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# Nominal exchange rates and monetary fundamentals Evidence from a small post-Bretton woods panel

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**Abstract**

We study the long-run relationship between nominal exchange rates and monetary fundamentals in a quarterly panel of 19 countries extending from 1973.1 to 1997.1. Our analysis is centered on two issues. First, we test whether exchange rates are cointegrated with long-run determinants predicted by economic theory. These results generally support the hypothesis of cointegration. The second issue is to re-examine the ability for monetary fundamentals to forecast future exchange rate returns. Panel regression estimates and panel-based forecasts confirm that this forecasting power is significant. © 2001 Elsevier Science B.V. All rights reserved.

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## 1. Introduction

This paper re-examines the nominal exchange rate–monetary fundamentals link within a panel data framework. Our paper is motivated by Kilian (1997), Berkowitz and Giorgianni (1997), Groen (1997), and Berben and van Dijk (1998) who question the statistical robustness of the results from studies finding that monetary fundamentals forecast nominal exchange rate returns (percent changes in the exchange rate) (see MacDonald and Taylor, 1993; Mark, 1995; Chinn and

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Meese, 1995; Chen and Mark, 1996; MacDonald and Marsh, 1997). Much of the favorable evidence for the prediction hypothesis centers around i) significant slope coefficient estimates in regressions of future exchange rate returns on the deviation of the log exchange rate from monetary fundamentals and ii) the dominance of prediction accuracy from these regressions over the random walk model in out out-of-sample forecasting. As in studies of stock returns (e.g. Fama and French, 1988; Campbell and Shiller, 1988; Hodrick, 1992), there is a tendency for exchange return regression slope coefficients and $R^2s$ to increase in magnitude as the return horizon is lengthened. Similarly, out-of-sample forecast accuracy of monetary fundamentals relative to the random walk tend to improve with prediction horizon.

The relatively short time-series used in these studies combined with the high degree of dependence across overlapping observations of long-horizon exchange rate returns make statistical inference a thorny issue. As a result, the robustness of the link between monetary fundamentals and the nominal exchange rate has been called into question. Along these lines, Kilian (1997) finds the evidence for exchange rate predictability to be less favorable when he updates Mark's (1995) data set and employs a less restrictive data generating process in building parametric bootstrap distributions upon which to draw inference. Similarly, Berkowitz and Giorgianni (1997) and Berben and van Dijk (1998) argue that noncointegration between exchange rates and their monetary fundamentals render the independent variable in these regressions nonstationary so that standard hypothesis testing procedures produce misleading inferences and need to be modified.[1] Moreover, all these papers argue that long-horizon regressions offer no statistical power gains over short-horizon regressions.

This paper, which motivated by these recent critiques, aims to improve on the imprecise univariate estimates and forecasts by exploiting available cross-sectional information in a panel data set and imposing modest homogeneity restrictions in estimation. We focus our analysis on two main issues. The first of these is whether nominal exchange rates are cointegrated with monetary fundamentals. The second issue concerns the forecasting power of monetary fundamentals in a panel version of the long-horizon regression of currency returns on the deviation of the log exchange rate from the monetary fundamentals. We attack both of these issues within the framework of the panel regression of the one-period ahead nominal exchange rate return on the current deviation of the exchange rate from its

[1] The fragility of the results is not due entirely to the choice of statistical design. By extending Mark's quarterly sample, which ends in 1992, through 1994 Groen (1996) finds considerable deterioration in the accuracy of out-of-sample monetary fundamentals forecasts of US dollar prices of the yen, deutschemark, and Swiss franc. We speculate that reasons for the collapse of yen and deutschemark forecast accuracy in the 1990s include the ongoing banking crisis in Japan and residual fiscal consequences from German re-unification introduce important transient nonmonetary factors into the pricing of exchange rates.

fundamental value. The analysis is conducted on quarterly observations that begin on 1973.1 and extend through 1997.1 for 19 countries.

We study the issue of cointegration by employing a new panel based test of cointegration that combines ideas presented in Berben and van Dijk (1998) and Mark and Sul (1999). In the single-equation case, Berben and van Dijk build on Hansen (1995) to show that the predictive regression is well-specified when the regressor is nonstationary, in the sense that the estimator and its $t$-ratio have well-defined but non-Gaussian asymptotic distributions. In the framework, the test that the slope coefficient is zero is a test of the null hypothesis of no cointegration between the exchange rate and the fundamentals. Our test for cointegration exploits this argument and extends it to panel data.

Under the null hypothesis of no cointegration, the regressor in the panel predictive regression is nonstationary and the true value of the slope coefficient is zero. The standard least-squares dummy variable (LSDV) estimator is consistent, but suffers from second-order asymptotic bias that causes test statistics – such as its $t$-ratio – to diverge asymptotically. In order to draw inference, we use the panel dynamic OLS estimator whose $t$-ratio is asymptotically standard normal. To guard against potential small sample size distortion of the asymptotic tests, we supplement our asymptotic tests with tests based on both parametric and nonparametric bootstraps. We find that the null hypothesis of no cointegration can be rejected at standard significance levels and that these results are invariant as to whether inference is drawn from the asymptotic distribution or from the bootstrap.

We then proceed under the assumption that the exchange rate and the fundamentals cointegrate and examine the predictive content of deviations of the exchange rate from its fundamental value for future exchange rate returns. There are two aspects to this investigation. First, we study the slope coefficient in the panel short-horizon regression which we estimate by LSDV. We confine this analysis to a one-period forecast horizon to avoid the complications arising from serially correlated error terms that would be included by overlapping multiperiod forecast horizons and to reflect the growing consensus that long-horizon regressions offer no statistical power advantages over short-horizon regressions. The second aspect of the prediction issue is studied by conducting an out-of-sample forecast experiment using the panel regression over the period extending from 1983.1 through 1997.1. In this analysis we report results at two forecast horizons, 1 and 16 quarters. We note that it is not the objective of the paper to build the best exchange-rate forecasting model. In that regard, a fixed coefficient linear regression model is quite naive. Instead, our intent is to examine the extent to which monetary fundamentals matter at all for nominal exchange rate dynamics.

As in the cointegration tests, we augment the asymptotic analysis of the predictive regression under the assumption of cointegration and the forecasting exercise with parametric and nonparametric bootstraps to control for potential small sample size distortion. The bootstrap also allows us to model cross-sectional dependence in the data which surely is present in the data but which typically violates the regularity conditions under which the available asymptotic theory is derived.

As a basis for comparison, we also examine the predictive power contained in purchasing power parity (PPP) based fundamentals. A growing body of empirical research using panel data methods on post 1973 data concludes that PPP holds over the float.[2] With the re-emergence of PPP as a viable long-run equilibrium condition for nominal exchange rate determination, and its central role in motivating the use of monetary fundamentals it is a logical and useful exercise to compare its predictive performance to those of the monetary fundamentals. Since the monetary model is build upon PPP but imposes additional restrictions, the presumption must be that the monetary model will have better asymptotic prediction performance if the additional restrictions are true, and will have worse prediction performance if they are false. Our evidence suggests that the linkage between the exchange rate and monetary fundamentals is tighter than that between the exchange rate and purchasing power parities.

The remainder of the paper is organized as follows. The next section describes the form of the monetary fundamentals predicted by theory that we use in our empirical analysis. Section 3 describes our data set. Section 4 describes the econometric framework that we use. The panel cointegration tests are developed in Section 5, the panel prediction analysis is covered in Section 6, and Section 7 concludes.

## 2. Monetary fundamentals and the exchange rate

Let $s_{it}$ be the time-$t$ log nominal exchange rate between country $i = 1, 2, \dots, N$ and the 'numeraire' country, which we label as country '0.' The exchange rate is country $i$'s currency price of a unit of currency 0 so an increase in $s_{it}$ means an appreciation in value of 0's money. Let the time-$t$ log nominal money stock and log real income of country $i$ be denoted by $m_{it}$ and $y_{it}$ respectively. Much of our analysis centers on the deviation $x_{it}$, of the exchange rate from it fundamental value,

$$x_{it} = f_{it} - s_{it}, \tag{1}$$

where $f_{it} = m_{it} - m_{0t} - \lambda(y_{it} - y_{0t})$ is the long-run equilibrium or the 'monetary fundamental value,' of the exchange rate. Notice that the long-run neutrality of money is imposed and $\lambda$ is a scalar common across countries.

We think of $f_{it}$ as a generic representation of the long-run equilibrium exchange rate implied by modern theories of exchange rate determination. The common feature shared by the various theories is that the long-run equilibrium exchange

[2] See, for example, Frankel and Rose (1996), Lothian (1997), MacDonald (1996), Papell (1997) and Wu (1996).

rate is governed by determinants of money market equilibrium at home and abroad. In the monetary models of Frenkel (1976) and Mussa (1976), for example, $\lambda$ can be interpreted as the income elasticity of money demand and is predicted to be positive. In Lucas's (1982) equilibrium model, $\lambda$, which can depend on preference parameters, can possibly be negative but its value is bounded from above by 1.[3] The Obstfeld and Rogoff (1995) model on the other hand, predicts that per capita consumption enter in place of real income. The particular details – whether to include income, as in Lucas, or consumption levels as in Obstfeld and Rogoff – differ, but the general theoretical prediction is the same. Namely that the exchange rate is determined by monetary fundamentals. This is not a controversial proposition but establishing this principle with a satisfactory degree of statistical accuracy has been difficult.

