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The overvaluation of purchasing power parity

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Abstract

Recent panel studies of purchasing power parity have reported strong evidence of mean-reversion in real exchange rates. However, these studies fail to control for cross-sectional dependence in the data. This failure has dramatic consequences, raising the significance level of tests with a nominal size of 5 percent to as much as 50 percent. It is shown in this paper that, controlling for cross-sectional dependence, no evidence against the random walk null can be found in panels of up to 64 real exchange rates. This finding cannot be attributed to low power, as there is ample power in panels of this size to reject the unit-root null. © 1998 Elsevier Science B.V.

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1. Introduction

The theory of purchasing power parity (PPP) is the simple proposition that national price levels should tend to be equal when expressed in a common currency. Most economists have, to use Rogoff's (Rogoff, 1996) expression, ''warm, fuzzy feelings'' toward this proposition, and indeed it is to be found nestled at the centre of many important models of the international economy.

Notwithstanding these warm fuzzy feelings, evidence to support PPP was, until the mid-1980s, quite scant. Just when the empirical standing of PPP reached its

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nadir, Frankel (1986) raised concerns about the power of the statistical tests commonly used to investigate PPP in short time series. This prompted testing of the PPP hypothesis on larger datasets, with much more favourable results. A large body of work now exists showing evidence of reversion to the PPP equilibrium in long time series of prices spanning between 60 and 700 years.[1] This work has suggested that deviations from PPP have half-lives of between 2.8 and 7.3 years.

These time-series studies appear to salvage PPP as a long-run theory of real exchange rate determination. However, they rely on data drawn from both fixed- and floating-rate periods. Moreover, they look only at real exchange rates between industrial countries. In an effort to circumvent the potentially serious biases that might arise from ''survivorship'' among countries or structural shifts in exchange rate behaviour, a number of researchers have instead expanded the cross-section dimension of their datasets to gain power.[2] Frankel and Rose (1996); Wei and Parsley (1995); Papell (1996); Oh (1996) and Wu (1996), amongst others, use panels of between 20 and 160 real exchange rates, and report mean-reversion to PPP at rates consistent with those found in the time series literature.

This paper examines the assumptions underlying such ''wide-sample'' panel studies. It is argued that these tests are incorrectly sized, owing to their failure to control for cross-sectional dependence in real exchange rates. These size biases are quite large, raising the significance levels of tests with nominal size 5 percent to as much as 50 percent. It is also shown that the adoption of a more realistic parameterization of the data generating process (DGP) for real exchange rate innovations materially affects the outcome of panel tests of PPP: no evidence in favour of the theory can be found in broad panels of CPI exchange rates over the 1973–1995 period. This finding is important, because it cannot be attributed to low power. Monte Carlo evidence indicates that there is ample power to reject the unit-root null in panels of this size. Rather, the results lend support to the conjecture by Froot and Rogoff (1995) that the long-sample PPP literature may suffer from sample-selection or survivorship bias. They are also consistent with the notion that there has been a structural change in the behaviour of real exchange rates since the advent of the modern float.

The paper is organized around two questions. First, how does the presence of cross-sectional correlation affect the size and power of panel unit root tests? And second, controlling for cross-sectional correlation, is there evidence of mean reversion in real exchange rates? As a preamble, the next section discusses why these are interesting questions to ask, and previews the answers.

[1] See the comprehensive surveys by Froot and Rogoff (1995) and Rogoff (1996) for a catalogue of the empirical literature on PPP.

[2] Lothian and Taylor (1994) and Hegwood and Papell (1996) directly address the possibility of structural shifts in real exchange rate behaviour.

2. Why care about cross-sectional dependence?

2.1. Real exchange rates are cross-sectionally dependent

Let p_{it} denote the local-currency price index of country i expressed in log terms, and s_{it} be the log dollar price of country i's currency. The real exchange rate between country i and the U.S. is defined as $q_{it} \equiv p_{it} - s_{it} - p_{\mathrm{US},t}$.

Consider the relationship between the French and German real exchange rates q_{Fr} and q_{Ge}. Hakkio (1984) was the first to pay explicit attention to the fact that q_{Fr} and q_{Ge} will naturally be correlated. This is because, by construction, they contain two common components, namely, independent variation in the value of the dollar and independent variation in the U.S. price index. These common components induced by the numeraire country can be quite large. For example, the actual correlation between q_{Fr} and q_{Ge}, calculated using quarterly CPIs from 1973:2–1994:4, is 0.966; if the Netherlands is used in place of the U.S. as the numeraire country, the correlation is 0.391. In addition to these common components, there are other likely sources of correlation between $q_{\mathrm{Fr},t}$ and $q_{\mathrm{Ge},t}$. For example, any EC-wide shock that influences prices or exchange rates will cause them these exchange rates to move together. Or as Hakkio (1984) argued, shocks which originate in Germany may propagate to France but not to the U.S.

While it may seem obvious that real exchange rates are cross-sectionally dependent, this fact has been overlooked all of the extant panel studies of PPP, bar two. The exceptions are Hakkio's (Hakkio, 1984) work, and Abauf and Jorion (1990). Hakkio's study falls under Froot and Rogoff's (Froot and Rogoff, 1995) rubric of ''stage-one tests,'' in that it did not directly test the hypothesis of a unit root in real exchange rates. Abauf and Jorion (1990) do pay careful attention to the impact of cross-sectional dependence on the statistical properties of their panel unit root test, and on these grounds their results are some of the most reliable ones available from the panel literature on PPP. In contrast to the more recent panel work, they fail to reject the unit-root null using post-1973 data.

