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Comment

Barbara Rossi

1 Reviewing Engel and West's (2005) Main Result

Let's focus on a simple monetary model of exchange rates (Obstfeld and Rogoff [1996]):

$$E_t(s_{t+1} - s_t) = -\frac{1}{\eta}(f_t - s_t). \tag{1}$$

where f_t is the fundamental and s_t is the nominal exchange rate (for simplicity, we let the fundamental be a scalar). Let $b \equiv [\eta/(1 + \eta)]$ denote the discount factor; the no-bubble solution is:

$$s_t = (1 - b)\sum_{s=0}^{\infty} b^s E_t f_{t+s} \equiv F_t.$$

The literally has tested these models by using either in-sample (e.g., OLS/GMM estimation of [1]), our out-of-sample methods. While the in-sample evidence tends to find significant fit, out-of-sample analyses usually find that the model performs worse than a random walk: $E_t(s_{t+1} - s_t) = 0$. The latter influential result was first discovered by Meese and Rogoff (1983a, 1988) and has become known as the "Meese-Rogoff puzzle."

In their important paper, Engel and West (hereafter EW) (2005) claim that it is not surprising that the random walk performs better, as this is exactly what the model predicts when $b = 1$. To understand this claim, consider the following data-generating process:

$$\begin{cases} \Delta f_{t+1} = \rho \Delta f_t + \varepsilon^f_{t+1} \\ s_{t+1} = -(1/\eta) f_t + (1 - 1/\eta) s_t + \varepsilon^e_{t+1} \end{cases},$$

where $\begin{pmatrix} \varepsilon^f_{t+1} \\ \varepsilon^e_{t+1} \end{pmatrix} = \begin{pmatrix} 1 & \sigma_{fe} \\ 0 & 1 \end{pmatrix} \begin{pmatrix} \eta^f_{t+1} \\ \eta^e_{t+1} \end{pmatrix}$ (3)

$\varepsilon^e_{t+1} = -E_t(s_{t+1} - s_t)$ from (1), $F_{t+1} \equiv (1-b)\Sigma^{\infty}_{s=0} b^s E_t f_{t+s}$ and $cov(\varepsilon^f_{t+1}, \varepsilon^e_{t+1}) = \sigma_{fe}$. EW (2005) assume $\sigma_{fe} = 0$. Also, let $\Phi(L) \equiv (1 - \rho L)$ be the autoregressive polynomial for the fundamentals, with L being the lag operator, so that (3) is equivalent to $\Phi(L)\Delta f_{t+1} = \varepsilon^f_{t+1}$. By standard manipulations, if $|b\rho| < 1$: $\Delta F_t - E_{t-1}\Delta F_t = \Sigma^{\infty}_{j=0} b^j (E_t \Delta f_{t+j} - E_{t-1}\Delta f_{t+j}) = (1 - b\rho)^{-1}\varepsilon^f_t$ and $E_{t-1}\Delta F_t = (1-b)E_{t-1}\Sigma^{\infty}_{j=0} b^j \Delta f_{t+j} = (1-b)\rho(1-b\rho)^{-1}\Delta f_t$. Thus, when the model is true ($s_{t+1} = F_{t+1}$, i.e. $\Delta s_{t+1} = \Delta F_{t+1}$), $\Delta s_t = (1 - b\rho)^{-1}\varepsilon^f_t + (1-b)\rho(1-b\rho)^{-1}\Delta f_t$, so that:

$$\Delta s_{t+1} = \Phi(b)^{-1}\, \varepsilon^f_{t+1} \text{ for } b \approx 1 \tag{4}$$

where $\Phi(b) \equiv (1 - \rho b)$. Equation (4) implies EW's (2005) important result that, even though exchange rates are determined in equilibrium as the net present value of fundamentals, nevertheless exchange rate changes are unpredictable given information at time t, when the discount factor b is sufficiently high. Note that the proposition says that exchange rates are unpredictable given information at time t, not that they are random walks completely unrelated to the fundamentals (in fact, σ_{fe} could be different from zero).

2 Empirical Evidence in Favor of EW's (2005) Conjecture

To substantiate their claims, EW (2004, 2005) report empirical evidence on variance bounds and Granger-causality tests. In what follows, we replicate their empirical findings by using the same database as in EW (2004). The database consists of quarterly data from 1974:1 to 2003:1 for bilateral exchange rates of six major G7 countries relative to the U.S. dollar.