Our analysis centers on two empirical questions. First, we examine whether the monetary fundamentals $f_{it}$, serve as an attractor for the nominal exchange rate. We address this problem in Section 5 by testing whether $\{f_{it}\}$ and $\{s_{it}\}$ are cointegrated using procedures developed for the analysis of panel data. Second, we examine the ability for deviations of the exchange rate from its monetary fundamentals value, to forecast future exchange rate returns in a panel regression.

## 3. The data

Our data consists of quarterly time series observations from 1973.1 through 1997.1 for the following 19 countries: Austria, Australia, Belgium, Canada, Denmark, Finland, France, Germany, Great Britain, Greece, Italy, Japan, Korea, the Netherlands, Norway, Spain, Sweden, Switzerland, and the United States. The composition of the sample was determined by data availability and by a requirement that the country's post Bretton Woods exchange rate experience was dominated by floating against the US dollar. While some of the countries in the sample did experience episodes of nominal exchange rate pegging, those periods were deemed to have been reasonably brief.

Nominal exchange rates are end-of-quarter observations from the IFS CD-ROM (line code AE). Quarterly GDP is unavailable for several countries in the sample so we used quarterly industrial production indices for all countries as a proxy for national income. The industrial production series are from the IMF's International Financial Statistics (IFS line code 66). Our measure of money is from the IFS and

[3] In the Lucas model, the log equilibrium nominal exchange rate is given by $m - m_0 + (y + \ln U_y) - (y_0 + \ln U_{y_0})$, where $U_y$ and $U_{y_0}$ is the representative agent's marginal utility of consumption. It is easy to see that a shock that raises $y$ can lower the marginal utility of consuming $y$ sufficiently to imply a negative value of $\lambda$. For example, let the period utility function $U = (Y_0^{1-\gamma_0})/(1-\gamma_0) + (Y^{1-\gamma})/(1-\gamma)$. Then $\lambda = 1 - \gamma$ and $\lambda = 1 - \gamma_0$. When the utility function displays curvature in excess of the log function, this model predicts negative $\lambda$ coefficients.

is the sum of money (line code 34) plus quasi-money (line code 35) for all countries with the following exceptions for Great Britain, Norway, and Sweden due to availability. Money is M0 from the IFS for Great Britain, M2 from the OECD's Main Economic Indicators for Norway, and M3 also from the OECD for Sweden. Price levels, which we need for the comparison to PPP, are measured using the CPI from the IFS (line code 64). Neither money nor the CPIs are seasonally adjusted. To control for seasonality, we filter the money and price series by applying a one-sided moving average of the current observation and 3-lagged values.

## 4. The econometric specification

Our econometric analysis centers on panel estimation of the short-horizon predictive regression,

$$\Delta s_{it+1} = \beta x_{it} + e_{it+1} \tag{2}$$

$$e_{it+1} = \gamma_i + \theta_{t+1} + u_{it+1}, \tag{3}$$

where $i$ indexes the country and $t$ is the time period. We give the regression error $e_{it+1}$ an unobserved components interpretation where $\gamma_i$ is an individual-specific effect, $\theta_t$ is a time-specific effect that allow us to account for a limited amount of cross-sectional dependence, and $u_{it+1}$ is the residual idiosyncratic error.

Eq. (2) is the panel version of the short-horizon predictive regression studied by Mark (1995), Berkowitz and Giorgianni (1997), Groen (1997), Kilian (1997), and Berben and van Dijk (1998) in connection with exchange rates and by Fama and French (1988), Campbell and Shiller (1988), and Hodrick (1992) in the study of stock returns. In the single equation context, the predictive regression is the linear least squares projection of the exchange rate return on the deviation of the exchange rate from its fundamental value so that $e_t$ is uncorrelated with $x_t$ by construction. The slope coefficient is an estimate of $\mathrm{Cov}(x_t, \Delta s_{t+1})/\mathrm{Var}(x_t)$ which does not disentangle contributions from short-run and long-run dynamics.

We follow the exchange rate studies cited above and condition our analysis by fixing $\lambda = 1$. An alternative strategy would be to estimate $\lambda$. Pedroni (1997) shows that when $\lambda$ is estimated by panel regression, it can be treated as fixed in the asymptotic analysis of residual based tests of cointegration. However, we are also interested in modeling the exact distribution of our test statistics via the bootstrap and it is unclear whether treating the estimated value of $\lambda$ as fixed is appropriate in this context. To avoid these complications, we proceed with $\lambda = 1$. We note that making such precise assumptions enables us to sharpen our testable predictions.

## 5. A panel cointegration test

For a single equation, Berben and van Dijk (1998) show that the predictive regression can be sensibly estimated whether $x_t$ is I(0) or I(1). Building on Hansen (1995), they show under the null hypothesis that $x_t$ is I(1) a test that $\beta = 0$ is a test of the hypothesis that $s_t$ and $f_t$ are not cointegrated. We extend this line of argument to panel data and take as the null hypothesis that $x_{it}$ is *nonstationary* for all $i = 1, \ldots, N$.[4] Because $\Delta s_{it+1}$ is stationary and $x_{it}$ is not, they are asymptotically independent and the true value of $\beta$ is zero under the null.[5]

Let $\Delta \underline{s}_i = (\Delta s_{1i}, \ \Delta s_{2i}, \ldots, \ \Delta s_{Ti})'$, and $\Delta \underline{s} = (\Delta \underline{s}_1, \ \Delta \underline{s}_2, \ldots, \ \Delta \underline{s}_N)'$ be the vectorization of the observations on exchange rate returns, $\underline{x}_i = (x_{1i}, x_{2i}, \ldots \ x_{T-1i})'$ be the $T-1 \times 1$ vector of observations on $x_{it}$ for country $i$, $\underline{0}$ be a $T-1 \times 1$ vector of zeros, $\underline{\iota}$ be a $T-1 \times 1$ vector of ones, and $\mathbf{I}$ a $T-1$ dimensional identity matrix, and

$$\mathbf{X} = \begin{bmatrix} \underline{x}_1 & \mathbf{I} & \underline{0} & \underline{0} & \cdots & \underline{0} \\ \underline{x}_2 & \mathbf{I} & \underline{\iota} & \underline{0} & \cdots & \underline{0} \\ \underline{x}_3 & \mathbf{I} & \underline{0} & \underline{\iota} & \cdots & \underline{0} \\ \vdots & & & & & \vdots \\ \underline{x}_N & \mathbf{I} & \underline{0} & \underline{0} & \cdots & \underline{\iota} \end{bmatrix}$$

The least-squares dummy variable estimator of $\beta$ is obtained by running OLS on the pooled observations, $\beta_{lsdv} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'(\Delta \underline{s})$. Under the null hypothesis that $x_{it}$ is I(1), $\beta_{lsdv} \xrightarrow{p} 0$ so that the LSDV estimator is a consistent estimator of the true value of $\beta = 0$. However, the panel regression is contaminated by second order asymptotic bias which causes $\sqrt{NT}\beta_{lsdv}$ to diverge. Since $\beta_{lsdv}$ does not have a well defined asymptotic distribution neither does its $t$-ratio which prevents construction of appropriate $t$-tests for testing hypotheses about the slope coefficient.

To control for this asymptotic bias, we employ the panel dynamic OLS estimator discussed in Mark and Sul (1999). In panel dynamic OLS, the current value and $p_i$ leads and lags of $\Delta x_{it-1}$ are included in the equation for country $i$, and we estimate the system of equations,[6]

$$\Delta s_{it} = \gamma_i + \theta_t + \beta x_{i,t-1} + \sum_{j=-p_i}^{p_i} \delta_{ij} \Delta x_{i,t-j-1} + u_{it}, \tag{4}$$

[4] Evans (1997) has applied this methodology to test whether economic growth evolves according to endogenous or exogenous growth theories.

[5] The arguments sketched in this section are developed in more detail in the appendix.

[6] To relate the test to Hansen (1995), let $X_t'$ be the vector of leads and lags of $\Delta x_{it}$, and subtract $\Delta f_{it}$ from both sides of Eq. (4), we get,

$$\Delta s_{it} - \Delta f_{it} = \gamma_i + \theta_t + \beta x_{it-1} + X_t' b + \Delta f_{it} + u_{it}$$

which is in the form of Hansen's unit root test (on $x_{it} = f_{it} - s_{it}$) with covariates. Hansen showed that his test had better power than augmented Dickey–Fuller tests.

