Kingdom	$\surd$	$\surd$	$\surd$	73Q1	97Q4	100

TABLE A.2

Univariate Unit Root Test of PPP
CPI Based Real Exchange Rates

	AIC Lag Selection						
Country	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	p-value	T
United Kingdom	$\surd$					0.09	95
Austria	$\surd$					0.17	95
Belgium	$\surd$					0.18	95
Denmark	$\surd$					0.13	95
France	$\surd$					0.16	95
Germany	$\surd$					0.16	95
Italy	$\surd$					0.16	95
Luxemburg	$\surd$					0.22	95
Netherlands	$\surd$					0.13	95
Norway	$\surd$					0.23	95
Sweden	$\surd$					0.28	95
Switzerland	$\surd$					0.12	95
Canada	$\surd$					0.57	95
Japan	$\surd$					0.28	95
Finland	$\surd$					0.08	95
Greece	$\surd$					0.20	95
Iceland	$\surd$					0.16	95
Ireland	$\surd$					0.09	95

TABLE A.2 (Continued)

Country	AIC Lag Selection[a]					p-value[b]	T
	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$		
Portugal	√					0.40	95
Spain	√					0.21	95
Turkey	√					0.61	95
Australia	√					0.36	95
New Zealand	√					0.18	95
Chile	√					0.39	83
Mexico	√					0.09	95
Barbados		√				0.09	94
Cyprus	√					0.16	95
Jordan	√					0.65	82
Hong Kong	√					0.81	80
Indonesia	√					0.95	95
South Korea	√					0.42	95
Malaysia	√					0.86	95
Singapore	√					0.13	95
Thailand	√					0.64	94
Botswana	√					0.16	71
Mauritius		√				0.60	95

Notes: Each country-specific ADF test includes m lags of the change in the real exchange rate, Δq_t, where m is determined by the minimum AIC.

[a] √ indicates the ADF specification with the minimum AIC.

[b] Probability value for the univariate ADF test of the null hypothesis that the real exchange rate contains a unit root.

TABLE A.3

Sample Membership
WPI Based Real Exchange Rates

Country	Sample EUROPE	Sample OECD	Sample OPEN	Start	End	T
Australia		$\surd$	$\surd$	73Q1	97Q4	100
Austria	$\surd$	$\surd$	$\surd$	73Q1	97Q4	100
Belgium	$\surd$	$\surd$	$\surd$	80Q2	97Q4	72
Canada		$\surd$	$\surd$	73Q1	97Q4	100
Chile			$\surd$	76Q1	97Q4	88
Denmark	$\surd$	$\surd$	$\surd$	73Q1	97Q4	100
Finland	$\surd$	$\surd$	$\surd$	73Q1	97Q4	100
France	$\surd$	$\surd$	$\surd$	73Q1	97Q4	100
Germany	$\surd$	$\surd$	$\surd$	73Q1	97Q4	100
Greece	$\surd$	$\surd$	$\surd$	73Q1	97Q4	100
Indonesia			$\surd$	73Q1	97Q4	100
Ireland	$\surd$	$\surd$	$\surd$	73Q1	97Q2	98
Italy	$\surd$	$\surd$	$\surd$	73Q1	97Q4	100
Japan		$\surd$	$\surd$	73Q1	97Q4	100
Korea		$\surd$	$\surd$	73Q1	97Q4	100
Luxemburg	$\surd$	$\surd$	$\surd$	80Q1	97Q4	72
Malaysia			$\surd$	84Q1	97Q2	54
Mexico		$\surd$	$\surd$	73Q1	97Q4	100
Netherlands	$\surd$	$\surd$	$\surd$	73Q1	97Q4	100
New Zealand		$\surd$		73Q1	97Q4	100
Norway	$\surd$	$\surd$	$\surd$	73Q1	97Q3	99
Singapore			$\surd$	74Q1	97Q4	96
Spain	$\surd$	$\surd$	$\surd$	75Q1	97Q4	92
Sweden	$\surd$	$\surd$	$\surd$	73Q1	97Q4	100
Switzerland	$\surd$	$\surd$	$\surd$	73Q1	97Q4	100
Taiwan			$\surd$	73Q1	97Q4	100
Thailand			$\surd$	73Q1	97Q2	99
United Kingdom	$\surd$	$\surd$	$\surd$	73Q1	97Q4	100

