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Long-Horizon Exchange Rate Predictability?

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Abstract

Several authors have recently investigated the predictability of exchange rates by fitting a sequence of long-horizon error-correction regressions. By considering the implied vector error-correction model, we show that little is to be gained from estimating such regressions for horizons greater than one time period. We also show that in small to medium samples the long-horizon procedure gives rise to spurious evidence of predictive power. A simulation study demonstrates that even when using this technique on two independent series, estimates, diagnostic statistics and graphical evidence incorrectly suggest a high degree of predictability of the dependent variable.

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SUMMARY

The importance to applied economists of having statistical tools that can reliably test for the presence of long-run predictability in time-series data can hardly be overstated. One such technique has gained prominence because of its apparent success in uncovering long-run relationships in international financial data. Recently, Mark (1995), Chinn and Meese (1995), and Bauer (1995), applied the long-horizon regression approach to investigate whether economic fundamentals have predictive power for exchange rates.

The regressions employed by Mark and Chinn and Meese contain an error-correction term for spot rates and monetary fundamentals. Their analysis thus assumes that spot rates and fundamentals cointegrate. This paper uses the bivariate error-correction model that is implied by this assumption to show that little may be gained from long-horizon regressions. In particular, if the slope coefficient of the one-period-ahead regression is zero, then the slope coefficients must be zero for all horizons; on the contrary, if the estimated one-period-ahead coefficient is not zero, then estimated coefficients increase as the horizon increases.

This paper further explores the conjecture that the existing evidence of long-run exchange rate predictability may be an artifact of the statistical technique. It shows that if spot exchange rates were independent of economic fundamentals, then long-horizon regressions would behave like spurious regressions. As a result, the finding of increasingly strong relationships at long horizons may not be evidence of an economic relationship.

Several simulation experiments are conducted in which two independent time series are generated, one modeled after quarterly exchange rates and the other after monetary fundamentals as in Mark and Chinn and Meese. The results confirm that several diagnostic statistics, such as *t*-statistics and R^2, are increasingly biased away from zero for longer horizons of interest. Finally, the paper finds that even the graphical evidence of strong predictability over long horizons is misleading.

I. INTRODUCTION

The importance to applied economists of having statistical tools which can reliably test for the presence of long-run predictability in time series data can hardly be overstated. One such technique has gained prominence in recent years because of its apparent success in uncovering long-run relationships in international financial data. Recently, Mark (1995), Chinn and Meese (1995) and Bauer (1995) applied the long-horizon regression approach to investigate whether economic fundamentals have predictive power for exchange rates. Earlier applications of this methodology include the study of equity return predictability (e.g., Fama and French (1988) and Campbell and Shiller (1988)) and inflation and interest rate predictability (e.g., Fama (1990) and Campbell and Shiller (1991)).

The regressions employed by Mark (1995) and Chinn and Meese (1995) contain an error-correction term for spot rates and monetary fundamentals. Their analysis thus assumes that spot rates and fundamentals cointegrate. We use the bivariate error-correction model which is implied by this assumption to show that little may be gained from long-horizon regressions. In particular, if the slope coefficient of the one period ahead regression is zero then the slope coefficients must be zero for all horizons.

Furthermore, we explore the conjecture that the existing evidence of long-run exchange rate predictability may be an artifact of the statistical technique. We show that if spot exchange rates were independent of economic fundamentals, then long-horizon regressions behave like spurious regressions. As a result, the finding of increasingly strong relationships at long horizons may not be evidence of an economic relationship.

We conduct several simulation experiments in which we generate two independent time series, one modeled after quarterly exchange rates and the other after monetary fundamentals as in Mark (1995) and Chinn and Meese (1995). The results confirm that several diagnostic statistics, such as t-statistics and R^2, are increasingly biased away from zero for longer horizons of interest, casting doubt on the reliability of inference from long-horizon regressions.

The remainder of this paper proceeds as follows. In Section II, we discuss the long-horizon regression methodology as commonly applied to monetary models of exchange rate dynamics. In Section III, we describe the results of the Monte Carlo experiments. Section IV discusses the estimation results of Mark (1995) in the context of our Monte Carlo critical values. Section V concludes.

II. LONG-HORIZON REGRESSIONS

The long-horizon regression approach entails estimating K individual equations,

$$\Delta^k s_{t+k}=\alpha_k+\beta_k z_t+\epsilon_{k,t}, \qquad k=1,\ldots,K, \tag{1}$$

where s_t and z_t are observed data, Δ^k is the k^{th} difference operator and α_k and β_k are the parameters to be estimated. If the β_k's, the associated t-statistics and the regression R_k^2's are found to increase with k, the researcher takes this as evidence that z_t can predict long-run changes in s_t better than short-run movements.