$i = 1, \ldots, N$, $t = p_i + 2, \ldots, T - p_i + 1$. Let $\bar{p}$ be the largest $p_i$ and let $\underline{z}_{it} = (\Delta x_{it+p_i-1}, \ldots, \Delta x_{it-p_i-1})$, $\mathbf{Z}_i = (\underline{z}_{1i}, \ldots \underline{z}_{Ti})'$, and

$$\tilde{\mathbf{X}} = \begin{bmatrix} \underline{x}_1 & \mathbf{Z}_1 & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{I} & \underline{0} & \underline{0} & \cdots & \underline{0} & \underline{0} \\ \underline{x}_2 & \mathbf{0} & \mathbf{Z}_2 & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{I} & \underline{\iota} & \underline{0} & \cdots & \underline{0} & \underline{0} \\ \underline{x}_3 & \mathbf{0} & \mathbf{0} & \mathbf{Z}_3 & \cdots & \mathbf{0} & \mathbf{I} & \underline{0} & \underline{\iota} & \cdots & \underline{0} & \underline{0} \\ \vdots & & & & & \vdots & \vdots & & & & & \vdots \\ \underline{x}_N & \mathbf{0} & \cdots & \mathbf{0} & \cdots & \mathbf{Z}_N & \mathbf{I} & \underline{0} & \underline{0} & \cdots & \underline{0} & \underline{\iota} \end{bmatrix}$$

Then the panel dynamic OLS estimator of $\beta$ is the first element of the vector $(\tilde{\mathbf{X}}'\tilde{\mathbf{X}})^{-1}\tilde{\mathbf{X}}'(\Delta \underline{s})$. Mark and Sul (1999) show that,

$$\sqrt{N}T(\beta_{pdols} - \beta)N(\underline{0}, 2\tilde{\mathbf{V}}) \tag{5}$$

as $T \to \infty$, $N \to \infty$ where $\tilde{\mathbf{V}}$ is consistently estimated by $\tilde{\mathbf{V}}_{NT} = \tilde{\mathbf{B}}_{NT}^{-1}\tilde{\mathbf{A}}_{NT}\tilde{\mathbf{B}}_{NT}^{-1}$, where $\tilde{\mathbf{B}}_{NT} = (1/NT^2)\,\Sigma_{i=1}^{N}\,\Sigma_{t=1}^{T}\,\tilde{x}_{it-1}\tilde{x}'_{it-1}$, $\tilde{\mathbf{A}}_{NT} = (1/NT^2)\,\Sigma_{i=1}^{N}\,\hat{\Omega}_i^2\,\Sigma_{t=1}^{T}\,\tilde{x}_{it-1}\tilde{x}'_{it-1}$ and $\hat{\Omega}_i^2$ is an estimate of the long run variance of $u_{it}$.[7]

*The bootstrap:* Mark and Sul report that the asymptotic distribution of $\hat{\beta}_{pdols}$ is reasonably accurate for their Monte Carlo experiments. But because there is no guarantee that this is true for all regions of the parameter space, we supplement the asymptotic analysis by drawing inference from the bootstrap. The data generating process (DGP) underlying the bootstrap is the restricted vector autoregression,

$$\begin{aligned} \Delta s_{it} &= \mu_s^i + \varepsilon_{st}^i \\ \Delta x_{it} &= \mu_x^i + \sum_{j=1}^{k_i} a_{21,j}^i\,\Delta s_{it-j} + \sum_{j=1}^{k_i} a_{22,j}^i\,\Delta x_{it-j} + \varepsilon_{xt}^i \end{aligned} \tag{6}$$

which imposes the null hypothesis that the exchange rate return is unpredictable and that $x_{it}$ is nonstationary. The lag length in the $\Delta x_{it}$ equations are determined by the Campbell–Perron rule on lagged $\Delta x_{it}$ variables from an initial OLS regression.[8]

[7] To estimate $\Omega_i^2 = \lim_{T\to\infty} \mathrm{Var}\ 1/\sqrt{T}\ \Sigma_{t=1}^{T}\ u_{it}$, we use the parametric autoregressive approximation described in Hamilton (1994) (p. 610). Let $\hat{u}_{it}$ be the panel dynamic OLS residuals. For each $i$, we fit the AR($g_i$) $\hat{u}_{it} = \Sigma_{j=1}^{g_i}\ \phi_{ij}\hat{u}_{it-j} + \eta_{it}$. Let $\tilde{T}_i = T - 1 - 2p_i - g_i$ and $\hat{\sigma}_{1i}^2 = (1/\tilde{T}_i)\ \Sigma\ \hat{\eta}_{it}^2$. The long run estimate is $\hat{\Omega}_i = \hat{\sigma}_{1i}/(1 - \Sigma_{j=1}^{g_i}\ \hat{\phi}_{ij})$. The lag length $g_i$ is determined by Campbell and Perron's (1991) top-down $t$-test approach. That is start with some maximal lag order $\ell$ and estimate the autoregression on $\hat{\epsilon}_{it}$. If the absolute value of the $t$-ratio for $\hat{\phi}_{i\ell}$ is less than some appropriate critical value, $c*$, reset $g_i$ to $\ell - 1$ and reestimate. Repeat the process until the $t$-ratio of the estimated coefficient with the longest lag exceeds the critical value $c*$.

[8] That is, we estimate by OLS beginning with $k_i = 8$. If the $t$-statistic on $a_{22,8}^i$ is significant, we stay with $k_i = 8$. If not, reset $k_i = 7$ and try again until we find a significant coefficient.

After determining the lag length, we fit the equations for $\Delta x_{it}$ by iterated seemingly unrelated regression (SUR).

Let $\underline{\varepsilon}_t = (\varepsilon_{st}^1, \ldots, \varepsilon_{st}^N, \varepsilon_{xt}^1, \ldots, \varepsilon_{xt}^N)'$ be the $(2N \times 1)$ error vector. We construct a *nonparametric* bootstrap by resampling the residual vectors $\{\hat{\varepsilon}_1, \hat{\varepsilon}_2, \ldots, \hat{\varepsilon}_T\}$ with replacement and build up the bootstrap observations of $s_{it}$ and $x_{it}$ recursively according to the estimated version of (6). Note that this resampling scheme preserves the cross-sectional dependence exhibited in the estimated residuals. We obtain start-up values for $\Delta s_{it}$ and $\Delta x_{it}$ by direct block resampling of the data.[9] Then we apply the estimation procedure outlined above for $\beta_{pdols}$ and its asymptotic $t$-ratio to the bootstrapped data. We do this 2000 times and the resulting 2000 $t$-ratios form the bootstrap distribution.

We also build a *parametric* bootstrap conditioned on a normality assumption for the error vector. To do this, we estimate the joint error covariance matrix $\Sigma = E(\varepsilon_t \varepsilon_t')$ using the SUR $\hat{\epsilon}_{xt}^i$ residuals and the $\Delta s_{it}$ residuals.[10] Now instead of resampling the residuals, the error terms in the DGP are drawn from $N(0, \hat{\Sigma})$. Vector sequences of the innovations of length $T + 100$ are initially drawn and pseudo values of $s_{it}$ and $x_{it}$ are built up recursively using the estimated versions of (6). The first 100 observations are then discarded and $\beta_{pdols}$ and its $t$-ratio are calculated with the pseudo-data. Again, the process is repeated 2000 times with the resulting collection of $t$-ratios forming the parametric bootstrap distribution. Analogous procedures are followed to bootstrap all other statistics that we study in the paper.

We note that we model the cross-sectional dependence of the sample only through the covariance of the innovations. Ideally, we would like a DGP to jointly model the evolution of all of the variables across all 18 bilateral country pairs. This would imply an unrestricted VAR for 36 variables and would provide a proper accounting for the cross-sectional dependence across countries but estimating such a large system turns out not to be feasible. A quick calculation modestly assuming say 3 lags of each variable means that for each equation we have 108 regression coefficients (plus a constant) for each equation, but we have only 97 time series observations.[11]

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[9]Let $r_{it} = (s_{it}, x_{it})'$. The data are arrayed as, $(r_{i1}, r_{i2}, \ldots, r_{iT})$. Four adjacent observations, $r_{it}, \ldots, r_{i,t-4}$, are required to start up the recursion. In a collection of $T$ such vectors, there are $T - 3$ possible blocks of 4 adjacent observations. For each replication in the bootstrap, we draw a 4-block at random to start up the recursion in (6).

[10]We do not combine the $\Delta s_{it}$ equations in the SUR estimation because they contain only a constant term.

[11]We did some checks for robustness. First, we looked (sequentially across $j \neq i$) to see if variables of country $j$ belonged in the equation for $x_{it}$ according to $t$-ratio size. They didn't. Secondly, we considered choosing lag length by BIC instead of the Campbell–Perron rule. Since we are letting lag length differ across individuals, we calculated BIC and determined lag length individually, then estimated the equations jointly by SUR. The main results are unaffected.

### 5.1. Panel cointegration test results

We consider three alternative numeraire countries: the US, Japan, and Switzerland. We run the panel dynamic OLS regressions with 2 leads and lags of first differences of the $x_{it-1}$, and 3 lags in the autoregression to estimate the long-run variance, $\Omega_i^2$. We report bootstrap results only for the asymptotic $t$-ratio because the evidence suggests that bootstrapping the $t$-ratio gives more reliable inference than bootstrapping the slope coefficient.[12] The results of the panel test for cointegration are reported in Table 1.

The asymptotic test easily rejects the null hypothesis of no cointegration between the exchange rate and the monetary fundamentals but it evidently exhibits some small sample size distortion as evidenced by comparing the bootstrap $P$-values to the asymptotic $t$-ratios. However, both the parametric and nonparametric bootstrap $P$-values allow the hypothesis of no cointegration to be rejected at the 5% level and the results are robust to the three numeraire currencies considered.

