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Purchasing power parity and the theory of general relativity: the first tests

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Abstract

We implement novel tests of general relative purchasing power parity (PPP), defined as a long-run unit elasticity of the nominal exchange rate with respect to relative national prices, allowing for potentially permanent real exchange rate shocks. The finite-sample properties of the estimators used are analyzed through Monte Carlo analysis, allowing for country heterogeneity, cross-sectional dependence and non-stationary disturbances. Application to panel data sets of industrialized and developing economies reveals that inflation differentials are on average reflected one-for-one in long-run nominal exchange rate depreciation—i.e. that general relative PPP holds.

JEL classification: C32; F31

Keywords: Real exchange rate; Purchasing power parity; Cross-sectional dependence; Monte Carlo

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1. Introduction

Purchasing power parity (PPP) involves a relationship between a country's foreign exchange rate and the level or movement of its national price level relative to that of a foreign country. *Absolute* PPP states that the purchasing power of a unit of domestic currency is exactly the same in the foreign economy, once it is converted into foreign currency at the absolute PPP exchange rate. *Relative* PPP implies that changes in national price levels are offset by commensurate changes in the nominal exchange rates between the relevant currencies. The voluminous research literature on PPP published in recent decades has been driven by econometric problems relating to univariate and panel unit root tests of necessary conditions for long-run absolute PPP to hold, in particular whether the real exchange rate has any tendency to settle down to a long-run equilibrium level.[1] These include issues such as low power, possible structural breaks, the mixture of stationary and non-stationary error terms in the relevant regressions, and neglected cross-sectional dependence when real exchange rate panel data are used.

In this paper, we generalize the concept of long-run *relative* PPP to the case where the *long-run* elasticity of the nominal exchange rate with respect to relative national prices is unity without restricting the innovation sequence to be stationary. This is what we term *general relative PPP*. We then develop methods to test for general relative PPP in a panel regression framework that is robust to country heterogeneity and cross-sectional dependence as well as—most importantly—permanent and transitory shocks to the real exchange rate. Thus, we allow for the long-run equilibrium real exchange rate to shift while still testing for a long-run unit elasticity of the nominal exchange rate with respect to the price relative.

In contrast, the extant empirical analysis of PPP generally precludes permanent shocks to the long-run real exchange rate. It is widely accepted, however, that over long periods, real shocks may permanently impact on the long-run equilibrium real exchange rate level due to productivity differentials as in the Harrod-Balassa-Samuelson effect (Froot and Rogoff, 1995; Sarno and Taylor, 2002; Lothian and Taylor, 2004; Bergin et al., 2003). By exploiting recent developments in the econometrics of non-stationary panel data, we can accommodate such shocks alongside transitory or monetary shocks. Moreover, Taylor (2001) has demonstrated how two problems—trading costs and risk aversion on the one hand and temporal aggregation on the other—can make the regression errors of nominal exchange rates on price relatives appear rather persistent or even non-stationary. In developing our test procedures, we extend the relevant econometric literature to allow for cross-sectional dependence and mixed stationary and non-stationary errors and compare the finite-sample properties of several panel estimators using Monte Carlo simulations.

Our empirical analysis is based on a unique, large data set for the 1970:1–1998:12 period that comprises 19 Organizations for Economic Cooperation and Development (OECD) member countries and 26 developing countries and both consumer price

[1] See Taylor (1995), Sarno and Taylor (2002) and Taylor and Taylor (2004) for overviews.

index (CPI) and producer price index (PPI) data. Analyzing developing and industrial country panels using the same methodology is interesting. The former show larger heterogeneity, more cross-sectional variation (higher signal) but more time series noise also due to measurement error. Our empirical work suggests strongly that general relative PPP held in each of the panels examined over the data period in question, thereby confirming the earlier analysis of Flood and Taylor (1996), which was based on informal scatter plots and regression analysis of long-period averages.

The remainder of the paper is organized as follows. In Section 2 we discuss further the notion of general relative PPP. In Section 3 we present the panel econometric framework and explore the finite-sample properties of the estimators employed. Our empirical results are discussed in Section 4 and we conclude in a final section.

2. General relative PPP

Denote the price level of the domestic currency by P_t and the corresponding foreign price level by P_t^*. If S_t is the nominal exchange rate (domestic price of foreign currency) and if absolute PPP holds, then expressing the domestic price in foreign currency terms must yield the foreign price, $P_t^* = P_t/S_t$. Taking logarithms (lower case) and rearranging, we have the short-term relationship:

$$s_t = p_t - p_t^* \tag{1}$$

which implies that the nominal exchange rate should be directly proportional to the relative price level even in the very short run. The short-run relative PPP condition may be written:

$$\Delta s_t = \Delta p_t - \Delta p_t^* \quad \text{or } \mathrm{d}s_t = \mathrm{d}p_t - \mathrm{d}p_t^* \tag{2}$$

where Δ and d denote the first difference and total differential operators, respectively. While empirical tests of these short-term relationships were not uncommon in the early 1970s (see, e.g., Frenkel, 1976; or the studies cited in Officer, 1982), the very high volatility of nominal exchange rates compared to relative national price levels or inflation rates during the recent floating period has adequately demonstrated that neither absolute nor relative PPP is a realistic description of short-run exchange rate behavior.

Instead, over the past few decades, PPP has been extensively tested as a *long-run* equilibrium condition, largely through unit-root and cointegration methods. Effectively, what unit-root studies do is firstly to capture the short-run variation in real exchange rates by adding an error term:

$$s_t = (p_t - p_t^*) + u_t \tag{3}$$

and then to test the hypothesis that the process u_t—the deviation from PPP—is non-stationary.[2] In particular, if u_t contains a random walk or unit-root component—u_t

[2] The cointegration variant of this is to estimate slope coefficient in this relationship rather than imposing that they be (1,−1) and then test for a unit root in u_t (Taylor, 1988).

is I(1)—then the implication is that deviations from PPP *never* settle down at an equilibrium level even in the long run.[3] This approach has spawned a vast literature which has, in general, found remarkable difficulty in supporting the hypothesis of long-run PPP using data for the recent floating rate period alone (Sarno and Taylor, 2002; Taylor and Taylor, 2004). Moreover, it has indicated that real exchange rates or deviations from long-run PPP are extremely persistent, a stylized fact which Rogoff (1996) has described as 'the PPP puzzle'.

While it is clear that unit root analysis involves a test of long-run PPP, the unit root approach is rather restrictive since it implies that the level of the exchange rate is not subject to permanent shocks. The concept of general relative PPP that we are proposing here operationalizes, in the context of PPP tests, the ceteris paribus assumption of traditional economic analysis. Suppose that u_t in Eq. (3) is observationally I(1), perhaps due to Harrod-Balassa-Samuelson effects or other real shocks. Now further assume that the equation still holds in the sense that the coefficient on the relative price term—the elasticity of the nominal exchange rate with respect to relative prices—is in fact unity, as in Eq. (3). This can be interpreted as a form of long-run relative PPP in the sense that a 1% increase in relative prices would still be offset one-to-one by a *long-run* depreciation of 1%, ceteris paribus, even though long-run PPP would be rejected in the conventional unit-root framework and both absolute and relative PPP would also be rejected.

The ceteris paribus clause here is crucial. The concept we are proposing is very general. It would allow, for example, for real shocks permanently to affect the real exchange rate so long as any given percentage movement in relative prices would lead to a commensurate movement in the nominal exchange rate in the long run, over and above any such permanent effect on the real exchange rate. It is because of the generality of the concept that we term it *general* relative PPP. Note that general relative PPP does not imply any particular causality. Although we are testing for a unit elasticity of the exchange rate with respect to relative prices, the concept makes no assertions concerning which way or ways causality runs between the variables concerned. It only asserts that, ceteris paribus, in the long run a given percentage change in relative prices will be offset by a commensurate percentage change in the nominal exchange rate.

Another way of highlighting the distinctive nature of our approach is explicitly to introduce the long-run, equilibrium real exchange rate, $\overline{q}_t$ in Eq. (3)[4]:

$$s_t=\overline{q}_t+\left(p_t-p_t^*\right)+v_t \tag{4}$$

where v_t is a stationary, zero-mean process. Thus the real exchange rate can be written as:

$$q_t=\overline{q}_t+v_t. \tag{5}$$

[3] A series is said to be 'integrated of order d', I(d), if it must be differenced d times to become stationary.