In the context of monetary models of exchange rate dynamics, Mark (1995), and Chinn and Meese (1995) estimate the following equations:

$$\Delta^k s_{t+k}=\alpha_k+\beta_k(f_t-s_t)+\epsilon_{k,t}, \qquad k=1,..,K, \tag{2}$$

where s_t is the log spot rate, $f_t=(m_t-m_t^*)-(y_t-y_t^*)$, m_t and y_t denote the log of M1 and of real GDP, respectively, and asterisks represent foreign quantities.[1]

This error-correction representation is motivated by the assumption that exchange rates cannot move independently of macroeconomic fundamentals over long time horizons. According to specification (2), if $\hat{\beta}_k>0$ and the error-correction term (f_t-s_t) is, for example, positive, the spot rate is expected to raise in the future. Such predictable movements contrast with the conventional view that floating exchange rates are best characterized by a driftless random walk (among others, Meese and Rogoff (1983), (1988), and Diebold and Nason (1990)). In light of this fact, specification (2) can be thought of a test of whether the inclusion of monetary fundamentals can beat the random walk forecast.

A. What Do We Learn from Estimating Long-Horizon Regressions?

Estimation of the long-horizon regressions (2) implicitly assumes that nominal exchange rates and monetary fundamentals cointegrate with cointegrating vector [1 -1]'.

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[1]Bauer (1995) estimates a multivariate regression, where the dependent variable is the (multiperiod) ex post excess return from forward speculation and the independent variables are an intercept term, the slope of the term-structure of interest rates in the foreign country, the dividend yield in the foreign country and the forward premium.

This implies, by the Granger representation theorem, the following Vector Error-Correction Model (VECM):[2]

$$\begin{aligned}\Delta s_{t+1} &= \lambda_1(f_t - s_t) + \omega_{1,t} \\ \Delta f_{t+1} &= \lambda_2(f_t - s_t) + \omega_{2,t}.\end{aligned} \tag{3}$$

Stationarity of the error correction term (f_t-s_t) requires that at least one of the loading coefficients, λ_1 or λ_2, be different from zero and that λ_2-λ_1,<0. In general, the error terms $\omega_{1,t}$ and $\omega_{2,t}$ need not be identically and independently distributed.

Again letting z_t=(f_t-s_t), it is easy to show that z_t=ρz_{t-1} +ω_t , where ρ=(1+λ_2-λ_1) and ω_t= $\omega_{2,t}$-$\omega_{1,t}$. Exploiting the autoregressive structure of the z-process, we can write z_{t+k}=$\rho^k z_t$+ξ_{t+k}, with $\xi_{t+k}=\sum_{j=1}^{k}\rho^{k-j}\omega_{t+j}$. Hence, the k-change in the log spot rate can be rewritten as:

$$\Delta^k s_{t+k} = [\lambda_1(\tfrac{1-\rho^k}{1-\rho})](f_t - s_t) + \sum_{j=1}^{k-1}(\lambda_1\xi_{t+j} + \omega_{1,t+j}) + \omega_{1,t+k}, \qquad k=1,..,K. \tag{4}$$

Several considerations emerge by comparing the long-horizon regression (2) with equation (4), i.e., the implied long-horizon regression from the VECM.

First, β_1=λ_1, so that:

$$\beta_k = \beta_1 \frac{1-\rho^k}{1-\rho}. \tag{5}$$

This implies that if β_1=0, then β_k=0 for all k>1. If the hypothesis β_1=0 is not rejected, nothing seems to be gained by estimating the long-horizon regressions for k>1.

Second, when z_t is positively autocorrelated (when ρ>0), if $\beta_1 \neq 0$, then β_k>β_1 for all k>1. The increase in the estimated slope parameters of long-horizon regressions when k grows large, a fact often observed in practice, is not surprising at all and does not imply that fundamentals have a stronger impact on exchange rates at long more than at short horizons.

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[2]The drift components are omitted from the VECM for simplicity.

Instead, the increase in β_k's simply reflects the positive sign attached to the term $\frac{1-\rho^k}{1-\rho}$ and its direct dependence on k.[3]

Lastly, the VECM representation (3) clarifies the nature of the null and alternative hypotheses of the testing procedure suggested by Mark (1995) and Chinn and Meese (1995). Testing the null hypothesis β_k=0, for all k's, in equation (2) is equivalent to testing the hypothesis that the spot rate is weakly exogenous for the cointegrating vector in the system (3), i.e., that λ_1=0.[4] This would imply that, although there is a long-run relationship between s_t and f_t, knowledge of the history of the fundamentals will not be helpful in predicting future values of the spot rate, no matter how long is the prediction horizon.[5]

The alternative hypothesis $\lambda_1 \neq 0$ corresponds to a situation in which the spot rate is not weakly exogenous for the cointegrating vector, so that knowledge of the history of f_t will be helpful in formulating forecasts of s_t. However, to construct valid multi-step forecasts of s_t from long-horizon equations, it is necessary that the spot rate does not feedback into the equation for the fundamentals in system (3), (i.e., that f_t is strongly exogenous).[6] Unfortunately, estimation of the long-horizon regression alone does not reveal anything regarding the exogeneity status of the fundamentals.