TABLE A.4

Univariate Unit Root Test of PPP
WPI Based Real Exchange Rates

	AIC Lag Selection[a]						
Country	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	p-value[b]	T
United Kingdom	$\surd$					0.25	95
Austria	$\surd$					0.11	95
Belgium	$\surd$					0.23	67
Denmark	$\surd$					0.20	95
France	$\surd$					0.11	95
Germany	$\surd$					0.15	95
Italy	$\surd$					0.18	95
Luxemburg	$\surd$					0.28	67
Netherlands	$\surd$					0.22	95
Norway	$\surd$					0.23	94
Sweden	$\surd$					0.18	95
Switzerland	$\surd$					0.11	95
Canada	$\surd$					0.17	95
Japan	$\surd$					0.25	95
Finland	$\surd$					0.14	95
Greece	$\surd$					0.13	95
Ireland	$\surd$					0.10	93
Spain	$\surd$					0.21	87
Australia	$\surd$					0.17	95
New Zealand	$\surd$					0.27	95
Chile	$\surd$					0.27	83
Mexico	$\surd$					0.06	95
Indonesia	$\surd$					0.95	95
South Korea	$\surd$					0.90	95
Malaysia	$\surd$					0.47	49
Singapore	$\surd$					0.54	91
Thailand	$\surd$					0.30	94
Taiwan			$\surd$			0.13	93

Notes: Each country-specific ADF test includes m lags of the change in the real exchange rate, Δq_t, where m is determined by the minimum AIC.

[a] $\surd$ indicates the ADF specification with the minimum AIC.

[b] Probability value for the univariate ADF test of the null hypothesis that the real exchange rate contains a unit root.

TABLE A.5

Monte Carlo Critical Values
Panel Data Unit Root Test: *OC–GLS*
CPI Based Real Exchange Rates

SAMPLE								
Four-Lag Pre-whitening Regression								
EUROPE			OECD			OPEN		
Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)		
1.0%	5.0%	10.0%	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%
-7.21	-6.60	-6.27	-7.84	-7.22	-6.90	-8.39	-7.79	-7.43
$N = 19$, $T = 95$			$N = 25$, $T = 95$			$N = 32$, $T = 93$		
Six-Lag Pre-whitening Regression								
EUROPE			OECD			OPEN		
Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)		
1.0%	5.0%	10.0%	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%
-7.22	-6.63	-6.30	-7.84	-7.23	-6.87	-8.36	-7.78	-7.44
$N = 19$, $T = 93$			$N = 25$, $T = 93$			$N = 32$, $T = 91$		
Eight-Lag Pre-whitening Regression								
EUROPE			OECD			OPEN		
Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)		
1.0%	5.0%	10.0%	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%
-7.20	-6.60	-6.27	-7.91	-7.22	-6.89	-8.40	-7.74	-7.39
$N = 19$, $T = 91$			$N = 25$, $T = 91$			$N = 32$, $T = 89$		

Notes: All critical values are based on 10,000 Monte Carlo replications. For each replication, N random walks of length $T + 26$ are generated as $q_{i,t} = q_{i,t-1} + \epsilon_{i,t}$, where $\epsilon_{i,t} \sim N(0,1)$ The first 25 observations are discarded to minimize the effect of the initial value bias. The following specification is estimated using O'Connell's (1998) GLS procedure: $\Delta q_{i,t} = \alpha_i + \rho q_{i,t-1} + \eta_{i,t}$, $t = 1, \ldots, T$, and the 1st, 5th, and the 10th percentile of the distribution of the t-statistic $t_{\widehat{\rho}}$ for the hypothesis $\rho = 0$ are reported.

TABLE A.6

Monte Carlo Critical Values
Panel Data Unit Root Test: *OC–GLS*
WPI Based Real Exchange Rates

SAMPLE								
Four-Lag Pre-whitening Regression								
EUROPE			OECD			OPEN		
Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)		
1.0%	5.0%	10.0%	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%
-6.79	-6.25	-5.93	-7.54	-6.94	-6.60	-7.92	-7.32	-6.96
$N = 16$, $T = 91$			$N = 22$, $T = 92$			$N = 26$, $T = 90$		
Six-Lag Pre-whitening Regression								
EUROPE			OECD			OPEN		
Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)		
1.0%	5.0%	10.0%	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%
-6.79	-6.22	-5.89	-7.52	-6.91	-6.57	-7.89	-7.27	-6.93
$N = 16$, $T = 89$			$N = 23$, $T = 90$			$N = 26$, $T = 88$		
Eight-Lag Pre-whitening Regression								
EUROPE			OECD			OPEN		
Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)		
1.0%	5.0%	10.0%	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%
-6.80	-6.20	-5.87	-7.51	-6.92	-6.58	-7.93	-7.31	-6.95
$N = 16$, $T = 87$			$N = 22$, $T = 88$			$N = 26$, $T = 86$		

