Real appreciation, exchange rate predictability, and output growth in a sample of developing countries

by

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Abstract

In this paper, we argue that real exchange rate appreciations can be costly because they raise uncertainty about the future path of the real exchange rate. The result is driven by the existence of multiple types of policymakers with differing costs of exchange rate intervention and by uncertainty about the type of next period's policymaker. We derive the result in a simple model with two types of policymakers who rotate in office stochastically: one who follows an Ss rule and the other an automaton who never intervenes. We test the model's prediction that higher real exchange rates are less predictable using a dynamic panel model that allows for cross-sectional dependence and contitional heteroskedastiticy and data from 14 developing countries from 1971 - 2000. We find strong evidence that real appreciation raises the conditional variance of the real exchange rate. We go on to show that, for a sub-group of these countries with available data, increased real exchange rate uncertainty significantly lowers output growth.

I. Introduction

Exchange rate management is one of the major challenges facing developing countries today and is the subject of a large amount of research attention. The issue is complicated in that successful control of the nominal exchange rate is not always sufficient to control the real exchange rate, which more directly impacts economic activity and welfare. We know that developing countries are loath to float (Calvo & Reinhardt (2000)), that pegging countries frequently experience real appreciations (Flood & Marion (1997)) and that real appreciations are generally reversed by nominal devaluations (Goldfajn & Valdés (1999)). In this paper, we argue that, in addition to the traditional costs of real exchange rate appreciation, such as the erosion of export competitiveness or increased unemployment, appreciation can also be costly because it raises uncertainty about the future path of the real exchange rate, which may adversely affect economic growth.[1]

While our primary aim in this paper is empirical, in order to better illustrate our argument, we also present a model based on Ball (1992) and Flood & Marion (1997) that predicts a positive relationship between real appreciation and uncertainty about the future path of the real exchange rate. The intuition is straightforward. Consider a polity where, in the absence of policymaker intervention, the real exchange rate evolves stochastically and can potentially create economic costs. If there are at least two types of policymakers who face different costs of intervening, then uncertainty about the type of the policymaker can affect uncertainty about the future course of the real exchange rate. In particular, when the real exchange rate is not generating significant economic costs, no type of policymaker would have an incentive to intervene. Thus there would be no uncertainty about next period's real exchange rate arising from uncertainty about the type of next period's policymaker. However, as the real exchange rate appreciates and generates greater costs, some types of policymakers will have an incentive to intervene and reset the real exchange rate, while other types will not. In this case, uncertainty over the type of next period's policymaker will generate increased uncertainty about next period's real exchange rate.

We test the hypothesis that real appreciations raise uncertainty about subsequent values of the real exchange rate in a panel of 14 developing countries from 1971.01 - 2000.12, using Cermeño & Grier's (2005) panel estimator. We find that higher real exchange rates are associated with significantly greater uncertainty, which means that, at least in some settings, models with multiple policymaker types can be empirically relevant. We then consider the economic effects of real exchange rate uncertainty on industrial production growth and demonstrate that real appreciations can be economically costly through their effect on uncertainty.

The paper is organized as follows. Section II presents our illustrative model of how higher real exchange rates may be less predictable. Section III describes our empirical method and presents the initial results. Section IV studies the output effects of real exchange rate uncertainty and Section V concludes.

II. A simple model of real exchange rate appreciation and uncertainty

In this section we present a simple formalization of our argument that real appreciation can raise uncertainty about future values of the exchange rate. We generate the result in a model with two types of policymakers: a pragmatic policymaker, who has a loss function which contains costs from being away from the ideal real exchange rate as well as costs of devaluing, and an ideological policymaker, in whose loss function the cost of devaluing is infinite.[2] When the real exchange rate is at a level where the pragmatic type would not intervene and devalue, then uncertainty about the type of the policymaker will not affect the conditional variance of the exchange rate. However, when the exchange rate is such that the pragmatic type would intervene, then uncertainty about the policymakers type increases the forecast error variance of the exchange rate.