To summarize, given that exogeneity of f_t or s_t cannot, in general, be ruled out a priori, it seems more appropriate to start a predictability analysis for the spot rate by estimating the full joint model (3), within which the cointegration and exogeneity status of the variables can be easily checked. To illustrate, we present estimates of λ_1 and λ_2 in

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[3]The present discussion deliberately ignores the power of the t-test associated with β_k. Under the alternative hypothesis, β_k increases with k, that is, the alternative hypothesis moves away from the null. Thus, the probability of rejecting a false null will increase with k, producing the impression of higher power of the associated t-test for large k's. However, a proper power comparison requires that the alternative is kept fixed. A priori, it is not clear what the power properties of the t-tests on β_k will be after accounting for the difference in the alternative hypotheses. In the present context, a power comparison would be further complicated by the presence of severe size distortions in the t-tests, a point well documented for large k's, by the simulation experiments of the next section. We are grateful to Hashem Pesaran for these insights.

[4]For a review of definitions and testing procedures of weak exogeneity in cointegrated systems see Ericsson (1992) or Johansen (1992).

[5]This is true only if the spot rate does not possess, under the null, significant short-run dynamics, i.e., if $\omega_{1,t}$~WN (the innovation is white noise).

[6]See, for example, Ericsson (1992).

Columns 1-2 of Table 1, using the same data as Mark (1995).[7] The associated Horvath and Watson (1995) test statistics for cointegration with a known cointegrating vector of [1 -1]' are displayed in Column 3. For the sample considered by Mark, we cannot reject the joint hypothesis that both $\lambda_1=0$ and $\lambda_2=0$ for any of the four exchange rates. Equivalently, the null that cointegration fails cannot be rejected for the four leading dollar spot rates. Had we assumed cointegration and proceeded to estimate the *single* error-correction equation for spot rates, we would have found fairly large t-statistics (displayed in parentheses) for three out of four spot rates. In fact, we would have incorrectly concluded that the λ_1 for the Swiss franc is significantly different from zero at the 90 percent confidence level. As shown in Section III, if cointegration fails the right-hand-side variable is nonstationary and the correct asymptotic critical values are of the unit root type (and hence higher).

Other authors have had similar difficulty in finding support for the hypothesis that spot rates and fundamentals cointegrate (e.g., Gardeazabal and Regúlez (1992) and MacDonald and Marsh (1995)). Indeed, Mark (1995) and Chinn and Meese (1995) themselves are unable to reject the null hypothesis that z_t is nonstationary for any of four exchange rates considered. In the remainder of this comment, we therefore focus on the null hypothesis that the two series are statistically unrelated (i.e., cointegration does not hold).

B. Econometric Problems Associated with Long-Horizon Regressions

In this section, we discuss the difficulties that may arise when making inference from long-horizon regressions, especially in presence of small samples and large k's. The discussion is organized around three main points.

First, the regressor in equation (2), z_t, is highly positively autocorrelated and is not orthogonal to all leads and lags of the residual, $\epsilon_{k,t}$. As such, the least squares (LS) estimate of the slope parameter, $\hat{\beta}_k$, is consistent but biased away from zero in small samples.[8] Even a small bias in $\hat{\beta}_k$ may, in turn, lead to a severe bias in the associated t-ratio. This amplification occurs because both the accuracy of the numerator and the denominator of the t-ratio depend on the precision of the estimate of β_k. The empirical distribution of the t-statistics will be shifted away from zero and skewed, regardless of the horizon considered. Indeed, when the regressor is highly persistent, the distribution of the t-statistics would be better approximated by the distribution of the Dickey-Fuller t-test, than by the usual asymptotic Gaussian counterpart (see Stambaugh (1986)). The correct small-sample critical values for a t-test of β_k

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[7]The data were kindly provided to us by Nelson Mark. For a description of the sources see Section IV.

[8]See Mankiw and Shapiro (1986), Stambaugh (1986), and Nelson and Kim (1993). The bias is an increasing function of the degree of autocorrelation of the regressor and of the size of the covariance between the innovation of the regressor and the error term of the estimated equation.

Table 1. Estimates of Vector Error-Correction Model

	λ_1	λ_2	Wald (HW)
Canadian Dollar	0.033 (1.54)	-0.015 (-1.23)	4.594
German Mark	0.033 (0.90)	0.003 (0.31)	0.879
Japanese Yen	0.063 (1.57)	-0.004 (-0.45)	2.745
Swiss Franc	0.073 (1.85)	-0.013 (-1.62)	6.491

Notes: The table presents estimated slope coefficients, λ_1 and λ_2, of the vector error-correction system (3) with t-statistics in parentheses. For each regression, the number of lagged dependent variables is selected by the BIC. Wald(HW) refers to the Horvath and Watson (1995) test statistic for cointegration with a known cointegrating vector. For the bivariate system under consideration, the 90 percent critical value is 6.63 and 95 percent critical value is 8.47.

in the long-horizon regression (2) will, in general, be very different (typically, higher) from the asymptotic ones.