Notes: All critical values are based on 10,000 Monte Carlo replications. For each replication, N random walks of length $T + 26$ are generated as $q_{i,t} = q_{i,t-1} + \epsilon_{i,t}$, where $\epsilon_{i,t} \sim N(0, 1)$ The first 25 observations are discarded to minimize the effect of the initial value bias. The following specification is estimated using O'Connell's (1998) GLS procedure: $\Delta q_{i,t} = \alpha_i + \rho q_{i,t-1} + \eta_{i,t}$, $t = 1, \ldots, T$, and the 1st, 5th, and the 10th percentile of the distribution of the t-statistic $t_{\widehat{\rho}}$ for the hypothesis $\rho = 0$ are reported.

TABLE A.7

Monte Carlo Critical Values
Panel Data Unit Root Test: *SUR–GLS*
CPI Based Real Exchange Rates

SAMPLE								
Four-Lag ADF Specification ($m = 4$)								
EUROPE			OECD			OPEN		
Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)		
1.0%	5.0%	10.0%	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%
-8.32	-7.65	-7.29	-9.60	-8.9	-8.52	-11.27	-10.54	-10.14
$N = 19$, $T = 95$			$N = 25$, $T = 95$			$N = 32$, $T = 93$		
Six-Lag ADF Specification ($m = 6$)								
EUROPE			OECD			OPEN		
Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)		
1.0%	5.0%	10.0%	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%
-8.31	-7.67	-7.29	-9.64	-8.92	-8.55	-11.46	-10.63	-10.19
$N = 19$, $T = 93$			$N = 25$, $T = 93$			$N = 32$, $T = 91$		
Eight-Lag ADF Specification ($m = 8$)								
EUROPE			OECD			OPEN		
Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)		
1.0%	5.0%	10.0%	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%
-8.39	-7.69	-7.32	-9.70	-8.96	-8.57	-11.57	-10.67	-10.22
$N = 19$, $T = 91$			$N = 25$, $T = 91$			$N = 32$, $T = 89$		

Notes: All critical values are based on 10,000 Monte Carlo replications. For each replication, N random walks of length $T + m + 26$ are generated as $q_{i,t} = q_{i,t-1} + \epsilon_{i,t}$, where $\epsilon_{i,t} \sim N(0, 1)$ The first 25 observations are discarded to minimize the effect of the initial value bias. The following N-equation system of ADF regressions is estimated in a SUR framework with iterative GLS: $\Delta q_{i,t} = \alpha_i + \rho q_{i,t-1} + \sum_{k=1}^{m} \lambda_k \Delta q_{i,t-k} + \eta_{i,t}$, $t = 1, \ldots, T$, and the 1st, 5th, and the 10th percentile of the distribution of the t-statistic $t_{\widehat{\rho}}$ for the hypothesis $\rho = 0$ are reported.

TABLE A.8

Monte Carlo Critical Values
Panel Data Unit Root Test: *SUR–GLS*
WPI Based Real Exchange Rates

SAMPLE								
Four-Lag ADF Specification ($m = 4$)								
EUROPE			OECD			OPEN		
Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)		
1.0%	5.0%	10.0%	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%
-7.74	-7.04	-6.71	-8.96	-8.30	-7.94	-9.86	-9.18	-8.84
$N = 16$, $T = 91$			$N = 22$, $T = 92$			$N = 26$, $T = 90$		
Six-Lag ADF Specification ($m = 6$)								
EUROPE			OECD			OPEN		
Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)		
1.0%	5.0%	10.0%	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%
-7.73	-7.06	-6.49	-8.99	-8.36	-7.95	-10.03	-9.25	-8.86
$N = 16$, $T = 89$			$N = 22$, $T = 90$			$N = 26$, $T = 88$		
Eight-Lag ADF Specification ($m = 8$)								
EUROPE			OECD			OPEN		
Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)			Critical Value ($t_{\widehat{\rho}}$)		
1.0%	5.0%	10.0%	1.0%	5.0%	10.0%	1.0%	5.0%	10.0%
-7.82	-7.07	-6.69	-9.13	-8.37	-7.97	-10.08	-9.31	-8.92
$N = 16$, $T = 87$			$N = 22$, $T = 88$			$N = 26$, $T = 86$		

Notes: All critical values are based on 10,000 Monte Carlo replications. For each replication, N random walks of length $T + m + 26$ are generated as $q_{i,t} = q_{i,t-1} + \epsilon_{i,t}$, where $\epsilon_{i,t} \sim N(0,1)$ The first 25 observations are discarded to minimize the effect of the initial value bias. The following N-equation system of ADF regressions is estimated in a SUR framework with iterative GLS: $\Delta q_{i,t} = \alpha_i + \rho q_{i,t-1} + \sum_{k=1}^{m} \lambda_k \Delta q_{i,t-k} + \eta_{i,t}$, $t = 1, \ldots, T$, and the 1st, 5th, and the 10th percentile of the distribution of the t-statistic $t_{\widehat{\rho}}$ for the hypothesis $\rho = 0$ are reported.

