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Mean Reversion in G-10 Nominal Exchange Rates

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Abstract

According to conventional wisdom, industrial country floating exchange rates contain unit roots. SUR tests on panels of monthly Group of Ten (G-10) log nominal rates reject the null of unit roots for various samples over the current float with significance levels from 0.5% to 15%. On average, in out-of-sample forecasts mean reversion models beat random walks significantly in some forecast periods. For monthly data, the range of expected USD-DEM appreciation rates exceeds 15% per year in the mean reversion model. Mean reversion places strong restrictions on international models: over the sample period, the G-10 had to run monetary policies consistent with stable long-run nominal rates.

I. Introduction

Conventional wisdom has long held that industrial countries' floating exchange rates contain unit roots (Logue, Sweeney, and Willett (1978), Mussa (1976), Meese and Singleton (1982), Engel and Hamilton (1990), Mark (1995), and Mark and Sul (2001)). As applied to industrial countries' nominal exchange rates, the unit root hypothesis implies that on average a large portion of changes in log exchange rates are permanent, and that after relatively minor patterns die out in a month or two, expected appreciation or depreciation is zero. The evidence below, however, supports the view that Group of Ten (G-10) log nominal rates are mean reverting, that is, in the absence of further disturbances they return to constant long-run levels. Mean reversion in G-10 nominal rates arises due to the fact that i) real rates are mean reverting and ii) changes in the logs of real and nominal rates are highly correlated (see Figure 1 for logs of nominal and real values

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of the Deutsche Mark (DEM) relative to the U.S. dollar (USD). For panels of monthly G-10 log nominal rates, Seemingly Unrelated Regression (SUR) tests reject the null of unit roots at significance levels from 0.5% to 15% for 14 overlapping sample periods during the current float. Because the unit root test results for real rates and nominal rates are highly correlated, observers who accept the evidence for mean reversion in G-10 real rates are hard pressed not to accept nominal rate mean reversion. Nominal rates appear to explain approximately 75% of real rate adjustment, and the logs of nominal and real rates appear to adjust at about the same speed, perhaps 1.5% to 2.5% per month. Moreover, panel tests reject the unit root null for relative national price levels over many sample periods. Mean-reverting nominal rates and relative price levels *jointly* drive real rates to their long-run values. Out-of-sample forecasting tests also reject unit roots in log nominal rates; mean reversion models beat unit root models in most forecasting periods, sometimes significantly.

FIGURE 1

Logs of DEM per USD and the Real Exchange Rate of DEM per USD

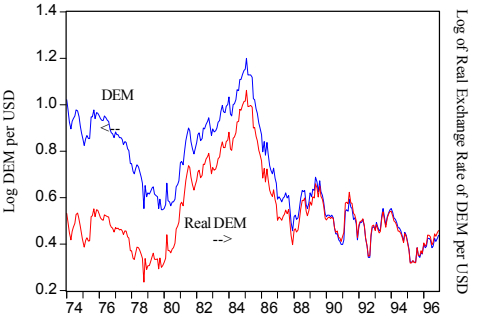


Figure 1 shows logs of DEM per USD and the real exchange rate of DEM per USD. The real and nominal exchange rates move closely together, and in the short run much of the movement in the real exchange rate can be explained by the nominal rate.

Source: International Monetary Fund

Implicitly assuming unit roots in nominal rates implies that expected appreciation is essentially zero for industrial countries. In contrast, over the 1974–1996 period, the range of expected appreciation implied by mean-reverting nominal rates has been large. Plausible estimates of the difference between the maximum and minimum expected appreciation rate of the USD against the DEM are from 15.82% to 26.36% per year after accounting for interest rate differentials, and for comparison the sample standard deviation of DEM/USD appreciation is approximately 12% per year. Taking into account these mean reversion effects on expected appreciation can be important for standard issues that arise in corporate finance, investments, and valuation. First, many firms practice active risk management, including international risk management. Risk management models, however, virtually always assume that nominal rates have unit roots (Oxelheim and Wihlborg (1997)). In light of this paper's results, these models are impor-

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tantly misspecified, neglecting predictable components in appreciation rates and hence overstating the rates' variances.

Second, for any investment with international risk, firms that use asset pricing models (APMs) in their decision making require estimates of appreciation rates' systematic risk. APMs that explain appreciation rates generally assume, however, that log nominal rates contain unit roots, or are integrated of order one (i.e., $I(1)$) (Dumas and Solnik (1995), Harvey (1991), and Roll and Solnik (1977)). In estimating equations, these models do not include parameters that allow an appreciation rate to vary predictably with the level of the log exchange rate as mean reversion implies. Because international APMs omit mean reversion effects, these effects are impounded in the errors for foreign assets. Indeed, entering mean reversion effects as an explanatory variable reduces the error variance for periods where these effects are large.

Third, portfolio allocation models with international assets assume log nominal rates contain unit roots, or are $I(1)$, rather than mean reverting (Dumas and Jacquillat (1990)), which implies that appreciation rates' means, variances, and covariances are misestimated and hence portfolio weights are suboptimal.

Fourth, in valuing an acquisition or project with international risk the analyst must account for appreciation rates' effects on expected cash flows and on risk-adjusted discount rates (Oxelheim and Wihlborg (1997), Copeland, Koller, and Murrin (2000), and Sweeney (2004)). Neglecting mean reversion implies misestimation of both expected cash flows and risk-adjusted discount rates.

This paper's results imply strong interdependence of G-10 long-run monetary policies over the sample period. To illustrate, consider a two-country monetary model where each country's price level is proportional to its money stock in the long run. Consistent with G-10 data for the floating rate period, suppose each log price level is $I(1)$, thus implying log money stocks are $I(1)$. Given this paper's empirical results that the log real rate and the log nominal rate are both mean reverting, that is, are integrated of order zero $(I(0))$, the log of relative national price levels must be $I(0)$ (as this paper finds empirically), or the difference in countries' log price levels must be $I(0)$. If the difference in log price levels is to be $I(0)$, then the difference in log money stocks must be $I(0)$, that is, the log money stocks must be cointegrated. This cointegration requires strong interdependence in long-run monetary policies, but allows for substantial short-run divergences. Taking account of long-run monetary interdependence may be useful in some applications, for example, investigating the extent to which the monetary models beat a random walk model in out-of-sample exchange rate forecasts for G-10 countries (see Meese and Rogoff (1983), Mark (1995), Chinn and Meese (1995), and Mark and Sul (2001) and papers cited therein).

For countries with large persistent inflation differences relative to the G-10 during the current float, the data do not support mean reversion in nominal exchange rates relative to the USD, even though the real rates show mean reversion. For example, Figure 2 shows the log of the DEM and Argentina and Brazil's currencies relative to the USD. The latter currencies show grossly different behavior from the DEM and obviously are not mean reverting. Argentina and Brazil's exchange rates reflect the fact that their inflation rates and monetary growth rates diverged sharply from the G-10's for long periods and caused permanent changes

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in their log price levels and log money stocks relative to the G-10's. Thus, the difference between say Argentina's and the U.S.' log price levels is not $I(0)$.

FIGURE 2
Logs of DEM, Argentina's and Brazil's Currencies per USD

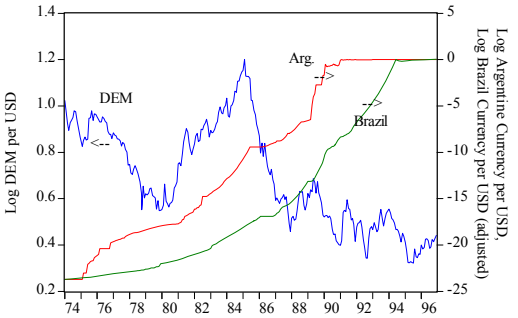


Figure 2 shows logs of nominal exchange rates for the DEM, Argentina's currency, and Brazil's currency. The DEM must be tested to determine if it is mean reverting or contains a unit root. It is clear that the currencies of Argentina and Brazil are not mean reverting. The log of Brazil's currency is normalized by multiplying by 0.8848508 to have the same range as the log of Argentina's currency.

Source: International Monetary Fund

The rest of this paper is organized as follows. Section II briefly surveys the literature on unit roots in nominal rates. Past work that tests individual log nominal rates cannot reject the unit root null. This paper's SUR panel tests are more powerful and reject the unit root null. Intuitively, panel tests are more powerful in much the way that using longer series adds to power in tests of individual rates. Section III discusses the panel unit root tests and the data. SUR techniques deal with the large contemporaneous cross-correlations in changes in log nominal rates. Similar techniques are used in SUR panel unit roots tests of real exchange rates, interest rates, and international stock markets. For cross-correlations in log nominal rates, SUR is superior to fixed-time effects models. Critical values used here are found from simulation.

Section IV presents test results for monthly data on G-10 currencies relative to the USD over the generalized managed float that began in mid-March 1973. Sample periods all end in December 1996, with 14 starting dates from January 1974 to January 1987 to gauge results' sensitivity. Significance levels range from 0.5% in five cases to 15% in four cases. Panels of log relative national price levels show comparable rejections. Further, results for panel tests of log real exchange rates are similar to those for log nominal exchange rates, as the large correlations between changes in the logs of real and nominal rates suggest.

Section V reports out-of-sample forecasting results that support the rejections in unit root tests: mean reversion models beat unit root models in most forecast periods, significantly in some. These results suggest that log nominal rates' speed of adjustment is perhaps 1.5% to 2.5% per month, comparable to adjustment speeds inferred for log real rates. Further, log nominal rate mean re-

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version explains approximately 75% of log real rate mean reversion. The range of variation in expected appreciation is economically important, for example, from 15.81% to 26.35% per year for the USD-DEM rate. Section VI offers a summary and conclusions.