2.2. Cross-sectional dependence adversely affects size and power

The next point is that this cross-sectional dependence is likely to have an important impact on the statistical properties of panel unit root tests. Levin and Lin (1992) analyze the power of panel unit root tests under the assumption of i.i.d. disturbances, and show that it is an order of magnitude higher than in a univariate setting. It is this which has prompted much of the panel work on PPP. However, if the disturbances are not independent, then two issues arise. First, the limiting distributions derived by Levin and Lin (1992) will no longer be correct, and alternative distributions must be derived that cater to the presence of cross-sectional correlation. Second, even if the true distribution of the test statistic is available, we might suspect that power is diminished, as the total amount of independent information contained in the panel is reduced. These two issues are explored in detail in Section 3. There it is shown that the use of the Levin and Lin (1992) critical values leads to very large size biases in the presence of cross-sectional dependence. Moreover, even if the true distribution of $\hat{\rho}$ is available, there is a severe loss of power to reject the null.

2.3. GLS restores power

Fortunately, cross-sectional dependence is not the nemesis of panel unit root tests that these results suggest. Drawing from theory for the stationary case, we might suspect that greater efficiency can be achieved by using generalized least squares (*GLS*) to control for the properties of the disturbance terms. Section 4 shows that this is indeed the case. In fact, as long as the number of countries in a panel is not too close to the number of time series observations in the panel, the power of a *GLS* panel unit root test when the disturbances are correlated does not fall far short of the power of the Levin–Lin test for the i.i.d. case. This result is discussed in greater detail in Section 4.

2.4. GLS renders PPP tests ''numeraire-invariant''

It has been argued in a number of studies that it is ''easier'' to reject the random walk null when Germany rather than the U.S. is used as the numeraire country.[3] An appealing facet of controlling for cross-sectional dependence in panel tests of PPP is that it makes the choice of numeraire country irrelevant.[4] This will be shown formally in Section 3. It follows from this that panel tests which are more favourable to PPP when Germany rather than the U.S. is chosen as the benchmark country are essentially misspecified. It should not be ''easier'' to reject the unit root hypothesis when one numeraire is substituted for another.

In summary, then, there are compelling reasons to take cognizance of cross-sectional dependence in testing for PPP. The next sections dissect these reasons in greater detail.

3. The impact of cross-sectional dependence on size and power

To gauge the importance of cross-sectional dependence, this section carries out a Monte Carlo investigation of the size and power of panel unit root tests that fail to account for it. This is not intended to be an exhaustive treatment of the

[3]Frenkel (1981) noted this using univariate data, while Jorion and Sweeney (1996), Papell (1996) and Wei and Parsley (1995) make the same observation in a panel setting.

[4]This invariance property is also discussed in Engel et al. (1996).

properties of unit root test statistics with correlated panel data. Rather, the goal is simply to illustrate how size and power can be adversely affected, especially when working with real exchange rates.

The first step is to choose null and alternative hypotheses. The archtypal panel test of PPP specifies the null hypothesis as

$$H_0\colon \Delta q_{it} = \epsilon_{it}, \quad i = 1,\ldots,N;\ t = 1,\ldots,T \tag{1}$$

and the alternative as

$$H_1\colon \Delta q_{it} = \alpha_i + \rho q_{i,t-1} + \epsilon_{it},\ \rho < 0 \quad i = 1,\ldots,N;\ t = 1,\ldots,T \tag{2}$$

where ϵ_{it} is a mean-zero disturbance term. The alternative allows for country-specific means owing to the fact that price indices rather than actual price levels are typically used to carry out the test. H_0 is tested against H_1 by estimating by ordinary least squares in the panel regression

$$\Delta q_{it} = \alpha_i + \rho q_{i,t-1} + \epsilon_{it}, \quad i = 1,\ldots,N;\ t = 1,\ldots,T \tag{3}$$

and then testing if $\rho < 0$.

The focus here is on the properties of the disturbance vector, $\epsilon_t \equiv [\epsilon_{1t}\epsilon_{2t}\cdots\epsilon_{Nt}]$. Levin and Lin (1992) have derived the asymptotic and finite sample properties of the distribution of $\hat{\rho}_{\mathrm{OLS}}$ under the assumption that $E(\epsilon_t\epsilon_t') = \mathbf{\Omega}$ is diagonal. Typically this is the assumption used in panel studies of PPP. In the simulations that follow, it is instead assumed that $E(\epsilon_t\epsilon_t')$ takes the form

$$\mathbf{\Omega} = \begin{bmatrix} 1 & \omega & \cdots & \omega \\ \omega & 1 & \cdots & \omega \\ \vdots & \vdots & \ddots & \vdots \\ \omega & \omega & \cdots & 1 \end{bmatrix}, \quad \omega < 1 \tag{4}$$

Though simple, this parameterization is economically relevant, as the dependence induced by independent variation in the value of the dollar and $p_{\mathrm{US},t}$ is the same for all real exchange rates. Note, however, that the empirical analysis in Section 5 allows for a completely general variance-covariance matrix. As the concern here is with cross-sectional dependence, for the purposes of the simulation the increments are assumed to be independent at all leads and lags: $E(\epsilon_{is}\epsilon_{jt}) = 0\ \forall\ i,j,\ s \neq t$.

For given values of N, T and ω, the distribution of the t-statistic $t_\rho = \hat{\rho}/\sigma_\rho$ under the null is derived by Monte Carlo simulation.[5] N and T are chosen to encompass the range of quarterly and annual real exchange rate data that is available from the modern floating rate period. Thus $N \in \{11\ 51\ 91\}$, $T \in \{20\ 60\ 100\}$. Columns 4–6 of Table 1 report 1%, 5% and 10% percentiles of these distributions. For $\omega = 0$, these match the critical values tabulated by Levin and Lin (1992). Columns 7–9 give the true size of the panel unit root test if the i.i.d. critical values are erroneously used for inference.

[5] See Appendix for details.

Table 1
The size of panel unit root tests with correlated disturbances.