Consistent with the time series properties of the data we use in the empirical section below, we assume that the real exchange rate has a stochastic trend. In this way, as emphasized by Drazen & Masson (1994) and Velasco (1997), the costs of a sub-optimal real exchange rate are persistent and cumulative. That is to say, if real exchange rate appreciation is causing costly unemployment, the dynamic costs of not resetting the real exchange rate now must be factored into the policymaker's decision rule. A simple way to incorporate this phenomenon is to have the pragmatic policymaker follow an Ss pricing rule, as discussed by Barro (1972) and Sheshinski & Weiss (1977, 1983). In these models, the policymaker balances the accumulated flow of the cost of being away from the ideal value of a variable against the fixed costs of changing the value of the variable in order to determine the limits of deviations that are acceptable and the size of interventions that will be undertaken.[3]

Specifically, we assume that the exchange rate follows a random walk with drift, subject to interventions by the policymaker.

$$R_t = * + R_{t-1} + V_t + g_t \qquad [g_t \sim \mathrm{IID}(0, F^2)] \qquad (1)$$

Here * measures trend appreciation, and V the intervention, if any, undertaken by the policymaker.[4] Given the stochastic trend, we assume that the pragmatic policymaker follows a one-sided Ss rule.[5] In implementing this type of rule, the pragmatic policymaker chooses a band for the real exchange rate. When the exchange rate hits the upper bound (S*), the policymaker intervenes with a nominal devaluation to reset the real rate to the lower bound (s*). The size of the band (S*-s*) depends on *, F^2, the loss function of the policymaker and the probability that future policymakers will be of the same type. For our purposes, it is not necessary to explicitly define the policymaker's target real exchange rate or her loss function. Given that one type follows (any) one sided Ss rule and the other is an automaton, there will be situations where uncertainty about the identity of the policymaker does not affect the accuracy of the public's forecast and other situations where such uncertainty is economically relevant.

We assume that the two types of policymakers rotate stochastically in office with a new policymaker selected in each period. This policymaker will be ideological with probability p and pragmatic with probability 1- p. We also assume the following sequence of events: (1) Given an information set that includes R_t, S*, s*, and p, the public forms their expectations of the next period's real exchange rate, $E_t[R_{t+1}]$; (2) The policymaker for period t is determined by a draw from our stochastic process; (3) The policymaker decides whether or not to intervene. Specifically, If R_t > S*, the Pragmatic policymaker will devalue, choosing a nominal rate that, in the absence of the macro shock (g_{t+1}) would reset the real rate to s*. The Ideological policymaker will always do nothing; (4) Finally, after the policymaker has taken action, the macro shock (g_{t+1}) occurs and R_{t+1} is realized. This sequence of events is then repeated.

We are now in a position to demonstrate our result of interest. The rational expectation of next period's real exchange rate is the mathematical expectation under each type of policymaker weighted by the probability that the type will be in office. That is to say,

$$E_t[R_{t+1}] = p\ E_t[R_{t+1}|\ \text{Ideologue}] + (1\text{-}p)E_t[R_{t+1}|\ \text{Pragmatic}] \tag{2}$$

The variance of the forecast error will be given by,

$$E_t[(R_{t+1} - E_t[R_{t+1}])^2] \qquad (3)$$

Let us consider the two relevant cases, first when $R_t < S^*$ (and neither type of policymaker will devalue) and second when $R_t > S^*$ (and the Pragmatic policymaker will devalue, lowering the real exhange rate by S*-s*). In the first case, the expected real exchange rate is given by,

$$E_t[R_{t+1}] = p(* + R_t) + 1\text{-}p(* + R_t) = * + R_t \qquad (4)$$

and the forecast error variance is

$$E_t[(R_{t+1} - * - R_t)^2] = Et(\, g_{t+1}{}^2\,) = F^2 \qquad (5)$$

In the second case, the expected real exchange rate is given by

$$E_t[R_{t+1}] = p(* + R_t) + 1\text{-}p(s^*) \qquad (6)$$

and the forecast error variance is,

$$E_t[(R_{t+1} - E_t[R_{t+1}])^2] = pEt[(* + R_t + g_{t+1} - p\,(* + R_t) \text{-} (1\text{-}p)s^*\,)^2] +$$

$$(1\text{-}p)Et[(s^* + \; g_{t+1} \text{-} p\,(* + R_t) - (1\text{-}p)s^*\,)^2] \qquad (7)$$