We are also able to reject the hypothesis of no cointegration between the exchange rate and PPP fundamentals at standard levels of significance with asymptotic as well as with bootstrap tests. These results are consistent with Frankel and Rose (1996), Wu (1996), Lothian (1997), and Papell (1997), and others who reject nonstationarity of real exchange rates with panel unit root tests. Curiously, our panel dynamic OLS estimates of the slope coefficient are negative. The reason is that the regression is misspecified under the alternative hypothesis that $x_{it}$ is stationary. We can use panel dynamic OLS to test for cointegration but cannot interpret its slope estimate of $\beta$ if the null hypothesis of no cointegration is rejected. Under the alternative hypothesis, the future $\Delta x_{it}$ do not belong in the regression. When the future $\Delta x_{it}$ are dropped from the PPP regression (not reported), the estimated slope coefficients are positive.

Table 1
Panel dynamic OLS based cointegration tests

| Fundamentals | Numeraire | $\beta_{pdols}$ | $t$-ratio | $P$-value[a] | $P$-value[b] |
|---|---|---|---|---|---|
| Monetary | US | 0.010 | **4.930** | **0.000** | **0.002** |
| | Switzerland | 0.006 | **2.219** | **0.050** | **0.067** |
| | Japan | 0.007 | **3.877** | **0.002** | **0.001** |
| PPP | US | −0.016 | **−4.626** | **0.998** | **0.999** |
| | Switzerland | −0.019 | **−7.417** | **0.992** | **0.989** |
| | Japan | −0.022 | **−4.077** | **1.000** | **1.000** |

[a] Parametric bootstrap $P$-value.

[b] Nonparametric bootstrap $P$-value. $P$-value is the proportion of the bootstrap distribution that lies to the *right* of the asymptotic $t$-ratio calculated from the data. A two-tailed test rejects the null hypothesis at the 5% level if the $P$-value is above 0.975 or below 0.025.

[12] See Maddala and Kim (1998).

To summarize the empirical results of this section, we reject the hypothesis of no cointegration between the nominal exchange rate and the monetary fundamentals at small levels of significance. We also reject the hypothesis of no cointegration between the exchange rate and relative national price levels. The strength of the evidence for the monetary fundamentals and PPP fundamentals is roughly equivalent.

## 6. Panel short-horizon prediction regression

We now proceed under the assumption that $x_{it}$ is stationary. Even under stationarity, however, the question remains whether the deviation of the exchange rate from the monetary fundamentals helps to predict future exchange rate returns. As discussed above, under the hypothesis of cointegration, the predictive regression is a regression of the stationary exchange rate return on stationary exchange rate deviations from the monetary fundamental $x_{it}$, and the study of monetary fundamentals forecasts of exchange rate returns can proceed along the standard analysis of a panel regression with stationary variables.

### *6.1. LSDV estimation results*

We focus on short-horizon estimates ($k=1$) first to avoid complications of residual serial dependence induced by forecasting over horizons exceeding the sampling interval of the data and second, to reflect the growing consensus that long horizons yield no power advantages over short horizons. Our first task here is to estimate $\beta$ and test the hypothesis that it is 0.

Because the regressor is only predetermined but not exogenous, in the single-equation context the OLS estimator of the slope coefficient in the predictive regression has been shown to exhibit small sample bias (Stambaugh, 1986; Mankiw and Shapiro, 1986). In Appendix A, we argue that this bias is attenuated, but not eliminated by panel estimation. We consider two alternative strategies to control for this small sample bias. Our first scheme is to correct for the bias using the bootstrap and then to do the asymptotic $t$-test using the bias corrected estimate. Our second strategy for accounting for small sample bias simply bootstraps the $t$-ratio of $\beta_{lsdv}$.

In the bootstrap, we assume that the exchange rate evolves according to a martingale but is cointegrated with the fundamentals. This null distribution is built from the DGP,

$$\begin{aligned} \Delta s_{it} &= \mu_s^i + \epsilon_{st}^i, \\ \Delta x_{it} &= \mu_x^i + \gamma_i x_{it-1} + \sum_{j=1}^{k_i} a_{21,j}^i \, \Delta s_{it-j} + \sum_{j=1}^{k_i} a_{22,j}^i \, \Delta x_{it-j} + \epsilon_{xt}^i. \end{aligned} \tag{7}$$

Table 2
Bias-adjusted LSDV estimates of panel predictive regression

| Fundamentals | Numeraire | $\beta_{bc}$ [a] | $t$-ratio[a] | $\beta_{bc}$ [b] | $t$-ratio[b] |
|---|---|---|---|---|---|
| Monetary | US | 0.033 | **6.076** | 0.023 | **4.149** |
| | Switzerland | 0.019 | **3.663** | 0.016 | **3.006** |
| | Japan | 0.037 | **6.399** | 0.026 | **4.594** |
| PPP | US | 0.031 | **3.608** | 0.026 | **3.016** |
| | Switzerland | 0.034 | **2.749** | 0.019 | **2.291** |
| | Japan | 0.033 | **3.608** | 0.029 | **3.094** |

[a] Bias correction by parametric bootstrap.
[b] Bias correction by nonparametric bootstrap.

Cointegration between $s_{it}$ and $f_{it}$ requires that $-2<\gamma_i<0$ so that Eq. (7) is equivalent to a restricted VAR in $(\Delta s_{it}, x_{it})$ and which in turn has an equivalent to a vector error-correction representation for $(\Delta s_{it}, \Delta f_{it})$ with cointegration vector $(1, -1)$. The estimation of the DGP and the buildup of the parametric bootstrap distribution follows as before.

To correct for bias, let $\beta^*$ be the median value of the bootstrap distribution for $\beta_{lsdv}$ generated under the null hypothesis that $\beta=0$. Then the bias-corrected estimate is $\beta_{bc}=\beta_{lsdv}-\beta^*$. Next, we divide $\beta_{bc}$ by the asymptotic LSDV standard error and conduct the standard $t$-test of the hypothesis that $\beta=0$.

The results of the panel tests of the null hypothesis that the deviation of the exchange rate from the fundamentals do not contain predictive content for the future exchange rate return are reported in Tables 2 and 3. First, all of the tests that we consider resoundingly reject the no-prediction hypothesis for both monetary and PPP fundamentals. Second, the PPP regressions exhibit larger bias but the bias corrected estimates for the monetary fundamentals and PPP fundamentals are similar.

In Table 4, we report the estimation results of the panel regression with both PPP and monetary fundamentals included in the regression,

Table 3
LSDV estimates and bootstrapped $t$-ratios for panel predictive regression

| Fundamentals | Numeraire | $\beta_{lsdv}$ | $t$-ratio | $P$-value[a] | $P$-value[b] |
|---|---|---|---|---|---|
| Monetary | US | 0.036 | **6.544** | **0.000** | **0.000** |
| | Switzerland | 0.032 | **5.932** | **0.001** | **0.004** |
| | Japan | 0.038 | **6.632** | **0.000** | **0.000** |
| PPP | US | 0.054 | **6.187** | **0.006** | **0.013** |
| | Switzerland | 0.047 | **5.541** | **0.023** | **0.031** |
| | Japan | 0.057 | **6.220** | **0.008** | **0.016** |

[a] Parametric bootstrap $P$-value.
[b] Nonparametric bootstrap $P$-value. $P$-value is the proportion of the bootstrap distribution that lies to the *right* of the asymptotic $t$-ratio calculated from the data.

Table 4
LSDV estimation with both monetary and PPP fundamentals $\Delta s_{it+1} = \beta_m x^{\mathrm{m}}_{i,t} + \beta_p x^{\mathrm{p}}_{it} + e_{it+1}$; $e_{it+1} = \gamma_i + \theta_{t+1} + u_{it+1}$; $x^{\mathrm{m}}_{it} = f_{it} - s_{it}$; and $x^{\mathrm{p}}_{it} = p_{it} - p_{0t} - s_{it}$

| | US | Japan | Switzerland |
|---|---|---|---|
| $\beta_m$ | 0.024 | 0.027 | 0.026 |
| $t$-ratio | 3.443 | 3.866 | 3.756 |
| $P$-value[a] | **0.004** | **0.001** | **0.012** |
| $P$-value[b] | **0.000** | **0.001** | **0.000** |
| $\beta_p$ | 0.030 | 0.024 | 0.033 |
| $t$-ratio | 2.718 | 2.080 | 2.984 |
| $P$-value[a] | 0.356 | 0.501 | 0.121 |
| $P$-value[b] | **0.084** | 0.190 | **0.070** |

[a] Parametric bootstrap $P$-value.
[b] Nonparametric bootstrap $P$-value. $P$-value is the proportion of the bootstrap distribution that lies to the *right* of the asymptotic $t$-ratio calculated from the data.

$$\Delta s_{it+1} = \beta_m x^{\mathrm{m}}_{i,t} + \beta_p x^{\mathrm{p}}_{it} + e_{it+1},$$

where $e_{it+1} = \gamma_i + \theta_{t+1} + u_{it+1}$, $x^{\mathrm{m}}_{it} = f_{it} - s_{it}$, and $x^{\mathrm{p}}_{it} = p_{it} - p_{0t} - s_{it}$. Here it can be seen that the coefficient on the monetary fundamentals maintain their statistical significance whereas the coefficient on the PPP fundamentals generally become statistically insignificant.