[4] We are grateful to an anonymous referee for this helpful suggestion.

The critical distinction between traditional tests of long-run absolute and relative PPP and our methodology is that the former two assume that q_t fluctuates randomly around a constant $\overline{q}_t = \overline{q}$. If absolute PPP holds then $\overline{q} = 0$ but relative PPP implies $\overline{q} = c$ where $c \neq 0$. No such restrictions apply in our test of long-run general relative PPP. Instead, $\overline{q}_t$ can be time-varying and behave like an I(1) process due to Balassa-Samuelson or other real effects.

Thus, a test of general relative PPP is an economically meaningful test irrespective of the behavior of u_{it} in the following log level panel regression

$$s_{it} = \alpha_i + \beta_i \left(p_{it} - p_{it}^* \right) + u_{it}, \quad t = 1, \ldots, T \tag{6}$$

where, since $\overline{q}_{it}$ is unobserved, one can assume that $u_{it} = \overline{q}_{it} + v_{it}$ for $i = 1, \ldots, N$ countries. The object is to estimate the mean of the slope β_i that can be interpreted as the long-run relative price elasticity of the nominal exchange rate for country i. The innovation sequence can be I(0) or I(1). The null hypothesis that general relative PPP holds is

$$H_0 : \beta \equiv E(\beta_i) = 1 \tag{7}$$

and the alternative is that $\beta \neq 1$. The expression for the slope, $\beta_i \equiv \mathrm{d}s_{it}/\mathrm{d}(p_{it} - p_{it}^*)$ can be obtained either by differentiating Eq. (6) with respect to the price differential or by rearranging the total differential in Eq. (2) as in the textbook exposition of relative PPP. Thus our null of a unit relative price elasticity is consistent with relative PPP but is more general due to the lack of restrictions on u_{it}.

We introduce below a robust panel framework to test for general relative PPP. Our approach can accommodate a number of factors germane to the PPP debate. One is the observed high persistence of real exchange rates that may reflect a combination of real and monetary (or permanent and transitory) shocks. It may also relate to the noise stemming from measurement error, transaction costs and other market imperfections such as limits to arbitrage in foreign exchange markets (Taylor and Taylor, 2004) that can make the regression disturbances observationally equivalent to I(1) series. Another important factor is cross-sectional dependence which has typically been neglected in much empirical analysis.

3. Econometric framework

3.1. Non-stationary panel regression

Suppose the data are generated according to the set of relationships

$$y_{it} = \alpha_i + \beta_i x_{it} + v_{it}, \quad i = 1, \ldots, N; \quad t = 1, \ldots, T \tag{8}$$

where $\alpha_i = \alpha + \eta_{\alpha,i}$ and $\beta_i = \beta + \eta_{\beta,i}$. This random coefficients model (RCM) assumes that:

(A.1) The coefficients are constant over time but may differ *randomly* across units, that is, $\eta_{\alpha,i} \sim \text{iid}(0,\sigma_\alpha^2)$, $\eta_{\beta,i} \sim \text{iid}(0,\sigma_\beta^2)$ and $(\eta_{\alpha,i},\eta_{\beta,i})'$ are distributed independently of the regressor x_{it} and disturbances v_{it} for all i and t.
(A.2) The disturbances have a zero mean, time constant but possibly heterogeneous variance and are uncorrelated across different units, i.e. $E(v_{it}) = 0$, $E(v_{it}^2) = \sigma_i^2$ and $E(v_{it}v_{jt}) = 0$ if $i \neq j$.
(A.3) The x_{it} and v_{is} are independently distributed for all t, s (strict exogeneity).

The goal is to measure the mean effect $\beta \equiv E(\beta_i)$ where β_i represents the long-run relation between two I(1) variables. For single time series ($N = 1$), analogously to the slope coefficient in the classical linear regression model, a long-run association between y_t and x_t is defined as $\beta = \sum_{yx}\sum_{xx}^{-1}$ where $\sum_{yx}$ and $\sum_{xx}$ are the long-run covariance and long-run variance, respectively. When the long-run variance–covariance matrix $\sum$ is rank deficient, β is a cointegrating coefficient. When y_t and x_t do not cointegrate (full rank $\sum$), β still represents a statistical long-run relationship as shown by Phillips and Moon (1999). How to estimate β is a different issue.

The OLS regression of y_t onto x_t when $\sum$ has full rank will be spurious (Granger and Newbold, 1974). However, suppose that independent observations $(y_{it}\, x_{it})'$ are available on a large number of countries $i = 1, \ldots, N$. Different panel procedures can be used to estimate β consistently. First, the within or fixed effects (FE) estimator imposes homogeneous slopes and error variances but allows for heterogenous intercepts. Second, the Pesaran and Smith (1995) mean group (MG) estimator averages over the individual OLS regression coefficients $\hat{\beta}_i$.[5] This estimator allows for heterogeneous intercepts, slopes and error variances. Third, the between or cross-section (CS) estimator involves running an OLS regression for individual means $\bar{y}_i$ and $\bar{x}_i$. Pesaran and Smith (1995) note that the spurious correlation problem does not arise in the case of the CS estimator under the RCM assumptions. Phillips and Moon (1999) further show that both $\hat{\beta}^{\text{FE}}$ and $\hat{\beta}^{\text{CS}}$ are $\sqrt{N}$ – consistent for β when the error term v_{it} in Eq. (8) is I(1).

Coakley et al. (2001) use Monte Carlo simulations and response surface regressions to evaluate the finite-sample properties of the FE and MG estimator for panel dimensions $N, T = \{(15, 300), (30, 25)\}$ typical of monthly and annual PPP studies, respectively. They show for a non-stationary regression such as Eq. (8) that both estimators appear unbiased with dispersion that falls at rate $T\sqrt{N}$ when v_{it} is I(0) and at rate $\sqrt{N}$ when v_{it} is I(1).[6] Moreover, standard t-tests based on the $N(0, 1)$ quantiles have good size properties in the MG case irrespective of whether the regression disturbances are I(0) or I(1). By contrast, inference based on the FE

[5] The MG estimator of β is defined as $\hat{\beta}^{\text{MG}} = N^{-1}\sum_i \hat{\beta}_i$ with variance $V(\hat{\beta}^{\text{MG}}) = 1/\text{N}(\text{N} - 1) \sum_i (\hat{\beta}_i - \hat{\beta}^{\text{MG}})^2$.

[6] This Monte Carlo evidence is particularly relevant for the MG estimator since its asymptotic properties have not been established as yet for panel regressions with I(1) disturbances.

estimator is likely to be misleading since the usual standard errors are severely underestimated when v_{it} is I(1) and robust Newey-West type covariance matrices are not valid. The FE based t-tests are also unacceptably oversized when the true slope coefficients are heterogeneous even if v_{it} is iid.

The asymptotic theory for panel estimators of non-cointegrating levels regressions in Kao (1999) and Phillips and Moon (1999) and the finite-sample analysis in Coakley et al. (2001) rest on the assumption of cross-sectional independence. To gauge how restrictive the latter is in the present context, Table 1 reports average pairwise correlations for relative prices (d_{it}), real exchange rates (r_{it}) and individual OLS residuals $\hat{v}_{it}^{\mathrm{OLS}}$ from Eq. (6). For comparative purposes, we also report the counterpart statistics for relative inflation (Δd_{it}), real exchange rate returns (Δr_{it}) and the residuals from the first-difference regressions.

The average (absolute) cross-sectional dependence measures are generally larger for the levels data than for the first-differenced data, as expected. Both the real exchange rates and residuals show higher pairwise correlations between industrialized countries (mostly positive and well above 0.5) than between developing countries. Overall, these summary statistics indicate that cross-sectional dependence should not be neglected in a panel analysis of PPP.