T	N	ω	Critical values			True size for given nominal size		
			1%	5%	10%	1%	5%	10%
20	10	0.0	−6.29	−5.65	−5.31	0.01	0.05	0.10
20	10	0.3	−6.80	−5.98	−5.58	0.03	0.09	0.15
20	10	0.5	−7.37	−6.43	−5.97	0.06	0.16	0.24
20	10	0.7	−8.46	−7.19	−6.62	0.14	0.26	0.33
20	10	0.9	−10.25	−8.46	−7.71	0.27	0.37	0.43
20	50	0.0	−11.23	−10.58	−10.24	0.01	0.05	0.10
20	50	0.3	−12.96	−11.79	−11.25	0.10	0.21	0.28
20	50	0.5	−15.09	−13.50	−12.62	0.26	0.38	0.44
20	50	0.7	−18.06	−15.51	−14.26	0.40	0.48	0.52
20	50	0.9	−21.90	−18.83	−17.21	0.48	0.53	0.55
20	90	0.0	−14.20	−13.59	−13.27	0.01	0.05	0.10
20	90	0.3	−17.11	−15.60	−14.88	0.19	0.31	0.37
20	90	0.5	−20.36	−17.76	−16.72	0.36	0.45	0.50
20	90	0.7	−24.08	−20.57	−18.97	0.46	0.52	0.55
20	90	0.9	−30.18	−25.52	−23.12	0.55	0.58	0.60
60	10	0.0	−6.13	−5.52	−5.19	0.01	0.05	0.10
60	10	0.3	−6.57	−5.79	−5.46	0.03	0.09	0.15
60	10	0.5	−7.21	−6.31	−5.84	0.07	0.16	0.24
60	10	0.7	−8.15	−6.97	−6.44	0.15	0.26	0.34
60	10	0.9	−9.71	−8.20	−7.41	0.26	0.37	0.44
60	50	0.0	−10.94	−10.29	−9.98	0.01	0.05	0.10
60	50	0.3	−12.69	−11.50	−10.99	0.11	0.22	0.29
60	50	0.5	−14.77	−12.93	−12.19	0.27	0.39	0.45
60	50	0.7	−17.24	−14.83	−13.77	0.40	0.48	0.52
60	50	0.9	−21.01	−18.18	−16.49	0.49	0.55	0.57
60	90	0.0	−13.90	−13.25	−12.93	0.01	0.05	0.10
60	90	0.3	−16.78	−15.25	−14.56	0.19	0.31	0.38
60	90	0.5	−19.52	−17.21	−16.22	0.37	0.47	0.52
60	90	0.7	−22.80	−19.93	−18.39	0.47	0.53	0.56
60	90	0.9	−27.82	−24.09	−22.00	0.54	0.58	0.60
100	10	0.0	−5.99	−5.45	−5.14	0.01	0.05	0.10
100	10	0.3	−6.51	−5.75	−5.40	0.03	0.09	0.15
100	10	0.5	−7.06	−6.25	−5.85	0.08	0.18	0.25
100	10	0.7	−8.14	−7.03	−6.44	0.17	0.28	0.35
100	10	0.9	−9.45	−8.09	−7.40	0.28	0.38	0.44
100	50	0.0	−10.88	−10.25	−9.94	0.01	0.05	0.10
100	50	0.3	−12.58	−11.46	−10.91	0.10	0.22	0.29
100	50	0.5	−14.47	−12.92	−12.17	0.27	0.38	0.44
100	50	0.7	−17.05	−14.79	−13.80	0.41	0.49	0.53
100	50	0.9	−21.08	−18.02	−16.52	0.49	0.53	0.56
100	90	0.0	−13.81	−13.21	−12.90	0.01	0.05	0.10
100	90	0.3	−16.49	−15.11	−14.41	0.18	0.30	0.37
100	90	0.5	−19.15	−17.08	−16.03	0.39	0.46	0.51
100	90	0.7	−23.09	−19.77	−18.47	0.49	0.55	0.57
100	90	0.9	−27.82	−24.09	−22.00	0.55	0.58	0.60

This table shows the true size of panel unit root tests that fail to control for cross-sectional dependence. The distribution of the *OLS* estimator $\hat{\rho}$ from the panel regression $\Delta q_{it} = \alpha_i + \rho q_{i,t-1} + \epsilon_{it}$ is obtained under the null by simulating 5,000 panels of real exchange rates for each combination of T, N and ω. ω is the contemporaneous correlation between real exchange rate innovations. The 1%, 5% and 10% percentiles of these distributions are shown in columns 4–6, while the proportion of the distributions falling below the i.i.d. (i.e. $\omega = 0$) critical values is shown in columns 7–9.

There are number of points to be made regarding these size calculations. First, significant size biases arise even with moderate amounts of cross-sectional dependence in the data. With $\omega = 0.5$, the probability of incorrect rejection for a test with nominal size 5% is 16% for $N = 10$ and $T = 20$, and rises to 45% for N equal to 90. This size bias is not attenuated by increasing the length of the sample; it remains roughly constant as T rises. As ω increases to 0.9, the size distortion becomes very large, rising to 53% for $N = 50$, and 58% for $N = 90$. In this case, it would be better to accept or reject the unit-root null on the basis of a coin-toss than to run a panel unit root test and assume i.i.d. disturbances.

The question then arises as to how effective the panel unit root test is if correct critical values are used. Table 2 shows the probability of rejecting $H_0\colon\rho = 0$ in favour of $H_1\colon\rho = -0.04$, using the critical values tabulated in Table 1. The value of -0.04 is chosen to be consistent with some of the existing estimates of reversion to PPP based on long time series. These estimates put the half-life of decay for deviations from PPP between 4 and 5 years, which implies that $-0.042 < \rho < -0.034$ for quarterly data. It is clear from the table that power is quite badly affected by the contemporaneous correlation. This is most manifest for the larger panels of over 600 observations. For example, for $T = 60$ and $N = 50$, power drops from 92% to just 30% using the 5% critical values when $\omega = 0.5$. When $\omega = 0.9$ for this panel, power is a paltry 9%.

To give these results more force, it is useful to gauge the amount of cross-sectional dependence that is present in real exchange rates. A crude estimate is provided by the average off-diagonal element of the sample correlation matrix of real exchange rate changes. For the sample of 64 countries examined in detail in Section 5, this average is 0.22, while for various subgroups it is substantially higher: Europe 0.73; Asia 68; South America 0.85; and Africa 0.35.