## 6.2. Out-of-sample prediction

We generate out-of-sample forecasts both at a short-horizon ($k=1$) and at a long-horizon ($k=16$). We begin by estimating Eq. (2) by LSDV on observations available through 1983.1. The $k=1$ regression is then used to forecast the 1-quarter ahead exchange rate return in 1983.2 and the $k=16$ regression to forecast the 16 quarter ahead exchange rate return through 1987.1. We then update the sample by one period by adding the observation for 1983.2 and repeat the procedure. This recursive updating scheme gives us 57 $k=1$ forecasts and 41 overlapping $k=16$ forecasts. We compare the panel regression forecasts against those implied by the random walk model.[13] We do this for both for the monetary and PPP fundamentals.

We measure relative forecast accuracy with Theil's $U$-statistic – the ratio of the root-mean-square prediction error (RMSPE) from two competing models. We avoided using other statistics of prediction evaluation, such as Diebold and Mariano (1995) because, as documented in Berben and van Dijk, the difficulty in accurately estimating long-run variances often results in misleading inference. The

[13] We follow Kilian (1997) who argues that it is appropriate to employ the random walk with drift.

null hypothesis is that the monetary fundamentals (or PPP) and the random walk provide equally accurate forecasts ($U = 1$). The alternative hypothesis is that the monetary fundamentals (or PPP) is more accurate than the random walk ($U < 1$). We also perform joint tests of the hypothesis of equal forecast accuracy by using joint test statistics formed alternatively by taking the mean value and the median value of the $U$-statistics. $P$-values are the proportion of the bootstrap distribution that lie below (to the left) of the $U$-statistic calculated from the data. $P$-values are constructed under the hypothesis of cointegration.

*US as numeraire*. The prediction results for the US are displayed in Table 5. At the 1-quarter horizon, monetary fundamentals point predictions dominate the random walk in RMSPE for 13 of 18 exchange rates (Australia, Denmark, Finland, Greece, and Japan are the exceptions). The improvement in forecast accuracy over the random walk is generally statistically significant at the 10% level for these 13 exchange rates. Both of the joint tests reject the hypothesis at the 10% level of equal prediction accuracy under the parametric bootstrap whereas the mean value is significant under the nonparametric bootstrap.

The statistical evidence is less favorable towards PPP forecasts. Qualitatively, PPP point predictions exhibit a similar degree of accuracy in that they dominate the random walk for 12 of 18 exchange rates, but the $U$-statistic are not generally statistically significant. Looking at the last column, it can be seen that monetary fundamentals forecasts dominate PPP forecasts in root-mean-square error for 13 of the 18 exchange rates.

Upon inspection of the table, one gets the impression that the $U$-statistic is tightly distributed around 1.0. This impression is accurate. To provide a coarse description of the properties of the parametric bootstrap distribution of the 1-quarter horizon $U$-statistic, we note that the distributions for the monetary fundamentals are generally symmetric about a modal value of 1.0 to four significant digits. The mean values range only from 1.001 for Canada to 0.999 for Korea and Sweden. The standard deviations range from 0.018 to 0.004 and have an average value of 0.003 over the 18 distributions. Under PPP, the grand mean of the $U$-statistic distributions is 1.003, indicating a small upward bias. The PPP distributions are also more spread out. The average standard deviation is 0.010, which exceeds those under the monetary model by an order of magnitude.

At the 16-quarter horizon, monetary fundamentals forecasts again dominate the random walk in RMSPE for 17 of 18 exchange rates (Greece is the lone exception). The hypothesis that the monetary fundamentals and the random walk provide equal forecast accuracy can be rejected for 15 exchange rates at the 10% level. Moreover, both joint test statistics are significant at the 5% level.

PPP performance at 16 quarters is inferior to that of the monetary fundamentals. Monetary fundamentals forecasts dominate PPP forecasts in RMSPE for 10 of 18 exchange rates. While PPP point predictions have lower RMSPE than the random walk for 17 of 18 exchange rates, the improvement in prediction accuracy is significant at the 10% level for 13 of the exchange rates.

Table 5
Out-of-sample forecasts of US dollar returns. Bootstrapped *P*-values generated assuming cointegration

| Country | $U$ [a] | *P*-value [d] | *P*-value [e] | $U$ [b] | *P*-value [d] | *P*-value [e] | $U$ [c] |
|---|---|---|---|---|---|---|---|
| *A. One-quarter ahead forecasts* | | | | | | | |
| Australia | 1.024 | 0.991 | 0.904 | **0.988** | **0.083** | 0.102 | 1.036 |
| Austria | **0.984** | **0.001** | **0.013** | **0.994** | 0.231 | 0.259 | **0.990** |
| Belgium | **0.999** | 0.269 | 0.424 | 1.000 | 0.441 | 0.442 | **0.998** |
| Canada | **0.985** | **0.020** | **0.074** | 1.003 | 0.534 | 0.496 | **0.982** |
| Denmark | 1.014 | 0.989 | 0.912 | **0.998** | 0.361 | 0.365 | 1.016 |
| Finland | 1.001 | 0.708 | 0.527 | **0.992** | 0.137 | 0.152 | 1.009 |
| France | **0.994** | **0.024** | 0.155 | 1.000 | 0.440 | 0.426 | **0.994** |
| Germany | **0.986** | **0.006** | **0.056** | **0.992** | 0.188 | 0.222 | **0.994** |
| Great Britain | **0.983** | **0.028** | **0.077** | **0.988** | 0.102 | 0.131 | **0.996** |
| Greece | 1.016 | 0.995 | 0.909 | 1.012 | 0.883 | 0.891 | **0.984** |
| Italy | **0.997** | 0.174 | 0.269 | 1.004 | 0.598 | 0.537 | **0.994** |
| Japan | 1.003 | 0.831 | 0.579 | **0.998** | 0.343 | 0.332 | 1.005 |
| Korea | **0.912** | **0.001** | **0.002** | **0.974** | **0.020** | **0.034** | **0.936** |
| Netherlands | **0.986** | **0.004** | **0.041** | **0.992** | 0.193 | 0.226 | **0.994** |
| Norway | **0.998** | 0.202 | 0.380 | **0.992** | 0.164 | 0.193 | 1.006 |
| Spain | **0.996** | 0.115 | 0.341 | 1.024 | 0.736 | 0.691 | **0.993** |
| Sweden | **0.975** | **0.008** | **0.034** | **0.987** | **0.079** | 0.101 | **0.988** |
| Switzerland | **0.982** | **0.002** | **0.008** | **0.988** | **0.073** | **0.092** | **0.995** |
| Mean | **0.991** | **0.002** | **0.010** | **0.996** | 0.135 | 0.145 | **0.995** |
| Median | **0.995** | **0.025** | 0.163 | **0.993** | 0.131 | 0.173 | **0.994** |
| *B. Sixteen-quarter ahead forecasts* | | | | | | | |
| Australia | **0.864** | 0.127 | 0.222 | **0.728** | **0.045** | **0.053** | 1.186 |
| Austria | **0.837** | **0.070** | 0.131 | **0.549** | **0.006** | **0.008** | 1.525 |
| Belgium | **0.405** | **0.001** | **0.001** | **0.577** | **0.009** | **0.015** | **0.703** |
| Canada | **0.552** | **0.005** | **0.009** | **0.601** | **0.015** | **0.023** | **0.919** |
| Denmark | **0.858** | **0.092** | 0.174 | **0.732** | **0.069** | **0.071** | 1.172 |
| Finland | **0.859** | **0.099** | 0.164 | **0.631** | **0.006** | **0.012** | 1.360 |
| France | **0.583** | **0.002** | **0.004** | **0.683** | **0.033** | **0.048** | **0.854** |
| Germany | **0.518** | **0.001** | **0.003** | **0.440** | **0.001** | **0.001** | 1.178 |
| Great Britain | **0.570** | **0.004** | **0.012** | **0.601** | **0.015** | **0.018** | **0.948** |
| Greece | 1.046 | 0.657 | 0.594 | **0.854** | 0.738 | 0.817 | **0.787** |
| Italy | **0.745** | **0.003** | **0.016** | **0.878** | 0.195 | 0.207 | **0.849** |
| Japan | **0.996** | 0.476 | 0.433 | **0.895** | 0.222 | 0.219 | 1.113 |
| Korea | **0.486** | **0.001** | **0.012** | **0.682** | **0.048** | **0.067** | **0.714** |
| Netherlands | **0.703** | **0.006** | **0.032** | **0.399** | **0.001** | **0.001** | 1.762 |
| Norway | **0.537** | **0.001** | **0.002** | **0.829** | 0.126 | 0.133 | **0.648** |
| Spain | **0.672** | **0.006** | **0.028** | 1.219 | 0.178 | 0.182 | **0.859** |
| Sweden | **0.372** | **0.001** | **0.001** | **0.541** | **0.004** | **0.004** | **0.687** |
| Switzerland | **0.751** | **0.019** | **0.049** | **0.575** | **0.007** | **0.007** | 1.307 |
| Mean | **0.686** | **0.001** | **0.001** | **0.690** | **0.001** | **0.001** | 1.032 |
| Median | **0.688** | **0.001** | **0.001** | **0.656** | **0.001** | **0.003** | **0.933** |

[a] Monetary fundamentals versus random walk with drift.
[b] PPP fundamentals versus random walk with drift.
[c] Monetary versus PPP fundamentals.
[d] *P*-values from parametric bootstrap.
[e] *P*-values from nonparametric bootstrap.