3.2. Monte Carlo analysis of panel estimators

Consider the stylized PPP equation

$$y_{it} = \alpha_i + \beta_i x_{it} + v_{it}, \quad i = 1, \dots, N; \ t = 1, \dots, T \tag{9}$$

and underlying data generating processes (DGP1 hereafter)

$$v_{it} = \rho_{v,i} v_{i,t-1} + \varepsilon_{v,it}, \varepsilon_{v,it} \sim \mathrm{iid} N\left(0, \sigma_{v,i}^2\right), \tag{10}$$

Table 1
Cross-section dependence statistics

Sample	Price relative		Real exchange rate		OLS residuals	
	Ave (ω_{ij})	Ave ($\lvert\omega_{ij}\rvert$)	Ave (ω_{ij})	Ave ($\lvert\omega_{ij}\rvert$)	Ave (ω_{ij})	Ave ($\lvert\omega_{ij}\rvert$)
i) Levels data						
Ind_CPI	0.1187	0.8540	0.6351	0.6525	0.7085	0.7085
Ind_PPI	0.0329	0.8867	0.6353	0.6363	0.6524	0.6524
Dev_CPI	0.7646	0.8854	0.2189	0.4388	0.1514	0.3095
Dev_PPI	0.8790	0.8790	0.0595	0.2712	0.0731	0.2139
ii) First-differenced data						
Ind_CPI	0.1908	0.1977	0.5798	0.5798	0.5922	0.5922
Ind_CPI	0.4175	0.4175	0.5298	0.5298	0.5275	0.5275
Dev_CPI	0.0563	0.0983	0.0147	0.0438	0.0139	0.0397
Dev_CPI	0.1189	0.1315	0.0382	0.0460	0.0190	0.0326

Ave (ω_{ij}) is the mean pairwise country correlation; $\lvert\omega_{ij}\rvert$ denotes absolute correlation.
Ind and Dev refer to industrialized and developing countries, respectively.
The price relative is $d_{it} = p_{it} - p_{it}^*$ and the real exchange rate is $s_{it} - p_{it} + p_{it}^*$.
The OLS residuals pertain to individual regressions of s_{it} (or Δs_{it}) on d_{it} (or Δd_{it}).

$$x_{it}=\rho_{x,i}x_{i,t-1}+\varepsilon_{x,it}, \varepsilon_{x,it}\sim \mathrm{iid}N\left(0,\sigma_{x,i}^2\right) \tag{11}$$

where $\varepsilon_{v,it}$ is independent of $\varepsilon_{x,is}$ for all t, s. We permit dependence in $\varepsilon_{v,it}$ (and $\varepsilon_{x,it}$) across i to arise in two ways. First, it can stem from idiosyncratic pairwise dependencies

$$E\left(\varepsilon_{v,t}\varepsilon_{v,t}^{'}\right)\equiv\Omega_v=\begin{bmatrix}1 & \omega_v^{12} & \cdots & \omega_v^{1N}\\ \omega_v^{21} & 1 & \cdots & \omega_v^{2N}\\ \vdots & \vdots & \ddots & \vdots\\ \omega_v^{N1} & \omega_v^{N2} & \cdots & 1\end{bmatrix}$$

where the diagonal terms are $\sigma_{v,i}^2\equiv E(\varepsilon_{v,it}^2)=1$ and the off-diagonal terms are $\omega_v^{ij}\equiv E(\varepsilon_{v,it}\varepsilon_{v,jt})\neq 0$ and likewise for $E(\varepsilon_{x,t}\varepsilon_{x,t}')\equiv\Omega_x$. Albeit simple, this parameterization captures the dependencies stemming from the variation in (or shocks to) the dollar and US price level. We set $\omega_x^{ij}=\omega_x=0.4$ (largest average correlation in Δx_{it} across our four panels) and consider various levels of cross-sectional dependence in the disturbances $\omega_v^{ij}=\omega_v\in\{0.0, 0.3, 0.5, 0.7, 0.9\}$. We set $\rho_{x,i}=1$ throughout. For the error term v_{it} we allow for: a) Weak dependence using $\rho_{v,i}=0.3$; b) Unit root non-stationarity, $\rho_{v,i}=1$; c) A mix of highly persistent but stationary errors ($\rho_{v,i}=0.9$, $i=1,\ldots,N_1$) and unit root errors ($\rho_{v,i}=1$, $i=N_1+1,\ldots,N$) for $N_1=7$ or roughly $N_1/N\simeq 50\%$.

Second, the cross-section dependence can stem from unobserved common factors (DGP2) as in

$$v_{it}=\rho_{v,i}v_{i,t-1}+\gamma_i z_t+\varepsilon_{v,it},\quad \varepsilon_{v,it}\sim \mathrm{iid}N\left(0,\sigma_{v,i}^2\right), \tag{12}$$

$$x_{it}=\rho_{x,i}x_{i,t-1}+\phi_i z_t+\psi_i f_t+\varepsilon_{x,it},\quad \varepsilon_{x,it}\sim \mathrm{iid}N\left(0,\sigma_{x,i}^2\right) \tag{13}$$

where the above Ω_x and Ω_v covariances ($\omega_v=0.5$) are used. The processes $(z_t, f_t)'$ represent two (orthogonal) unobserved country-invariant factors; z_t affects both x_{it} and v_{it} whereas f_t is a regressor-specific global factor. They are generated by

$$z_t=\rho_z z_{t-1}+\varepsilon_{z,t},\quad \varepsilon_{z,t}\sim \mathrm{iid}N(0,1),$$

$$f_t=\rho_f z_{t-1}+\varepsilon_{f,t},\quad \varepsilon_{f,t}\sim \mathrm{iid}N(0,1)$$

where $\varepsilon_{z,t}$ is independent of $(\varepsilon_{v,t}, \varepsilon_{x,t})'$ and likewise for $\varepsilon_{f,t}$. We set $\rho_f=0.3$ and $\rho_z\in\{0.3, 1\}$. The latter case ($\rho_z=1$) is considered so that the non-stationarity of x_{it} and v_{it} is induced by z_t and we set $-1<(\rho_{x,i}, \rho_{v,i})<1$ since otherwise x_{it} and v_{it} would be I(2).

DGP2 generalizes DGP1 in several directions: i) The cross-sectional dependence is partly determined by the effect of unobserved common factors z_t—global macroeconomic variables or shocks (e.g. oil price innovations)—which may be correlated with the regressors; ii) The non-stationarity in disturbances and/or regressor may arise from I(1) common factors; iii) The unobserved (common) factors z_t and f_t have different effects on the countries (random coefficients γ_i, ϕ_i and ψ_i) and so heterogenous cross-sectional correlations are introduced. A uniform density is adopted to generate these coefficients. Three cases are considered. First, $\gamma_i \sim \text{iid}U[-1,3]$, $\phi_i \sim \text{iid}U[-1,3]$ and $\psi_i = 0$ for all i so that there is perfect correlation between z_t and $\overline{x}_t$ as $N \rightarrow \infty$.[7] Second, $\gamma_i \sim \text{iid}U[-1,3]$, $\phi_i \sim \text{iid}U[-1,3]$ and $\psi_i \sim \text{iid}U[-1,3]$. Third, $\gamma_i \sim \text{iid}U[-3,-1.5]$, $\phi_i \sim \text{iid}U[-1,3]$ and $\psi_i \sim \text{iid}U[3.5,5]$ so that the coefficients take values in different intervals.