2.1 *Implications for Variance Ratios*

How much of the volatility of exchange rates can the model explain? EW (2004) note that (4) implies that the variance of Δs_t explained by the net present value of the fundamentals is $var(\Delta F_t) = var\,[\Phi(b)^{-1}\varepsilon^f_t]$. To estimate the latter, they estimate an autoregression for the fundamentals: $\Phi(L)\Delta f_t = \alpha + \varepsilon^f_t$, where $\Phi(L) = 1 - \Sigma^p_{j=1}\Phi_j L^j$, using $p = 4$. The estimates of $\Phi_1, \ldots, \Phi_4$ and of the time series of the fitted residuals ε^f_t together with

Table 6C2.1
Estimated Variance Ratios (i.e., Fraction of the Variance of Exchange Rates Explained by Fundamentals)

Δf:	Canada	France	Italy	Germany	Japan	U.K.
$\Delta(m-m^*)-\Delta(y-y^*)$	**1.212**	**0.352**	**0.373**	**0.345**	**0.446**	**0.644**
$\Delta(p-p^*)$	0.211	0.186	0.134	**0.422**	0.090	0.298
$\Delta(p-p^*)-\Delta(i-i^*)$	0.198	0.145	0.100	**0.343**	0.025	0.283
$\Delta(m-m^*)$	**1.447**	**0.423**	**0.703**	0.173	**0.388**	**0.686**
$\Delta(i-i^*)$	0.005	0.003	0.001	0.002	0.001	0.002
$\Delta(y-y^*)$	0.097	0.040	0.144	0.035	0.069	0.024

Note: Bold indicates fractions above 30%.

a calibrated value of b allow them to estimate the contribution of the variability of the net present value of fundamentals to the total variability of exchange rates: *Variance ratio* $\equiv var[\Phi(b)^{-1}\varepsilon_t^f]/var(\Delta s_t)$. Table 6C2.1 reports variance ratio estimates by calibrating $b = 0.99$ and using the same fundamentals as in EW (2004): money/income differentials $[\Delta(m - m^*) - \Delta(y - y^*)]$, price differentials $[\Delta(p - p^*)]$, and price/interest rate differentials $[\Delta(p - p^*) - \Delta(i - i^*)]$. We also experimented with other fundamentals considered in EW (2005), including money differentials $[\Delta(m - m^*)]$, interest rate differentials $[\Delta(i - i^*)]$, and income differentials $[\Delta(y - y^*)]$. Table 6C2.1 replicates EW's (2004) finding that when $b \approx 1$ the variability of fundamentals explain about 40 percent of the variability of exchange rates. Indeed, the fraction of variability of exchange rates that the procedure attributes to fundamentals is high (about or above 40 percent) for most fundamentals, with the exception of interest rate and income differentials.[1]

- *EW (2004, p. 124) therefore conclude that: "models in which the exchange rate is . . . a discounted sum of . . . future fundamentals can account for a sizeable fraction of the variance of . . . exchange rates when the discount factor is large. . . ."*

2.2 *Implications for Granger Causality Tests*

Equation (2) implies that exchange rates must Granger-cause fundamentals. Table 6C2.2 replicates EW's (2005) finding that exchange rates Granger-cause a variety of fundamentals (panel A) and that the reverse is not true (panel B). The table reports p-values of the Granger-causality tests—numbers below 0.05 imply evidence in favor of Granger causality[2].

Table 6C2.2
Bivariate Granger Causality Tests, Different Measures of Δf_t

Δf:	Canada	France	Italy	Germany	Japan	U.K.
A. p-values of H_0: $\beta_0 = \beta_1 = 0$ *in* $\Delta f_{t+1} = \beta_0 + \beta_1 \Delta s_t + \gamma \Delta f_t$						
$\Delta(m - m^*)$	0.10	**0.01**	**0**	0.63	0.31	**0.03**
$\Delta(p - p^*)$	0.82	0.67	**0**	**0**	**0**	**0**
$\Delta(i - i^*)$	0.21	0.15	0.42	0.27	**0.01**	**0.01**
$\Delta(m - m^*) - \Delta(y - y^*)$	0.22	**0.01**	0.40	**0**	0.31	**0.01**
$\Delta(y - y^*)$	0.31	**0.10**	0.28	0.15	1	0.12
$\Delta(p - p^*) - \Delta(i - i^*)$	0.88	**0**	**0**	**0**	**0**	**0**
B. p-values of H_0: $\beta_0 = \beta_1 = 0$ *in* $\Delta s_{t+1} = \beta_0 + \beta_1 \Delta f_t + \gamma \Delta s_t$						
$\Delta(m - m^*)$	0.16	0.21	0.31	0.69	0.38	0.69
$\Delta(p - p^*)$	0.23	0.32	0.33	0.67	0.51	0.36
$\Delta(i - i^*)$	0.25	0.91	0.25	1	0.75	0.71
$\Delta(m - m^*) - \Delta(y - y^*)$	0.21	0.17	0.12	0.78	0.51	0.50
$\Delta(y - y^*)$	0.11	0.72	0.31	0.85	0.31	0.55
$\Delta(p - p^*) - \Delta(i - i^*)$	0.32	0.46	0.37	0.35	0.77	0.48

Note: Bold denotes p-value lower than 5%.

- *EW (2005) therefore conclude that, even though there is no evidence that fundamentals Granger-cause future exchange rates, there is substantial empirical evidence that exchange rates Granger-cause fundamentals, in accordance with the net present value models of nominal exchange rates.*

2.3 *Implications for Out-of-Sample Forecasts*

In order to provide further evidence that fundamentals help predict exchange rates, Engel, Mark, and West report forecasts based on long-horizon panel regressions. They argue that fundamentals and exchange rates are cointegrated if one uses panel unit root tests. They also show that, if one exploits the panel dimension, fundamentals are able to provide better forecasts of future exchange rates than a simple random walk model, especially at long horizons.