Second, a careful examination of equation (4), the implied long-horizon regression from the VECM, reveals the presence of a moving average process of order k-1 in the error term, as always in regressions with overlapping observations. Thus, the least squares standard errors will be inconsistent.

Third, and most important, if there is no statistical relationship between s_t and f_t, the long-horizon regressions become 'close' to a classical spurious regression as k increases. To see this, note that if the exchange rate is well approximated by a random walk, then we may write $s_t=\sum_{i=1}^{t}\eta_i$, where $\eta_i \sim WN(0,\sigma_\eta^2)$, so that equation (2) becomes:

$$\sum_{i=t+1}^{t+k}\eta_i=\alpha_k+\beta_k(f_t-s_t)+\epsilon_{k,t}, \qquad k=1,..,K. \qquad (6)$$

For large k the dependent variable is itself approximately a random walk. Since the right-hand-side variable is highly persistent, one might reasonably expect to find that this regression behaves like a true spurious regression.[9] These observations cast doubt upon the reliability of inference from the long-horizon regression methodology.

The usual asymptotic inference associated with long-horizon regressions is thus likely to be misleading, especially with small samples and large k's. The main problems are the presence of a very persistent stochastic regressor, autocorrelation in the residuals and high persistence of the left-hand-side variable (for k large).

Mark (1995), Chinn and Meese (1995) and Bauer (1995), following an established practice in the stock-return predictability literature (see, for example, Hodrick (1992)), attempt to correct for these problems by generating bootstrap (Monte Carlo) critical values for the diagnostic statistics associated with regression (2). For example, in Mark (1995), pseudo-data are generated by fitting a restricted vector autoregression for the change in the exchange rate and the error-correction term, $(\Delta s_t, z_t)$. Mark thus conditions on the stationarity of z_t. In Section III, we conduct a Monte Carlo experiment where s_t and f_t are not cointegrated so that z_t is nonstationary. In practice, this difference in the stationarity status of z_t results in very different empirical critical values. Mark's bootstrapped empirical

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[9]Phillips (1986) shows that, for a true spurious regression, conventional t-statistics diverge as the sample size grows (there are no asymptotically correct critical values). The slope parameter of a bivariate spurious regression is shown to possess a degenerate limiting distribution, while the estimate of the intercept diverges. The R^2 converges to a random variable.

distributions will produce critical values which are 'too small,' and he will err on the side of significance (see Section 4).[10] Even if z_t were stationary, Mark's bootstrap is likely to be very unreliable without suitably bias-correcting the initial slope coefficients on the lags of z_t, given the presence of persistent stochastic regressors (see, e.g., Kilian (1995)).

III. Simulation Experiment

The existing empirical evidence, discussed in Section II, is not supportive of the hypothesis of cointegration between exchange rates and fundamentals. Therefore, we emphasize that the appropriate null hypothesis associated with estimation of equation (2) is the independence of the two time series. Our simulation experiment investigates the small sample distribution of conventional diagnostic statistics associated with long-horizon regressions, when the two series are statistically unrelated (i.e., cointegration does not hold).

We generate independent Gaussian random variables, s_t and f_t, with the relative variances of the innovations of the two processes calibrated to quarterly U.S. and German data. The exchange rate is modeled as a random walk and the fundamental as an AR(2) with persistence parameters, 1.25 and -0.305.[11] This choice for the fundamental was made by fitting ARMA models to the actual U.S.-German data for the period from 1973:2 to 1991:4, with the BIC selecting the lag orders. We generate 2000 Monte Carlo iterations. For each Monte Carlo dataset, the long-horizon regressions (equation 2) are run and the associated diagnostic statistics are computed for k=1, 4, 8, 12 and 16. The results are presented in Table 2, panel A. Column 3 displays the median, 90th percentile and 95th percentile of the estimated slope coefficients across Monte Carlo trials for each horizon of interest. Despite the independence of the series, the median $\hat{\beta}_k$ rises with k to a maximum of 0.760 for k=16. The associated naive LS t-statistics displayed in column 4 also increase with the horizon. Columns 5 and 6 display t-statistics corrected for autocorrelation with a truncation lag of 20 and with Andrews' (1991) rule (labeled t(20) and t(A), respectively). Again, as the horizon increases so do median values of the slope coefficient's t-statistics. The right-shift of the empirical distribution of the t-statistics inflates the empirical critical values. For example, when k=16 the one-sided empirical 95th percentile for t(A) is 9.06 instead of 1.64, i.e., the corresponding asymptotic critical value from a Gaussian distribution.

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[10]Mark (1995) reports that his empirical critical values are not sensitive to the size of the largest autoregressive root estimated for the z-process. However, Stambaugh (1986), Mankiw and Shapiro (1986) and Hodrick (1992) find such sensitivity in their Monte Carlo experiments.