We set $\alpha_i \sim \text{iid}U[-0.5,5]$ and $\beta_i \sim \text{iid}U[0.5,1.5]$ to typify the range of variation in the individual OLS estimates for the industrialized, PPI panel.[8] The parameter of interest is the mean effect of x_{it} on y_{it} with true value $\beta \equiv E(\beta_i) = 1$. The results are based on 5000 replications of panels with dimensions $N = 15$, $T = 300 + T_0$ that resemble our actual sample. The first $T_0 = 50$ observations are discarded to reduce the initialization effects, $x_{i0} = v_{i0} = z_0 = f_0 = 0$. We consider the CS estimator, two pooled estimators—FE (1-way fixed effects), 2FE (2-way fixed effects)—and four mean group estimators—MG (based on individual OLS estimates), SUR-MG (individual SUR-GLS estimates), DMG (individual OLS estimates for cross-sectionally demeaned data) and CMG (individual OLS estimates of regressions augmented by $\overline{y}_i$ and $\overline{x}_i$).[9]

Some of these estimators already control for cross-sectional dependence. The 2FE estimator amounts to FE for cross-sectionally demeaned data, $y_{it} - \overline{y}_t$ and $x_{it} - \overline{x}_t$, and so it can be seen as the pooled counterpart of DMG. If the common factor has the same effects on all units ($\gamma_i = \gamma$), the 2FE estimator is unbiased because the time effects α_t capture the unobserved common factor z_t whether or not it is correlated with x_{it}. A similar argument applies to the DMG estimator. The SUR-MG (and baseline MG) estimator will be biased if z_t is correlated with x_{it}. Pesaran (2002) proposes the CMG approach, namely, augmenting the regression of interest by the cross-section means of the variables to capture the unobserved factor(s) that induce cross-country dependence. He shows analytically that the CMG estimator is consistent (as $T \rightarrow \infty$ and $N \rightarrow \infty$) in a rather general setup, which DGP2 seeks to mimic, where the latent factors are I(0) or I(1) and may be correlated with the regressor.

Tables 2 and 3 summarize the simulation results for DGP1 and DGP2, respectively. We report the sample mean (SM) and standard deviation (SSD) of the $\hat{\beta}$ estimates over replications. The SSD is compared with the average estimated

[7] Pesaran (2002) shows analytically that when $[\sigma_{\overline{x}z} < \sigma_{\overline{x}}\sigma_z]$, the principal components estimator for cross-sectionally dependent panels proposed by Coakley et al. (2002) is biased and inconsistent.

[8] The range is $[-0.43,5.55]$ and $[0.60,1.70]$ for $\hat{\alpha}_i$ and $\hat{\beta}_i$, respectively. The heterogeneity in $\hat{\alpha}_i$ is smaller when the spot rates are standardized (to the same base year as the price indexes) but still significant as suggested by a LR test for H_0: $\alpha_i = \alpha$ in the FE model. Using more widely dispersed parameters $\alpha_i \sim U[-1,6]$ and $\beta_i \sim U[0.1,1.9]$ we find qualitatively similar results in the simulations.

[9] The CS estimator requires the strict exogeneity assumption (A.3) for consistency. Weak exogeneity suffices for the other estimators and so the (real) exchange rate may feedback on the price relative as VAR analyses suggest.

Table 2
Simulation results for DGP1

Design			Between		Pooled				Mean group							
			CS		FE		2FE		MG		SUR-MG		DMG		CMG	
#	ρ_v	ω_u	SM JB	SSD SE	SM JB	SSD SE	SM JB	SSD SE	SM JB	SSD SE	SM JB	SSD SE	SM JB	SSD SE	SM JB	SSD SE
a1	0.3	0.0	0.990	0.146	1.000	0.092	1.000	0.104	1.000	0.075	1.001	0.075	1.001	0.085	1.001	0.075
			0.703	0.105	0.032	0.005	0.038	0.006	0.841	0.074	0.843	0.74	0.282	0.079	0.796	0.071
a2	0.3	0.3	0.997	0.147	1.001	0.092	1.002	0.104	1.002	0.074	1.001	0.074	1.002	0.085	1.001	0.074
			0.000	0.105	0.000	0.005	0.002	0.006	0.107	0.074	0.100	0.074	0.868	0.079	0.107	0.070
a3	0.3	0.5	0.999	0.151	1.001	0.094	1.001	0.106	1.000	0.076	1.004	0.076	1.000	0.088	1.000	0.076
			0.000	0.105	0.000	0.005	0.004	0.006	0.396	0.074	0.067	0.074	0.084	0.079	0.071	0.069
a4	0.3	0.7	0.998	0.147	0.999	0.093	0.998	0.105	0.999	0.074	0.998	0.074	0.999	0.086	0.999	0.074
			0.000	0.105	0.007	0.005	0.038	0.006	0.307	0.074	0.168	0.074	0.114	0.079	0.118	0.069
a5	0.3	0.9	1.000	0.149	0.999	0.093	0.999	0.106	1.000	0.075	1.001	0.075	1.000	0.086	1.000	0.075
			0.001	0.105	0.003	0.005	0.018	0.005	0.396	0.074	0.347	0.074	0.189	0.079	0.296	0.069
b1	1	0.0	0.994	0.405	1.003	0.190	1.001	0.245	1.002	0.180	1.002	0.156	1.002	0.233	0.999	0.188
			0.000	0.374	0.030	0.016	0.228	0.021	0.577	0.174	0.206	0.152	0.529	0.218	0.000	0.174
b2	1	0.3	1.004	0.345	1.007	0.251	1.005	0.207	1.005	0.241	1.005	0.197	1.002	0.199	1.002	0.161
			0.000	0.320	0.000	0.016	0.089	0.018	0.000	0.168	0.001	0.145	0.678	0.189	0.389	0.151
b3	1	0.5	0.988	0.301	1.012	0.298	1.003	0.189	1.010	0.285	1.008	0.224	1.005	0.175	1.002	0.143
			0.000	0.275	0.000	0.015	0.670	0.015	0.000	0.164	0.000	0.139	0.085	0.165	0.002	0.132
b4	1	0.7	0.996	0.254	1.005	0.324	0.997	0.161	1.005	0.312	1.004	0.229	0.998	0.145	0.999	0.120
			0.000	0.224	0.000	0.015	0.219	0.012	0.000	0.154	0.000	0.130	0.656	0.137	0.038	0.112
b5	1	0.9	0.999	0.189	1.000	0.355	1.002	0.127	1.011	0.344	1.007	0.221	1.001	0.110	1.001	0.093
			0.000	0.155	0.000	0.015	0.638	0.008	0.000	0.148	0.000	0.118	0.111	0.102	0.772	0.086
c1	Mix	0.0	1.011	0.149	0.999	0.093	0.999	0.106	1.000	0.075	1.000	0.075	1.000	0.086	1.000	0.075
			0.000	0.105	0.003	0.005	0.018	0.006	0.396	0.074	0.348	0.074	0.189	0.079	0.296	0.070
c2	Mix	0.3	1.000	0.286	1.004	0.177	1.006	0.180	1.004	0.166	1.004	0.142	1.003	0.170	1.004	0.131
			0.007	0.258	0.000	0.012	0.986	0.015	0.008	0.134	0.088	0.119	0.015	0.158	0.002	0.123
c3	Mix	0.5	1.006	0.276	1.002	0.194	0.999	0.174	1.001	0.185	1.001	0.151	0.997	0.163	0.998	0.122
			0.000	0.248	0.000	0.012	0.004	0.014	0.000	0.133	0.000	0.116	0.000	0.152	0.044	0.113

c4	Mix	0.7	1.004	0.268	0.997	0.209	0.998	0.166	0.999	0.198	0.999	0.151	1.000	0.154	1.000	0.110
			0.000	0.228	0.000	0.012	0.000	0.013	0.000	0.129	0.000	0.110	0.000	0.141	0.271	0.102
c5	Mix	0.9	0.994	0.240	1.002	0.218	0.997	0.156	1.003	0.208	1.001	0.147	0.997	0.142	0.998	0.097
			0.000	0.203	0.000	0.012	0.000	0.011	0.000	0.126	0.000	0.104	0.000	0.131	0.699	0.089

Idiosyncratic cross-section dependence.
5000 replications. The ‘mix’ panels comprise cointegrating (N_1) and non-cointegrating equations (N–N_1), $N_1/N = 0.5$. $N = 15$, $T = 300$. SM and SSD are the sample mean and standard deviation of $\hat{\beta}$. SE is the mean standard error. JB is the Jarque-Bera test p-value. Values below SM and SSD denote the JB and SE values, respectively.