To sum up, panel tests of PPP that presume i.i.d. disturbances suffer from severe size biases. The reason is that with cross-sectional dependence, distributions for tabulated under the i.i.d. assumption are incorrect. More seriously, even if the correct distribution is available, the power to reject the unit-root null can be greatly diminished.

3.1. Time dummies

A number of panel studies of PPP (e.g. Frankel and Rose (1996)) include time dummies in the panel unit root regression. Before concluding this section, it is worth looking at the consequences of this for cross-sectional dependence. With time dummies, the estimated regression takes the form

$$\Delta q_{it} = \alpha_i + \gamma_t + \rho q_{i,t-1} + \epsilon_{it}, \quad i = 1, \ldots, N;\ t = 1, \ldots, T \tag{5}$$

The inclusion of such time dummies is tantamount to differencing each real exchange rate q_{it} from the average of the real exchange rates in period t prior to running the regression:

Table 2
The power of panel unit root tests with correlated disturbances

T	N	ω	Power for given size: $\rho=-0.04$		
			1%	5%	10%
20	10	0.0	0.02	0.09	0.17
20	10	0.3	0.01	0.08	0.16
20	10	0.5	0.01	0.09	0.16
20	10	0.7	0.02	0.07	0.14
20	10	0.9	0.01	0.07	0.12
20	50	0.0	0.06	0.22	0.37
20	50	0.3	0.02	0.14	0.25
20	50	0.5	0.02	0.08	0.15
20	50	0.7	0.01	0.08	0.17
20	50	0.9	0.02	0.07	0.12
20	90	0.0	0.15	0.38	0.53
20	90	0.3	0.02	0.13	0.24
20	90	0.5	0.02	0.10	0.19
20	90	0.7	0.02	0.09	0.18
20	90	0.9	0.02	0.06	0.13
60	10	0.0	0.10	0.33	0.50
60	10	0.3	0.07	0.27	0.42
60	10	0.5	0.05	0.19	0.32
60	10	0.7	0.03	0.17	0.27
60	10	0.9	0.03	0.12	0.20
60	50	0.0	0.68	0.91	0.96
60	50	0.3	0.21	0.55	0.68
60	50	0.5	0.06	0.31	0.45
60	50	0.7	0.03	0.20	0.30
60	50	0.9	0.02	0.09	0.18
60	90	0.0	0.96	0.99	1.00
60	90	0.3	0.23	0.57	0.71
60	90	0.5	0.08	0.36	0.51
60	90	0.7	0.06	0.22	0.35
60	90	0.9	0.03	0.12	0.20
100	10	0.0	0.38	0.68	0.83
100	10	0.3	0.23	0.56	0.71
100	10	0.5	0.15	0.40	0.55
100	10	0.7	0.06	0.26	0.43
100	10	0.9	0.05	0.17	0.29
100	50	0.0	1.00	1.00	1.00
100	50	0.3	0.64	0.85	0.91
100	50	0.5	0.30	0.60	0.72
100	50	0.7	0.13	0.36	0.48
100	50	0.9	0.05	0.17	0.26
100	90	0.0	1.00	1.00	1.00
100	90	0.3	0.73	0.89	0.94
100	90	0.5	0.33	0.66	0.77
100	90	0.7	0.11	0.35	0.50
100	90	0.9	0.05	0.15	0.27

This table shows the power of panel unit root tests when the disturbances are contemporaneously correlated. The distribution of the *OLS* estimator $\hat{\rho}$ from the panel regression $\Delta q_{it}=\alpha_i+\rho q_{i,t-1}+\epsilon_{it}$ is obtained under the alternative by simulating 5,000 panels of real exchange rates for each combination of T, N and ω. ω is the contemporaneous correlation between real exchange rate innovations. The proportion of these distributions falling below the relevant 1%, 5% and 10% critical values tabulated in Table 1 is shown in columns 7–9.

$$\Delta(q_{it} - \overline{q_{.t}}) = \alpha_i - \overline{\alpha} + \rho(q_{i,t-1} - \overline{q_{.,t-1}}) + \epsilon_{it} - \overline{\epsilon_{.t}}$$
$$i = 1, \ldots, N;\ t = 1, \ldots, T \tag{6}$$

Since mean-reversion to the average real exchange rate is a sufficient and indeed necessary condition for PPP to hold, it is valid to use this regression to test for PPP. Moreover, the amount of contemporaneous correlation across the disturbances $\epsilon_{it} - \overline{\epsilon_{.t}}$ can be lower than for the regression run without time dummies. To see this, note that $E[(\epsilon_t - \overline{\epsilon_t})(\epsilon_t - \overline{\epsilon_t})']$ is given by $\mathbf{B}'\mathbf{\Omega}\mathbf{B}$, where B is the symmetric idempotent matrix

$$\mathrm{B} = \frac{1}{N} = \begin{bmatrix} N-1 & -1 & \cdots & -1 \\ -1 & N-1 & \cdots & -1 \\ \vdots & \vdots & \ddots & \vdots \\ -1 & -1 & \cdots & N-1 \end{bmatrix} \tag{7}$$

If $\mathbf{\Omega}$ takes the form (4), then $\mathbf{B}'\mathbf{\Omega}\mathbf{B} = (1-\omega)/N\mathrm{B}$, and so the off-diagonal elements are of order $[1/(N-1)]$ relative to the diagonal elements. Nonetheless, these off-diagonal elements continue to have an impact on test size, especially when N is small (i.e. below 10). Moreover, if the true variance-covariance matrix takes a different form—for example if countries are groupwise highly correlated–then the removal of the global mean from each series will do little to reduce the amount of cross-sectional dependence that is present.