With some algebra, (7) can be simplified to:

$$E_t[(R_{t+1} - E_t[R_{t+1}])^2] = F^2 + p(1\text{-}p)(s^* - R_t)^2 \qquad (7^*)$$

Equation (7) is unambiguously greater than F^2, the forecast error variance in case one, meaning that uncertainty about the type of the future policymaker creates a positive link between real appreciation and increased uncertainty about future exchange rates. The link is not simply due to the existence of a policymaker who is not fully committed to the peg. In fact, in a world with only pragmatic policymakers, there would be no increased uncertainty at higher real exchange rates because the public would know exactly when the devaluation will come, as in Flood & Marion (1997).

In section III below, we briefly review some related empirical papers, describe our exact empirical method and present a test of whether higher real exchange rates are more unpredictable in a panel of 14 developing countries.

III. Empirical Model and Tests

A. Other Relevant Empirical Studies

There is a growing literature on the effects of exchange rate uncertainty on Investment. Byrne & Davis (2005) review earlier work and estimate a model of the relationship using heterogeneous panel techniques. There is also a huge literature on the effects of exchange rate uncertainty on trade as reviewed by XXX (19cc). In both literatures, papers vary by whether they use a panel approach or study one country at a time, whether they use bivariate or effective exchange rates, whether said rates are real or nominal, and whether they use a volatility measure such as a moving standard deviation, or a parametric uncertainty measure such as the conditional error variance of the process under study. Given this methodological diversity, it is perhaps not surprising that the reported results vary as well.

In our case, we take a panel approach to study 14 developing countries, though we do consider the possibility that the panel is heterogeneous. We choose to use real effective exchange rates as we are taking a macro perspective and arguably, the real exchange rate should affect real quantities more directly than does the nominal rate. We also measure uncertainty parametrically by the estimated conditional variance of the RER.[6] We then go on to use our set of conditional variance measures to investigate the effect of RER uncertainty on overall industrial production in those countries in our sample where monthly data is available.[7]

B. Statistical Model

We want to investigate the relationship between real exchange rates and uncertainty. We also want to measure uncertainty, rather than simple volatility. The usual choices of experimental design are to average the data and estimate a cross-country or panel regression using the sample standard deviation as the uncertainty measure, or to estimate a GARCH model for one country (or a few countries) at a time.[8] However, existing Multivariate GARCH models are limited in the number of series that can be considered because the number of coefficients to be estimated rises very rapidly with the number of series under consideration.

In this paper, we implement a version of Cermeño & Grier (2005) model of the real exchange rate. Rather than trying to estimate an intractable number of covariance matrix parameters, we estimate a pooled diagonal vech GARCH model with an exogenous variable in the conditional variance as shown in (8) - (10) below.[9]

$$R_{it} = *_{i} + E\$_{j} R_{it-j} + g_{it} \qquad (8)$$

$$h_{iit} = " + EN_{i}\, g_{it-i}^{2} + EQ_{i} h_{iit-i} + 8\, R_{it-1} \qquad \text{For all } i = 1\text{- }N \qquad (9)$$

$$h_{ijt} = 2 + E(_{i}\, g_{it-i} g_{jt-i} + ER_{i} h_{ijt-i} \qquad \text{For all } i \ldots j \qquad (10)$$

Here R is the real exchange rate and the error terms are assumed to be distributed multivariate normal with mean zero and variance $H_{t.}$ The diagonal elements of H are given in (9) and the off-diagonal elements in (10). We allow for both conditional heteroskedasticity via the GARCH process and for unconditional heteroskedasticity via the lagged dependent variable in (9). The model allows for individual effects in the mean equation but assumes the rest of the parameters are homogeneous. Assuming that a GARCH(1,1) process adequately describes the conditional heteroskedasticity in these data, the model requires the estimation of 6 covariance coefficients. By contrast, the BEKK model of Engle and Kroner (1995) (a typical multivariate GARCH model), would require the estimation of 497 coefficients for a 14 series GARCH(1,1) covariance matrix.