3 Robustness Checks

It is important to realize that EW's (2004, 2005) and EMW's results rely on a variety of assumptions:

1. An autoregression with 4 lags captures well the behavior of fundamentals. But how well do 4 lags of the fundamentals forecast future values of fundamentals?

2. The variance ratios are precisely estimated. But how much uncertainty is there around the point estimates of the variance ratios?

3. The variance ratios are informative about the contribution of fundamentals in explaining the variability of exchange rates. But how informative are variance ratios?

4. The Granger-causality tests are performed over the full sample (1973–2003), therefore assuming stability in both the exchange rates and the fundamentals in the last three decades. However, that period witnessed a variety of structural changes in the G7 countries (e.g., changes in monetary policy in the United States [Clarida, Galí, and Gertler 2000], the introduction of a common currency in Europe). Are the Granger-causality results robust to instabilities?

5. The long-horizon regressions are valid only if the nominal exchange rates and the fundamentals are cointegrated. Is the empirical evidence in favor of cointegration robust?

6. The long-horizon panel regression forecasts are evaluated by using tests of equal out-of-sample forecasting ability. Are the results of such tests robust to the lack of cointegration?

In what follows, we check the robustness of the results to each of these assumptions.

3.1 Lag Length and Fit of the Autoregression

A detailed analysis of the AR(4) model in EW (2004) shows that only a few of the estimates are statistically different from zero (a Bayesian Information Criterion [BIC] would pick one lag for all countries as the optimal lag length). We therefore checked whether results in table 6C2.1 were robust to setting the order of the autoregression to 1. Table 6C2.3 reports the results. Overall, the estimates of the variance ratios drop. For example, when the money/income ratio is used as the fundamental, it drops from 40 percent to between 20 and 30 percent.

- *We therefore conclude that, although the actual fraction of variance of exchange rates explained by fundamentals is sensitive to the underlying dynamics of the fundamentals, the results are very robust, as this fraction is still sizeable.*

Table 6C2.3
Variance Ratios: Robustness to the Order of the Autoregression

Δf:	Canada	France	Italy	Germany	Japan	U.K.
$\Delta(m-m^*)-\Delta(y-y^*)$	**0.865**	0.181	0.190	0.216	**0.300**	**0.327**
$\Delta(p-p^*)$	0.158	0.050	0.041	0.145	0.022	0.094
$\Delta(p-p^*)-\Delta(i-i^*)$	0.153	0.031	0.038	0.073	0.012	0.097
$\Delta(m-m^*)$	**0.899**	0.195	0.246	0.126	0.291	**0.375**
$\Delta(i-i^*)$	0.006	0.008	0.002	0.009	0.003	0.006
$\Delta(y-y^*)$	0.097	0.031	0.073	0.037	0.043	0.035

Note: Bold indicates fractions above 30%.

3.2 How Much Uncertainty Is There around EW's (2004) 40 Percent Point Estimate?

To evaluate the estimation uncertainty around the variance ratio statistic, we calculate confidence intervals. Since the Monte Carlo empirical distribution of the estimated variance ratio statistic is highly asymmetric, the normal approximation and the use of the mean as a point estimate may not be appropriate. We thus use Kilian's (1998) bias-adjusted bootstrap, setting $b = 0.99$ and the autoregressive lag length equal to 4. Table 6C2.4 reports median unbiased estimates of the variance ratio as well as 90 percent confidence intervals in parentheses. Note that, due to the asymmetry, the point estimates in Table 6.8 are a poor approximation of the median: median estimates are significantly higher. Note also that the confidence intervals are really wide.

- *We therefore conclude that EW's (2004) point estimates actually underestimate the true variance ratios, therefore providing additional evidence in favor of their conjecture. However, there seems to be substantial uncertainty around such estimates, which generally can be anywhere between 10 percent to above 100 percent.*

3.3 Do the Dynamics in the Net Present Value of Fundamentals Explain Exchange Rates?

How informative are variance ratios? How should we interpret the result that fundamentals explain about 40 percent of exchange rate variability? We generate independent white noise fundamentals with variance equal to the estimated variance of the fundamentals. The estimated

Table 6C2.4
90 Percent Confidence Intervals for the Variance Ratios, Killian's (1998) Bootstrap