II. Literature on Unit Roots in Nominal Exchange Rates

A number of papers from the mid-1970s report results of serial correlation tests and conclude that during the period of managed floating [1] that began in mid-March 1973, log nominal exchange rates contain unit roots (Dooley and Shafer (1976), Cornell and Dietrich (1978), Logue, Sweeney, and Willett (1978), and Mussa (1976)). Using more sophisticated tests, a number of papers from the 1980s report that the data cannot reject the unit root null (in particular, Meese and Singleton (1982)).

Starting in the 1980s, some authors report unit root tests of nominal rates as a preliminary to their papers' main issues, but more frequently authors simply assume unit roots to get on to their main issues. Baillie and Bollerslev (1989), as a preliminary to cointegration tests, report that on balance in tests on individual series the data cannot reject the unit root null for log nominal and log forward rates.[2] Mark (1990) examines whether nominal rates and relative national price levels are cointegrated for a subset of G-10 countries; as a preliminary, he tests whether individual nominal rates and relative prices contain unit roots, and cannot reject the unit root null for any country for either variable. Tests on individual currencies are standard practice. The present paper is the first to report SUR panel unit root tests of log nominal rates.

Meese and Rogoff (1983) compare forecasts of nominal rates based on statistical models and also monetary models with driftless random walks. They do not report unit root tests but note previous articles supporting the unit root assumption (p. 3, fn. 1). Diebold and Nason (1990) test out-of-sample nonparametric estimated models of exchange rate changes against random walks, assuming but not testing for unit roots. Meese and Rogoff (1988) examine real exchange rates; they test for unit roots in real rates but assume nominal rates contain unit roots. Similar to Meese and Rogoff (1983), Mark (1995) examines the predictive ability of fundamentals regarding nominal exchange rates. His work requires that nominal rates contain unit roots but he does not test for unit roots. Mark and Sul (2001) also examine fundamentals' predictive ability for nominal rates. As an important preliminary, they test whether fundamentals and nominal rates are cointegrated,

[1] During the period of managed floating, the values of the USD, the DEM, and the Japanese Yen relative to each other were largely determined by market forces, with sporadic and minor intervention relative to exchange market volume or other measures (Sweeney (2004)). During some periods, a number of European Union (EU) countries kept their currencies relatively close to each other, sometimes intervening heavily to do so. This paper's sample includes five of these countries: Belgium, France, Germany, Italy, and the Netherlands. On the one hand, the USD-DEM rate was largely market determined. On the other hand, in some periods the French Franc-DEM rate was heavily influenced by policy. The USD-Franc rate, however, thus fluctuated mainly from market forces. Below, the text discusses the econometric implications of these EU arrangements.

[2] Diebold, Gardeazabal, and Yilmaz (1994) reject Baillie and Bollerslev's (1989) cointegration results, but use their results on unit roots in nominal rates as a maintained hypothesis. In their response, Baillie and Bollerslev (1994) do not reexamine their previous conclusion of unit roots in nominal rates.

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but do not report tests of the unit root null for nominal rates. Presumably, Mark (1995) and Mark and Sul (2001) rely on the unit root tests in Mark (1990).

Engel and Hamilton (1990) investigate a unit root case where changes in the log nominal rate fluctuate randomly around a mean that shifts between two values according to an unobserved Markov process. They conclude that this "stochastic segmented trends" model is superior to "the simple random walk" (pp. 697–699). They do not, however, report unit root tests of nominal rates, but simply assume unit roots.

III. Unit Root Tests

This paper's panel tests apply SUR techniques to systems of augmented Dickey-Fuller (ADF) equations. The test design is purposely close to SUR panel tests of mean reversion in log real exchange rates.[3] The ADF estimating system is

$$
\begin{aligned}
(1) \qquad \Delta \ln S_{i,t} &= \ln S_{i,t} - \ln S_{i,t-1} \\
&= a_i + b \ln S_{i,t-1} + \sum_{j=1}^{pi} c_{i,j} \Delta \ln S_{i,t-j} + u_{i,t}, \\
&\qquad i = 1, n, \quad t = 1, T,
\end{aligned}
$$

where $\ln S_{i,t}$ is the natural logarithm of country i's spot exchange rate (foreign currency per USD), a_i is the intercept for i, and p_i is the order of i's autoregressive terms. Below, the lags p_i are assumed to be the same across countries, $p_i = p$, but allowing differing p_i has trivial effects on the empirical results. T is the number of time-series observations and $n = 10$ for the G-10 countries.

The test statistic is the t-value, t_b, of the common slope b. An alternative approach is to allow separate slopes, b_i, for each currency (Im, Pesaran, and Shin (IPS) (2003). In experiments discussed below, tests that impose $b_i = b$ have greater power, even when the slopes are unequal.

The $u_{i,t}$ follow standard SUR assumptions: the errors are mean zero, with the positive definite contemporaneous covariance matrix Ω_{SUR}. This generalizes Levin and Lin's (LL) (1992), (1993), and Levin, Lin, and Chu's (LLC) (2002) approaches for the case where all $u_{i,t}$ are $IN(0, \sigma_u^2)$, or without loss of generality the covariance matrix is $\Omega_{\mathrm{LL}} = I$. LL (1992) demonstrate that as $T \to \infty$ and $n \to \infty$ simultaneously, subject to the condition that $n^{1/2}/T \to 0$, then $t_b \to^d [N(0,1) - (1.875n)^{1/2}]/1.25^{1/2} \equiv t_b^*$. Further, LL (1992) show that t_b has the same asymptotic distribution as t_b^* for all $p_i = p \geq 0$ and $c_{i,j} \gtrless 0$ (with $n^{1/2}/(T - p) \to 0$ in place of $n^{1/2}/T \to 0$); LLC (2002) demonstrate equivalent results.[4]

[3] See Abuaf and Jorion (1990), Jorion and Sweeney (1996), MacDonald (1996), Papell (1997), Papell and Theodoridis (1998), O'Connell (1998), and Sarno and Taylor (1998). For related tests on interest rates, see Wu and Zhang (1996) and Balz (1998), and for international stock markets, Balvers, Wu, and Gilliland (2000).

[4] LLC (2002), a revision of LL (1992), (1993), give a more elegant proof and a superior discussion with references to important results in Phillips and Moon (1999) for the case where $T \to \infty$ and $n \to \infty$ simultaneously, rather than the more common and tractable case where $T \to \infty$ and then $n \to \infty$ sequentially. Note that instead of using the asymptotic t-statistic in the text above (from LL), LLC normalize it to make it $N(0,1)$.

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Appendix 2 shows that for fixed n, as $T \to \infty$, the same asymptotic results hold under SUR.

Let β denote the dominant root in the log nominal rates. Then, in the specification in (1), b corresponds to $(\beta - 1)$. In this paper, the null and alternative hypotheses with respect to b are

$$\mathrm{H}_0\text{: } b_1 = b_2 = \ldots = b_n = 0, \quad \mathrm{H}_A\text{: } b_1 = b_2 = \ldots = b_n < 0.$$

For the intercept, the null and alternative hypotheses are

$$\mathrm{H}_0\text{: } a_1 = a_2 = \ldots = a_n = 0, \quad \mathrm{H}_A\text{: } a_1 \gtrless 0, a_2 \gtrless 0, \ldots, a_n \gtrless 0.$$

This pair of null plus alternative hypotheses is not the only possible pair. The results might be reversed if the researcher considers some other pairs of null and alternative hypotheses. On the one hand, the process may be subject to deterministic or random parameter shifts that are likely to bias the test in favor of the null, that is, against the results below. For example, Perron (1989) presents cases where tests are unlikely to reject the unit root null against the $I(0)$ alternative if the process is mean reverting but contains known parameter shifts.[5] Much of the subsequent literature investigates related cases, especially cases where the timing of the parameter shifts is unknown (e.g., Zivot and Andrews (1992)) or the process contains outliers (e.g., Perron and Rodríguez (2003)). On the other hand, the series may be the sum of a unit root and a mean-reverting process (see Huizinga (1987) and Engel (2000) for real exchange rates). For example, the disturbance might be $u_{i,t} = \varepsilon_{i,t} + \gamma\nu_{i,t}$, where $\varepsilon_{i,t}$ is an error with SUR properties, $\gamma \geq 0$ is a constant, and $\nu_{i,t}$ is an error with a unit root. If $\gamma(\sigma_\nu/\sigma_\varepsilon)$ is small, in finite samples tests may reject the unit root null in favor of reversion to a constant mean, when instead the nominal rate reverts to a mean that is subject to small, permanent changes over time. Note that for many applications, this case does not differ importantly from reversion to a constant mean.

A. Critical Values from Simulation for SUR Tests

SUR techniques are used to deal with the large contemporaneous cross-correlations in changes in log nominal rates, similar to a number of panel tests of mean reversion in real exchange rates. For autoregressions of changes in log nominal exchange rates, White (1980) tests indicate that the residuals cannot reject the no-heteroskedasticity null for any currency. Thus, this paper finds critical values from SUR estimates on simulated data generated with homoskedastic errors. The data-generating process (DGP) for the errors in (1) is $u_{i,t} \sim N(0, \Omega_{\mathrm{SUR}})$, where Ω_{SUR} is non-diagonal positive definite rather than $u_{i,t} \sim N(0, I)$ as in LL (1992). Critical values are found from bootstrapping simulations that use the $\Delta \ln S_{i,t}$ sample covariance matrix, Ω_{sample}, as the estimator of Ω_{SUR}. Other Ω_{SUR} estimators include the residual covariance matrix from SUR estimates of (1); in experiments, critical values do not change importantly across Ω_{SUR} estimators.