*Switzerland as Numeraire Country.* The out-of-sample forecast results are shown in Table 6. At the 1-quarter horizon, monetary fundamental forecasts outperform the random walk for 17 exchange rates. The improvement in accuracy is significant at the 10% level in each of these cases under the null of cointegration and for 16 of these countries under both the parametric and nonparametric bootstraps. PPP forecasts dominate the random walk for these same 17 currencies. The monetary fundamentals dominate PPP forecasts in RMPSE in 13 instances.

At the 16 quarter horizon, monetary fundamentals forecasts outperform the random walk in terms of RMPSE for 15 exchange rates. The $U$-statistics are significant at the 10% level in 12 cases under the parametric and nonparametric bootstrap. PPP forecasts are qualitatively similar, but are dominated in terms of point prediction accuracy by the monetary fundamentals in 10 cases. Joint tests soundly reject the hypothesis that the monetary fundamentals contain no predictive content.

*Japan as Numeraire Country*. The out-of-sample prediction results for the yen, displayed in Table 7 are less successful. At the 1-quarter horizon, monetary fundamentals forecasts dominate the random walk in terms of RMPSE for 8 exchange rates whereas PPP forecasts outperform the random walk for 10 exchange rates.

At the 16 quarter horizon, monetary fundamentals forecasts outperform the random walk in terms of RMPSE for 10 exchange rates but only 4 of the $U$-statistics are significant at the 10% level under the parametric bootstrap and 3 are significant under the nonparametric bootstrap. PPP forecasts outperform the random walk in terms of RMPSE for 9 exchange rates but only 5 of the individual $U$-statistics are significantly less than 1 at the 10% level under the bootstraps. The monetary fundamentals forecasts do dominate PPP forecasts in terms of RMPSE in 10 of the 18 yen exchange rates.

To summarize, full sample LSDV estimates of the panel predictive regression yield statistically significant slope coefficients on the monetary and PPP fundamentals. When both sets of fundamentals are included in the regression, only the coefficient on the monetary fundamentals maintain statistical significance. Dominance of monetary fundamentals over the random walk in out-of-sample forecasts for US dollar exchange rates and Swiss Franc exchange rates provide confirmatory evidence consistent with the full sample evidence. Out-of-sample forecasts from monetary fundamentals dominate forecasts from PPP fundamentals but the difference in accuracy is not overwhelming.

## 7. Conclusions

Univariate analyses of the relation between exchange rate returns and monetary fundamentals are imprecise. We sharpen our inference about this connection by

Table 6
Out-of-sample forecasts of SF returns. Bootstrapped $P$-values generated assuming cointegration

| Country | $U$[a] | $P$-value[d] | $P$-value[e] | $U$[b] | $P$-value[d] | $P$-value[e] | $U$[c] |
|---|---|---|---|---|---|---|---|
| *A. One-quarter ahead forecasts* | | | | | | | |
| Australia | **0.988** | **0.031** | **0.060** | **0.979** | **0.018** | **0.018** | 1.009 |
| Austria | **0.982** | **0.016** | **0.020** | **0.982** | **0.031** | **0.040** | **0.999** |
| Belgium | **0.952** | **0.002** | **0.002** | **0.948** | **0.001** | **0.001** | 1.005 |
| Canada | **0.995** | 0.223 | 0.257 | **0.987** | 0.116 | 0.135 | 1.008 |
| Denmark | **0.960** | **0.002** | **0.004** | **0.972** | **0.008** | **0.006** | **0.988** |
| Finland | **0.962** | **0.001** | **0.002** | **0.978** | **0.017** | **0.014** | **0.984** |
| France | **0.915** | **0.001** | **0.001** | **0.957** | **0.001** | **0.002** | **0.956** |
| Germany | **0.979** | **0.015** | **0.029** | **0.962** | **0.001** | **0.001** | 1.018 |
| Great Britain | **0.966** | **0.003** | **0.008** | **0.981** | **0.027** | **0.036** | **0.984** |
| Greece | **0.985** | **0.023** | **0.046** | **0.995** | **0.068** | **0.094** | **0.963** |
| Italy | **0.965** | **0.006** | **0.012** | **0.995** | 0.270 | 0.276 | **0.970** |
| Japan | 1.003 | 0.551 | 0.657 | 1.005 | 0.621 | 0.605 | **0.999** |
| Korea | **0.976** | **0.003** | **0.003** | **0.988** | **0.077** | **0.083** | **0.988** |
| Netherlands | **0.950** | **0.001** | **0.001** | **0.972** | **0.008** | **0.006** | **0.977** |
| Norway | **0.960** | **0.001** | **0.001** | **0.959** | **0.005** | **0.008** | 1.002 |
| Spain | **0.958** | **0.001** | **0.001** | **0.989** | 0.252 | 0.264 | **0.996** |
| Sweden | **0.948** | **0.002** | **0.005** | **0.960** | **0.001** | **0.001** | **0.987** |
| USA | **0.984** | **0.055** | **0.086** | **0.988** | 0.120 | 0.137 | **0.995** |
| Mean | **0.968** | **0.001** | **0.001** | **0.978** | **0.001** | **0.001** | **0.990** |
| Median | **0.966** | **0.001** | **0.001** | **0.980** | **0.005** | **0.006** | **0.992** |
| *B. Sixteen-quarter ahead forecasts* | | | | | | | |
| Australia | **0.795** | **0.062** | **0.082** | **0.385** | **0.001** | **0.001** | 2.063 |
| Austria | **0.652** | **0.008** | **0.012** | **0.775** | **0.076** | **0.078** | **0.842** |
| Belgium | **0.653** | **0.027** | **0.042** | **0.477** | **0.003** | **0.003** | 1.370 |
| Canada | **0.587** | **0.002** | **0.006** | **0.681** | **0.046** | **0.056** | **0.862** |
| Denmark | **0.695** | **0.032** | **0.045** | **0.865** | 0.156 | 0.183 | **0.804** |
| Finland | **0.701** | **0.024** | **0.034** | **0.915** | 0.246 | 0.258 | **0.766** |
| France | **0.315** | **0.001** | **0.001** | **0.726** | **0.062** | **0.082** | **0.434** |
| Germany | **0.486** | **0.002** | **0.002** | **0.402** | **0.001** | **0.001** | 1.208 |
| Great Britain | 1.474 | 0.949 | 0.884 | **0.850** | 0.151 | 0.150 | 1.735 |
| Greece | **0.845** | 0.116 | 0.134 | **0.982** | **0.080** | **0.096** | **0.491** |
| Italy | **0.575** | **0.003** | **0.006** | 1.119 | 0.653 | 0.628 | **0.514** |
| Japan | 1.006 | 0.468 | 0.565 | 1.503 | 0.922 | 0.932 | **0.670** |
| Korea | **0.382** | **0.001** | **0.001** | **0.849** | 0.127 | 0.147 | **0.450** |
| Netherlands | 1.382 | **0.001** | **0.001** | **0.720** | **0.001** | **0.004** | 1.920 |
| Norway | **0.382** | 0.874 | 0.812 | **0.417** | **0.042** | **0.049** | **0.916** |
| Spain | **0.482** | **0.001** | **0.001** | **0.808** | 0.361 | 0.369 | 1.046 |
| Sweden | **0.954** | 0.425 | 0.340 | **0.519** | **0.002** | **0.002** | 1.837 |
| USA | **0.783** | 0.130 | 0.152 | **0.619** | **0.016** | **0.019** | 1.265 |
| Mean | **0.731** | **0.002** | **0.002** | **0.756** | **0.002** | **0.003** | 1.066 |
| Median | **0.674** | **0.001** | **0.003** | **0.750** | **0.005** | **0.007** | **0.889** |

[a] Monetary fundamentals versus random walk with drift.
[b] PPP fundamentals versus random walk with drift.
[c] Monetary versus PPP fundamentals.
[d] $P$-values from parametric bootstrap.
[e] $P$-values from nonparametric bootstrap.