Canada	France	Italy	Germany	Japan	U.K.
		$\Delta(m - m^*)$			
1.6994	**0.6455**	**1.2579**	0.2207	**0.4865**	**1.0233**
(0.75, 4.10)	(0.16, 3.60)	(0.24, 10.00)	(0.08, 0.65)	(0.17, 1.43)	(0.29, 4.41)
		$\Delta(p - p^*)$			
0.2559	**0.5676**	0.2819	1.1136	0.1799	**0.5182**
(0.09, 077)	(0.05, 11.34)	(0.04, 5.43)	(0.13, 27.62)	(0.03, 2.49)	(0.10, 4.96)
		$\Delta(i - i^*)$			
0.0055	0.0031	0.0017	0.0019	0.0018	0.0025
(.002, .01)	(.001, .005)	(.0008, .003)	(.0008, .004)	(.0008, .003)	(.0014, .004)
		$\Delta(m - m^*) - \Delta(y - y^*)$			
1.3521	**0.5093**	**0.5083**	**0.4585**	**0.5423**	**0.8736**
(0.61, 2.87)	(0.13, 2.25)	(0.15, 1.85)	(0.14, 1.59)	(0.20, 1.48)	(0.30, 3.07)
		$\Delta(y - y^*)$			
0.112	0.0449	0.1814	0.0385	0.0811	0.0262
(0.05, 0.25)	(0.02, 0.10)	(0.05, 0.58)	(0.01, 0.08)	(0.03, 0.20)	(0.01, 0.05)
		$\Delta(p - p^*) - \Delta(i - i^*)$			
0.2392	0.259	0.1546	**0.8603**	0.0341	**0.4381**
(0.09, 0.64)	(0.05, 2.17)	(0.04, 0.81)	(0.10, 26.8)	(0.01, 0.12)	(0.09, 2.88)

Note: bold denotes fractions above 30%.

Table 6C2.5
Variance Ratios with Independent Fundamentals

	Canada	France	Italy	Germany	Japan	U.K.
$p = 1$	0.9540	0.1863	0.2666	0.1006	0.1488	0.0949
$p = 4$	0.7534	0.1916	0.0723	0.500	0.1857	0.0678

variance ratios are reported in table 6C2.5 for a choice of the lag length (p) equal to 1 or 4. The table shows that even completely unrelated fundamentals can explain a sizeable fraction of the variability of exchange rate fluctuations, provided that their variance is similar to that of the net present value of the fundamentals. In other words, variance ratios do not provide much information on the nature of the dynamic relationship between exchange rates and fundamentals—they only provide information on the size of their relative unconditional variances.

Table 6C2.6
Correlations between Δs_t and ΔF_{t+j}

j	−5	−4	−3	−2	−1	0	1	2	3	4	5
Canada	−0.03	0.00	−0.05	0.08	−0.01	0.07	−0.09	−0.16	0.14	−0.19	−0.03
France	0.06	−0.05	0.06	0.14	0.14	0.00	**0.31**	0.01	−0.02	0.16	0.20
Italy	0.06	0.05	−0.11	0.13	0.10	−0.10	0.02	−0.13	0.02	0.03	0.06
Germany	−0.06	0.07	−0.16	0.06	0.06	−0.05	**0.32**	−0.13	0.00	0.10	0.06
Japan	0.23	0.14	0.04	0.00	0.02	0.12	0.13	−0.14	0.02	−0.06	0.02
U.K.	0.05	0.07	−0.07	0.12	0.07	−0.11	−0.07	−0.08	0.01	0.02	−0.02

Note: bold indicates correlations above 20%.

What is, then, the dynamic relationship between fundamentals and exchange rates? Table 6C2.6 shows that there is some correlation but it is sizeable (around 30 percent) only for France and Germany at one lag.

- *We therefore conclude that, although the variance ratios are high, such measures do not capture correlations between exchange rates and fundamentals—and such correlations are small. It is therefore important to complement the analysis with Granger-causality tests, as in EW (2005).*

3.4 *How Robust Are the Granger-Causality Results to Parameter Instabilities?*

Are there parameter instabilities in the data? And how do these affect EW's (2005) results in table 6C2.2? Table 6C2.7 reports p-values of the Andrews (1993) test for parameter instabilities in regressions where exchange rates Granger-cause fundamentals (panel A), and where fundamentals Granger-cause exchange rates (panel B). Values less than 0.05 in the table imply evidence in favor of parameter instabilities at 5 percent significance level. Recall that EW (2005) found evidence that exchange rates Granger-cause fundamentals, but no evidence that fundamentals Granger-cause exchange rates. Table 6C2.7 shows that there is evidence of instabilities exactly in the situations in which EW (2005) find empirical evidence of Granger-causality. In other words, the evidence that exchange rates Granger-cause fundamentals is plagued by instabilities, whereas there is no evidence of parameter instabilities when examining whether fundamentals Granger-cause exchange rates.[3]

In principle, the presence of parameter instabilities could invalidate the empirical evidence in favor of Granger-causality reported in table