[5] Engel and Hamilton (1990) investigate a unit root case where $\Delta \ln S_{i,t}$ fluctuates randomly around a mean that shifts between two values according to an unobserved Markov process. They conclude that this "stochastic segmented trends" model is superior to "the simple random walk" (pp. 697–699).

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Three possible DGPs suggested by the literature are

$$\text{(DGP.1)} \qquad \Delta \ln S_{i,t} = u_{i,t},$$

$$\text{(DGP.2)} \qquad \Delta \ln S_{i,t} = \sum_{j=1}^{pi} \hat{c}_{i,j} \Delta \ln S_{i,t-j} + u_{i,t}, \quad \text{and}$$

$$\text{(DGP.3)} \qquad \Delta \ln S_{i,t} = \hat{a}_i + \sum_{j=1}^{pi} \hat{c}_{i,j} \Delta \ln S_{i,t-j} + u_{i,t},$$

where $u_{i,t} \sim N(0, \Omega_{\text{SUR}})$ in all three cases, and $\hat{a}_i$ and $\hat{c}_{i,j}$ are the estimated values of the intercepts and the slopes on the lagged $\Delta \ln S_{i,t-j}$. The first DGP is suggested by IPS (2003); for unit root tests on real exchange rates, Papell (1997) and O'Connell (1998) use the second DGP, and Sarno and Taylor (1998) use a version of the third.

If the true $a_i = 0$, but $\hat{a}_i \neq 0$ are used as in (DGP.3), then as Appendix 1 shows the true size is larger than the nominal size and the null is rejected too frequently when it is true.[6] For this reason, (DGP.3) is not used in the tests below. Note that for critical values found from (DGP.3), the null is rejected in Appendix 1 in all cases, and at more impressive significance levels than the text reports below.

If the true values of $c_{i,j}$ are known, then using them in the DGP maximizes the power of the tests in finite samples, ceteris paribus. IPS (2003) recommend using (DGP.1) rather than (DGP.2) to avoid estimating nuisance parameters. They show in simulations that this procedure has good size and power properties. Because the $\hat{c}_{i,j}$ from the sample data used here are small in absolute value and imprecisely estimated, using (DGP.2) may give less precise critical values than (DGP.1). In experiments, (DGP.1) and (DGP.2) give critical values that are very close, and the results from using them in tests are much the same as discussed below.[7]

Appendix 1 shows that whatever the true value of $p = p^*$, it is important to estimate (1) with p^*. On the one hand, as the results from Ng and Perron (1995) suggest, using $p < p^*$ often makes the actual size larger than the nominal size, and the null is rejected too frequently when true. Thus, Ng and Perron's results suggest that using $p < p^*$ is most costly when the errors are generated by a moving average process with a large, negative coefficient. Here only two of the currencies show small negative first-order serial correlations in changes in log nominal rates[8] (Canada, -0.040, and France, -0.023). On the other hand, using

[6]This suggests that Sarno and Taylor's (1998) use of $\hat{a}_i$ in their DGPs biases their tests toward rejecting the null.

[7]Estimates of the $c_{i,j}$ are sensitive to estimation method (for example, ordinary least squares (OLS) versus SUR) and sample period. For the first lag, $c_{i,1}$, in the 1974:01–1996:12 sample period with OLS two coefficients are significant at the 10% level (Sweden, U.K.), and with SUR four are significant (Italy, Japan, Sweden, U.K.); for the second lag, $c_{i,2}$, none is significant with OLS, and one is significant with SUR (Belgium, 10%). A table showing autocorrelation functions is available from the author.

[8]If the DGP is $\Delta \ln S_{i,t} = u_{i,t}$, where $u_{i,t}$ is an MA(1), $u_{i,t} = \varepsilon_{i,t} + \theta_{i,1}$ and $\varepsilon_{i,t-1}$, $\varepsilon_{i,t} \sim N(0, \Omega_{\text{SUR}})$, then the first-order correlation coefficient is $\theta_{i,1}/(1 + \theta_{i,1}^2) < 0$ for $\theta_{i,1} < 0$.

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$p > p^*$ gives lower power than if $p = p^*$. Test results are reported for a range from $p = 0, \ldots, 12$, revealing that inferences are relatively insensitive to p.[9]

B. Comparison of Critical Values

Critical values are found by fitting the ADF equations in (1) with iterated SUR on simulated data for $p_i = p = 0, \ldots, 12$, $n = 10$, $\Omega_{\text{SUR}} = \Omega_{\text{sample}}$, and 10,000 replications. Representative critical values for $T = 276$ (the 1974:01–1996:12 sample period) are:

		1974–1996 ($T = 276$)					
Asymptotic[a]		$p = 0$	$p = 1$[b]	$p = 1$[c]	$p = 2$	$p = 9$	$p = 12$
0.5%	−6.178	−6.3026	−6.3278	−6.3408	−6.3901	−6.4056	−6.4072
1%	−5.954	−6.1240	−6.1797	−6.0855	−6.1642	−6.1557	−6.2071
5%	−5.345	−5.5527	−5.5366	−5.5174	−5.5452	−5.5600	−5.5753
10%	−5.020	−5.2460	−5.1858	−5.2189	−5.2088	−5.2149	−5.2508
15%	−4.799	−4.9877	−4.9696	−4.9833	−4.9860	−5.0017	−5.0260
Mean	−5.295	−5.6426	−5.6399	−5.6292	−5.6589	−5.6676	−5.6933

[a]Asymptotic values are from LL (1992). [b]$a_i = b_i = c_{i,j} = 0$. [c]$a_i = b_i = 0$, $\hat{c}_{i,1} \neq 0$.

SUR critical values from simulation are only modestly larger in absolute value than asymptotic critical values, despite large cross-correlations in the $\Delta \ln S_{i,t}$ (for the DEM, the average cross-correlation is 0.746, with three larger than 0.90); of course, using asymptotic critical values would make the actual size somewhat larger than the nominal size. Further, critical values from simulation differ relatively little on average across p. Finally, critical values for $p = 1$ are very close whether the simulations use (DGP.1) with $a_i = b_i = c_{i,j} = 0$ or (DGP.2) with $a_i = b_i = 0$, $\hat{c}_{i,1} \neq 0$. This illustrates the general result for using $\hat{c}_{i,j}$ in the DGP.

C. Power of the Tests

The t_b test used here has good power as Appendix 1 discusses. For example, if each currency's root is 0.985, the unit root null is rejected at the 0.5% level in more than 20% of the cases, and at the 10% level in more than 80%.

D. Fitting Equations with Unconstrained Slopes

IPS (2003) propose fitting (1) without the constraint $b_i = b$. Appendix 1 shows that in simulations, freely fitting the b_i reduces power for the large roots

[9]Papell (1997) uses estimated first-order coefficients in his DGP, but fits (1) to the simulated data with p_i from 11 to 22 to find critical values; fitting p_i larger than the true p adversely affects power. O'Connell (1998) uses the DGP

$$\text{(A)} \qquad \Delta y_{i,t} = u_{i,t}, \quad u_{i,t} = \sum_{j=1}^{p} c_j u_{i,t-j} + v_{i,t}, \quad v_{i,t} \sim N(0, \Omega_{\text{SUR}}).$$

To find DGP parameters, he estimates (A) with SUR on the data, and restricts the $c_{i,j}$ to be the same across countries—homogeneous dynamics—to conserve degrees of freedom; the residual covariance matrix is used as Ω_{SUR}. O'Connell's ps range across panels from $p = 3$ to $p = 12$ on quarterly data. He fits the test equation $\Delta y_{i,t} = a_i + b y_{i,t-1} + u_{i,t}$, with $u_{i,t} = \sum_{j=1}^{p} c_j u_{i,t-j} + v_{i,t}$, and $v_{i,t} \sim N(0, \Omega_{\text{SUR}})$ for the same ps. For the present paper, G-10 log nominal rate changes clearly have heterogeneous dynamics, or $c_{i,j}$ differ across i; further, for nominal rates the ps appear much smaller than the large ps O'Connell uses, and if the fitted ps are larger than the true p, power is adversely affected.

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and large contemporaneous cross-correlations of changes in log nominal rates that characterize G-10 data. If countries have a root of 0.985, then with the b_i fitted freely the null is rejected in 7.47% of the cases at the 0.5% level and in 45.28% at the 10% level; with the b_i constrained, the rejection rates are 21.55% and 80.33%. If the roots vary across countries around a mean of 0.975 with the first country's root equal to 0.965, the second country's root equal to 0.985, etc., then with the b_i fitted freely, the null is rejected in 7.600% of the cases at the 0.5% level, 45.70% at the 10% level; and with the b_i constrained, the rejection rates are 34.77% and 56.43%. As might be expected from these power comparisons, test results are less impressive when the b_i are fit freely, though the null is rejected in eight of 14 samples (results available from the author).

E. Fixed Time Effects as a Method of Adjusting for Cross-Correlation

LL (1992) and IPS extend their models to allow for fixed time effects (FTEs), which is a restrictive form of cross-correlation.[10] SUR is preferable here. An appendix available from the author shows that G-10 log nominal rates grossly violate FTE model assumptions, and that FTE results are biased in favor of the null.

IV. Results of Panel Unit Root Tests

Consumer price indices and month-ending market exchange rates are from *International Financial Statistics* (IFS). Interest rates are one-month Euro rates from DataStream for later years; earlier data are domestic series from IFS, linked to the later data.[11] The G-10 are Belgium, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, the U.K., and the U.S. Switzerland was informally associated with the G-10 from the start, and thus is often included in studies that focus on the G-10, giving 10 exchange rates relative to the USD.