TABLE A.9

Mean and Standard Deviation Adjustment Factors
Panel Data Unit Root Test: *LL2–GLS*
CPI Based Real Exchange Rates

SAMPLE					
Four-Lag ADF Specification $(m = 4)$					
EUROPE		OECD		OPEN	
$\mu^*_{\tilde{T}}$	$\sigma^*_{\tilde{T}}$	$\mu^*_{\tilde{T}}$	$\sigma^*_{\tilde{T}}$	$\mu^*_{\tilde{T}}$	$\sigma^*_{\tilde{T}}$
-0.485	0.892	-0.484	0.889	-0.480	0.947
$N = 19$, $T = 95$		$N = 25$, $T = 95$		$N = 32$, $T = 93$	
Six-Lag ADF Specification $(m = 6)$					
EUROPE		OECD		OPEN	
$\mu^*_{\tilde{T}}$	$\sigma^*_{\tilde{T}}$	$\mu^*_{\tilde{T}}$	$\sigma^*_{\tilde{T}}$	$\mu^*_{\tilde{T}}$	$\sigma^*_{\tilde{T}}$
-0.471	0.903	-0.470	0.931	-0.465	0.990
$N = 19$, $T = 93$		$N = 25$, $T = 93$		$N = 32$, $T = 91$	
Eight-Lag ADF Specification $(m = 8)$					
EUROPE		OECD		OPEN	
$\mu^*_{\tilde{T}}$	$\sigma^*_{\tilde{T}}$	$\mu^*_{\tilde{T}}$	$\sigma^*_{\tilde{T}}$	$\mu^*_{\tilde{T}}$	$\sigma^*_{\tilde{T}}$
-0.457	0.951	-0.454	0.988	-0.450	1.030
$N = 19$, $T = 91$		$N = 25$, $T = 91$		$N = 32$, $T = 89$	

Notes: The mean and the variance adjustment factors used to standardize the *LL2–GLS* statistic are based on 10,000 Monte Carlo replications. For each replication, N random walks of length $T + m + 26$ are generated as $q_{i,t} = q_{i,t-1} + \epsilon_{i,t}$, where $\epsilon_{i,t} \sim N(0, 1)$ The first 25 observations are discarded to minimize the effect of the initial value bias. As described in the text, first a GLS transformation is performed on the data, rendering the error term cross-sectionally homoscedastic, then the computational test procedure follows Levin and Lin (1993).

TABLE A.10

Mean and Standard Deviation Adjustment Factors
Panel Data Unit Root Test: *LL2–GLS*
WPI Based Real Exchange Rates

SAMPLE					
Four-Lag ADF Specification $(m = 4)$					
EUROPE		OECD		OPEN	
$\mu^*_{\tilde{T}}$	$\sigma^*_{\tilde{T}}$	$\mu^*_{\tilde{T}}$	$\sigma^*_{\tilde{T}}$	$\mu^*_{\tilde{T}}$	$\sigma^*_{\tilde{T}}$
-0.486	0.869	-0.482	0.902	-0.480	0.921
$N = 16$, $T = 91$		$N = 22$, $T = 92$		$N = 26$, $T = 90$	
Six-Lag ADF Specification $(m = 6)$					
EUROPE		OECD		OPEN	
$\mu^*_{\tilde{T}}$	$\sigma^*_{\tilde{T}}$	$\mu^*_{\tilde{T}}$	$\sigma^*_{\tilde{T}}$	$\mu^*_{\tilde{T}}$	$\sigma^*_{\tilde{T}}$
-0.467	0.926	-0.469	0.934	-0.466	0.958
$N = 16$, $T = 89$		$N = 22$, $T = 90$		$N = 26$, $T = 88$	
Eight-Lag ADF Specification $(m = 8)$					
EUROPE		OECD		OPEN	
$\mu^*_{\tilde{T}}$	$\sigma^*_{\tilde{T}}$	$\mu^*_{\tilde{T}}$	$\sigma^*_{\tilde{T}}$	$\mu^*_{\tilde{T}}$	$\sigma^*_{\tilde{T}}$
-0.453	0.972	-0.452	0.973	-0.451	0.993
$N = 16$, $T = 87$		$N = 22$, $T = 88$		$N = 26$, $T = 86$	