As such the inclusion of time dummies is at best a partial solution to the problem of cross-sectional dependence. As will become clear in the next section, it is much more effective to control for contemporaneous correlation directly by estimating the disturbance covariance matrix.[6]

4. GLS panel unit root tests

What can be done to salvage panel unit root tests in the presence of cross-sectional dependence? Drawing on the theory of panel estimation for the stationary case, we might suspect that *GLS* offers an avenue to increased power. To define the *GLS* estimator of ρ, let $\mathbf{Y}$ be the $T \times N$ matrix of first-differenced real exchange rates:

$$\mathbf{Y}_{T\times N} = \begin{bmatrix} \Delta q_{11} & \Delta q_{22} & \cdots & \Delta q_{N1} \\ \Delta q_{12} & \Delta q_{22} & \cdots & \Delta q_{N2} \\ \vdots & \vdots & \ddots & \vdots \\ \Delta q_{1T} & \Delta q_{2T} & \cdots & \Delta q_{NT} \end{bmatrix}$$

[6]As a practical matter, the inclusion of time dummies appears to be a poor control for cross-sectional dependence in testing for PPP. In results not reported here, it was found that panel unit root tests can give the same result with and without time dummies, results that are overturned by using the *GLS* test described below.

Similarly, let X be the $T \times N$ matrix of lagged real exchange rates. Then the *GLS* estimate of ρ is given by

$$\hat{\rho}_{GLS} = \text{tr}(X'Y\Omega^{-1})/\text{tr}(X'X\Omega^{-1}) \tag{8}$$

where, as before, $\Omega = E(\epsilon_t \epsilon_t')$.

4.1. Invariance to choice of numeraire

The *GLS* estimator possesses an appealing feature that aids in the interpretation of cross-country estimates of ρ.

Proposition 1. In testing for a unit root in panels of real exchange rates, the GLS estimate ρ_{GLS} is invariant to the numeraire price index used to construct the real exchange rates.

The proof is given in appendix 1. A basic intuition is that the sets of real exchange rates generated by different choices of numeraire are linear combinations of one another (Engel et al., 1996). Thus changing the numeraire does not change the information that is used in the estimator, only its configuration–i.e. its interdependence. By nature, *GLS* controls for interdependence in the data. As a result, the *GLS* estimator is invariant to the linear combination of real exchange rates that is used as numeraire.

It is not necessary for Ω to be known for this to hold: invariance carries over to the feasible *GLS* estimator

$$\hat{\rho}_{FGLS} = \text{tr}(X'Y\hat{\Omega}^{-1})/\text{tr}(X'X\hat{\Omega}^{-1}) \tag{9}$$

where $\hat{\Omega}$ is some consistent estimate of Ω. Moreover, restrictions can be imposed on $\hat{\Omega}$ for the purposes of estimation without affecting the property, as long as no element is constrained to be 0. This can be particularly useful when working with panels in which $N < T$, as might be the true with annual data. In this case, Ω might be parameterized as

$$\Omega = \begin{bmatrix} \sigma_1 & \sigma_{N+1} & \cdots & \sigma_{N+1} \\ \sigma_{N+1} & \sigma_2 & \cdots & \sigma_{N+1} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{N+1} & \sigma_{N+1} & \cdots & \sigma_N \end{bmatrix} \tag{10}$$

subject to the constraint that Ω is positive definite. This requires the estimation of $N+1$ rather than $N(N+1)$ parameters, and still renders $\hat{\rho}_{GLS}$ invariant to numeraire choice. Of course, when $T > N$, as in the empirical analysis in Section 5, it may be preferable to use an unrestricted estimate of.

This proposition implies that panel studies which find that it is ‘‘easier'' to reject the unit root hypothesis when one numeraire is substituted for another are essentially misspecified.

4.2. Power of GLS panel tests

In this section, we replicate the power analysis of Section 3, but this time use the *FGLS* rather than the *OLS* estimator or ρ. Thus the null is (1), the alternative is (2), and the true cross-sectional dependence is captured by the unique off-diagonal element of Ω, ω. To implement the test, a consistent estimate of Ω is needed. This is provided by the covariance matrix of the first-differences of the vector of real exchange rates, which is consistent under the null. It is computationally expedient to estimate Ω without restrictions. This requires that $T>N$, and for this reason, power is only examined for those panels whose dimensions satisfy this property.[7] As before, the distribution of the *FGLS* t-statistic $t_\rho = \hat{\rho}/\sigma_\rho$ is derived under the null by Monte Carlo simulation for various values of N, T and ω.[8] Columns 4–6 of Table 3 report the 1%, 5% and 10% percentiles of these distributions, while Columns 7–9 give the power to reject H_0 in favour of H_1.

Three features of these power calculations are striking. First, the distribution of $\hat{\rho}_{\mathrm{FGLS}}$ is seen to be invariant to ω, and to depend only on T and N. Second, the power to reject H_0 is also invariant to. Third, and perhaps most interesting, as long as N is not too close to T, power comes close to the level that is available for the standard (i.e. *OLS*) panel unit root test when the true disturbances are i.i.d. Of course, when N gets close to T, there are greater efficiency losses associated estimating, and so the power of the *GLS* test can be below that of the Levin–Lin test with i.i.d. disturbances.

Some intuition for the performance of the *GLS* test can be gleaned from the properties of *GLS* estimation. $\hat{\rho}_{GLS}$ can be obtained by transforming the data to render it i.i.d., and then running *OLS*. The transformation to independence, which can be accomplished by postmultiplying X and Y by the inverse of the Cholesky decomposition of Ω, produces a set of variables that are linear combinations of the original real exchange rates. Now any linear combination of q_t, say $r_t = \mathrm{w}'\mathrm{q}_t$, follows

$$r_t = \alpha_r + \rho r_{t-1} + \epsilon_{rt} \tag{11}$$

where $\alpha_r = \mathrm{w}'$, $\epsilon_{rt} = \mathrm{w}'\epsilon_t$. Thus it shares the same dynamics as the individual q_{it}. True, it will have a different variance, given by $E(\epsilon_{rt}{}^2) = \mathbf{w}'\boldsymbol{\Omega}\mathbf{w}$. However, we know from the theory of unit root tests for the stationary case that size and power are unaffected by variance. It is therefore not surprising that there is little loss of power due to a nondiagonal Ω under *GLS* estimation. A small amount of power

[7] As with the invariance property, it is not necessary to have $T>N$ to benefit from *GLS*: a restricted estimate of Ω can be used instead.