Examination of the autocorrelation and partial autocorrelation functions for the 10 currencies suggests that six countries need no lagged change in the exchange rate but four (Italy, Japan, Switzerland, and the U.K.) may require one lag. This suggests setting $p = 1$ in system tests, but results for $p = 0, 1, 9, 12$ are reported below.

Sample periods end in December 1996 with periods starting in January 1974, January 1975, . . . , January 1987 for 14 overlapping samples. Results are not independent across samples, of course, but this presentation reveals the results' sensitivity to the sample period. For real rates, Papell (1997) uses a similar approach to judge sensitivity for real rates. Because countries joining the Euro countries (Belgium, France, Germany, Italy, and the Netherlands in the G-10) had progressively tighter bounds with each others' currencies in the run-up to the Euro's introduc-

[10] Wu (1996), Oh (1996), Culver and Papell (1997), Coakley and Fuertes (1997), Cecchetti, Mark, and Sonora (1998), and Fleisig and Strauss (1999) use FTEs in panel unit root tests. Period dummies, an alternative approach to fixed time effects, are used in some tests by Wei and Parsley (1995) and Frankel and Rose (1996).

[11] Domestic series used are always market rates and are, in order of preference, one-month interbank, T-bill, call money, and bond rates.

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tion in January 1999, the end of the sample periods was chosen as December 1996 without examining the data.[12]

A. Results for G-10 Log Nominal Exchange Rates

Table 1, Panel A shows panel unit root test results for $p_i = p = 0, 1, 9, 12$, and also shows estimated slope coefficients on the lagged level of the nominal rates for $p = 0$. Significance levels vary with the sample's starting date, from 0.5% in five cases to 15% in four cases, across $p = 0, 1, 9$; significance is somewhat less for $p = 12$.

Results are generally insensitive to whether critical values obtain from simulations using (DGP.1) or (DGP.2). Table 1 illustrates this for the case of $p = 1$; the critical values are quite close for the two DGPs (see above and notes to Table 1), and no level of significance is altered.

For the six periods starting before 1980, results are significant at the 15% level in four cases and at the 0.5% level in two; rejections are somewhat stronger in the last eight periods. One might conjecture that log nominal rates had unit roots in the 1970s and were mean reverting thereafter. However, this view is undercut by rejections at the 0.5% level for samples starting in 1976 and 1977.

The relatively weak rejections for sample periods starting in 1974 and 1975 may arise from sampling variation or from a shift in process after 1975. From Perron (1989) and subsequent work, parameter changes in an AR(1) process will bias the test against rejecting unit roots unless the test equation explicitly includes the parameter shift. Thus, differences in process before and after 1975 might be due to the "turbulence" that accompanied the introduction of the float as governments and markets adjusted to the new exchange rate regime and searched for equilibrium market rates. As an indication of possible changes in process, the sample means of the log nominal rates, which are estimators of their long-run values, are substantially different for several countries before and after 1975. In a version of (1) that allows for different intercepts a_i before and after 1975:12, the unit root null is rejected at the 0.97% level with critical values found from simulation. This improvement should be expected given the better significance levels from the sample that started in 1976 as compared to samples starting earlier, and strictly speaking is not a test of changes in process.[13]

The null may be rejected because some—but not all—log nominal rates are $I(0)$ (see Karlsson and Löthgren (2000), Sarno and Taylor (1998)). From simulation results in Appendix 1, the rejections of the null reported here are much more likely to arise because all log nominal rates are $I(0)$, rather than just a subset.[14]

[12] When the systems are rerun for sample periods ending in 1998:12, the results are approximately the same. Three *t*-values are larger, 11 are smaller, and on average the *t*-values are a bit smaller, by approximately 0.15.

[13] Further, assuming that the process changed after 1975, there are too few observations to be confident that log nominal rates from 1974–1975 are better modeled as AR(1)s or random walks; in tests using (1), the data reject the unit root null at the 45.60% significance level for the 1974–1975 sample period.

[14] Related, some doubt that Italy's Lira and Japan's Yen show mean reversion. Note that this view implies the tests are biased in favor of the unit root null. Systems of nine countries (the G-10 less Italy) and eight countries (the G-10 less Italy and Japan) show results similar to those in Panel A, though a

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TABLE 1

Panel Unit Root Tests for G-10 Nominal Exchange Rates and Relative Prices

Panel A. Log Nominal Exchange Rates, t_b for $p = 0, 1, 9, 12$

Start	1974	1975	1976	1977	1978
$\hat{b}$ $(p = 0)$	−0.009368	−0.009868	−0.013711	−0.012809	−0.012656
t_b $(p = 0)$	−5.1107^{+}	−5.1773^{+}	−6.5550****	−5.6504**	−4.9867
t_b $(p = 1)$	−5.0874^{+}	−5.1665^{+}	−6.5080****	−6.6528****	−5.0080^{+}
t_b $(p = 9)$	−5.0548^{+}	−5.1785^{+}	−6.4029***	−5.6937**	−5.0067^{+}
t_b $(p = 12)$	−4.7324	−4.8608	−5.6295**	−5.4700*	−4.8971
Start	1979	1980	1981	1982	1983
$\hat{b}$ $(p = 0)$	−0.014247	−0.019037	−0.026107	−0.029648	−0.025508
t_b $(p = 0)$	−5.1761^{+}	−6.2120***	−7.2753****	−6.8550****	−5.3018*
t_b $(p = 1)$	−5.1845^{+}	−6.1139**	−7.2500****	−6.9316****	−5.3816*
t_b $(p = 9)$	−5.1786^{+}	−6.0243**	−7.1721****	−6.9964****	−5.2398*
t_b $(p = 12)$	−5.0210	−5.7204**	−6.6497****	−6.6821****	−5.0454^{+}
Start	1984	1985	1986	1987	
$\hat{b}$ $(p = 0)$	−0.027233	−0.034498	−0.044034	−0.045687	
t_b $(p = 0)$	−5.1508^{+}	−5.8399**	−6.2176***	−5.5968**	
t_b $(p = 1)$	−5.2764*	−6.0182**	−6.3862****	−5.7392**	
t_b $(p = 9)$	−5.1320*	−5.7883**	−6.5067****	−5.5912**	
t_b $(p = 12)$	−5.2442^{+}	−5.8525**	−6.1920**	−5.3569*	

Panel B. Log Relative National Price Levels, t_b for $p = 1$

Start	1974	1975	1976	1977	1978
t_b (RP)	−10.6338****	−10.1447****	−11.5081****	−12.2973****	−12.8834****
Start	1979	1980	1981	1982	1983
t_b (RP)	−13.6451****	−11.6859****	−9.7773****	−8.7839****	−7.9595****
Start	1984	1985	1986	1987	
t_b (RP)	−6.1459***	−4.9699	−3.8509	−3.7151	

****, ***, **, *, $^{+}$ significant at the 0.5%, 1%, 5%, 10%, and 15% levels, respectively.

Table 1 shows the results of SUP panel estimates of the ADF equation $\Delta \ln S_{i,t} = a_i + b \ln S_{i,t-1} + c_i \Delta \ln S_{i,t-1} + u_{i,t}$ $(i = 1, 10)$, where $S_{i,t}$ is the number of units of currency i per USD. The 10 currencies relative to the USD are for Belgium, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, and the U.K. t_b is the t-value of the slope b. The panel is also run for relative national price levels. Exact critical values are from simulations with iterated SUR. The DGP is $\Delta \ln S_{i,t} = u_{i,t}$, where $u_{i,t} \sim N(0, \Omega_{\text{DGP}})$; the DGP covariance matrix equals the sample covariance matrix of the $\Delta \ln S_{i,t}$ over a given sample. Critical values are found for $T = 276$ (1974:01 to 1996:12), and for $T = 120$, (1987:01 to 1996:12) with 10,000 replications each:

	Log Nominal Exchange Rates						Log Relative Price Levels			
	1974–1996 ($T = 276$)						1987–1996 ($T = 120$)		1974–1996	1987–1996
	$p = 0$	$p = 1^{a}$	$p = 1^{b}$	$p = 2$	$p = 9$	$p = 12$	$p = 0$	$p = 1$	$p = 1$	$p = 1$
0.5%	−6.3026	−6.3278	−6.3408	−6.3901	−6.4056	−6.4072	−6.3073	−6.5351	−6.3402	−6.5392
1%	−6.1240	−6.1797	−6.0855	−6.1642	−6.1557	−6.2071	−6.1030	−6.3066	−6.1166	−6.3270
5%	−5.5527	−5.5366	−5.5174	−5.5452	−5.5600	−5.5753	−5.5200	−5.7015	−5.5478	−5.6722
10%	−5.2460	−5.1858	−5.2189	−5.2088	−5.2149	−5.2508	−5.2165	−5.3512	−5.2302	−5.3348
15%	−4.9877	−4.9696	−4.9833	−4.9860	−5.0017	−5.0260	−4.9990	−5.1281	−5.0121	−5.0734

[a] $a_i = b_i = c_{i,j} = 0$. [b] $a_i = b_i = 0,\ c_{i,1} \neq 0$.

B. Results for Relative National Price Levels

Much previous work documents mean reversion in log real exchange rates.[15] At the same time, many researchers believe that log nominal rates contain unit roots. This is reconciled by noting that the log real rate is the sum of the log nominal rate and the log relative national price level; thus, if both the log nominal rate and the log relative national price level are $I(1)$, but they are cointegrated,

little weaker; if Italy and Japan's log nominal exchange rates contain unit roots, the impressiveness of the rejection would be expected to rise.