Table 3
Simulation results for DGP2. Common factor structure

							Between		Pooled				Mean group							
Design							CS		FE		2FE		MG		SUR-MG		DMG		CMG	
#	ρ_x	ρ_v	ρ_z	γ_i	ϕ_i	ψ_i	SM	SSD	SM	SSD	SM	SSD	SM	SSD	SM	SSD	SM	SSD	SM	SSD
							JB	SE	JB	SE	JB	SE	JB	SE	JB	SE	JB	SE	JB	SE
A1	1	0.3	0.3	U[−1,3]	0	0	1.000	0.148	1.001	0.094	1.001	0.105	1.001	0.077	1.001	0.076	1.001	0.086	1.001	0.076
							0.000	0.105	0.039	0.006	0.033	0.007	0.679	0.074	0.405	0.074	0.326	0.079	0.226	0.070
A2	1	0.3	0.3	U[−1,3]	U[−1,3]	0	0.996	0.139	1.003	0.103	0.998	0.114	1.002	0.075	0.999	0.074	0.998	0.107	0.998	0.076
							0.390	0.101	0.106	0.005	0.028	0.006	0.612	0.075	0.663	0.074	0.000	0.099	0.695	0.071
A3	1	0.3	0.3	U[−1,3]	U[−1,3]	U[−1,3]	1.000	0.150	1.003	0.113	0.999	0.126	1.004	0.075	1.001	0.074	1.002	0.103	1.001	0.079
							0.006	0.089	0.002	0.004	0.000	0.005	0.283	0.074	0.225	0.074	0.000	0.089	0.298	0.071
A4	1	0.3	0.3	U[−3,−1.5]	U[−1,3]	U[3.5,5]	1.001	0.161	0.997	0.131	1.002	0.146	0.993	0.077	0.999	0.076	1.003	0.111	1.001	0.085
							0.000	0.084	0.000	0.004	0.000	0.005	0.135	0.074	0.053	0.074	0.053	0.074	0.017	0.071
B1	0.3	0.3	1	U[−1,3]	U[−1,3]	0	1.000	0.506	1.423	0.241	0.996	0.300	1.262	0.699	1.239	0.572	0.998	0.652	0.999	0.112
							0.000	0.348	0.019	0.014	0.239	0.016	0.000	0.648	0.000	0.564	0.000	0.598	0.002	0.104
B2	0.3	0.3	1	U[−1,3]	U[−1,3]	U[−1,3]	0.990	0.485	1.421	0.238	0.992	0.290	1.238	0.536	1.259	0.664	0.996	0.577	0.998	0.106
							0.000	0.342	0.003	0.014	0.832	0.016	0.000	0.514	0.000	0.607	0.000	0.539	0.000	0.099
B3	0.3	0.3	1	U[−3,−1.5]	U[−1,3]	U[3.5,5]	1.000	0.368	0.070	0.204	0.999	0.156	0.392	0.963	0.481	0.688	1.001	0.233	0.999	0.082
							0.000	0.204	0.000	0.018	0.005	0.008	0.000	0.899	0.000	0.739	0.000	0.216	0.109	0.071
C1	Mix	1	0.3	U[−1,3]	0	0	0.999	0.688	0.996	0.652	0.998	0.414	0.999	0.629	0.999	0.437	1.002	0.401	1.003	0.200
							0.000	0.582	0.000	0.034	0.000	0.034	0.000	0.332	0.001	0.249	0.000	0.344	0.000	0.179
C2	Mix	1	0.3	U[−1,3]	U[−1,3]	0	0.997	0.305	1.317	0.248	0.997	0.246	1.236	0.327	1.209	0.279	0.992	0.295	1.004	0.164
							0.000	0.285	0.003	0.015	0.002	0.016	0.000	0.277	0.000	0.245	0.000	0.283	0.000	0.154
C3	Mix	1	0.3	U[−1,3]	U[−1,3]	U[−1,3]	0.999	0.274	1.234	0.225	0.999	0.209	1.207	0.297	1.184	0.255	1.001	0.255	0.999	0.148
							0.000	0.227	0.000	0.013	0.005	0.013	0.000	0.251	0.000	0.223	0.000	0.235	0.000	0.137
C4	Mix	1	0.3	U[−3,−1.5]	U[−1,3]	U[3.5,5]	0.999	0.203	0.626	0.296	1.001	0.159	0.553	0.412	0.616	0.333	1.001	0.138	0.998	0.118
							0.206	0.142	0.000	0.014	0.000	0.007	0.000	0.344	0.000	0.293	0.527	0.111	0.077	0.108

See legend of Table 2.

standard error (SE) and the Jarque-Bera normality test is conducted to assess the adequacy of conventional inference.

For DGP1, all estimators are unbiased irrespective of whether the regression disturbances are I(0) or I(1), with or without cross-sectional dependence. However, the sample variability of the FE (and 2FE) estimates is seriously underestimated for all designs. The Newey-West standard error formulae are correct in the autocorrelated I(0)-error case but are not valid for I(1) errors nor do they account for cross-sectional dependence. The CS estimates are highly dispersed and their standard errors are somewhat downward biased. The latter is because the error term in the CS regression is $e_i = \overline{v}_i + \eta_{\alpha,i} + \eta_{\beta,i}\overline{x}_i$ with variance $V(e_i|x) = V(\overline{v}_i) + \sigma_\alpha^2 + \sigma_\beta^2\overline{x}_i^2$ and so heteroskedasticity arises but White's robust standard errors can be used to account for it.

For stationary disturbances (a1–a5) the standard errors of the mean group type estimators are correct. For our large $T = 300$, the MG, SUR-MG and CMG estimators are equally efficient whereas DMG incurs some efficiency loss because demeaning reduces the signal-noise ratio. In the non-cointegration designs (b1–b2) or mixed error designs (c1–c5), the SUR-MG estimator shows efficiency gains relative to MG as expected but the standard errors of both are underestimated especially for high levels ($\omega_u > 0.3$) of cross-sectional dependence.

The DMG and CMG approaches are the most efficient in accounting for cross-sectional dependence in non-cointegration settings and their standard errors are essentially correct. In the mixed error settings, the CMG estimator is the most accurate. Despite the relatively large T and normal innovations, the sampling distribution of CS, FE and 2FE is generally not normal. By contrast, all mean group type estimators are essentially normal for the I(0)-error designs (a1–a5). When the error terms are all I(1) or a mixture, only DMG and CMG generally retain normality in the presence of cross-sectional dependence.

For DGP2 where cross-sectional dependence is due to a latent common factor also, the CS, 2FE, DMG and CMG estimators remain unbiased when this factor is correlated with the regressor (B1–B3, C2–C4) in contrast with the remaining estimators.[10] None of the estimators is biased in the cointegration designs even if the latent factor is present in disturbances and regressor (A1–A4) because the correlation between the I(0) disturbance and the I(1) regressor goes to zero for large T. Allowing the factor loadings γ_i, ϕ_i and ψ_i to take values randomly in different intervals does not change the results qualitatively (c.f. B2 and B3), namely, FE, MG and SUR-MG are markedly biased whilst CS, 2FE, DMG and CMG are centered at unity.

The results for the designs where $\psi_i \neq 0$ are qualitatively similar to those for $\psi_i = 0$ (or $\sigma_{\overline{x}z} = \sigma_{\overline{x}}\sigma_z$). If anything, the biases of FE, MG and SUR-MG are smaller in the former because the signal (variance of x_{it}) has increased. The remaining estimators are all unbiased. Our findings for CMG are in line with the theoretical

[10] For the simple case $\rho_{x,i} = \rho_{v,i} = 0$ the theoretical bias for each unit is $\sigma_{vx,i}/\sigma_{x,i} = (\gamma_i\phi_i\sigma_z^2)/(\phi_i^2\sigma_z^2\psi_i^2\sigma_f^2 + \sigma_{x,i}^2)$. Design B1 is modified so that the factors affect all countries in the same direction (i.e. $\gamma_i \sim U[0.5,1.5]$ and $\phi_i \sim U[0.5,1.5]$). The bias of FE, MG and SUR-MG is now larger at 1.919, 2.068 and 1.936, respectively.

results in Pesaran (2002) which show that CMG is unbiased both when $\sigma_{\bar{x}z} = \sigma_{\bar{x}}\sigma_z$ and $\sigma_{\bar{x}z} < \sigma_{\bar{x}}\sigma_z$.