[11]In a second experiment, we generated both Monte Carlo series as random walks. The results were nearly identical.

Table 2. Long-Horizon Monte Carlo Estimates: Random Walks and Independent AR(2)

k	Percentile	$\hat{\beta}_k$	t(LS)	t(20)	t(A)	R_k^2	OUT/RW	DM/(20)	DM(A)
Panel A: Sample Size = 1076									
1	50	0.056	1.521	2.226	1.604	0.032	1.023	-1.063	-0.850
	90	0.144	2.570	4.209	2.810	0.086	0.987	0.843	0.548
	95	0.175	2.925	5.084	3.290	0.109	0.972	1.802	1.023
4	50	0.222	3.090	2.626	2.003	0.125	1.096	-1.133	-0.981
	90	0.505	5.434	5.484	4.654	0.306	0.938	1.175	0.881
	95	0.610	6.171	6.864	5.584	0.362	0.890	2.312	1.590
8	50	0.428	4.572	3.187	3.038	0.250	1.179	-1.186	-1.078
	90	0.850	8.011	7.024	6.429	0.505	0.868	1.530	1.188
	95	0.960	9.084	8.453	7.641	0.567	0.786	2.712	2.023
12	50	0.614	5.520	3.702	3.697	0.341	1.215	-1.240	-1.114
	90	1.075	9.943	8.497	8.109	0.626	0.818	1.831	1.423
	95	1.216	11.48	10.68	9.524	0.691	0.724	2.798	2.006
16	50	0.760	6.352	4.110	4.106	0.424	1.205	-1.299	-1.100
	90	1.270	11.75	9.522	9.059	0.715	0.746	2.387	1.862
	95	1.380	13.58	12.28	10.74	0.770	0.664	3.546	2.427
Panel B: Sample Size = 1076									
1	50	0.004	1.509	1.564	1.515	0.002	1.002	-0.974	-0.979
	90	0.010	2.446	2.532	2.472	0.006	0.999	0.598	0.536
	95	0.012	2.728	2.942	2.775	0.007	0.998	0.984	0.893
4	50	0.016	3.055	1.617	1.622	0.009	1.007	-0.989	-0.985
	90	0.038	4.891	2.696	2.719	0.022	0.997	0.602	0.602
	95	0.048	5.473	3.080	3.131	0.027	0.993	1.077	1.077
8	50	0.032	4.374	1.698	1.705	0.018	1.015	-1.012	-0.971
	90	0.076	6.989	2.830	2.859	0.044	0.993	0.598	0.609
	95	0.092	7.768	3.211	3.328	0.054	0.986	1.117	1.162
12	50	0.048	5.274	1.802	1.768	0.026	1.022	-1.047	-0.967
	90	0.113	8.611	2.970	3.003	0.065	0.989	0.609	0.624
	95	0.136	9.585	3.375	3.444	0.080	0.979	1.115	1.218
16	50	0.064	6.123	1.900	1.791	0.034	1.030	-1.066	-0.952
	90	0.150	10.01	3.116	3.100	0.087	0.987	0.613	0.614
	95	0.187	11.18	3.582	3.686	0.106	0.972	1.141	1.218

Notes: The table presents estimated slope coefficients, $\hat{\beta}_k$, for equation (2) with the LS t-statistics, heteroskedasticity and autocorrelation-corrected t-statistics using a Bartlett kernel and a truncation lag of 20 and Andrews' (1991) rule, respectively, t(LS), t(20) and t(A). OUT/RW denotes the ratio of regression mean-squared out-of-sample forecast error to the random walk mean-squared out-of-sample forecast error. DM(20) and DM(A) denote the Diebold-Mariano statistics with a Bartlett kernel and truncation lags of 20 and truncation via Andrews' (1991) rule, respectively.

Column 8 of Table 2, panel A, displays the ratio of root-mean-squared error for out-of-sample regression forecasts over root-mean-squared error implied by the random walk model. Thus, for values below 1 the regression appears to deliver more accurate forecasts than the benchmark random walk.[12] As k increases, the finite sample distribution of this statistic becomes more fat-tailed. This is due in good measure to the fact that as k increases, the number of forecast observations decreases. As a result, empirical critical values decrease dramatically with k.

Columns 9-10 display the Monte Carlo Diebold and Mariano (1995) statistics, again with either a truncation lag of 20 or using Andrews' (1991) rule (labeled DM(20) and DM(A), respectively).[13] For both truncation rules, the median values of the Diebold-Mariano statistics are negative, implying that the random walk forecast beats the regression. Again, the empirical distribution of the DM statistics are fat-tailed for large k. The 95th percentile of the DM(A) increases from 1.02 for k=1 to 2.23 for k=16.