The key coefficient for testing our economic hypothesis is 8 in (9). If appreciated real exchange rates significantly raise uncertainty, then this coefficient should be positive and significant.

C. Data

To test the hypothesis that higher values of the real exchange rate (a more valuable local currency) create more uncertainty, we use monthly observations of J.P. Morgan's real exchange rate index for the period 1971.01 - 2000.12. [10] The base year for the real exchange rate index is 1990, and the index is trade weighted and based on comparing "wholesale prices of finished manufactures." (Morgan Guaranty Trust Company 1994). Higher values of the index imply a higher real value of the currency under study, meaning that real appreciations are denoted by increases in the index. We have complete time series for 14 developing countries.[11] Figure 2 displays the real exchange rate data for each country in the sample. The 14 countries in our sample are not all officially classified as having fixed exchange rate regimes from 1971 - 2000. However, as noted in our introduction, Calvo & Reinhart (2000) show that most developing countries, regardless of their official regime have a strong "fear of floating" indicating that the nominal exchange rate is typically tightly controlled.[12]

We proceed in the following manner. First, we test for real exchange rate stationarity in the panel with Im, Pesaran & Shin (1997) panel unit root tests. If we fail to reject the null of a unit root in the panel, we will then estimate the model using first differences of the data. Differencing will also serve to sweep out any individual fixed effects in the panel. Second, we test for the existence and persistence of time-varying heteroskedasticity in our panel. Third, if significant conditional heteroskedasticity is present in the data, we choose an initial panel GARCH model and estimate our model via maximum likelihood. Finally, we check the adequacy of the chosen GARCH model by testing for conditional heteroskedasticity in the Panel GARCH squared residuals.

D. Panel unit root tests

There is a large and contentious literature on whether real exchange rates are stationary. Individual time series unit root tests generally fail to reject the null of a unit root while panel tests are somewhat (but not universally) more supportive of stationarity. We use the two tests developed by Im, Pesaran & Shin (1997): the t-bar test, which assumes that there is no serial correlation in the individual country Dickey-Fuller equations, and the Q-bar test, which allows for idiosyncratic serial correlation in these first difference equations. We find that we cannot reject the null hypothesis of a unit root with either test at the 0.05 level (see the Appendix for the details of the tests). Thus, we will estimate the model in growth rates, changing (8) to (8*) below.[13]

$$) \ln(R_{it}) = * + E\$_j \ ) \ln(R_{it-j}) + g_{it} \qquad (8^*)$$

E. Testing for conditional heteroskedasticity

To test for conditional heteroskedasticity, we estimate (8*) with 11 lagged difference terms on the right hand side via Least Squares and conduct tests using the estimated residuals. An 11th order autoregression is sufficient to remove patterns from the residuals, as the null hypothesis of no autocorrelation cannot be rejected at any meaningful significance level.[14]

Table 1 presents a panel regression of the squared residuals on their first five lags. The null hypothesis of no conditional heteroskedasticity can be tested by multiplying the R^2 of this equation times the number of observations. This statistic is asymptotically distributed P^2 with 5 degrees of freedom in this case. The calculated statistic is 44.7, which is sufficient to reject the null at the 0.01 level. Inspection of the individual coefficients reveals that the first, second and fifth lagged squared residuals are positive and significant. This degree of persistence indicates that a GARCH(1,1) specification would be an appropriate starting point.

F. Results

We estimate (8*), (9), & (10) simultaneously via direct numerical maximization of the likelihood function.[15] Table 2 presents the results from the 14 country sample. The results show that these data indeed display significant conditional heteroskedasticity, and that as the real exchange rate appreciates, it becomes less predictable. The conditional variance/covariance parameters are all positive and significant at the 0.01 level and there is no evidence that any patterns remain in the squared normalized residuals. The alert reader will note that we use the first four lags of RER growth plus lags 7, 9 and 11 in the estimation. This is done to minimize the number of coefficients estimated. We have experimented with other sets of lags, and none of our results about appreciation and uncertainty depend on the chosen lag structure.