Table 7
Out-of-sample forecasts of Yen returns. Bootstrapped *P*-values generated assuming cointegration

| Country | *U* [a] | *P*-value [d] | *P*-value [e] | *U* [b] | *P*-value [d] | *P*-value [e] | *U* [c] |
|---|---|---|---|---|---|---|---|
| *A. One-quarter ahead forecasts* | | | | | | | |
| Australia | **0.996** | **0.050** | 0.211 | **0.987** | **0.082** | **0.099** | 1.008 |
| Austria | **0.997** | **0.088** | 0.342 | 1.007 | 0.670 | 0.626 | **0.990** |
| Belgium | 1.039 | 0.999 | 0.972 | 1.010 | 0.706 | 0.658 | 1.029 |
| Canada | 1.015 | 0.988 | 0.875 | 1.000 | 0.425 | 0.390 | 1.016 |
| Denmark | **0.996** | **0.066** | 0.292 | **0.987** | **0.077** | **0.092** | 1.009 |
| Finland | **0.978** | **0.001** | **0.007** | **0.987** | **0.079** | **0.088** | **0.991** |
| France | 1.007 | 0.933 | 0.696 | **0.984** | **0.046** | **0.067** | 1.023 |
| Germany | 1.006 | 0.951 | 0.792 | 1.017 | 0.819 | 0.763 | **0.990** |
| Great Britain | 1.051 | 1.000 | 0.954 | **0.979** | **0.022** | **0.032** | 1.074 |
| Greece | **0.993** | **0.018** | 0.155 | **0.981** | 0.759 | 0.648 | **0.995** |
| Italy | **0.979** | **0.037** | **0.048** | **0.976** | **0.009** | **0.014** | 1.003 |
| Korea | **0.988** | **0.005** | **0.072** | **0.981** | **0.035** | **0.043** | 1.007 |
| Netherlands | 1.001 | 0.713 | 0.582 | 1.016 | 0.805 | 0.741 | **0.985** |
| Norway | 1.044 | 1.000 | 0.957 | **0.997** | 0.318 | 0.345 | 1.047 |
| Spain | **0.976** | **0.001** | **0.006** | 1.008 | **0.028** | 0.034 | **0.986** |
| Sweden | 1.024 | 0.994 | 0.900 | **0.993** | 0.179 | 0.199 | 1.031 |
| Switzerland | 1.005 | 0.944 | 0.733 | 1.009 | 0.745 | 0.694 | **0.997** |
| USA | 1.009 | 0.970 | 0.761 | 1.000 | 0.419 | 0.397 | 1.010 |
| Mean | 1.006 | 0.956 | 0.724 | **0.996** | 0.152 | 0.162 | 1.010 |
| Median | 1.003 | 0.934 | 0.674 | **0.995** | 0.179 | 0.204 | 1.007 |
| *B. Sixteen-quarter ahead forecasts* | | | | | | | |
| Australia | **0.959** | 0.342 | 0.317 | 1.087 | 0.555 | 0.533 | **0.881** |
| Austria | **0.945** | 0.305 | 0.363 | 1.487 | 0.953 | 0.948 | **0.636** |
| Belgium | 1.551 | 0.999 | 0.964 | 1.724 | 0.970 | 0.953 | **0.900** |
| Canada | **0.913** | 0.192 | 0.247 | **0.897** | 0.243 | 0.265 | 1.017 |
| Denmark | **0.832** | **0.056** | 0.140 | **0.915** | 0.222 | 0.238 | **0.910** |
| Finland | **0.657** | **0.002** | **0.014** | **0.792** | **0.071** | **0.095** | **0.830** |
| France | **0.973** | 0.382 | 0.359 | **0.941** | 0.285 | 0.287 | 1.034 |
| Germany | 1.342 | 0.988 | 0.954 | 2.012 | 0.995 | 0.995 | **0.667** |
| Great Britain | 2.089 | 1.000 | 0.988 | **0.782** | **0.080** | **0.096** | 2.670 |
| Greece | **0.910** | 0.188 | 0.250 | **0.621** | 0.946 | 0.884 | **0.904** |
| Italy | **0.771** | **0.002** | **0.032** | **0.649** | **0.011** | **0.013** | 1.187 |
| Korea | **0.909** | 0.195 | 0.263 | **0.533** | **0.002** | **0.005** | 1.706 |
| Netherlands | 1.000 | 0.513 | 0.505 | 1.841 | 0.988 | 0.980 | 0.543 |
| Norway | 1.768 | 0.999 | 0.965 | 1.210 | 0.769 | 0.726 | 1.462 |
| Spain | **0.562** | **0.001** | **0.004** | 1.389 | **0.008** | **0.010** | **0.656** |
| Sweden | 1.020 | 0.999 | 0.940 | 1.594 | 0.863 | 0.820 | **0.640** |
| Switzerland | 1.567 | 0.555 | 0.505 | 1.323 | 0.983 | 0.979 | 1.185 |
| USA | 1.079 | 0.734 | 0.585 | **0.961** | 0.344 | 0.357 | 1.123 |
| Mean | 1.103 | 0.860 | 0.697 | 1.153 | 0.744 | 0.688 | 1.053 |
| Median | **0.966** | 0.304 | 0.322 | 1.024 | 0.432 | 0.418 | **0.907** |

[a] Monetary fundamentals versus random walk with drift.
[b] PPP fundamentals versus random walk with drift.
[c] Monetary versus PPP fundamentals.
[d] *P*-values from parametric bootstrap.
[e] *P*-values from nonparametric bootstrap.

exploiting cross-sectional information available in a small panel. The weight of the evidence – both from a panel cointegration test and the examination of panel short-horizon regression slope coefficients – suggests that the nominal exchange rate is cointegrated with monetary fundamentals and that the monetary fundamentals contain significant predictive power for future exchange rate movements. Moreover, the evidence does not appear to be solely a US dollar phenomenon.

Our results raise an economic question that is not solved by our analysis. The puzzle is why monetary fundamentals evidently dominate PPP in terms of predictive content despite the fact that PPP is one of the building blocks upon which the link between the exchange rate and monetary fundamentals are formed. When both PPP and monetary fundamentals are included in the panel predictive regression, significance is maintained only on the slope coefficient on the monetary fundamentals. Additionally, monetary fundamentals point predictions most clearly dominated those of PPP for US dollar exchange rates. Root-mean-square prediction errors for the alternative measures of the fundamentals were more evenly matched for the Swiss franc and yen exchange rates but the $U$-statistics of PPP forecasts displayed lower levels of statistical significance.

Engel and Kim (1999) and Canzoneri et al. (1999) report evidence that real exchange rates themselves contain relatively small, slow moving permanent components. One point of speculation for the poor PPP forecast performance may be the failure to account for embedded random walk dynamics. A second possibility may be that the monetary fundamentals provide a better estimate of the long-run equilibrium price level than does the currently observed price level. A third explanation may be that the long-run nominal exchange rate is determined directly by monetary fundamentals and not by relative price levels.

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## Appendix A

### *A.1. Panel regression when $x_{it} \sim I(1)$*

We assume the following regularity conditions. First, the data generating process is given by,

$$\begin{bmatrix} \Delta s_{it} \\ \Delta x_{it} \end{bmatrix} = \begin{bmatrix} u_{it} \\ v_{it} \end{bmatrix} = \underline{w}_{it} = \mathbf{\Psi}_i(L)\underline{\epsilon}_{it} \tag{A.1}$$

where $\underline{w}_{it}$ is a covariance stationary vector process and is independent across $i=1,\ldots,N$, $\underline{w}_{i0}=\underline{0}$, $\underline{\epsilon}_{it} \overset{iid}{\sim} N(0, \mathbf{I})$, $\mathbf{\Psi}_i(L)=\Sigma_{j=0}^{\infty} \mathbf{\Psi}_{ij}L^j$ is a $(k+1)\times(k+1)$ dimensional matrix lag polynomial in the lag operator L, where $\Sigma_{r=0}^{\infty} r|\psi_{ir}^{mn}|<\infty$, and $\psi_{ir}^{mn}$ is the $m$,$n$th element of the matrix $\mathbf{\Psi}_{ir}$. (A.1) is the vector Wold moving average representation.

(A.1) could equivalently be represented in terms of $(\Delta s_{it}, \Delta f_{it})$, but the algebra is messier. (A.1) implies that

$$\frac{1}{\sqrt{T}}\sum_{t=1}^{[Tr]} \underline{w}_{it}\mathbf{\Psi}_i(1)\underline{W}_i(r) = \underline{B}_i(r, \mathbf{\Omega}_i), \tag{A.2}$$

$$\mathbf{\Omega}_i = \sum_{j=-\infty}^{\infty} \mathbf{\Gamma}'_j = \sum_{j=-\infty}^{\infty} \mathrm{E}(\underline{w}_{it}\underline{w}'_{it}) = \mathbf{\Gamma}_0 + \sum_{j=1}^{\infty} (\mathbf{\Gamma}_j + \mathbf{\Gamma}'_j), \tag{A.3}$$

$$\mathbf{\Gamma}_j = \mathrm{E}(\underline{w}_{it}\underline{w}'_{it-j}) \tag{A.4}$$

where $\overset{D}{\rightarrow}$ denotes convergence in distribution, $\underline{W}(r)$ is a vector standard Brownian motion for $0\le r\le 1$, $[Tr]$ denotes the largest integer value of $Tr$ for $0\le r\le 1$, $\underline{B}_i(r, \mathbf{\Omega}_i)$ is a randomly scaled mixed Brownian motion with conditional (on individual i) covariance matrix, $\mathbf{\Omega}_i$. For each i, $\mathrm{E}_i(\int \underline{B}_i\underline{B}'_i) = \frac{1}{2}\mathbf{\Omega}_i$, $\mathbf{\Omega}_i$ is independent and identically distributed across individuals $i$ and satisfies the law of large numbers, $1/N\ \Sigma_{i=1}^{N} \mathbf{\Omega}_i \overset{D}{\rightarrow} \mathrm{E}(\mathbf{\Omega}_i) = \mathbf{\Omega}$.