[15] See the citations in footnote 3.

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then the log real rate is mean reverting (i.e., is $I(0)$).[16] In words, the nominal exchange rate wanders with no mean reversion as does the relative national price level, but the two series' wanderings offset each other in the long run. In contrast to this view of the world, if both the nominal and real exchange rates show mean reversion, as this paper finds, then so must the relative national price level.

Conditional on mean reversion in real exchange rates, evidence of mean reversion in relative prices provides additional support for the view that nominal rates are mean reverting. With appropriate rewriting, (1) can be used to test for unit roots in relative prices. Table 1, Panel B shows results for systems of changes in log relative national price levels (RPs) for the G-10. Because changes in log RPs often show first-order autocorrelation, the estimated ADF regressions set $p_i = p = 1$. Critical values for SUR estimates are found from simulation in the same way as for changes in log nominal rates. The data reject the null of a unit root at the 0.5% level for all periods that start before 1984; the null is rejected at the 1% level for the period starting in 1984.

C. Results for Real Exchange Rates

It has long been known that variations in nominal rates are the dominant component of variations in G-10 real rates, especially for periods as short as a month (Obstfeld (1985), Mark (1990)). For the 1974–1996 sample period, monthly changes in log nominal and log real rates have an average correlation of 0.9847. This suggests that results of panel unit root tests should be close for log nominal and log real rates. Table 2 shows results for real rates and repeats nominal rate results from Table 1. For both, nominal rate critical values are used. The results are similar across nominal and real rates, stronger for nominal rates for some starting years, weaker for others.

V. Out-of-Sample Forecasts

Jorion and Sweeney (1996) and Siddique and Sweeney (1998) present evidence that, for equally weighted portfolios of log real exchange rates for G-10 countries, mean reversion models with $p=0$ provide better forecasts than driftless random walks in terms of root mean square errors (RMSEs). Results are reported below for out-of-sample forecasting tests of mean reversion models of the log nominal rates $\ln S_{i,t}$, where the mean reversion model is $\Delta \ln S_{i,t} = \delta(\ln S_i^* - \ln S_{i,t})$, where $\delta > 0$ is the adjustment speed, $\ln S_i^*$ is the long-run log nominal rate for currency i, and in terms of equation (1), $\delta = -b$. Mean reversion model forecasts are compared to i) random walks, $\Delta \ln S_{i,t} = u_{i,t}$, a frequent benchmark, and to

[16] Let S_t denote the number of units of foreign currency per USD, $P_{\mathrm{US},t}$ the U.S. price level, $P_{\mathrm{Ger},t}$ the German price level, and R_t the real exchange rate, where $R_t \equiv S_t(P_{\mathrm{US},t}/P_{\mathrm{Ger},t})$ and $\ln R_t = \ln S_t + \ln(P_{\mathrm{US},t}/P_{\mathrm{Ger},t})$. On the one hand, suppose that the log real rate and the log nominal rate contain unit roots $[\ln R_t \sim I(1), \ln S_t \sim I(1)]$. Now suppose the log relative national price level contains a unit root $[\ln(P_{\mathrm{US},t}/P_{\mathrm{Ger},t}) \sim I(1)]$, and the log nominal rate and the log relative national price level are cointegrated. Then, in the regression equation $\ln S_t = \alpha + \beta \ln(P_{\mathrm{US},t}/P_{\mathrm{Ger},t}) + \varepsilon_t$, the error ε_t is stationary $[\varepsilon_t \sim I(0)]$. Further, if $\beta = 1$, then $\ln R_t = \ln S_t + \ln(P_{\mathrm{US},t}/P_{\mathrm{Ger},t}) = \alpha + \varepsilon_t$, consistent with mean reversion in the real rate. On the other hand, if $\ln R_t$ and $\ln S_t$ do not contain unit roots $[\ln R_t \sim I(0), \ln S_t \sim I(0)]$, then $\ln(P_{\mathrm{US},t}/P_{\mathrm{Ger},t})$ must not contain a unit root $[\ln(P_{\mathrm{US},t}/P_{\mathrm{Ger},t}) \sim I(0)]$—if $\ln(P_{\mathrm{US},t}/P_{\mathrm{Ger},t})$ did contain a unit root, then $\ln R_t$ would have to contain a unit root.

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TABLE 2

Panel Unit Root Tests for G-10 Nominal and Real Exchange Rates

	Start	1974	1975	1976	1977	1978
Nom.	t_b $(p=0)$	−5.1107^{+}	−5.1773^{+}	−6.55496****	−5.6504**	−4.9867^{+}
Nom.	t_b $(p=1)$	−5.0874^{+}	−5.1665^{+}	−6.5080****	−6.6528****	−5.0080^{+}
Real	t_b $(p=0)$	−5.1629^{+}	−5.0732^{+}	−5.2921*	−6.4948****	−6.0137**
Real	t_b $(p=1)$	−5.8574**	−5.7813**	−5.8891**	−6.8628****	−6.4450****
	Start	1979	1980	1981	1982	1983
Nom.	t_b $(p=0)$	−5.1761^{+}	−6.21201***	−7.2753****	−6.8550****	−5.3018*
Nom.	t_b $(p=1)$	−5.1845^{+}	−6.1139**	−7.2500****	−6.9316****	−5.3816*
Real	t_b $(p=0)$	−5.8954**	−5.7079**	−5.7075**	−5.0767^{+}	−5.5232*
Real	t_b $(p=1)$	−6.3172***	−6.0785**	−6.2093***	−5.7250**	−5.8519**
	Start	1984	1985	1986	1987	
Nom.	t_b $(p=0)$	−5.1508^{+}	−5.8399**	−6.2176***	−5.5968**	
Nom.	t_b $(p=1)$	−5.2764^{+}	−6.0182**	−6.3862****	−5.7392**	
Real	t_b $(p=0)$	−5.7088**	−6.0142**	−6.2725***	−5.7299**	
Real	t_b $(p=1)$	−6.1315**	−6.4026****	−6.7740****	−6.1718***	

****, ***, **, *, $^{+}$ significant at the 0.5%, 1%, 5%, 10%, and 15% levels, respectively.

Table 2 shows the results of SUP panel estimates of the ADF equation $\Delta \ln S_{i,t} = a_i + b \ln S_{i,t-1} + c_i \Delta \ln S_{i,t-1} + u_{i,t}$ $(i = 1, 10)$, where $S_{i,t}$ is the number of units of currency i per USD. The 10 currencies relative to the USD are for Belgium, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, and the U.K. t_b is the t-value of the slope b. The panel is also run for real exchange rates for the same currencies, where the real rate is the nominal rate times the relative national price level. Exact critical values are from simulations with iterated SUR; the same critical values are used for nominal and real exchange rates. The DGP is $\Delta \ln S_{i,t} = u_{i,t}$, where $u_{i,t} \sim N(0, \Omega_{\text{DGP}})$; the DGP covariance matrix equals the sample covariance matrix of the $\Delta \ln S_{i,t}$ over a given sample. Critical values are found for $T = 276$ (1974:01 to 1996:12), and for $T = 120$, (1987:01 to 1996:12), with 10,000 replications each:

	1974–1996 ($T = 276$)						1987–1996 ($T = 120$)	
	$p=0$	$p=1$[a]	$p=1$[b]	$p=2$	$p=9$	$p=12$	$p=0$	$p=1$
0.5%	−6.3026	−6.3278	−6.3408	−6.3901	−6.4056	−6.4072	−6.3073	−6.5351
1%	−6.1240	−6.1797	−6.0855	−6.1642	−6.1557	−6.2071	−6.1030	−6.3066
5%	−5.5527	−5.5366	−5.5174	−5.5452	−5.5600	−5.5753	−5.5200	−5.7015
10%	−5.2460	−5.1858	−5.2189	−5.2088	−5.2149	−5.2508	−5.2165	−5.3512
15%	−4.9877	−4.9696	−4.9833	−4.9860	−5.0017	−5.0260	−4.9990	−5.1281

[a] $a_i = b_i = c_{i,j} = 0$. [b] $a_i = b_i = 0$, $c_{i,1} \neq 0$.

ii) AR(1) models of $\Delta \ln S_{i,t}$, or $\Delta \ln S_{i,t} = a_i + c_{i,1} \Delta \ln S_{i,t-1} + u_{i,t}$. Mean reversion model forecasts are superior in most samples, sometimes significantly.

To allow comparison, Siddique and Sweeney's test design for real rates is closely followed: 12-month-ahead forecasts, 10-year estimation periods, and rolling five-year forecast periods are used. Further, results are reported for a range of adjustment speeds. Twelve-month-ahead forecasts are used because long forecast horizons are likely to give more informative results: the absolute value of the difference between mean reversion and random walk forecast errors is increasing in the forecast horizon h.[17] Ten-year estimation periods are used because, if parameters are constant, longer estimation periods are likely to produce better estimates and hence superior forecasts. Long-run log nominal rates, $\ln S_i^*$, are estimated as the sample means in the preceding estimation period.[18] For AR(1) forecasting models, the ADF system (1) is fit with $b = 0$ and $p_i = p = 1$. To illustrate the procedure, the first line in Table 3, for the five-year forecast period ending in 1989:12,

[17] For h-month-ahead forecasts, the random walk and mean reversion forecast errors are $\text{FE}_{\text{RW}} = \ln S_{i,t+h} - \ln S_{i,t}$ and $\text{FE}_{\text{M}} = \ln S_{i,t+h} - \ln \hat{S}_{i,t+h} = \ln S_{i,t+h} - \{\ln S_i^* [1 - (1+b)^h] + (1+b)^h \ln S_{i,t}\}$. Thus, for $b < 0$, $|\text{FE}_{\text{M}} - \text{FE}_{\text{RW}}| = |(\ln S_{i,t} - \ln S_i^*)|[1 - (1+b)^h]$ increases in h.