Most important for our purposes, the coefficient on the lagged real exchange rate in the conditional variance equation (i.e. 8) is positive (0.18) and significant at the 0.01 level (asymptotic t-statistic of 7). A one standard deviation rise in the real exchange rate is predicted to raise the conditional variance of the future exchange rate by about 5.5 percentage points. We thus find strong empirical support for the proposition that appreciated real exchange rates are less predictable.

Our 14 countries can be split geographically into two distinct groups, in that we have 7 Latin American and 7 East Asian countries in the sample. It is possible that the effect of real appreciation on future predictability differs between the two regions.

In our model presented above, when the real rate crosses S*, uncertainty increases by $p(1-p)(s^* - R_t)^2$. If pragmatic policymakers in one region have, on average, a greater distaste for the adverse effects of real appreciation or a lower cost of intervention, then their optimal Ss bandwidth will be narrower and the increase in uncertainty will be smaller than in the other region.

The proportion of the two types of policymakers in the population (given by p and (1-p)) also influences the size of the effect. If there is only a very small chance that either of the types is going to be in office, the increase in uncertainty will be smaller than if the chances are closer to 50-50. In both cases, there is some reason to think that the effect of real appreciation on uncertainty will be larger in Latin America, given the greater amount of variability in trade policies and greater political turnover in these countries during our sample period.[16]

Table 3 reports the results of re-estimating our model with the addition of an interaction term ($LA*R_{t-1}$) in the conditional variance equation. Here, LA is an indicator variable that equals 1.0 for the Latin American half of the sample and 0.0 for the East Asian half. The estimated coefficient on the $LA*R_{t-1}$ term is -0.023 and its t-statistic of 2.2 indicates that it is significant at the 0.05 level. The coefficient on the lagged real exchange rate rises slightly to .19 and its t-statistic rises to over 12. These results indicate that the coefficient for East Asia (.19) is roughly 12% larger than the coefficient for Latin America (.167), though both effects are significant at the 0.01 level.

However, this does not necessarily imply that the quantitative effect of real appreciation on uncertainty is larger in East Asia. In fact, a one standard deviation swing in the real exchange rate amounts to a 25.3 percentage point change in the East Asian sample and a 35.5 percentage point change in the Latin American sample. The higher volatility of the real exchange rate in Latin America more than makes up for the larger estimated coefficient in East Asia. A one standard deviation real appreciation raises uncertainty by 5.92 percentage points in Latin America and by 4.81 percentage points in East Asia.

These results demonstrate two points. First, the positive effect of real appreciation on uncertainty holds in both geographic regions and not just in crisis-plagued Latin America. Second, despite the counterintuitive coefficient pattern, the effect is quantitatively stronger in Latin America.

While our technique has the advantage of controlling for cross-country error covariances, it does assume that the coefficients are shared across all the countries. We have shown at least one exception in that coefficient of interest varies between the two geographic regions. Another way to estimate this coefficient is the Group Mean Estimator (Pesaran & Smith, (1995)) which is the coefficient derived from estimating equations 8* and 9 separately for each country and then averaging the estimated 8s .[17] This approach gives a large positive estimate for 8 of 4.75 (standard error of 2.63) when considering all 14 countries, and estimates of 7.68 for the 7 Latin American countries and 1.79 for the 7 East Asian nations. These results provide reinforcement for our main results. Higher RERs are less predictable in these countries and the effect is greater in Latin America than in East Asia, which accords well with the prediction of our theoretical model.

IV. The effect of real exchange rate uncertainty on output growth

In this section, we investigate the effect of real exchange rate uncertainty on the growth rate of industrial production in a sub-sample of 9 countries. Monthly data on industrial production is only available for Argentina, Brazil, Chile, Colombia, Korea, Malaysia, Mexico, and Taiwan. Because of some gaps in the data, we will employ an unbalanced panel with a total of 2,557 observations.[18]

A. Panel Results

Table 4 presents the results of estimating a pooled OLS regression of industrial production growth in this sub-sample on four lags of real exchange rate growth, industrial production growth, US industrial production growth, and the conditional standard deviation from our variance estimates in Table 2. The model also includes 11 seasonal dummy variables which are highly significant as a group but not reported to save space.