These findings result from the combination of problems which arise with long-horizon regressions, when the two series fail to cointegrate. For example, although we argue that explanatory power appears to increase with k (e.g., high median R_k^2's and high empirical critical values of the t-statistics), there are sizeable distortions even for k=1. These biases arise because of the presence of stochastic and highly persistent regressors. To further complicate matters, the distribution of the estimated slope coefficient would be different if the regression were estimated without a constant term (as in Dickey and Fuller (1979)). However, we report only the results which are relevant for the regressions in Mark (1995), Chinn and Meese (1995) and Bauer (1995) where constants are always estimated.

Such stark results obtain in sample sizes typical of available data. For any fixed and finite k, a long-horizon regression will deliver consistent estimates as the sample size tends to infinity.[14] In panel B of Table 2, we report the results of an identical simulation experiment with a sample size of 1076. Now, the median $\hat{\beta}_k$'s are all lower, but the bias is still sizable for large k; for example, the median of $\hat{\beta}_k$ is 0.064 for k=16. R_k^2 are low and the ratios of RMSE of regression to random walk forecasts are very close to 1 for all horizons. However, the

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[12]At each Monte Carlo trial, the out-of-sample forecasting exercise precisely mimics the procedure in Mark (1995). For a sample size of 76, this results in 40 1-step ahead forecasts and 25 16-step ahead forecasts.

[13]Notice that the values (and empirical critical values) of our Diebold-Mariano statistics are different from Mark's. The difference is due to an unconventional procedure adopted by Mark for estimating the autocovariances (see footnote 8 of Mark (1995)).

[14]However, Richardson and Stock (1989) show that LS estimates of the slope of regressions (2) are inconsistent when the forecast horizon grows with the sample size (so that $k/T \rightarrow \delta$, a constant).

presence of small bias in the LS slope parameters introduces large distortions at all horizons in the empirical critical values of the t-statistics. These distortions do not seem to vanish quickly with the increase in the sample size.

It is important that finite sample inference from long-horizon regressions be assessed by means of empirical distributions of the statistics of interest simulated under the null of no statistical relationship between the series. If standard Gaussian asymptotic theory is adopted, spurious evidence of predictability arises at practically all horizons and regardless of the length of the sample considered.

Lastly, we suggest that even the graphical evidence of predictability presented by Mark (1995) --and reproduced in Figure 1-- may be spurious. In Figure 2, the actual k-period changes in the log dollar/German mark rate is plotted against a regression forecast with *simulated* fundamental data. As with the actual fundamentals, these plots appear to suggest predictive accuracy for longer horizons. Since in Figure 2 the exchange rate is obviously independent of the randomly generated fundamental, we conclude that even the graphical evidence from long-horizon regressions is misleading.

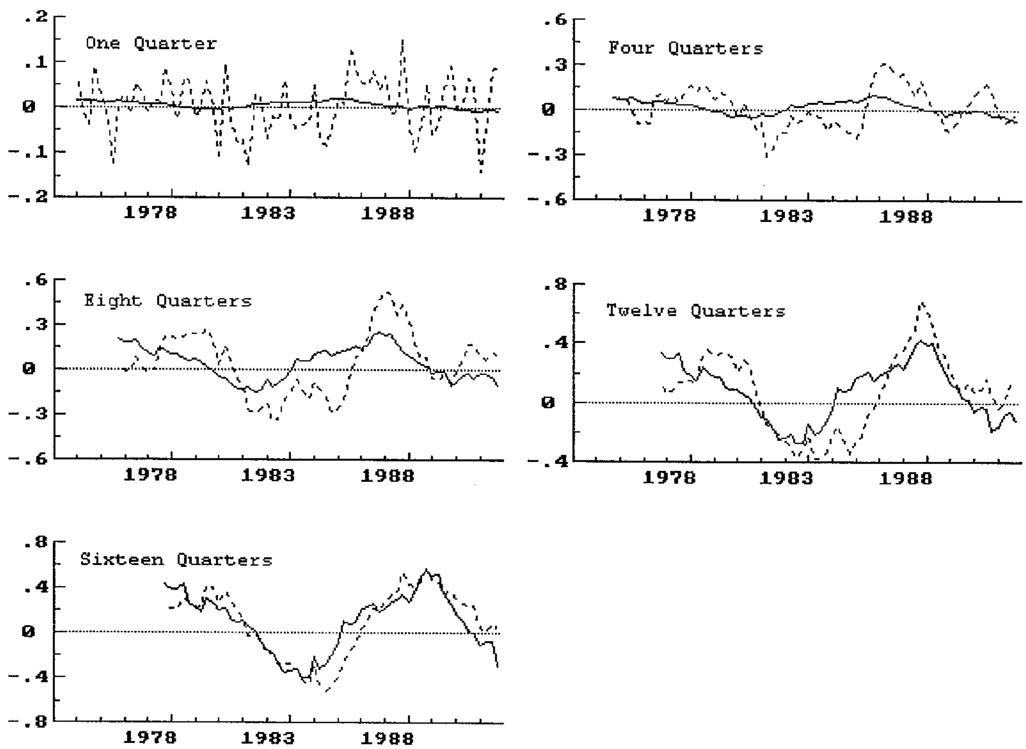
IV. Long-run Exchange Rate Predictability: Mark's (1995) Results Revisited