Table 6C2.7
Andrews' (1991) QLR Test for Time-Varying Parameters

Δf:	Canada	France	Italy	Germany	Japan	U.K.
A. p-values of stability of (β_{0t}, β_{1t}) *in:* $\Delta f_{t+1} = \beta_{0t} + \beta_{1t}\Delta s_t + \gamma \Delta s_t$						
$\Delta(m-m^*)$	**0**	**0.02**	**0**	**0.02**	**0.09**	**0**
$\Delta(p-p^*)$	0.11	**0**	**0**	**0**	**0**	**0**
$\Delta(i-i^*)$	0.44	**0**	0.12	**0.03**	**0**	**0**
$\Delta(m-m^*)-\Delta(y-y^*)$	**0.05**	0.45	**0**	**0**	**0**	**0**
$\Delta(y-y^*)$	**0**	**0.06**	0.28	**0.06**	**0.05**	1
$\Delta(p-p^*)-\Delta(i-i^*)$	**0.08**	**0**	**0**	**0**	0.21	**0**
B. p-values of stability of (β_{0t}, β_{1t}) *in:* $\Delta s_{t+1} = \beta_{0t} + \beta_{1t}\Delta f_t + \gamma \Delta s_t$						
$\Delta(m-m^*)$	0.43	0.62	0.32	0.66	0.20	1
$\Delta(p-p^*)$	**0.02**	**0**	**0**	0.52	**0**	0.15
$\Delta(i-i^*)$	0.82	0.47	0.56	0.36	**0.09**	0.74
$\Delta(m-m^*)-\Delta(y-y^*)$	0.35	0.54	0.61	0.12	0.58	0.81
$\Delta(y-y^*)$	0.18	0.82	0.51	0.72	0.76	0.16
$\Delta(p-p^*)-\Delta(i-i^*)$	0.20	0.23	0.26	0.73	**0.02**	0.14

Note: bold denotes significant at 10%.

6C2.2, since a maintained hypothesis of Granger-causality tests is that parameters are stable.[4] To assess the robustness of EW's (2005) result—that exchange rates Granger-cause fundamentals, we perform a joint test of parameter stability and Granger-causality by using the test proposed by Rossi (2005a, 2006). Table 6C2.8 reports p-values for the Exp-W* test in Rossi (2005a); p-values less than 0.05 mean that there is evidence that the regressor has some explanatory power, although such a relationship might be unstable over time. The results show that there is ample evidence that exchange rates Granger-cause fundamentals even though their relationship is unstable over time. Interestingly, now we also find (for some fundamentals and some countries) empirical evidence that fundamentals Granger-cause future exchange rates, although, again such causal relationship is unstable over time, and therefore could be very difficult to exploit for forecasting purposes.

- *Therefore, we conclude that EW's (2005) results that exchange rates predict future fundamentals are very robust to the presence of parameter instabilities at unknown times. Interestingly, however, there is some evidence that fundamentals also Granger-cause future exchange rates for some fundamentals and some countries, although such a relationship is unstable over time.*

Table 6C2.8
Optimal Joint Test for Significance and Instability (Rossi [2005])

Δf:	Canada	France	Italy	Germany	Japan	U.K.
	A. p-values of $H_0: \beta_t = \beta = 0$ *in* $\Delta f_{t+1} = \beta_{0t} + \beta_{1t}\Delta s_t + \gamma \Delta f_t$					
$\Delta(m - m^*)$	**0.01**	**0**	**0**	**0.03**	0.33	**0.05**
$\Delta(p - p^*)$	0.48	**0**	**0**	**0**	**0**	**0**
$\Delta(i - i^*)$	0.61	**0.02**	0.43	0.17	**0.01**	**0.01**
$\Delta(m - m^*) - \Delta(y - y^*)$	0.14	**0.04**	**0**	**0**	**0.01**	**0.03**
$\Delta(y - y^*)$	**0.07**	**0.02**	**0**	**0.05**	0.44	0.49
$\Delta(p - p^*) - \Delta(i - i^*)$	0.70	**0**	**0**	**0**	**0**	**0**
	B. p-values of $H_0: \beta_t = \beta = 0$ *in* $\Delta s_{t+1} = \beta_{0t} + \beta_{1t}\Delta f_t + \gamma \Delta s_t$					
$\Delta(m - m^*)$	0.25	0.38	0.35	1	0.54	1
$\Delta(p - p^*)$	0.18	**0**	**0.04**	0.80	**0.03**	**0**
$\Delta(i - i^*)$	0.77	0.87	0.65	0.84	0.39	1
$\Delta(m - m^*) - \Delta(y - y^*)$	0.20	0.40	0.50	**0**	0.75	1
$\Delta(y - y^*)$	0.24	1	0.62	1	0.21	0.53
$\Delta(p - p^*) - \Delta(i - i^*)$	0.50	0.33	0.27	0.72	**0.06**	**0.03**

Note: bold denotes significant at 10%.

3.5 *How Robust Are Panel Cointegration Results?*

As further evidence in support of the usefulness of economic models of exchange rate determination, EMW report that out-of-sample forecasts of exchange rates at long horizons improve substantially when using economic fundamentals as regressors. They focus on the predictive regression

$$s_{i,t+h} - s_{i,t} = \beta_h z_{i,t} + \varepsilon_{i,t+h}, \tag{5}$$

where $z_{i,t} = x_{i,t} - s_{i,t}$, $x_{i,t}$ is the fundamental, $\varepsilon_{i,t+h} = \alpha_i + \theta_t + u_{i,t}$, i indexes the country, t indexes the time period, and h is the forecast horizon. EMW estimate (5) both with panel regression methods and with univariate VECMs for each country. In both cases, they find substantial improvements in the forecasting ability of models relying on fundamentals at long horizons relative to the random walk. Such improvements are most striking when using PPP fundamentals.