[8] See Appendix for details.

Table 3
The power of *GLS* panel unit root tests with correlated disturbances.

T	N	ω	Critical values			Power for given size: $\rho = -0.04$		
			1%	5%	10%	1%	5%	10%
20	10	0.0	−5.36	−4.90	−4.66	0.02	0.10	0.17
20	10	0.3	−5.33	−4.92	−4.68	0.02	0.10	0.18
20	10	0.5	−5.32	−4.91	−4.68	0.02	0.11	0.19
20	10	0.7	−5.36	−4.95	−4.68	0.03	0.11	0.20
20	10	0.9	−5.32	−4.91	−4.69	0.02	0.11	0.18
60	10	0.0	−5.85	−5.31	−5.01	0.10	0.29	0.43
60	10	0.3	−5.79	−5.26	−4.95	0.12	0.30	0.46
60	10	0.5	−5.81	−5.28	−4.99	0.09	0.30	0.45
60	10	0.7	−5.79	−5.25	−4.95	0.12	0.31	0.47
60	10	0.9	−5.82	−5.27	−4.98	0.10	0.30	0.46
60	50	0.0	−9.61	−9.29	−9.13	0.26	0.45	0.56
60	50	0.3	−9.65	−9.30	−9.13	0.26	0.46	0.56
60	50	0.5	−9.62	−9.30	−9.14	0.28	0.46	0.56
60	50	0.7	−9.70	−9.31	−9.15	0.23	0.47	0.58
60	50	0.9	−9.65	−9.30	−9.14	0.24	0.44	0.56
100	10	0.0	−5.90	−5.34	−5.06	0.34	0.66	0.80
100	10	0.3	−5.86	−5.34	−5.04	0.36	0.68	0.82
100	10	0.5	−5.87	−5.35	−5.04	0.35	0.67	0.82
100	10	0.7	−5.88	−5.36	−5.05	0.35	0.65	0.81
100	10	0.9	−5.90	−5.35	−5.01	0.34	0.66	0.81
100	50	0.0	−10.23	−9.74	−9.49	0.92	0.98	0.99
100	50	0.3	−10.33	−9.75	−9.51	0.91	0.98	0.99
100	50	0.5	−10.25	−9.74	−9.50	0.92	0.98	0.99
100	50	0.7	−10.22	−9.76	−9.50	0.93	0.98	0.99
100	50	0.9	−10.21	−9.75	−9.52	0.94	0.98	0.99
100	90	0.0	−12.40	−12.12	−11.99	0.63	0.77	0.83
100	90	0.3	−12.40	−12.13	−11.98	0.60	0.77	0.83
100	90	0.5	−12.41	−12.12	−11.99	0.64	0.79	0.84
100	90	0.7	−12.42	−12.12	−11.98	0.60	0.78	0.85
100	90	0.9	−12.40	−12.12	−11.98	0.62	0.76	0.82

This table shows the power of *GLS* panel unit root tests when the disturbances are contemporaneously correlated. The distribution of the *GLS* estimator *GLS* from the panel regression $\Delta q_{it} = \alpha_i + \rho q_{i,t-1} + \epsilon_{it}$ is obtained under both the null and the alternative by simulating 5,000 panels of real exchange rates for each combination of T, N and ω. ω is the contemporaneous correlation between real exchange rate innovations. The 1%, 5% and 10% percentiles of the null distributions are shown in columns 4–6, while the proportion of the alternative distributions falling below the null critical values is shown in columns 7–9.

does leak away owing to the fact that is not known, and therefore has to be estimated.

The implication is that once contemporaneous correlation that is controlled for via *FGLS*, it is still possible to implement powerful panel tests of the random walk null.

5. Controlling for cross-sectional dependence, is there evidence of PPP?

It is clear from the preceding section that cross-sectional dependence in panels of real exchange rates has a significant impact on the statistical properties of panel tests of PPP. This is interesting in and of itself. However, the pragmatist could rightly ask whether it makes any difference to the outcome of tests of PPP. This section shows that in fact it does. Assuming independence across real exchange rates, it is possible to find evidence in favour of PPP in a variety of real exchange rate panels. However, this evidence is extremely fragile: once cross-sectional dependence is controlled for, no such evidence can be found.

5.1. Data

Data is drawn from the IMF publication, *International Financial Statistics*.[9] A panel of quarterly CPI real exchange rates is constructed spanning the modern floating-rate period 1973:2–1995:4. The breadth of the panel is dictated largely by data availability—only the 64 countries with complete data for the entire sample period were included.[10] We test PPP using the panel as a whole, as well as four subsamples: Europe (20 countries), Asia (13 countries), South America (13 countries) and Africa (13 countries).

5.2. Test implementation

Within each of the subsamples, real exchange rates are constructed with reference to a member-country price series, rather than the U.S. price index. Thus the focus is on within-group price convergence. Two tests are carried out on each of the five panels. Test 1 ignores cross-sectional dependence by restricting Ω to be diagonal, while Test 2 controls for it by estimating Ω unrestricted. Both tests allow for serial correlation.[11] A feature of the first test is that it will be sensitive to the choice of numeraire. Since the objective in the section is to illustrate how misspecification can lead to the wrong result, for each subsample we choose a numeraire that lends support to PPP. Thus for the full panel, the numeraire is chosen to be the UK; for Europe, France; for Asia, Sri Lanka; and for South America, Argentina. For the African subsample, no numeraire choice produced evidence against the random walk null, and so Gambia's price index was arbitrarily chosen as the benchmark.

[9]The source is the 5/96 CD-ROM version. The data were checked for errors using graphical techniques.

[10]The reason for using a balanced panel is that it greatly simplifies decomposition of the disturbance covariance matrix for the purposes of estimation.

[11]None of the extant panel studies cater to the presence of both contemporaneous and serial correlation, though both have been considered separately. Abauf and Jorion (1990) allow for cross-sectional dependence, while Papell (1996) controls for serial correlation.