The Monte Carlo critical values generated under the hypothesis of statistical independence between exchange rates and fundamentals need not be the same as the ones constructed when cointegration between these series is imposed in the design of the simulation, as in Mark (1995). The assessment of the significance of fundamentals in long-horizon regression clearly depends on the critical values adopted. Because of this, in the present section we reconsider Mark's (1995) estimation results of equation (2), with bias-corrections and significance levels calculated from Monte Carlo distributions simulated under the hypothesis of statistical independence between exchange rates and fundamentals, as in the Monte Carlo experiment of Section III. The sample includes Canada, Germany, Japan and Switzerland. The data are quarterly observations collected from the *Main Economic Indicators* of the OECD, from 1973:2 to 1991:4.

Table 3 displays our estimation results. The estimated slope coefficients, t-statistics and R_k^2 are identical to those in Table 2 of Mark (1995). Column 3 displays our bias-adjusted slope estimates. The bias is estimated by our Monte Carlo median. The bias-corrections result in severe reductions in point estimates towards zero. Column 5, labeled p-val, displays the one-sided marginal significance levels associated with the empirical distributions of t(A) from our Monte Carlo.

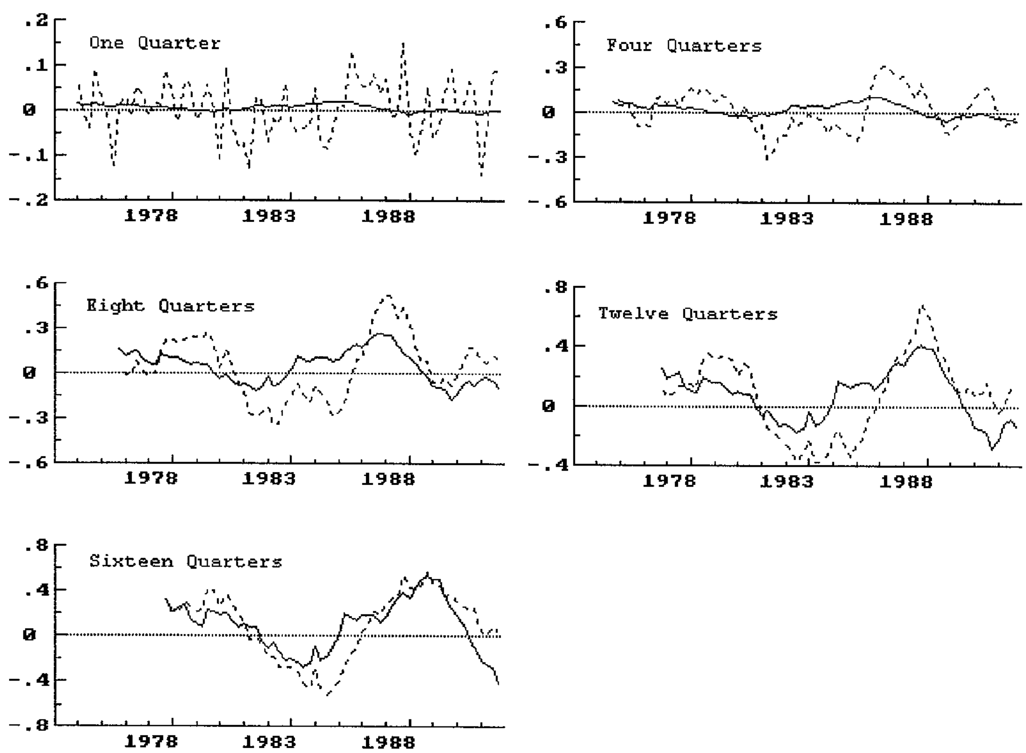
Mark (1995), employing his 95 percent empirical critical values for a one-sided alternative hypothesis (i.e., $\beta_k>0$), finds significant slope coefficients at long horizons; namely, for the German mark and the Swiss franc, in the 12 and 16 quarter horizon regressions

Figure 1. Changes in the Log U.S. Dollar/German Mark Exchange Rate and Monetary Fundamentals.



Notes to Figure: For each horizon of interest, k=1, 4, 8, 12 and 16, actual k-period changes in the log dollar/mark are depicted as dashed lines. Solid lines indicate predicted k-period changes from long-horizon regressions on a monetary fundamental. Quarterly data from 1973:2 to 1991:4 were obtained from the *Main Economic Indicators* of the OECD.

Figure 2. Changes in the Log U.S. Dollar/German Mark Exchange Rate and Simulated Fundamentals.



Notes to Figure: For each horizon of interest, k=1, 4, 8, 12 and 16, actual k-period changes in the log dollar/mark are depicted as dashed lines. Solid lines indicate predicted k-period changes from long-horizon regressions on an independent simulated AR(2) process.