As pointed out by EMW, the predictive regression makes sense when z is a stationary variable (that is when the exchange rate and the fundamentals are cointegrated). This may be problematic in the case of PPP fundamentals, as real exchange rates are very persistent variables, with roots that are statistically indistinguishable from unity (see Rossi 2005c). They report empirical evidence in favor of stationarity based on Sul's

Table 6C2.9
Unit Root Tests and the Robustness of Panel Forecasting Tests

A. Unit root tests on the factors				*C. Panel regressions*		*D. VECM single equation*	
	constant	constant & trend	h	I(1)	I(0)	I(1)	I(0)
F_{1t}	–2.519	–2.615	1	0.054	0.052	0.053	0.044
	B. Pooled unit root tests		2	0.094	0.053	0.066	0.059
	constant	constant & trend	5	0.124	0.062	0.091	0.070
$P_{\hat{e}}^{\tau}$	1.068	1.068	10	0.150	0.079	0.170	0.086
$P_{\hat{e}}^{c}$	2.069*	2.069*	20	0.201	0.113	0.226	0.120

Note: Asterisks denote significance at 5% (5% critical values are: –1.95 in panel A and ±1.64 in panel B). Panels C and D report empirical rejection frequencies of out-of-sample tests of equal forecast accuracy against a random walk. Nominal size is 0.05. Columns labeled I(1) and I(0) denote, respectively, cases where fundamentals and the exchange rates have a unit root and when they are stationary. The forecast horizon is h.

(2006) test. We therefore examine the robustness of EMW's results to other tests for stationarity of z. We consider Bai and Ng's (2004) panel unit root tests for the presence of unit roots in the common factors and in the idiosyncratic components of z_{it}. We focus on the case of PPP fundamentals for which Bai and Ng's (2002) test selects 1 common factor. Unreported results show that the largest roots in the common factors and in the idiosyncratic components are close to unity. Panels A and B in table 6C2.9 show that we cannot reject a unit root in the common factor, nor in the pooled regression tests with a deterministic trend. There seems to be less evidence of nonstationarity in the pooled regressions with a constant. Unreported results for monetary fundamentals show that unit root tests on the idiosyncratic component again do find some nonstationarity, while the pooled tests do not find any nonstationarity.

- *We conclude that there is high persistence in the relationship between exchange rates and PPP fundamentals, and the evidence on cointegration may not be robust to the use of other panel unit root tests, as the results depend on the specification. Results for monetary fundamentals are more robust.*

3.6 How Robust Are Out-of-Sample Long-Horizon Panel Forecasts?

The fact that the exchange rate and the fundamentals may not be cointegrated could imply that the long horizon regression results are spurious. However, they might still provide good out-of-sample forecasts, as EMW show. Whether such forecasts are statistically better than the random walk's forecast depends on the outcome of tests of forecast comparison. Such tests, however, may have poor properties if the regressors have unit roots.[5] We therefore consider what happens to rejection rates of tests for equal predictive ability in the presence of high persistence.

We consider the following data-generating process:

$$s_{i,t} = \lambda_i' F_t + u_{i,t}, \tag{6}$$

where F_t is a $(r \times 1)$ vector containing the factors $F_{j,t}$, $F_{j,t} = \rho_j F_{j,t-1} + e_{j,t}$, $j = 1, \ldots, r$, and $u_{i,t} = \rho_{i,e} u_{i,t-1} + e_{i,t}$, $i = 1, \ldots N$. We let $\rho_f = 1$ to mimic the realistic situation in which the PPP fundamental has a unit root. We follow EMW and use the Clark and West's (2006) test to evaluate out-of-sample predictive ability.[6] The null hypothesis of the test is that the nominal exchange rates are random walks and the alternative is that the fundamentals help forecasting the nominal exchange rates. To check the properties of the test, we let the nominal exchange rate be uncorrelated with the fundamental ($\lambda_i = 0$) and let the nominal exchange rate be highly persistent ($\rho_{i,e} = 1$). We generated 2,000 Monte Carlo simulations of (6) and forecasted future exchange rates using the same estimation procedures as in EMW, namely panel regressions and single-equation VECM regressions applied to each series in the long-horizon regression model (5). We consider horizons from 1 to 20, which encompass horizons 1 and 16, considered by EMW. Panels C and D in table 6C2.9 report rejection frequencies of nominal 5 percent tests of the null hypothesis that the true model is a random walk. Columns labeled I(1) denote situations in which $\rho_{i,e} = 1$ (similar results hold if the root is not exactly unity but close to unity). As a comparison, we also report rejection frequencies for the stationary case ($\rho_{i,e} = \rho_{i,f} = 0$), labeled I(0). The horizon is denoted by h. It is clear that in the stationary case, rejection frequencies are very close to their nominal value, whereas the tests grossly over-reject the random walk at long horizons in the presence of nonstationarity.