In this model, the 4 lags of the conditional standard deviation of the real exchange rate are jointly significant at the 0.01 level. The sum of these coefficients is -.36 which is significantly less than zero at the 0.01 level. We also calculate the GME estimate of this sum and find it to be -.26 with a standard error of .014.

B. On the Quantitative Effects of RER Uncertainty

Beyond showing signs and significance levels, it is useful to consider the quantitative importance of the estimated negative effect that RER uncertainty has on output growth. Figure 3 illustrates the effects of a temporary surge in the RER in our estimated model. We normalize the initial RER to 100, the steady state level of output growth to 3% and assume that US industrial production growth is constant. We then simulate the effects of the RER rising by 10 units for 4 consecutive months before returning to its initial level (the sequence is 100, 110, 120, 130, 140, 100, 100, ...). Panel A illustrates the RER time path chosen, while Panel B displays the effect this RER surge has on uncertainty using the coefficients estimated in Table 2. It takes about 15 periods (months) before the effects of the 4 period RER surge are eliminated from uncertainty.

Panel C is our main focus. It shows the time path of industrial production growth as simulated using the time paths for the RER and uncertainty shown in panels A and B along with the coefficients estimated in Table 4. Given that there is one positive coefficient for lagged RER uncertainty on output growth and negative autoregressive coefficients for output growth, the time path is not smooth. It takes about 18 periods before the effect of this temporary depreciation is no longer felt in output growth and at that time, the level of output is just over 1% lower than it would have been without the appreciation.

V. Conclusions

We demonstrate the existence of a strong positive and significant link between appreciation of the real exchange rate and its future predictability in a sample of 14 developing countries.

We present an illustrative model which demonstrates such a positive relationship, assuming stochastic turnover between two types of policymakers. In our model, when the real exchange rate is not overvalued, neither type of policymaker will devalue. When the real exchange rate becomes overvalued, one type of policymaker will devalue and the other will not. Thus, as the real exchange rate appreciates there is increased uncertainty over the future value of the real exchange rate.

Our results show that real appreciations can be costly in polities where there is uncertainty about the goals of future policymakers, in the sense that exchange rate uncertainty frequently associated with negative effects on trade or growth. Our results also show that models with multiple types of policymakers have a potentially important role to play in explaining real world behavior.

Table 1: LM ARCH Test for 14 Country OLS Model's Residuals

$$(\varepsilon_t^{ols})^2 = \alpha_0 + \Sigma\alpha_i (\varepsilon_{t-i}^{ols})^2$$

Variable	Coefficient	T-statistic
$(\varepsilon_{t-1}^{ols})^2$	20.7	5.62
$(\varepsilon_{t-2}^{ols})^2$	0.05	3.77
$(\varepsilon_{t-3}^{ols})^2$	0.02	1.68
$(\varepsilon_{t-4}^{ols})^2$	0.01	1.01
$(\varepsilon_{t-5}^{ols})^2$	0.05	3.23

$N=4970$, $R^2=.006276$, $\chi^2_{(5)} = 44.76^{**}$

Table 2: A Model of the Real Exchange Rate for 14 Latin American & East Asian Countries

$$
\begin{array}{llllll}
)\ln(R_{it}) = & -0.67 & +\ .098\ )\ln(R_{it-1}) & -\ .11\ )\ln(R_{it-2}) & -\ .04\ )\ln(R_{it-3}) & -\ .01\ )\ln(R_{it-4}) \\
 & (3.6) & (3.8) & (5.2) & (2.4) & (0.5)
\end{array}
$$

$$
\begin{array}{lll}
-\ .06\ )\ln(R_{it-7}) & -\ .02\ )\ln(R_{it-9}) & -\ .05\ )\ln(R_{it-11}) \\
(4.6) & (2.1) & (4.8)
\end{array}
$$

$$
\begin{array}{lllll}
h_{it} = & 1.10 & +\ .47\ g_{it-i}^{2} & +\ .73\ h_{it-i} & +\ .18\ R_{it-1} \\
 & (0.4) & (20.9) & (16.6) & (7.4)
\end{array}
$$

$$
\begin{array}{lll}
h_{ijt} = & 10.8 & +\ 0.07\ g_{it-i}g_{jt-i} \\
 & (8.6) & (2.9)
\end{array}
$$