Notes: The mean and the standard deviation adjustment factors used to standardize the *LL2–GLS* statistic are based on 10,000 Monte Carlo replications. For each replication, N random walks of length $T + m + 26$ are generated as $q_{i,t} = q_{i,t-1} + \epsilon_{i,t}$, where $\epsilon_{i,t} \sim N(0, 1)$ The first 25 observations are discarded to minimize the effect of the initial value bias. As described in the text, first a GLS transformation is performed on the data, rendering the error term cross-sectionally homoscedastic, then the computational test procedure follows Levin and Lin (1993).

TABLE A.11

Mean and Variance Adjustment Factors
Panel Data Unit Root Test: *IPS–GLS*
CPI Based Real Exchange Rates

SAMPLE					
Four-Lag ADF Specification $(m = 4)$					
EUROPE		OECD		OPEN	
a_{NT}	b_{NT}	a_{NT}	b_{NT}	a_{NT}	b_{NT}
-1.433	0.825	-1.414	0.836	-1.394	0.857
$N = 19$, $T = 95$		$N = 25$, $T = 95$		$N = 32$, $T = 93$	
Six-Lag ADF Specification $(m = 6)$					
EUROPE		OECD		OPEN	
a_{NT}	b_{NT}	a_{NT}	b_{NT}	a_{NT}	b_{NT}
-1.412	0.847	-1.391	0.866	-1.362	0.887
$N = 19$, $T = 93$		$N = 25$, $T = 93$		$N = 32$, $T = 91$	
Eight-Lag ADF Specification $(m = 8)$					
EUROPE		OECD		OPEN	
a_{NT}	b_{NT}	a_{NT}	b_{NT}	a_{NT}	b_{NT}
-1.382	0.882	-1.359	0.901	-1.330	0.921
$N = 19$, $T = 91$		$N = 25$, $T = 91$		$N = 32$, $T = 89$	

Notes: The mean and the variance adjustment factors used to standardize the *IPS–GLS* statistic are based on 10,000 Monte Carlo replications. For each replication, N random walks of length $T + m + 26$ are generated as $q_{i,t} = q_{i,t-1} + \epsilon_{i,t}$, where $\epsilon_{i,t} \sim N(0, 1)$ The first 25 observations are discarded to minimize the effect of the initial value bias. As described in the text, first a GLS transformation is performed on the data, rendering the error term cross-sectionally homoscedastic, then the computational test procedure follows Im, Pesaran, and Shin (1995).

TABLE A.12

Mean and Variance Adjustment Factors
Panel Data Unit Root Test: *IPS–GLS*
WPI Based Real Exchange Rates

SAMPLE					
Four-Lag ADF Specification $(m = 4)$					
EUROPE		OECD		OPEN	
a_{NT}	b_{NT}	a_{NT}	b_{NT}	a_{NT}	b_{NT}
-1.437	0.823	-1.424	0.835	-1.406	0.846
$N = 16, T = 91$		$N = 22, T = 92$		$N = 26, T = 90$	
Six-Lag ADF Specification $(m = 6)$					
EUROPE		OECD		OPEN	
a_{NT}	b_{NT}	a_{NT}	b_{NT}	a_{NT}	b_{NT}
-1.412	0.851	-1.392	0.869	-1.377	0.880
$N = 16, T = 89$		$N = 22, T = 90$		$N = 26, T = 88$	
Eight-Lag ADF Specification $(m = 8)$					
EUROPE		OECD		OPEN	
a_{NT}	b_{NT}	a_{NT}	b_{NT}	a_{NT}	b_{NT}
-1.384	0.879	-1.363	0.899	-1.346	0.916
$N = 16, T = 87$		$N = 22, T = 88$		$N = 26, T = 86$	

Notes: The mean and the variance adjustment factors used to standardize the *IPS–GLS* statistic are based on 10,000 Monte Carlo replications. For each replication, N random walks of length $T + m + 26$ are generated as $q_{i,t} = q_{i,t-1} + \epsilon_{i,t}$, where $\epsilon_{i,t} \sim N(0, 1)$ The first 25 observations are discarded to minimize the effect of the initial value bias. As described in the text, first a GLS transformation is performed on the data, rendering the error term cross-sectionally homoscedastic, then the computational test procedure follows Im, Pesaran, and Shin (1995).