- *We conclude that out-of-sample forecast comparison tests tend to over-reject the null hypothesis of a random walk in the presence of roots close to unity.*

4 How Do We Reconcile These In-Sample Results with Meese-Rogoff's Stylized Fact?

First, is the Meese-Rogoff stylized fact still alive? Table 6C2.10 shows forecast comparison results between models of exchange rate determi-

Table 6C2.10
Tests for Out-of-Sample Forecasting Ability, Different Measures of Δf_t

	Canada	France	Italy	Germany	Japan	U.K.
A. MSE difference between the model: $\Delta f_{t+1} = \beta_{0t} + \beta_{1t}\Delta s_t + \beta_{2t}\Delta f_t$ and the random walk						
$\Delta(m - m^*)$	0.75	–1.29***	–0.23***	–0.93***	–1.01***	–1.48***
$\Delta(p - p^*)$	0.97	–0.46***	0.43***	0.28***	–2.16***	0.42***
$\Delta(i - i^*)$	0.98***	2.54	3.47	1.55	–0.13***	2.10
$\Delta(m - m^*) - \Delta(y - y^*)$	0.65	–0.12***	–0.77**	–0.23***	–0.57***	–0.75***
$\Delta(y - y^*)$	1.38	–0.09***	1.92	–0.35***	1.29	–0.27***
$\Delta(p - p^*) - \Delta(i - i^*)$	1.35	2.12	0.70**	–0.10***	–2.65***	0.64***
B. MSE difference between the model: $\Delta s_{t+1} = \beta_{0t} + \beta_{1t}\Delta f_t + \beta_{2t}\Delta s_t$ and the random walk						
$\Delta(m - m^*)$	0.60	1.41	1.35	1.45	1.38	1.26
$\Delta(p - p^*)$	1.78	0.68	0.91***	1.02	1.09	1.42*
$\Delta(i - i^*)$	1.03	1.84	0.78**	2.10	0.08	0.87*
$\Delta(m - m^*) - \Delta(y - y^*)$	0.82	1.52	0.67**	1.63	1.93	1.19
$\Delta(y - y^*)$	0.98	2.01	1.16	1.37	1.14***	0.86
$\Delta(p - p^*) - \Delta(i - i^*)$	1.65	1.44	0.97***	1.96	0.49	1.30**

Note: Positive values imply that the model forecasts worse than the random walk. Asterisks denote rejections of the null hypothesis of equal predictive ability at 1% (***), 5% (**), and 10% (*) significance levels.

nation with various fundamentals and the random walk. Parameters are reestimated over time using a rolling forecasting scheme, with a window equal to half of the sample size. The table reports mean square error differences between the model and the random walk, rescaled by a measure of standard deviation.[7] Positive values in the table imply that the random walk forecasts perform better than the model. The table shows that even though the fundamentals may explain a sizeable proportion of the in-sample total variance of exchange rates, they are still not better than a random walk for forecasting exchange rates out of sample. Interestingly, instead, lagged exchange rates not only Granger-cause fundamentals in-sample, but also for some currencies significantly help in forecasting future fundamentals, even out of sample.

Note that the results in table 6C2.10 rely on forecast comparisons of models in which the fundamentals are estimated in first differences. This specification has been chosen here because of consistency with the analysis in tables 6C2.7 and 6C2.8 and EW (2005), although it is different from that used in the original Meese and Rogoff (1983a, 1988) papers. The economic models (in levels) considered by Meese and Rogoff (1983a, 1988) are such that $s_t = \beta f_t + u_t$, where the residuals u_t are typically serially highly correlated, for example, $u_t = \rho u_{t-1} + \varepsilon_t$, where ε_t is an unforecastable error. Meese and Rogoff (1983a, 1988) estimate the serial correlation to better forecast the exchange rates: $E_t s_{t+1} = \beta E_t f_{t+1} + \rho(s_t - \beta f_t)$. Note that this is somewhat similar to including a lagged cointegrating vector in the model. However, in the data $\rho \approx 1$, and usual estimation procedures typically lead to a downward-biased estimate of such parameter in this case. When comparing a model with a random walk (that imposes $\beta = 0$, $\rho = 1$), the random walk's mean square forecast error could be lower because the bias in the estimate of ρ could more than offset the gain in exploiting the information on the fundamentals if β is not "big." Therefore, the random walk model might even forecast better if the model is the true data-generating process. Rossi (2005b) shows that once parameter estimation error in ρ is taken into account, tests of equal predictive ability do not reject the hypothesis that the model and the random walk are equivalent. If we were sure that $\rho = 1$, then we might impose that in the estimation to improve the forecasting ability of the model. An interesting remark is that Meese and Rogoff (1983b) did allow $\rho = 1$ in their grid search, but this did not improve the model's forecasting ability.[8] Imposing $\rho = 1$ in the estimation would mean estimating the model in first differences. As we have seen throughout this discussion, models estimated in first differences are plagued by parameter instabilities. So that could justify why the model does not forecast better than a random walk, even when the model is estimated in first differences, and is consistent with Meese and Rogoff's (1983b) results.