To sum up, these experiments illustrate some potential effects of misspecification on several panel estimators. Pooled, cross-section and mean group type estimators are all unbiased in the context of I(1) disturbances when there is no cross-sectional dependence. If the cross-sectional dependence is induced by omitted common factors, the unbiasedness remains as long as factors and regressors are uncorrelated. However, if the latter is violated then FE, MG and SUR-MG can exhibit substantial biases whereas CS, 2FE, DMG and CMG appear quite robust.[11]

4. Testing for general relativity: empirical results

4.1. Data

Data were gathered from the International Monetary Fund's *International Financial Statistics* for industrialized and developing economies on the exchange rate of the national currency against the US dollar and two price measures, the consumer price index (CPI) and producer price index (PPI) with 1995 as base year. While the CPI series may contain a lower proportion of traded goods than the PPI series, it is generally more widely available. The data are monthly over the 1970:1–1998:12 period ($T = 348$). The nominal exchange rate data are middle rates, end-of-period quotations. To ensure a more satisfactory match between price and exchange rate data, the nominal exchange rates are scaled so that 1995 = 100. We use variables in logarithms throughout.

The composition of the four panels is as follows. The industrialized, CPI panel (Ind_CPI: $N = 19$) comprises Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Israel, Italy, Japan, Netherlands, Norway, Portugal, South Africa, Spain, Sweden, Switzerland, and the UK. The industrialized, PPI panel (Ind_PPI: $N = 14$) includes Austria, Canada, Denmark, Finland, Germany, Greece, Ireland, Israel, Japan, Netherlands, South Africa, Spain, Switzerland, and the UK. The developing country, CPI panel (Dev_CPI: $N = 26$) includes Argentina, Chile, Colombia, Dominican Republic, Ecuador, Egypt, El Salvador, Ghana, Guatemala, Honduras, India, Indonesia, Jamaica, South Korea, Malaysia, Mexico, Myanmar, Pakistan, Paraguay, Peru, Philippines, Sri Lanka, Sudan, Thailand, Turkey and Venezuela. Finally, the developing, PPI panel (Dev_PPI: $N = 12$) comprises Brazil, Chile, Colombia, Costa Rica, Egypt, El Salvador, India, Korea, Mexico, Pakistan, Philippines and Thailand.

We found little or no evidence against the unit root hypothesis for the nominal exchange rate and relative price series, whereas it is clearly rejected when applied to

[11] A note of caution is needed for the CS, 2FE and DMG estimators because (in contrast with the CMG estimator) their asymptotic properties have not been established under general common-factor settings.

their first differences. Therefore, in keeping with the literature, it seems reasonable to take s_{it} and d_{it} as I(1) series.[12]

4.2. Graphical analysis

As a preliminary motivation to our formal empirical work, we followed Flood and Taylor (1996) in constructing simple scatter plots of depreciation of the dollar exchange rate against the relative (to the US) inflation rate over different time horizons using our panel data set. For each of the panels, we construct non-overlapping measures of the 12-month percentage change in the nominal exchange rate and of the 12-month percentage change in the relative price level. This is done for each country in the panel and a scatter plot of annual depreciation against relative annual inflation is drawn. Thus in the scatter plots of 1-year movements, 29 points are plotted for each of the countries in the panel. We then repeat this procedure using 5-year averages of the annual movements and 29-year averages. In the latter case we have one point per country in the scatter plots.[13]

Fig. 1 gives the plots for the CPI panels.[14] Perhaps surprisingly, the scatter plots even at the 1-year horizon show a reasonably close degree of correlation between relative inflation and exchange rate depreciation for industrialized and developing countries, although one needs to be careful about the different scales in these graphs when interpreting them. Strikingly, there is the tendency of the scatter plots to collapse towards the 45° ray through the origin as the averaging horizon increases to 29 years. This impression is reinforced when outliers are excluded.[15]

Overall the scatter plots confirm the informal analysis of Flood and Taylor (1996) in providing strong visual confirmation of relative PPP holding quite closely for both developed and developing countries, at least on average over the 29-year period under consideration. Although this evidence is only informal, it provides a strong motivation for pursuing our formal econometric exercise.

4.3. Panel estimates and inference

The parameter of interest is the long-run elasticity of the exchange rate with respect to the relative price level. The specified model is the log-levels Eq. (6) where the error sequence u_{it} is allowed to be autocorrelated, possibly in the unit root sense. In this framework, the long-run general relative PPP hypothesis is $H_0: \beta = 1$. Test statistics

[12] The results for the augmented Dickey-Fuller and the Phillips-Perron unit root tests are available from the authors on request. The tests are not applied to the residual series for two reasons. On the one hand, they are unlikely to yield conclusive results over a span of just 29 years (Lothian and Taylor, 1997). Panel unit root tests are more powerful but have weaknesses (Taylor and Sarno, 1998). On the other hand, the novelty of our formulation is precisely that it sidesteps the cointegration debate.

[13] This informal graphical approach is an extension of the analysis in Flood and Taylor (1996).

[14] The PPI plots look very similar and so are not reported.

[15] We also constructed plots using 10- and 15-year averages of the annual movements. These and the outlier-robust plots are available on request from the authors.

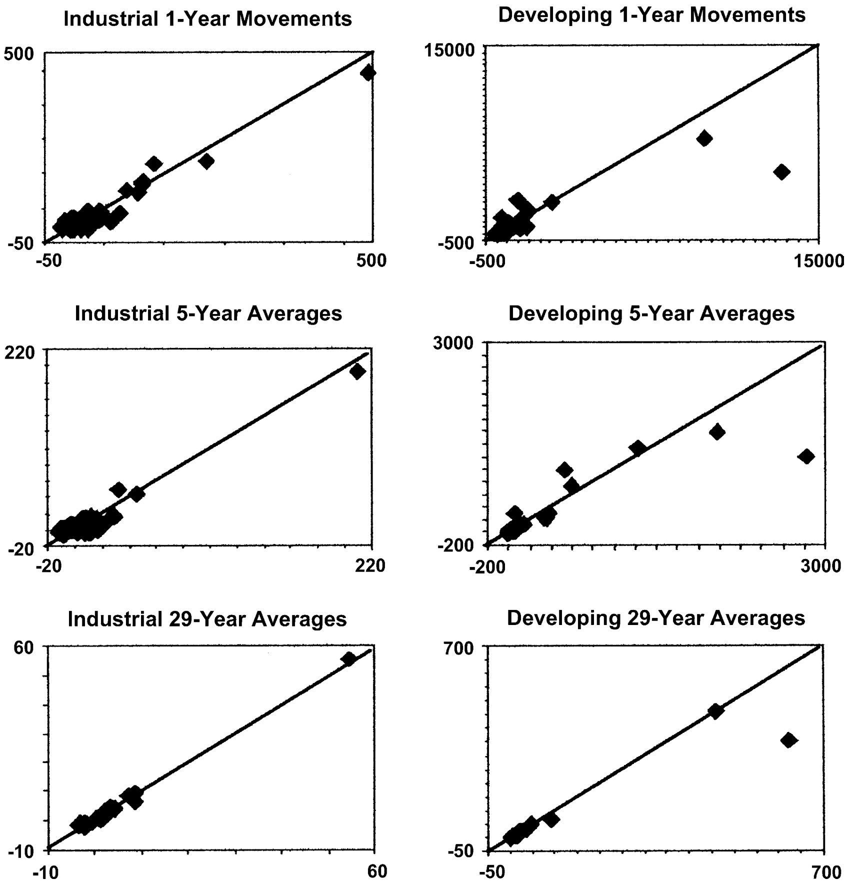

Fig. 1. Relative PPP scatter diagrams (CPI series).

for $H_0 : \beta = 0$ are also reported. We use three basic methods—cross-section, pooled and mean group—to exploit the panel structure of the data in different ways.

Tables 4 and 5 present the results for the Ind_CPI and Ind _PPI panels, respectively and Tables 6 and 7 those for the Dev_CPI and Dev_PPI panels, respectively.

The between (CS) and pooled (FE, 2FE) estimates are quite close to the MG estimates in each panel. This suggests that the heterogeneous elasticities are uncorrelated (or weakly so) with the price relative since otherwise biases would appear in the between and pooled estimates. Insignificant diagnostic tests for heteroskedasticity indicate that the OLS standard errors are appropriate in the CS regressions.[16] The hypothesis $\beta = 0$ is strongly rejected on the basis of the latter for

[16] For the industrialized countries, White's LM test statistic (?p-value) is 1.07 (0.58) and 0.96 (0.62) using CPI and PPI data, respectively. For the developing countries, the counterpart statistics are 0.21 (0.90) and 1.66 (0.44).