[18] Various estimators of $\ln S_i^*$ are available. Without experimentation, the estimation period's mean log exchange rate, $m_i = T^{-1} \sum_{t=1}^{T} \ln S_{i,t}$, is used; if $\ln S_{i,t}$ is stationary, m_i is consistent.

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reports RMSEs for forecasts where the estimation period for $\ln S_i^*$ is 1974:01 to 1983:12, and data from 1984:01 to 1988:12 are used to produce 12-month-ahead forecasts for 1985:01 to 1989:12.

TABLE 3

Out-of-Sample Forecasts of G-10 Log Nominal Exchange Rates
(10-year estimation period, five-year forecasting period, 12-month-ahead forecasts)

Fore. End.	RW	0.025	0.015	0.0125	0.0100	0.0075	0.0050	Raw Estimated Adjustment Speed (% per mo.)
1989:12	0.143786	*0.116200****	*0.123604****	*0.126184****	*0.129070****	*0.132270****	*0.135787****	0.649
1990:12	0.141255	*0.108176****	*0.119491****	*0.122708***	*0.126086***	*0.129627*^^*	*0.133334*^^*	0.605
1991:12	0.101111	*0.098257*	*0.098194*	*0.098399*	*0.098706*	*0.099123*	*0.099658*	1.344
1992:12	*0.084863*	0.093071	0.088299	0.087348	0.086524	0.085846	0.085331	1.113
1993:12	0.092259	*0.087664*	*0.086940*	*0.087232*	*0.087743*	*0.088489*	*0.089483*	0.940
1994:12	0.089737	0.091180	*0.088268*	*0.087950*	*0.087833*	*0.087936*	*0.088276*	0.985
1995:12	0.084945	0.091465	0.086057	0.085173	*0.084532*	*0.084161*	*0.084089*	1.897
1996:12	0.080418	0.087376	0.081237	*0.080259*	*0.079572*	*0.079213*	*0.079214*	3.254
Average	0.102297	*0.096674*	*0.096511*	*0.096907*	*0.097508*	*0.098333*	*0.099397*	
RW/MR		5.817%	5.995%	5.562%	4.911%	4.031%	2.918%	

***, **, *, ^^, ^ significant at the 0.5%, 1.0%, 2.5%, 5.0%, and 10% levels, respectively.

Table 3 shows out-of-sample forecasting results for random walk (RW) models and mean reversion models, and compares results. The criterion is the root mean squared error (RMSE). For the random walk and mean reversion models, results are an average of the RMSEs across 10 currencies. Other columns show RMSEs for various values of the slope δ in the mean reversion models $\Delta \ln S_{i,t} = \delta(\ln S_i^* - \ln S_{i,t})$, where δ is the speed of adjustment, $\ln S_{i,t}$ is the log of the number of units of foreign currency per USD for currency i, and $\ln S_i^*$ is the log of the long-run exchange rate for currency i. The 10 currencies relative to the USD are for Belgium, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, and the U.K. Average shows the average of the RMSEs in each column. RW/MR is the percentage amount by which the average for the $\text{RMSE}_{\text{RW}} = 0.102297$ exceeds the average RMSE_{M} for each adjustment speed. The RW column shows RMSEs for forecasts based on random walks without drifts. The final six columns impose a priori speeds of adjustment: 2.5%, 1.5%, 1.25%, 1.0%, 0.75%, and 0.50% per month. In these columns, the estimated long-run value of each nominal exchange rate is its estimation period sample mean. Five-year forecast periods are used. The final line of results is for forecasts ending in 1996:12. For 12-month-ahead forecasts, the final data point used for generating forecasts is 1995:12. Data used for generating 12-month-ahead forecasts for 1992:01 to 1996:12 are from 1991:01 to 1995:12. Parameter estimates for these forecasts (the S_i^*) are mean exchange rates from the 10-year estimation period, 1981:01 to 1990:12.

In tests of mean reversion models, the speed of adjustment to the long-run rate is a key parameter. Let β denote the dominant root. Then the speed of adjustment is $(1 - \beta)$. From the specification in (1), $b = -(1 - \beta)$ and, hence the estimated speed of adjustment is $-\hat{b}$. For purposes of the discussion below, it is useful to show the $\hat{b}$ and the estimated speeds for the eight estimation periods used in the out-of-sample forecasts in Table 3:

Start of 10-Year Estimation Period	$\hat{b}$ Estimate of $(\beta - 1)$	Adjustment Speed $(1 - \beta) \times 100 = -\hat{b} \times 100$ (% per mo.)
1974	−0.006492	0.6492
1975	−0.006047	0.6047
1976	−0.013441	1.3441
1977	−0.011128	1.1128
1978	−0.009402	0.9402
1979	−0.009854	0.9854
1980	−0.018970	1.8970
1981	−0.032535	3.2535
Mean		1.2093

In considering adjustment speeds, three points are important. First, the range of plausible adjustment speeds is pretty tightly constrained for nominal rates. The

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dominant root in nominal rates must be close to unity because it is difficult for the data to reject the unit root null. The $\hat{b}$ in the text above suggests $(1 - \beta) \times 100$ is somewhere between 0.5% to 2%–3% (that is, β is from 0.995 to 0.98–0.97). Second, under both the unit root null and the mean reversion alternative, $\hat{b}$ is biased down and thus the estimated speed is biased up,[19] suggesting that raw estimates of adjustment speeds should be adjusted downward. Adjusting the speeds for bias is sensible. Indeed, in a variety of contexts, applying a priori knowledge to estimated parameter values improves out-of-sample forecasts.[20] From the $\hat{b}$ just above, without correcting for downward bias the estimated adjustment speeds have a range of 0.61% to 3.25% with a mean of 1.2093%. The above estimates from individual 10-year estimation periods—0.65%, 0.61%, 1.34%, 1.11%, 0.94%, 0.99%, 1.90%, and 3.25% per month—suggest ad hoc corrections for bias to give adjustment speeds of perhaps 0.5%, 0.75%, 1.0%, 1.25%, 1.50%, and 2.5% per month, and these are used in Table 3, which contains a column with the raw estimates of adjustment speeds for each forecast period. Results for these raw adjustment speeds can be approximated by interpolation.[21]

Third, the estimation error in $\hat{b}$ is large. Supposing the true slope in (1) is approximately constant over time, the above estimates illustrate large sampling variability relative to the slope: the first and last estimates differ by a factor of 5.01 (= 0.32535/0.006492). Because sampling variability is substantial, Table 3 shows results for each period for the speed suggested by the raw estimates above, adjusted for bias, and also shows results for the range of speeds.

In comparing out-of-sample forecast results, the RMSEs from random walk (RW) models are smaller than those from AR(1) models, $\Delta \ln S_{i,t} = a_i + c_{i,1} \Delta \ln S_{i,t-1} + u_{i,t}$, where $\hat{a}_i$ and $\hat{c}_{i,1}$ are found from the preceding 10-year estimation periods (and higher order ARs do no better). Intuitively, this seems due to the fact that the $\hat{a}_i$ and $\hat{c}_{i,1}$ are unstable over time.[22] The results for AR(1) models are thus omitted, and RW forecasts are compared to forecasts from mean reversion models.

In Table 3, the RMSEs for equally weighted portfolios of mean reversion models for rolling five-year forecast periods are in general smaller than for fore-

[19]Under the unit root null, the estimate of b is asymptotically biased downward. Under the stationary alternative the estimate of b is biased downward in small samples but is consistent with the bias becoming increasingly severe as the root increases (Hamilton (1994), pp. 216–217).

[20]In forecasts using VARs, authors report that Bayesian adjustments of parameter estimates produce superior out-of-sample forecasting performance on average (Ashley (1988), Holden and Broomhead (1990), Artis and Zhang (1990), and LeSage and Magure (1991)).

[21]In experiments, interpolation of results in Table 3 gives good approximations. For example, interpolating between 2.5 and 1.5 to find an estimate of results from 2.0 gives a good approximation to what is found by using 2.0.

[22]For the AR(1) model $\Delta \ln S_{i,t} = a_i + c_{i,1} \Delta \ln S_{i,t-1} + u_{i,t}$, misestimates of a_i and $c_{i,1}$ can have important effects on forecast errors. As of time t, the 12-period-ahead forecast and forecast error are:

$$\begin{aligned} E \ln S_{i,t+12} &= S_{i,t} + 12a_i + 11c_i a_i + 10c_i^2 a + 2c_i^{10} a + c_i^{11} a \\ &\quad + \left[c_i + c_i^2 + c_i^3 + \ldots + c_i^{12}\right] \Delta \ln S_{i,t}, \\ \ln S_{i,t+12} - E \ln S_{i,t+12} &= (\ln S_{i,t+12} - S_{i,t}) - \left[12a_i + 11c_{i,1} a_i + \ldots + c_{i,1}^{11} a\right] \\ &\quad - \left[c_{i,1} + c_{i,1}^2 + c_{i,1}^3 + \ldots + c_{i,1}^{12}\right] \Delta \ln S_{i,t}. \end{aligned}$$

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casts from RW models, $\Delta \ln S_{i,t} = u_{i,t}$. The column RW shows the RMSE_{RW} for RW model forecasts; the remaining columns show the RMSE_{M} for mean reversion models for six adjustment speeds, 2.5% to 0.50% per month; RMSE_{M} that beat the RMSE_{RW} are in italics, as are cases where the RW is superior. The average RMSE_{RW} exceeds the RMSE_{M} by 5.817%, 5.995%, 5.562%, 4.911%, 4.030%, and 2.918% across adjustment speeds from 2.5% to 0.50% per month as the row RW/MR shows. In seven of the eight forecast periods, some mean reversion model beats the RW model.