Table 3. Long-Horizon Regression LS Estimates

	K	$\hat{\beta}_k$	$\hat{\beta}_k$-adj	t(A)	p-val	R_k^2	R_k^2-adj
Canadian Dollar	1	0.040	0.020	2.172	0.135	0.059	0.046
	4	0.155	0.076	2.168	0.289	0.179	0.126
	8	0.349	0.206	2.520	0.314	0.351	0.247
	12	0.438	0.216	1.936	0.475	0.336	0.191
	16	0.450	0.352	1.514	0.577	0.254	0.064
German Mark	1	0.035	-0.021	0.929	0.645	0.015	0.000*
	4	0.205	-0.016	2.290	0.555	0.104	0.000*
	8	0.554	0.120	3.558	0.436	0.265	0.015
	12	0.966	0.348	6.510	0.393	0.527	0.186
	16	1.324	0.576	9.156	0.389	0.762	0.338
Japanese Yen	1	0.047	-0.008	1.285	0.631	0.020	0.000*
	4	0.263	0.048	2.055	0.536	0.125	0.004
	8	0.575	0.168	3.385	0.414	0.301	0.064
	12	0.945	0.348	4.427	0.354	0.532	0.201
	16	1.273	0.560	4.934	0.375	0.694	0.286
Swiss Franc	1	0.074	0.031	2.073	0.235	0.051	0.026
	4	0.285	0.120	3.196	0.209	0.180	0.083
	8	0.568	0.256	4.694	0.174	0.336	0.153
	12	0.837	0.396	8.178	0.070	0.538	0.274
	16	1.086	0.544	12.19	0.030	0.771	0.445

Notes: The data are from the OECD *Main Economic Indicators*, 1973:2-1991:4. $\hat{\beta}_k$ are estimated slope coefficients for equation (2). $\hat{\beta}_k$-adj and R_k^2-adj are Monte Carlo bias-adjusted estimates. * denotes an R_k^2 that would be negative if bias-adjusted.

(see Table 2 of Mark (1995)). In contrast, using our empirical critical values, we do not find any significant slope coefficients even at the 90 percent confidence level for three out of four exchange rates. Only for the Swiss franc at k=12 and k=16, do the Andrews corrected t-statistics exceed the 90 percent critical values for a one-sided test. (See Table 3.)

Lastly, although our bias-adjusted R_k^2's increase with the horizon for three of four currencies, (see Column 7 of Table 3), these values are much lower than those reported in Mark (1995).

It is clear from the above analysis, that some of the encouraging findings of Mark (1995) vanish when bias-corrections and empirical critical values are computed under the more stringent hypothesis of noncointegration between fundamentals and exchange rates.

V. Conclusion

Economists have long conjectured that economic fundamentals are important determinants of nominal exchange rates. Unfortunately, empirical evidence has so far proven elusive. We believe that the available evidence on this matter is not conclusive and welcome the contribution to the literature of Mark (1995), Chinn and Meese (1995) and Bauer (1995). However, we do not agree that the long-horizon regressions estimated, for example, by Mark suggest that there are "systematic exchange rate movements that are determined by economic fundamentals." (Mark (1995), p. 215.)

Our skepticism is motivated by several considerations: first, by ignoring the pronounced absence of evidence of any short-horizon relationships between fundamentals and exchange rates and focusing on the long-horizons, Mark and other authors challenge the intuitive result that the long-horizon coefficients on error-correction terms are inherently linked to their short-horizon counterparts. We show that if the slope coefficient from a one-period regression is zero, the coefficients of the long-horizon regressions will also be zero, regardless of the length of the horizon. In this sense, nothing seems to be gained by running a sequence of long-horizon regressions. We also show that if the estimated one-step ahead coefficient is nonzero, then estimated coefficients increase as the horizon increases. This implies that the empirical finding of increasing coefficients cannot be taken as evidence of a *stronger* impact of fundamentals on exchange rates.

Second, by imposing, a priori, cointegration between spot rates and the monetary fundamentals and deriving empirical critical values under this assumption, Mark's (1995) interpretation of the evidence of the presence of a statistical relationship between fundamentals and exchange rates errs on the side of significance. We demonstrate that Monte Carlo critical values tabulated under the null hypothesis that cointegration does not hold are much higher than Mark's (1995).

In addition, we show that even the graphical evidence of strong predictability over long-horizons may not be reliable. We produce graphs very similar to those in Mark (1995) with *simulated* fundamentals which are generated independently of exchange rates.

Lastly, a careful examination of Mark's (1995) recursive out-of-sample forecasts from the long-horizon regressions indicate very little evidence of predictability at long horizons (Table 4 in Mark (1995)). Mark uses the Diebold and Mariano (1995) statistic to compare the performance of the out-of-sample forecasts from the long-horizon regressions with the random walk forecast. In only one case (the German mark with k=16) can Mark reject the hypothesis that his estimated model produces forecasts no better than the random walk (we refer to the Diebold-Mariano with the bandwidth selected by the Andrews (1991) rule).

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