Table 4
Industrialized countries (CPI series)

Estimates	$\hat{\beta}$	$se(\hat{\beta})$	t-Statistics		$\hat{\beta}_i,\ i=1,\ldots,N$		
			$H_0: \beta = 1$	$\beta = 0$	Sk	K	JB
i) Between							
CS	1.026	0.0349	0.742 (0.458)	29.395** (0.000)	–	–	–
ii) Pooled							
FE	0.996	0.0024 [0.067]	−0.060 (0.952)	14.859** (0.000)	–	–	–
2FE	1.016	0.0016 [0.061]	0.264 (0.792)	16.746** (0.000)	–	–	–
iii) Mean group							
MG	1.045	0.099	0.456 (0.654)	10.588** (0.000)	0.684	0.157	1.502 (0.472)
(Japan)	*0.991*	*0.087*	*−0.105 (0.918)*	*11.323 (0.000)*	*0.414*	*−0.371*	*0.616 (0.735)*
SUR-MG	1.013	0.101	0.129 (0.899)	10.060** (0.000)	0.809	0.206	2.107 (0.349)
(Japan)	*0.953*	*0.086*	*−0.545 (0.593)*	*11.132 (0.000)*	*0.447*	*−0.433*	*0.740 (0.691)*
DMG	0.999	0.056	−0.020 (0.985)	17.806** (0.000)	−0.275	0.081	0.245 (0.885)
(Spain)	*1.029*	*0.050*	*0.570 (0.576)*	*20.449 (0.000)*	*0.087*	*2.998*	*0.023 (0.989)*
CMG	0.724	0.114	−2.430* (0.015)	6.365** (0.000)	−1.577	3.964	20.319** (0.000)
(Canada)	*0.812*	*0.075*	*−2.487* (0.024)*	*10.805 (0.000)*	*0.433*	*0.018*	*0.563 (0.755)*

$N = 19$, $T = 348$. In parentheses for CS, FE and 2FE are p-values from an $N(0,1)$. The Pooled t-tests are based on sieve bootstrap standard errors (in brackets) from 1000 replications. For the Mean group, outlier-robust statistics are in italics; Sk and K are the skewness and kurtosis of $(\hat{\beta})$ and JB is the Jarque-Bera normality statistic (p-values); the t-test is based on exact p-values from a Student t with $N-1$ d.f. if normality is not rejected or asymptotic p-values from an $N(0,1)$. * and ** indicate rejection at the 5% and 1% levels, respectively. The R^2 of the CS regression is 0.981.

Table 5
Industrialized countries (PPI series)

Estimates	$\hat{\beta}$	$se(\hat{\beta})$	t-Statistics		$\hat{\beta}_i,\ i=1,\ldots,N$		
			$H_0: \beta = 1$	$H_0: \beta = 0$	Sk	K	JB
i) Between							
CS	1.024	0.519	0.920 (0.358)	39.088** (0.000)	–	–	–
ii) Pooled							
FE	0.985	0.0020 [0.049]	−0.305 (0.760)	20.033** (0.000)	–	–	–
2FE	1.002	0.0013 [0.055]	0.0362 (0.971)	18.119** (0.000)	–	–	–
iii) Mean group							
MG	1.101	0.081	1.249 (0.234)	13.609** (0.000)	0.250	−0.157	0.160 (0.923)
(Japan)	*1.054*	*0.071*	*0.758 (0.463)*	*14.774** (0.000)*	*−0.175*	*−0.943*	*0.548 (0.761)*
SUR-MG	1.028	0.063	0.452 (0.659)	16.607** (0.000)	0.359	0.368	0.380 (0.827)
(Japan)	*0.988*	*0.051*	*−0.236 (0.817)*	*19.349 (0.000)*	*−0.493*	*−0.304*	*0.577 (0.750)*
DMG	1.024	0.033	0.726 (0.481)	31.122** (0.000)	0.429	0.239	0.463 (0.793)
(S. Africa)	*1.003*	*0.028*	*0.123 (0.904)*	*36.222 (0.000)*	*−0.134*	*0.104*	*0.045 (0.978)*
CMG	0.892	0.093	−1.157 (0.268)	9.584** (0.000)	−0.468	0.652	0.759 (0.684)
(Finland)	*0.951*	*0.078*	*−0.628 (0.542)*	*12.213 (0.000)*	*0.122*	*4.042*	*0.620 (0.733)*

See legend of Table 4. $N = 14$, $T = 348$, $R^2_{CS} = 0.992$.

Table 6
Developing countries (CPI series)

Estimates	$\hat{\beta}$	$se(\hat{\beta})$	t-Statistics		$\hat{\beta}_i,\ i=1,\ldots,N$		
			$H_0: \beta = 1$	$H_0: \beta = 0$	Sk	K	JB
i) Between							
CS	0.958	0.176	−1.579 (0.114)	36.015** (0.000)	–	–	–
ii) Pooled							
FE	1.001	0.0014 [0.045]	0.022 (0.982)	22.449** (0.000)	–	–	–
2FE	0.969	0.0017 [0.054]	−0.570 (0.569)	17.822** (0.000)	–	–	–
iii) Mean group							
MG	1.101	0.087	1.171 (0.242)	12.732** (0.000)	−1.067	3.152	15.700 (0.000)
(2 outliers)	*1.199*	*0.058*	*3.431 (0.001)*	*20.720 (0.000)*	*1.182*	*4.391*	*7.524 (0.023)*
SUR-MG	1.092	0.085	1.087 (0.277)	12.852** (0.000)	−0.879	2.121	8.222* (0.016)
(3 outliers)	*1.153*	*0.050*	*3.192 (0.004)*	*24.000** (0.000)*	*0.981*	*0.433*	*5.652 (0.060)*
DMG	0.997	0.036	−0.081 (0.935)	27.697** (0.000)	1.590	2.409	17.248** (0.000)
(2 outliers)	*0.956*	*0.023*	*−1.881 (0.072)*	*40.903 (0.000)*	*0.650*	*0.205*	*1.730 (0.421)*
CMG	0.913	0.133	−0.656 (0.512)	6.874** (0.000)	−2.249	5.895	59.570** (0.000)
(Sri Lanka)	*1.014*	*0.089*	*0.159 (0.874)*	*11.346 (0.000)*	*−1.124*	*4.877*	*8.934 (0.011)*

See legend of Table 4. $N = 26$, $T = 348$. $R^2_{CS} = 0.982$. The outliers are Malaysia, Myanmar (MG); India, Malaysia, Myanmar (SUR-MG); El Salvador, Myanmar (DMG).

Table 7
Developing countries (PPI series)

Estimates	$\hat{\beta}$	$se(\hat{\beta})$	*t*-Statistics		$\hat{\beta}_i,\ i=1,\ldots,N$		
			$H_0: \beta = 1$	$H_0: \beta = 0$	Sk	K	JB
i) Between							
CS	0.937	0.071	−0.887 (0.375)	13.197** (0.000)	–	–	–
ii) Pooled							
FE	0.985	0.0009 [0.024]	−0.623 (0.533)	40.905** (0.000)	–	–	–
2FE	0.972	0.0010 [0.023]	−1.238 (0.216)	42.990** (0.000)	–	–	–
iii) Mean group							
MG	1.096	0.061	1.564 (0.118)	17.904** (0.000)	2.095	5.669	24.847** (0.000)
(India)	*1.042*	*0.033*	*1.288 (0.227)*	*31.697 (0.000)*	*0.138*	*0.199*	*0.053 (0.974)*
SUR-MG	1.087	0.066	1.322 (0.186)	16.566** (0.000)	1.892	3.343	12.746** (0.002)
(India)	*1.028*	*0.034*	*0.847 (0.417)*	*30.178*** *(0.000)*	*0.114*	*0.588*	*0.182 (0.913)*
DMG	0.960	0.021	−1.923 (0.081)	45.923** (0.000)	0.871	1.039	2.057 (0.358)
(Philippines)	*0.944*	*0.015*	*−3.764 (0.004)*	*63.381 (0.000)*	*−0.527*	*2.185*	*0.814 (0.666)*
CMG	0.889	0.049	−2.214* (0.050)	17.786** (0.000)	−0.518	0.057	0.538 (0.764)
(Egypt)	*0.923*	*0.039*	*−1.987 (0.075)*	*23.738*** *(0.000)*	*0.313*	*−1.089*	*0.724 (0.696)*

$N = 12$, $T = 348$. See legend of Table 4, $R^2_{CS} = 0.946$.

both industrialized and developing economies (using either CPI or PPI) and the coefficient is insignificantly different from unity even at the 10% level.[17]

We report the conventional asymptotic OLS standard errors for the pooled estimates. Since the latter are likely to be downward biased, we also calculate bootstrap standard errors using a procedure that preserves autocorrelation and cross-sectional dependence in the disturbances.[18] The OLS standard errors are dwarfed by comparison with those for the MG estimates (discussed below) and more than 10 times smaller than the bootstrap standard errors.[19] The bootstrap *t*-statistics strongly reject the $\beta = 0$ hypothesis and support general relative PPP or $\beta = 1$ in the long run for all four panels.