For the first two forecast periods, the mean reversion model significantly outperforms the RW model for all adjustment speeds. Results are not significant for the other six periods; in particular, the RW model never significantly outperforms the mean reversion model. For a given forecast period, results are positively correlated across adjustment speeds. Thus, the six results for the first forecast period cannot be interpreted as independent tests. Because forecast periods are overlapping, in principle results are correlated across periods for a given adjustment speed. In practice, the correlations are seen to be modest in Table 3. On balance, the forecast results provide important but not overwhelming support for mean reversion.[23]

Test result significance levels are from exact critical values derived from bootstrap simulations using the sample covariance matrix of the $\Delta \ln S_{i,t}$. A note available from the author discusses the distribution of the test statistic $\text{DR} = \text{RMSE}_{\text{M}}^2 - \text{RMSE}_{\text{RW}}^2$ and the simulation experiments used to find critical values. Standard tests of prediction accuracy, for example, that in Diebold and Mariano (1995), cannot be used because they require both models' forecast errors to be stationary: under the unit root null, the mean reversion error is non-stationary.

A. Speed of Adjustment

Results in Table 3 provide evidence on the speed of adjustment. Across all forecast periods, speeds of 2.5% and 1.5% per month give the best performances in the sense of minimizing forecast errors. Intuitively, adjustments of 1.5% to 2.5% per month seem slow, but slow adjustment does not imply that nominal rates do a poor job equilibrating the system. Judging whether adjustment speeds are too slow requires a benchmark—presumably, the optimal speed of adjustment. The literature, however, contains no estimates of optimal adjustment speed. For comparison, Siddique and Sweeney find that 2.5% per month gives the best performance for real rates in terms of minimizing forecast errors.

For log real rates, Siddique and Sweeney report that for adjustment speeds of 2.5%, 1.5%, and 1.0% per month, the RW/MR are 9.627%, 7.975%, and 6.059%—an average of 7.887%. For log nominal rates and the same adjustment speeds, the average RW/MR is 5.791%. By this measure, the superior performance of nominal rate mean reversion models explains 73.4% [= (5.791/7.887) 100] of the superior performance of real rate mean reversion models.

[23] An appendix available from the author considers whether the mean reversion model works better when the USD is over- rather than undervalued by some criterion; evidence supporting this view is weak.

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B. Economic Importance of Time Variation in Expected Appreciation Rates

Mean reversion effects on expected appreciation can be large when rates are far from their long-run values. Over the 1974–1996 sample period, the maximum and minimum DEM per USD were 3.3225 and 1.3805—in natural logs, $\ln(3.3225) = 1.201$ and $\ln(1.3805) = 0.3224$. The expected depreciation rate at the DEM/USD maximum was $b(1.201 - \ln S_i^*)$, and at the minimum was $b(0.3224 - \ln S_i^*)$, for a difference of $b(1.201 - 0.3224) = b(0.8786)$. At an adjustment speed of 1.5% per month, the difference in expected appreciation of the USD is $0.015 \times 0.8786 = 0.013179$, or 1.3179% per month and 15.815% per year in continuously compounded terms; if the adjustment speed is 2.5% per month, the difference is 26.358% per year. For comparison, the approximate sample standard deviation of DEM/USD appreciation is 12% per year.

These mean reversion effects are not proxies for interest rate differential effects on expected appreciation. If the differential is included as a right-hand side variable in (1) with $p = 0$, and with its coefficients constrained to be equal across countries in some experiments and unconstrained in others, t_b increases in some cases and decreases in others:

Start	1974	1980	1981	1987
— (from Table 1)	−5.1107^{+}	−6.2120***	−7.2753****	−5.5968**
Unconstrained	−5.9591**	−6.1623***	−6.9419****	−5.9285**
Constrained	−5.6696**	−5.5139*	−6.2554***	−5.6908**

****, ***, **, *, $^{+}$ significant at the 0.5%, 1%, 5%, 10%, and 15% levels, respectively.

VI. Conclusions

Conventional wisdom holds that industrial country nominal exchange rates contain unit roots. The unit root hypothesis implies that a large portion of changes in log nominal exchange rates are permanent, on average, and that after relatively minor patterns die out in a month or two, expected appreciation or depreciation is zero. In this paper's SUR tests for G-10 countries' log nominal rates relative to the USD during the current float, the data reject the unit root null at significance levels from 0.5% to 15% across sample periods. Further, out-of-sample forecast tests support mean reversion in nominal rates: mean reversion models almost always beat unit root models, sometimes significantly. In contrast to the conventional view, then, this paper's results imply that expected rates of appreciation or depreciation are often nonzero over substantial time periods.

The estimated difference between the mean reversion model's maximum and minimum expected appreciation of the USD relative to the DEM is between 15% and 26% per year over the sample period. Thus, international applications that ignore mean reversion effects will often misestimate expected appreciation.

Further, rejection of unit roots in G-10 log nominal rates implies substantial interdependence in long-run monetary policies among G-10 countries. If both real and nominal log rates are stationary, then log relative national price levels must be cointegrated. In many monetary models, this implies that log money stocks must

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be cointegrated. Neglecting this long-run monetary interdependence may lead to costly specification errors in international models where inflation and money stock growth rates are important.

Related, in panels that contain countries with high inflation relative to the G-10, the data cannot reject unit roots in nominal exchange rates, even if the real rates show mean reversion. High inflation countries' exchange rates reflect their inflation rates and monetary growth rates, which diverge sharply from the G-10's and cause permanent changes in log price levels and log money stocks relative to the G-10's.

In a simple monetary model that allows for mean reversion in G-10 nominal rates, this paper uses two assumptions that roughly fit reality. First, during the sample period 1974–1996, the U.S. and Germany ran monetary policies jointly consistent with a stable long-run USD-DEM rate. Second, other G-10 countries ran long-run monetary policies aimed at stabilizing their rates relative to either the DEM (as a number of European Union countries did) or the USD (as Canada often did). Intuitively, sometimes Germany was the low inflation, stable, safe harbor country, and sometimes the U.S. was. Because each country's long-term monetary policy kept the other from establishing permanent dominance along these lines, long-run monetary policy in each country was consistent with a stable long-run bilateral nominal rate, and other G-10 countries fell in line.

Appendix 1. As T Grows Large, SUR Tests Have the Asymptotic Properties of the LL and IPS Tests

To start, suppose the $\Delta S_{i,t}$ are generated without serial correlation but with an $N \times N$ positive-definite covariance matrix Ω whose element in the ith row and jth column is $\sigma_{ij} = E(u_{i,t}u_{j,t}) \gtrless 0$ for $i \neq j$. A representative IPS equation is $\Delta S_{i,t} = a_i + b_i S_{i,t} + u_{i,t}$, and under the null, $\Delta S_{i,t} = u_{i,t}$. Because Ω is positive-definite, its $N \times N$ inverse Ω^{-1} exists and there exists a positive-definite $N \times N$ matrix P, such that $P'P = \Omega^{-1}$ (Hamilton (1994), Theil (1971)), with $P_{i,j}$ the element in the ith row and jth column of P. Form the $N \times 1$ column vectors ΔS_t and S_{t-1} for each period $t = 1, T$, with the ith elements $\Delta S_{i,t}$ and $S_{i,t-1}$. Pre-multiply these vectors by P to give the $N \times 1$ column vectors $P\Delta S_t$ and PS_{t-1}. This generates new time series $\Delta s_{i,t}$ and $s_{i,t-1}$, where $\Delta s_{i,t} = \sum_{j=1}^{N} P_{i,j}\Delta S_{j,t}$ and $s_{i,t-1} = \sum_{j=1}^{N} P_{i,j}S_{j,t-1}$. The correlation matrix for the N series $\Delta s_{i,t} = \varepsilon_{i,t}$ is $\Omega_1 = \sigma^2 I$, where σ^2 is the common variance and I is the order-N identity matrix (Hamilton (1994), pp. 315–318). The IPS model is now

$$\text{(A.1)} \qquad \Delta s_{i,t} = s_{i,t} - s_{i,t-1} = a_i + b_i s_{i,t-1} + \varepsilon_{i,t}, \quad \varepsilon_{i,t} \sim \Omega_1 = \sigma^2 I, \quad i = 1, \ldots, N,$$

where $a_i = b_i = 0$ under the null.

Consistent Estimator of Ω. Ω is unknown. If $\hat{\Omega}$ is a consistent estimator of Ω, as $T \to \infty$ then $\hat{\Omega} \to \Omega$, and asymptotically the LL and IPS assumptions hold and their results are valid. One estimator $\hat{\Omega}$ is the sample covariance matrix of the $\Delta S_{i,t}$. Under the unit root null, and with all $p_i = 0$, so that $\Delta S_{i,t} = u_{i,t}$, this estimator is consistent. If $p_i \geq 0$, and

$$\text{(A.2)} \qquad \Delta S_{i,t} = a_i + b_i S_{i,t-1} + \Sigma_{j=1}^{pi} c_j \Delta S_{i,t-j} + u_{i,t} \qquad i = 1, \ldots, N,$$

is estimated with all $b_i = 0$, the residual covariance matrix is a consistent estimator of Ω.