More specifically, the null and alternative hypotheses are the same as those considered in Section 3: H_0: $\rho = 0$ is tested against the alternatives H_1: $\rho < 0$. The only difference is in the parameterization of the disturbance term. Papell (1996) has shown that serial correlation has an impact on the size of panel unit root tests. It is important, therefore, to allow for it here. For each panel considered, the vector of disturbance terms ϵ_t is assumed to be generated by a restricted *VAR*(*p*) process of the form

$$\epsilon_t = \phi_1 \mathbf{I}_N \epsilon_{t-1} + \phi_2 \mathbf{I}_N \epsilon_{t-1} + \cdot\cdot\cdot + \phi_p \mathbf{I}_N \epsilon_{t-p} + \nu_t \tag{12}$$

or $\Phi(L)\epsilon_t = \nu_t$, where $E(\nu_t \nu_t') = \Omega$. Ω is estimated unrestricted, and parsimony is instead achieved by restricting the *VAR* coefficient matrices to be diagonal. While in principle it is possible to permit fewer restrictions on this *VAR*, the short span of data available precludes this. For example, even if the *VAR* coefficient matrices are restricted to be diagonal, identification requires that the lag length, *p*, satisfy $N_p \le T - p - 1$.[12]

It is worth noting that with this disturbance DGP, the invariance property of *FGLS* is preserved. This is because the serial correlation properties of each real exchange rate are assumed to be the same. Thus as in Eq. (11), the dynamics of the linear combinations constructed in forming the *FGLS* estimate will be unaffected by numeraire choice. If the serial correlation properties are permitted to be heterogeneous across countries, then the invariance property breaks down.[13]

A separate lag length is chosen for each panel and test using a data-dependent procedure. The process (12) is fitted by maximum likelihood to the first differences of the real exchange rates for values of *p* from 0 to 12. A likelihood ratio test is then used to select the best characterization of the data from these nested models.[14] Serial correlation does emerge as an important feature of the data: the values of *p* selected by the likelihood ratio test when Ω is constrained to be diagonal (Test 1) are World 12, Europe 12, Asia 3, South America 6 and Africa 12; while when is Ω unrestricted (Test 2) the values selected are World 12, Europe 9, Asia 3, South America 3 and Africa 10.

Having estimated the serial correlation and cross-sectional dependence properties of the disturbance vector under the null, the test statistic is then formed in the usual fashion. That is to say, the matrices **Y** and **X** are each transformed by the estimated *VAR* lag polynomial $\Phi(L)$ to yield **Y*** and **X***, and the *FGLS* estimate of ρ is calculated as

$$\hat{\rho}_{FGLS} = \mathrm{tr}(\mathbf{X}^{*\prime}\mathbf{Y}^{*}\hat{\mathbf{\Omega}}^{-1}) / \mathrm{tr}(\mathrm{X}^{*\prime}\mathrm{X}^{*}\hat{\mathbf{\Omega}}^{-1}) \tag{13}$$

[12] For *p* such that $N_p > T - p$, the matrix of country residuals will be of less than full row rank, preventing estimation of Ω.

[13] O'Connell (1997) shows that the restriction of homogenous serial correlation across countries is valid for many panels of real exchange rates.

[14] These fitted *VAR*s and associated likelihood ratio tests are available from the author on request.

Critical values for this test statistic are tabulated by parametric bootstrap. This involves drawing bootstrap samples of real exchange rate innovations from the fitted *VAR* processes (12), and simulating the distribution of $\hat{\rho}_{FGLS}$ estimated from these samples.

5.3. Results

Table 4 presents the results from the application of both Test 1 and Test 2 to each set of real exchange rates. In each case, $\hat{\rho}_{FGLS}$ and its accompanying t-statistic (in parentheses) are shown, together with the 10% critical value for the test and the t-statistic's p-value. Test 1 finds reasonably persuasive evidence in favour of PPP. For the sample as a whole, and for 3 of the 4 subsamples, the unit-root null is rejected at better than the 10% level. Only for Africa is there no evidence of reversion to PPP. By contrast, using Test 2, no evidence against the

Table 4
Panel unit root tests of PPP, quarterly CPI real exchange rates, 1973:2–1995:4.

Panel		Test 1 Serially correlated	Test 2 Contemporaneously serially correlated	N
World	$\hat{\rho}_{GLS}$	−0.053	−0.032	63
	t_ρ	−11.940	−8.534	
	10% crit. value	−9.335	−9.416	
	p-value	0.000	0.403	
Europe	$\hat{\rho}_{GLS}$	−0.055	−0.036	19
	t_ρ	−6.213	−5.065	
	10% crit. value	−5.815	−6.007	
	$p-$value	0.042	0.428	
Asia	$\hat{\rho}_{GLS}$	−0.061	−0.025	12
	t_ρ	−7.002	−3.125	
	10% crit. value	−5.293	−5.323	
	p-value	0.000	0.881	
South America	$\hat{\rho}_{GLS}$	−0.084	−0.043	12
	t_ρ	−6.655	−4.379	
	10% crit. value	−5.258	−5.323	
	p-value	0.001	0.404	
Africa	$\hat{\rho}_{GLS}$	−0.039	−0.027	12
	t_ρ	−3.955	−3.305	
	10% crit. value	−4.991	−5.036	
	p-value	0.487	0.763	

Estimates of ρ the parameter in *GLS* panel unit root regressions of the form $\Delta q_{it} = \alpha_i + \rho q_{i,t-1} + \epsilon_{it}$. The test is run under two different assumptions concerning the data generating process of the disturbance term. The first (column 1) allows for heteroscedasticity and serial correlation, but not contemporaneous correlation. The second (column 2) allows in addition for contemporaneous correlation. t-statistics appear below the point estimates,together with 10% critical values and test statistic p-values obtained byparametric bootstrap (see Appendix for details).

unit-root null can be found in any of the panels. This result is striking, because it cannot be attributed to low power. The results in Table 3 indicate that there is ample power in panels of these dimensions to reject the random walk in favour of $\rho = -0.04$.[15] From this it is clear that the hypothesis of PPP is overvalued as a true characterization of real exchange rate behaviour by the tests which do not pay attention to cross-sectional dependence.