- *We therefore conclude that Meese and Rogoff's stylized fact is still present in the data, no matter whether the models are estimated in first differences, or with a serial correlation correction, as in Meese and Rogoff's original works.*

Why is there such a big difference between in-sample and out-of-sample performance, then? The previous analysis suggests that there are a variety of complementary explanations, which lead EMW to conjecture that "exchange rate models are not as bad as you think":

1. *EW's (2005) important and influential conjecture.* The results in table 6C2.10, panel A, provide additional empirical evidence that exchange rates do have predictive content for fundamentals, which is an important piece of evidence used in EW (2005) in favor of net present-value models. The results in table 6C2.10, panel B, are also consistent with EW's (2005) conjecture—that high discount factors might undermine

the explanatory power of fundamentals so that exchange rates are better forecasted by a random walk.[9]

2. *Parameter instabilities.* The latter results are also compatible with the empirical evidence discussed in table 6C2.8, that fundamentals may have predictive content for future exchange rates, but this relationship is time-varying and therefore very difficult to exploit for forecasting purposes. The possibility that time variation was empirically relevant in predicting exchange rates was first explored in Meese and Rogoff (1988). We have shown that parameter instabilities are important and might provide another piece of evidence that demonstrates why economic models of exchange rate determination do not work so well in forecasting.[10]

3. *Parameter estimation error.* As discussed above, when comparing a model estimated with a serial correlation correction for the cointegrating vector with a random walk, the random walk's forecasts could be better because the bias in the estimate of the serial correlation could more than offset the gain in exploiting the information on the fundamentals—if the fundamentals are not too informative regarding the exchange rate fluctuations. Therefore, the random walk model might forecast better even if the model is true (see Rossi 2005b).

• *To summarize, although the Meese and Rogoff's stylized fact is still present in the data, we have several possible conjectures for it.*

5 Conclusions

Even though the Meese-Rogoff stylized fact is still alive, we now have a variety of conjectures regarding why it might be the case that economic models do not outperform a random walk in forecasting exchange rates: (a) high discount factors might undermine the predictive content of fundamentals for exchange rates, even theoretically (EW's [2005] important result); (b) widespread instabilities in predictive regressions make it hard, anyway, to use such predictive relationships to forecast exchange rates out of sample; (c) parameter estimation error (Rossi 2005b).

This note showed that, while it is unclear how much variability of exchange rate fundamentals can be explained by looking at the variance ratios, the evidence on Granger-causality tests is quite robust to both uncertainty in the estimation and parameter instabilities. However, there is some evidence that fundamentals have a predictive but time-varying content for future exchange rates.

Does this imply, as in EMW's (2007) words, that: "beating a random walk in forecasting is too strong a criterion for accepting an exchange rate model"? It is certainly a strong criterion, because, as shown by EW (2005) and Rossi (2005b), there are reasons why a random walk may forecast better than the economic model, even if the economic model is true. Nevertheless, out-of-sample forecast comparisons seem to be an important reality check to evaluate the performance of models, and are becoming a standard for evaluating the empirical performance of macroeconomic models as well (Del Negro, Schorfheide, Smets, and Wouters 2007). Understanding and overcoming the reasons of such poor forecasting performance seem to be important tasks for future research, and could be addressed in a variety of ways—for example, by using high-frequency data to capture short-lived effects of news, or time-varying techniques to exploit the time variation in such predictive relationships.

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Endnotes

1. Variance ratios can be longer than 1 in the presence of unmodeled fundamentals (see EW 2004).

2. Throughout, results are similar if the Granger-causality tests are not performed on the constant.

3. Stock and Watson (2003) similarly document widespread instabilities in macroeconomic data.

4. To partially address this issue, Engel and West (2005) report subsample Granger-causality tests, but such results are conditional on knowing the time of the structural break, which in principle is unknown.

5. The concern is related to similar findings in univariate time series models: Corradi, Swanson, and Olivetti (2001) show that out-of-sample tests of equal predictive ability are valid in the presence of cointegration, but Rossi (2005b) shows that they can be misleading when cointegration does not hold. Although there are no similar analyses undertaken in the context of panel regressions, we expect similar results to hold.

6. The fact that the Clark and West (2006) statistic will turn out to be oversized in the presence of roots equal to 1 is not special to their statistic nor a drawback of their procedure: Clark and West (2006, 161) clarify that their results hold if the variables are covariance stationary. Similar results are expected to hold for any tests of out-of-sample forecast comparison. Here we implemented the Clark and West (2006) statistic with an HAC correction for serial correlation with a bandwidth equal to $(h - 1)$ to take into account the fact that h-step-ahead forecasts have a moving average serial correlation structure of order $(h - 1)$.

7. The table reports the Diebold and Mariano (1995) and West (1996) statistic for forecast error comparisons without the adjustment for parameter estimation error. The reason is that the models are nested under the null, so the test statistic is not informative except qualitatively for the fact that when it is positive it means that random walk forecasts better. The critical values used to assess significance are from Clark and McCracken (2001).

8. I thank Ken Rogoff for pointing this out to me.

9. Results are robust to not including the lagged dependent variable.

10. Rossi (2006) examined forecast-combination techniques and models with time-varying parameters and found some evidence that exploiting parameter instability might help in forecasting exchange rates.

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