Using the Consistent Estimator $\hat{\Omega}$ in SUR. Instead of transforming the series, the same estimates are obtained by using the consistent estimator $\hat{\Omega}$ in generalized least squares,

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in this case SUR. As a practical matter, experiments show that the results are virtually unchanged whether $\hat{\Omega}$ is the covariance matrix of the $\Delta S_{i,t}$ or is the SUR residual covariance matrix. This is to be expected because the SUR residual covariance matrix is consistent as $T \to \infty$ under both the null and the alternative.

Appendix 2. Power of the Tests

The t_b test statistic has substantial power against the null that all log nominal rates are $I(1)$. Further, the text's rejections are much more likely if all rather than some rates are $I(0)$.

For power experiments, data are generated to correspond to the 1974:01–1996:12 sample period, where the error covariance matrix in the DGPs is the sample covariance matrix of the $\Delta \ln S_{i,t}$, and all $c_{i,j} = 0$ in the DGP (see relevant footnotes in text). For the generated data, tests results are evaluated with the text's critical values for $p = 0$.

Results are shown for cases where $I(0)$ series have a root of 0.95, 0.975, and 0.985, corresponding to adjustment speeds of 5.0%, 2.5%, and 1.5% per month; the results in Section IV suggest adjustment speeds of 2.5% or 1.5%. Results are also shown for the case where a single currency has a unit root, either the Belgian Franc to represent European Union currencies with high correlations (Belgium, Germany, and the Netherlands), or the U.K. pound.

Power When All Currencies Are $I(0)$. Table A-1 shows the percentage of cases in which the unit root null is rejected. For all roots equal to 0.95, the t_b test rejects in 100.0% of the cases at all significance levels. For roots of 0.985, at the 10% significance level the t_b test rejects in 80.33% of the cases. The table also shows results for the case where the roots vary around a grand mean, ρ, with the first root equal to $\rho - 0.1$, the second equal to $\rho + 0.1$, etc. Power tends to fall off as compared to the cases where all roots are equal, but remains substantial.

Power When Some Currencies Are $I(1)$. If the null that all currencies are $I(1)$ is false, the observer may care whether all currencies or only a subset are $I(0)$. Sarno and Taylor (1998) use a Wald test of the null that all currencies are $I(1)$, and a Johansen test of the null that at most one of the currencies is $I(1)$. Karlsson and Löthgren (2000) use simulation to examine the power of systems tests against the null that all series are $I(1)$ when only some are $I(1)$.

Table A-1 shows the percentage of cases in which the null that all currencies are $I(1)$ is rejected, when the truth is that only the Belgian Franc is $I(1)$—ceteris paribus, systems tests are most likely to reject when only one currency is $I(1)$, rather than several. The other nine countries all have roots of 0.95, 0.975, or 0.985. For roots of 0.95, the t_b test rejects the null at the 5% significance level in 23.10% of cases, versus 100% when all roots are $I(0)$. As expected, the fraction of rejections declines as the roots increase. For roots of 0.985, at the 5% level the test rejects 10.35% versus 64.50% when all roots are $I(0)$.

When the single unit root currency is the pound, Table A-1 shows the percentage of rejections for the case where the other currencies have a root of 0.985. At the 5% level the test rejects in 38.81% of the cases as compared to 10.35% when the Belgian Franc has the unit root. In general, if the single unit root currency is among the highly correlated EU currencies (Belgium, Germany, and the Netherlands), the test seldom rejects; the test rejects more frequently if the single unit root currency in not among these three EU currencies.

In Table 1 in the text, the test rejects the null in five cases at the 0.5% level for $p = 0$, 1. From Table A-1, these rejections seem unlikely for large roots, say 0.985, if even one rate is $I(1)$.

Treatment of Lagged Coefficients in the DGP. The following discussion shows how the choice of p and treatment of the lagged coefficients $c_{i,j}$ in the DGP affect results. In these experiments, $p_i = p = 1$ in the DGP, and the DGP uses the estimated coefficients for a lag of 1 ($\hat{c}_{i,1} \neq 0$), means of zero ($a_i = 0$), and a root of 0.985 (results are available for 0.950 and 0.975) On the simulated data, the ADF system (1) is estimated with $p =$

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0, 1, . . . , 12, etc. In judging the results, the critical values used are found from simulations with $a_i = b_i = c_{i,j} = 0$ in the DGP. For comparison purposes, for $p = 1$ the critical values are also found with $a_i = b_i = 0$ but $c_{i,1} = \hat{c}_{i,1} \neq 0$ in the DGP.

The results for $b = 0.985$ illustrate general patterns. If the true p is p^*, then in simulations where $p = p^*$, power is substantial. Here with $p^* = 1$, the null is rejected in 83.35% of the cases at the 10% level when the critical values are found with $c_{i,1} = 0$ in the DGP, and in 82.25% of the cases when the critical values are found with $\hat{c}_{i,1} \neq 0$ in the DGP. It appears that with such low estimated values of $c_{i,j}$, for finding critical values, it does not matter whether the DGP uses estimated values of $c_{i,j}$ or sets $c_{i,j} = 0$. From Table A-2, in simulations where $p < p^*$ (that is, $p = 0$), the power is exaggerated for significance levels of 0.5% and 1.0%, but is adversely affected for levels of 5% and 10%. In simulations where $p > p^*$ (that is, $p = 2$), power is adversely affected. Thus, it is important to choose a large enough p so that the test's size is accurate but power is not needlessly reduced.

Sample Means in the DGP. Table A-3 compares the critical values found when the DGP is $\Delta \ln S_{i,t} = u_{i,t}$ with those found when the DGP is $\Delta \ln S_{i,t} = \hat{a}_i + u_{i,t}$, where the $\hat{a}_i$ are the sample means for the 1974:01–1996:12 period. The critical values fall substantially in absolute value when sample means are included in the DGP, and the null is much more likely to be rejected. The text takes the more conservative position of using critical values found in simulations where the DGP has zero means.

TABLE A-1

Power of the System Test
(percentage of rejections (10,000 replications), $p = 0$)

	No Unit Roots			Root = $\rho \pm 0.1$		One Unit Root: Belgium			One Unit Root: U.K.
Roots	0.95	0.975	0.985	0.975	0.985	0.95	0.975	0.985	0.985
Sig. Level									
0.5%	100.0	78.55	21.55	71.25	34.77	12.78	6.240	2.320	10.61
1%	100.0	86.23	29.83	75.13	38.25	15.08	8.050	3.610	16.13
5%	100.0	97.94	64.50	83.83	49.62	23.10	16.01	10.35	38.81
10%	100.0	99.43	80.33	87.71	56.43	27.90	21.12	15.72	52.83

TABLE A-2

Power When $c_{i,j} = 0$ and When $c_{i,1} = \hat{c}_{i,1} \neq 0$

$b = 0.985$	$p_i = p$/	0^a	1^a	1^b	2^a
	Significance Level	Percentage of Cases Rejected			
	0.5%	25.51	23.16	22.48	21.15
	1%	34.19	30.31	35.40	31.62
	5%	66.47	67.54	68.61	65.97
	10%	81.33	83.35	82.25	82.07

[a] $a_i = b_i = c_{i,j} = 0$. [b] $a_i = b_i = 0$, $\hat{c}_{i,1} \neq 0$.

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TABLE A-3

Critical Values: DGPs with Zero Means ($a_i = 0$); DGPs with Sample Means ($\hat{a}_i \neq 0$)

	Means Equal Zero	Sample Means
0.5%	−6.293072	−5.127561
1%	−6.081252	−4.885833
5%	−5.514822	−4.218519
10%	−5.204722	−3.824502
15%	−4.987682	−3.592897

Notes: Tables A-1, A-2, and A-3 show results for various issues that relate to power. Table A-1 shows power that corresponds to different values of dominant roots less than unity. For Table A-1, the log nominal rate changes are generated as $\Delta \ln S_{i,t} = (\rho_i - 1) \ln S_{i,t-1} + u_{i,t}$, where ρ_i is the root for i and $u_{i,t}$ is an error. In the DGP, the error covariance matrix is the same as for the $\Delta \ln S_{i,t}$ in the sample for 1974:01 to 1996:12. Slopes are found by estimating the systems $\Delta \ln S_{i,t} = a_i + b \ln S_{i,t-1} + u_{i,t}$. In Table A-1, $\rho_i = 0.950, 0.975, 0.985$ is the common root. In one set of experiments, Belgium has a unit root with log nominal rate changes generated as $\Delta \ln S_{\text{Bel},t} = u_{\text{Bel},t}$, and similarly for the case where the U.K. has the only unit root. In another experiment, the grand mean root is $0 < \rho < 1$. Roots alternate from $\rho - 0.01$ for the first country, to $\rho + 0.01$ for the second, etc. For $\rho = 0.975$, the first root is 0.965, etc.

Table A-2 addresses the issue of how the critical values differ when the DGP does or does not use estimated lagged slopes from $\Delta \ln S_{i,t} = a_i + b \ln S_{i,t-1} + c_{i,1} \Delta \ln S_{i,t-1} + u_{i,t} (i = 1, 10)$. The critical values in the cases $a_i = b_i = c_{i,j} = 0$ and $a_i = b_i = 0$, $\hat{c}_{i,1} \neq 0$ are

0.5%	−6.3278	−6.3408	5%	−5.5366	−5.5174;
1.0%	−6.1797	−6.0855	10%	−5.1858	−5.2119.

In Table A-3, critical values are shown for the DGPs $\Delta \ln S_{i,t} = u_{i,t}$, and $\Delta \ln S_{i,t} = \hat{a}_i + u_{i,t}$, where the $\hat{a}_i$ are sample means.

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