Let $\xi_{it} = (s_{it}, x_{it})'$. Then from Hamilton's (1994) proposition 18.1, we have,

$$\frac{1}{T^2}\sum_{t=1}^{T} \begin{bmatrix} s_{i,t-1}^2 & s_{i,t-1}x_{i,t-1} \\ x_{i,t-1}s_{i,t-1} & x_{i,t-1}^2 \end{bmatrix} \overset{D}{\rightarrow} \begin{bmatrix} \int B_{1i}^2 & \int B_{1i}B_{2i} \\ \int B_{2i}B_{1i} & \int B_{2i}^2 \end{bmatrix} \tag{A.5}$$

$$\frac{1}{T}\sum_{t=1}^{T} \begin{bmatrix} s_{i,t-1}u_{it} & s_{i,t-1}v_{it} \\ x_{i,t-1}u_{it} & x_{i,t-1}v_{it} \end{bmatrix} \overset{D}{\rightarrow} \int \underline{B}_i d\underline{B}'_i + \sum_{j=0}^{\infty} \mathbf{\Gamma}'_j \tag{A.6}$$

*A.2. Properties of panel OLS*

Our main points can be made efficiently by assuming there are no individual-specific or time-specific effects so LSDV simplifies to OLS run on pooled observations. Extensions to incorporate these factors is straightforward but tedious. The panel OLS estimator of $\beta$ in (3) is,

$$\beta_{\text{pols}} = \frac{\sum_i \sum_t x_{it}\Delta s_{i,t+1}}{\sum_i \sum_t x_{it}^2} = \frac{\frac{1}{TN}\sum_i \frac{1}{T}\sum_t (x_{it}\Delta s_{i,t+1})}{\frac{1}{N}\sum_i \frac{1}{T^2}\sum_t x_{it}^2} \tag{A.7}$$

The key features of panel OLS are, first, $\beta_{\text{pols}} \xrightarrow{p} 0$, and second, $\sqrt{N}T\beta_{\text{pols}}$ diverges. We sketch out heuristically why this is true.

We begin with the denominator of (A.7). It follows from (A.5) that for each $i$, $1/T^2 \Sigma_t x_{it}^2 \xrightarrow{D} \int B_{2i}^2$. Now $\mathrm{E}_i B_{2i}^2 = \frac{1}{2}\Omega_{22,i}$ and $1/N \Sigma_i \mathbf{\Omega}_i \xrightarrow{p} \mathrm{E}(\mathbf{\Omega}_i) = \mathbf{\Omega}$, so $1/N \Sigma_i 1/T^2 x_{it}^2 \xrightarrow{p} \frac{1}{2}\Omega_{22}$, which is a constant. Now turning to the numerator of (A.7), for each $i$, $1/T \Sigma_t x_{it}\Delta s_{i,t+1} = 1/T \Sigma_t x_{it}u_{i,t+1} \xrightarrow{D} \int B_{2i}\, \mathrm{d}B_{1i} + \Lambda_{21,i}$ where $\Lambda_{21,i} = \Sigma_{j=0}^{\infty} \mathrm{E}u_{it}v_{i,t-j}$ is the 2,1th element of $\Sigma_{j=0}^{\infty} \mathbf{\Gamma}_{j,i} = \mathbf{\Lambda}_i$. We get this term because we do not have a-priori restrictions to rule out possible correlation between $\Delta s_{1,t+1}$ and $\Delta x_{it}$. This is exactly the correlation that creates the second-order asymptotic bias that necessitates corrections in panel dynamic OLS so that we can do inference when estimating the cointegration vector. By the law of large numbers, $1/N \Sigma_{i=1}^{N} \Lambda_{21,i} \xrightarrow{p} \mathrm{E}(\Lambda_{21,i}) = \Lambda_{21}$, thus for fixed $N$, $1/N \Sigma_{i=1}^{N} 1/T^2 \Sigma_{t=1}^{T} x_{it-1}u_{it} \xrightarrow{p} 0$ as $T \to \infty$, so it follows that $\beta_{\text{pols}} \xrightarrow{p} 0$.

Panel OLS is a *consistent* estimator of the true value, which is zero. The problem with panel OLS, is that it is second-order asymptotically biased in which $\sqrt{N}T\beta_{\text{pols}}$ diverges. That means that test statistics constructed for $\beta_{\text{pols}}$ will converge and are useless for conducting inference. Divergence can be seen by examination of

$$\sqrt{N}T\beta_{\text{pols}} = \frac{\frac{1}{\sqrt{N}}\sum_i \frac{1}{T}\sum_t x_{it}\Delta s_{i,t+1}}{\frac{1}{N}\sum_i \frac{1}{T^2}\sum_t x_{it}^2} \tag{A.8}$$

The denominator in (A.8) is the same as that in (A.7). The numerator in (A.8) is $\sqrt{N}$ times the numerator in (A.7). Since the numerator in (A.7) converges to a constant in probability, when we multiply by $\sqrt{N}$, it will diverge as $N$ gets large. This is the issue that comes up in panel dynamic OLS.

### A.3. Panel dynamic OLS

In this section, we sketch the intuition behind panel dynamic OLS. These results are developed more carefully in Mark and Sul (1999).

The offending term in panel OLS is $\Lambda_{21,i} = \Sigma_{j=0}^{\infty}$ E$(\Delta x_{it-j} u_{it})$. Assume that $u_{it}$ is correlated with at most $p_i$ leads and lags of $v_{it} = \Delta x_{it}$. Let $z_{it-1} = (\Delta x_{it+p_i-1}, \ldots, \Delta x_{it-p_i-1})$, and project $\Delta s_{it}$ onto $z_{i,t-1}$. Using (2), the projection error can be written as, $e_{it} = \beta h_{it-1} + \tilde{u}_{it}$ where $e_{it} = \Delta s_{it} - \mathrm{P}(\Delta s_{it} | z_{it-1})$, $h_{it-1} = x_{it-1} - \mathrm{P}(x_{it-1} | z_{it-1})$, and $\tilde{u}_{it} = u_{it} - \mathrm{P}(u_{it} | z_{it-1})$. The projection error, $\tilde{u}_{it}$ is by construction orthogonal to $\Delta x_{i,t-j}$ for all $j$. Regressing $e_{it}$ on $h_{it-1}$ gives us the panel dynamic OLS estimator of $\beta$. The asymptotic distribution of the estimator is derived in Mark and Sul (1999).

### *A.4. LSDV bias when $x_{it} \sim I(0)$*

In the single equation context, Stambaugh (1986) and Mankiw and Shapiro (1986) show that the OLS estimator in the predictive regression is biased in small samples. To see why the bias arises, let the predictive regression be $\Delta s_{it} = \beta x_{it-1} + u_{it}$ and suppose that $x_{it}$ evolves according to an AR(1) process, $x_{it} = \rho x_{it-1} + v_{it}$, where $(u_{it}, v_{it})' \overset{iid}{\sim} N(0, \Sigma_i)$.

In the single equation context, for any $i$, $(\hat{\beta} - \beta) = \Sigma\ x_{it-1} u_{it} / \Sigma\ x_{it-1}^2$. Following Stambaugh, since $u_{it}$ and $v_{it}$ are contemporaneously correlated, we can project $u_{it}$ onto $v_{it}$ and represent it as $u_{it} = (\sigma_{12,i}/\sigma_{22,i}) v_{it} + \epsilon_{it}$ where $\epsilon_{it}$ is the projection error, which is orthogonal to $x_{it-1}$. Substitute the projection representation into the above expression and taking expectations yields, E$(\hat{\beta} - \beta) = (\sigma_{12,i}/\sigma_{22,i})$E$(\hat{\rho} - \rho) = \mathrm{Bias}(\hat{\beta})$, where $\hat{\rho}$ is the OLS estimator of $\rho$. The bias in $\hat{\rho}$ has long been understood, and shown by Kendall (1954) to be E$(\hat{\rho} - \rho) = -(1 + 3\rho)/T$. Thus, for any individual, the OLS bias is E$(\hat{\beta} - \beta) = -(\sigma_{12,i}/\sigma_{22,i})(1 + 3\rho)/T$.

If we mimic the calculations above, we have in the panel context, $\hat{\beta} - \beta = \Sigma_i\ \Sigma_t\ x_{it-1} u_{it} / \Sigma_i\ \Sigma_t x_{it-1}^2 = \Sigma_i\ \Sigma_t x_{it-1} [(\sigma_{12,i}/\sigma_{22,i}) v_{it} + \epsilon_{it}] / \Sigma_i\ \Sigma_t x_{it-1}^2$. Now taking expectations, we have E$(\hat{\beta} - \beta) = \Sigma_i\ (\sigma_{12,i}/\sigma_{22,i})$E$(\Sigma_t\ x_{it-1} v_{it} / \Sigma_i\ \Sigma_t x_{it-1}^2)$. We can simplify further if we assume $\Sigma_i = \Sigma$, in which case, E$(\hat{\beta} - \beta) = (\sigma_{12}/\sigma_{22})$E$(\hat{\rho} - \rho)$. The bias in the estimator of $\rho$ is attenuated, but not eliminated in the panel. Formulae for the bias E$(\hat{\rho} - \rho)$ are given in Hsiao (1986).

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