One should expect the FE and 2FE estimates to differ markedly when there are unobserved common shocks that are correlated with the regressors. Under the Hausman test null, the common shocks are uncorrelated with the regressors and so both FE and 2FE are consistent but the former is efficient. Under the alternative, only 2FE is consistent.[20] For all four panels, the two estimates are insignificantly different which suggests that, if the cross-sectional dependence is induced by latent common factors, these are not correlated (or weakly so) with the regressors.

All the MG estimators point in the same direction: the long-run elasticity is significantly different from zero and insignificantly different from unity. The robust CMG approach provides unambiguous support for long-run PPP on the basis of the Ind_PPI and Dev_PPI data sets and borderline support for the Dev_PPI panel. However, the Ind_CPI panel rejects $\beta = 1$ at the 5% level.[21] As the averaging is sensitive to outliers, we checked for their potential effects in all MG variants by removing cases for which $Z(\hat{\beta}_i) \equiv |\hat{\beta}_i - \hat{\beta}^{\mathrm{MG}}|/\sigma_{\hat{\beta}} > 2$ where $\sigma_{\hat{\beta}}$ is the sample standard deviation of $\hat{\beta}_i, \quad i = 1, \ldots, N$. Tables 4–7 report (in italics) the outlier-robust estimates. The mean group estimates move closer to unity, the associated standard errors fall and so does the *t*-ratio in most cases. The outlier-robust CMG estimator strengthens the evidence in favour of general relative PPP. More specifically, the *t*-statistic ($\beta = 1$) for the Dev_PPI panel is now clearly insignificant at the 5% level adding to the clear-cut evidence for the Ind_PPI and Dev_CPI panels. Therefore, the

[17] The support for $\beta = 1$ using the CS estimator is in line with the assumption of strict exogeneity.

[18] We use a residual-based sieve bootstrap approach that is shown to provide a reasonably good approximation to the true variability of the FE estimates in the presence of autocorrelated, possibly non-stationary errors (Fuertes, 2004). The resampling approach is based on pseudo-disturbances that follow AR(I)MA processes. Cross-section dependence in the residuals is preserved by resampling rows ($t = 1, 2, \ldots, T$?) with replacement.

[19] Newey-West standard errors increase only slightly relative to OLS, e.g. at 0.0040 (FE) and 0.0039 (2FE) for the Ind_CPI panel. This is not surprising given that the Newey-West covariance matrix is inappropriate when the regression errors are I(1) and when cross-section dependence is relevant.

[20] The test statistic is $H = \hat{q}' \left[V(\hat{q})\right]^{-1} \hat{q}$. In this case $\hat{q} = \hat{\beta}^{\mathrm{FE}} - \hat{\beta}^{\mathrm{2FE}}$, $V(\hat{q}) = V(\hat{\beta}^{\mathrm{FE}}) - V(\hat{\beta}^{\mathrm{2FE}})$ and the squared bootstrap standard errors are used to compute the latter. The *p*-values from a $\chi^2(1)$ are 0.79 (Ind_CPI), 0.83 (Ind_PPI), 0.74 (Dev_CPI) and 0.68 (Dev_PPI).

[21] The simulations suggested that the CMG estimator is more efficient in the presence of cross-section dependence. However, all four panel samples give relatively large CMG standard errors which may reflect some bias-efficiency trade off resulting from aspects of the true DGP not captured by Eqs. (10)–(13).

deviation of the long-run elasticity from unity suggested by the CMG estimate in the errant Ind_CPI panel, although significant, may be small in economic terms.

Overall, it seems reasonable to conclude that the long run relative price elasticity is insignificantly different from unity. Nominal exchange rates and price differentials tend to move one-for-one in the long run. How can this finding be reconciled with the extant literature? The difficulty of testing for long-run relative PPP and hence, the mixed to unfavorable evidence in the literature, stems from the fact that the long-run equilibrium real exchange rate may be a moving function of I(1) factors. Our econometric framework permits testing for general relative PPP when the long-run equilibrium level of the exchange rate is time-varying and subject to permanent shocks.

5. Conclusions

In a log-levels equation relating the nominal exchange rate to the national price differential, general relative PPP implies a long-run unit slope coefficient but no restrictions on the error term. Measurement errors, transaction costs or limits to arbitrage in foreign exchange markets can make the latter appear observationally equivalent to a unit root sequence. In addition, real exchange rates can be subject to transitory (nominal) or permanent (real) shocks. This paper proposes and implements the first tests of the general relative PPP hypothesis, which posits a long-run unit elasticity of the nominal exchange rate with respect to the price differential, in a robust framework that accommodates shifts in the equilibrium level of the real exchange rate. Simply put, if general relativity holds, then in the long run and other things equal, a 1% movement in relative prices will be offset by a commensurate movement in the nominal exchange rate, and vice versa.

Our work builds on panel estimators that have been shown to be able to identify the true long-run relationship between non-stationary variables even if they do not cointegrate (Pesaran and Smith, 1995; Phillips and Moon, 1999; Kao, 1999; Coakley et al., 2001). The intuition is that by pooling or averaging over countries one can attenuate the effect of the noise while retaining the strength of the signal. Several approaches are implemented in the empirical analysis in order to capture different aspects of the panel structure of the data over and above persistent disturbances. These include country heterogeneity and cross-sectional dependence. The finite-sample properties of the panel estimators utilized are analyzed using Monte Carlo simulations.

Cross-sectional dependence may arise from the common variation in the bilateral value of the dollar and the US price index (numéraire effect) and, more importantly, from latent global macroeconomic factors that may be correlated with the price relative. In this context, a major role is given to inference based on the robust common correlated effects estimator recently proposed by Pesaran (2002) to deal with cross-sectional dependence. The empirical analysis is based on a unique large dataset for 19 industrialized and 26 developing countries, 1970:1–1998:12. Both informal graphical analysis and formal statistical tests overall support the hypothesis of a long-run unit price elasticity—i.e. general relativity. We conclude that inflation differentials are reflected one-for-one in nominal exchange rate depreciation on average in the long run. Relative prices matter as PPP posits but it is not just relative prices that matter. Other (unobservable) non-stationary factors may be responsible for the fluctuations of the real exchange rate.

There are further implications of our results that are worth drawing out. The first is that it may make no sense to speak of speed of adjustment (or half life) to equilibrium in the cointegration sense because the equilibrium is not constant but a moving function of unobserved I(1) factors—perhaps due to Harrod-Balassa-Samuelson productivity effects, changes in tastes or other real shocks (Bergin et al., 2003; Lothian and Taylor, 2004). Indeed, if this is the case, then empirical measures of the speed of real exchange rate adjustment that do not account for this shifting equilibrium will be severely biased towards zero—as the literature on 'the PPP puzzle' attests (Rogoff, 1996). Second, it may be fruitful to analyze further the underlying economic determinants of this potentially shifting equilibrium to try and identify it. In this context, it is perhaps comforting that—as Taylor and Taylor (in press) note—the literature has already begun to turn in this direction.

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