6. Conclusion

This paper has highlighted the importance of controlling for cross-sectional dependence when testing for a unit root in panels of real exchange rates. The consequences of not doing so for statistical size and power can be dramatic. Moreover, cross-sectional dependence affects test outcomes: real exchange rate panels which support rejection of the unit-root null when cross-sectional dependence is ignored no longer do so when it is properly accounted for. This result is important, because it cannot be attributed to low power. Monte Carlo evidence indicates that contemporaneously correlated panels retain much of the power of their i.i.d. counterparts under *FGLS* estimation.

The question arises as to how this failure to reject the random walk be reconciled with the time series evidence that has been found in favour of PPP? If the time series evidence is correct, then one explanation might be heterogeneity in the cross section dimension. Froot and Rogoff (1995) suggest that the long-sample PPP literature suffers from sample-selection bias, since it has focused on those few industrial countries for which long time series of data are available. This excludes many of the countries studied here. The prices levels in two countries may exhibit a tendency to converge towards one another, while at the same diverging from another country's price index. Such cross-sectional heterogeneity might lead to acceptance of the unit-root null in a large cross-section. The other possibility is that there has been a structural change in the behaviour of real exchange rates since the advent of the modern float.

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[15]The power calculations in Table 3 assume serially uncorrelated disturbances. However, the presence of serial correlation makes little difference to power once it is incorporated in the estimation procedure.

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Appendix 1

Proof of proposition 1

Proposition 1. In testing for a unit root in panels of real exchange rates, the GLS estimate ρ_{GLS} is invariant to the numeraire price index used to construct the real exchange rates.

Proof. Define **Y**, **X** and **Ω** as in the main text. Suppose we construct a new panel of real exchange rates by benchmarking against a different country than the US. Without loss of generality, choose this alternative numeraire to be country 1. Then the new real exchange rates are $\tilde{q}_{it}=p_{it}-s_{it}-p_{1t}+s_{1t}$, $i=2,\ldots,N$, and $q_{\mathrm{US},t}\equiv p_{\mathrm{US},t}-p_{1t}+s_{1t}$. Their first differences can be written in matrix form as

$$\tilde{\mathbf{Y}}=\mathbf{YA} \tag{14}$$

where

$$A=\begin{bmatrix} -1 & -1 & -1 & \cdots & -1 \\ 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{bmatrix}$$

Similarly, the new matrix of lagged real exchange rates is

$$\tilde{\mathbf{X}}=\mathbf{XA} \tag{15}$$

Finally, the covariance matrix of the real exchange rates becomes

$$\tilde{\mathbf{\Omega}}=\mathbf{A}'\mathbf{\Omega}\mathbf{A} \tag{16}$$

Together, these yield the *GLS* estimator

$$\begin{aligned} \tilde{\rho}_{GLS} &= \mathrm{tr}(\tilde{\mathbf{X}}'\tilde{\mathbf{Y}}\tilde{\mathbf{\Omega}}^{-1})/\mathrm{tr}(\tilde{\mathbf{X}}'\tilde{\mathbf{X}}\tilde{\mathbf{\Omega}}^{-1}) \\ &= \mathrm{tr}(\mathbf{A}'\mathbf{X}'\mathbf{YA}(\mathbf{A}'\mathbf{\Omega}\mathbf{A})^{-1})/\mathrm{tr}(\mathbf{A}'\mathbf{X}'\mathbf{XA}(\mathbf{A}'\mathbf{\Omega}\mathbf{A})^{-1}) \\ &= \mathrm{tr}(\mathbf{X}'\mathbf{YAA}^{-1\prime}\mathbf{\Omega}^{-1}(\mathbf{A}')^{-1}\mathbf{A}')/\mathrm{tr}(\mathbf{X}'\mathbf{XAA}^{-1\prime}\mathbf{\Omega}^{-1}(\mathbf{A}')^{-1}\mathbf{A}') \\ &= \hat{\rho}_{GLS} \end{aligned} \tag{17}$$

Monte Carlo and parametric bootstrap simulations

The Monte Carlo simulations reported in Tables 1 and 2 are conducted as follows. For each triplet $\{T\ N\ \omega\}$, 5,000 panels of real exchange rates of dimension $T+51\times N$ are simulated under the null, with $q_0=0$. The inclusion of an extra 50 observations is to control for initial-value bias. Conditional on q_{51}, the 51st observation, $\hat{\rho}$ is estimated by running the panel regression (3) on the N observations $\{q_t\}_{t=52}^{N+51}$ of each panel, and from this the distribution of the test statistic and the 1%, 5% and 10% critical values are derived. The power estimates are obtained by simulating 1,000 panels of real exchange rates *under the alternative*, and calculating the proportions of the resulting distributions of $\hat{\rho}$ and $\hat{\rho}_{\mathrm{FGLS}}$ that lie below the test critical values.

The simulations reported in Table 3 are carried out in a similar fashion. 5,000 panels of real exchange rates are generated for each triplet $\{T\ N\ \omega\}$, under the null, and 1,000 panels under the alternative. *FGLS* estimation of ρ is then undertaken, using an unrestricted estimate of the variance-covariance matrix Ω obtained under the null. Finally, the distribution of ρ_{FGLS} under both the null and alternative is tabulated, providing the critical values and power of the test.

The critical values and *p*-values in Table 4 are derived by parametric bootstrap. 5,000 panels of real exchange rates are generated under the null. The moments of the real exchange rate innovations are chosen to match the estimates of $\{\phi_i\}_{i=1}^{p}$ and Ω obtained from (12). As the focus is on cross-sectional dependence, is estimated unrestricted, and parsimony is instead achieved by constraining the *VAR* coefficient matrices to be diagonal. Once again, 50 additional observations are included to counter any initial-value bias.

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