Maximized Log-Likelihood = - 19232
N=14, T=360; Numbers in parentheses are asymptotic t-statistics

LM Tests for ARCH in the Maximum Likelihood Squared Residuals:

ARCH (1): 0.00001
ARCH (5): 0.789
ARCH (10): 1.375

The critical values of the Chi-square statistic at the .1 level with 1, 5 and 10 degrees of freedom are 2.71, 9.24, and 15.99, respectively.

Table 3: A Model of the Real Exchange Rate for 14 Latin American & East Asian Countries

$$
\begin{array}{llllll}
)\ln(R_{it}) = & -0.62 & + .09\ )\ln(R_{it-1}) & - .11\ )\ln(R_{it-2}) & - .05\ )\ln(R_{it-3}) & - .01\ )\ln(R_{it-4}) \\
 & (3.4) & (3.8) & (5.3) & (2.5) & (0.4)
\end{array}
$$

$$
\begin{array}{lll}
- .06\ )\ln(R_{it-7}) & - .02\ )\ln(R_{it-9}) & - .05\ )\ln(R_{it-11}) \\
(4.5) & (1.96) & (4.6)
\end{array}
$$

$$
\begin{array}{llllll}
h_{it} = & 0.02 & + .48\, g_{it-i}^{2} & + .72\, h_{it-i} & + .19\, R_{it-1} & - 0.023\, R_{it-1}\text{*LADUMMY} \\
 & (0.1) & (20.7) & (16.2) & (12.2) & (2.2)
\end{array}
$$

$$
\begin{array}{lll}
h_{ijt} = & 10.8 & + 0.07\, g_{it-i} g_{jt-i} \\
 & (8.9) & (2.9)
\end{array}
$$

Maximized Log-Likelihood = - 19229
N=14, T=360; Numbers in parentheses are asymptotic t-statistics

LM Tests for ARCH in the Maximum Likelihood Squared Residuals:

ARCH (1): 0.004
ARCH (5): 1.002
ARCH (10): 1.683

The critical values of the Chi-square statistic at the .1 level with 1, 5 and 10 degrees of freedom are 2.71, 9.24, and 15.99, respectively.

Appendix: Panel Unit Root Tests

Country	DF Test	Lagged Differences in ADF Test	ADF Test
Argentina	3.24	9	2.87
Brazil	2.88	9	2.64
Chile	3.49	11	2.35
Colombia	0.64	11	1.23
Hong Kong	1.39	6	1.49
Indonesia	0.79	10	0.73
South Korea	1.83	10	2.10
Malaysia	0.64	7	1.05
Mexico	2.61	9	2.96
Peru	2.27	11	0.83
Singapore	1.48	11	1.57
Taiwan	2.24	2	3.00
Thailand	1.31	10	1.25
Venezuela	2.42	2	2.17

IPS T-bar statistic = 1.94 IPS Q-bar statistic = 1.73

The T-bar statistic is the average of the 14 Dickey Fuller tests. It is asymptotically distributed standard normal.

The Q-bar statistic is also asymptotically distributed standard normal and is given by the following formula:

$$\mathrm{Q} = \mathrm{N}^{.5} \left(\bar{t}_{NT} - 1/\mathrm{N} \sum_{i=1}^{N} E\,[t_{iT}] \right) \; / \; \{1/\mathrm{N} \sum_{i=1}^{N} VAR\,[t_{iT}]\}^{.5}$$

Values for $E\,[t_{iT}]$ and $VAR\,[t_{iT}]$ are taken from IPS (1997).

Figure 1. Real Exchange Rate Indices for the 14 sample Countries

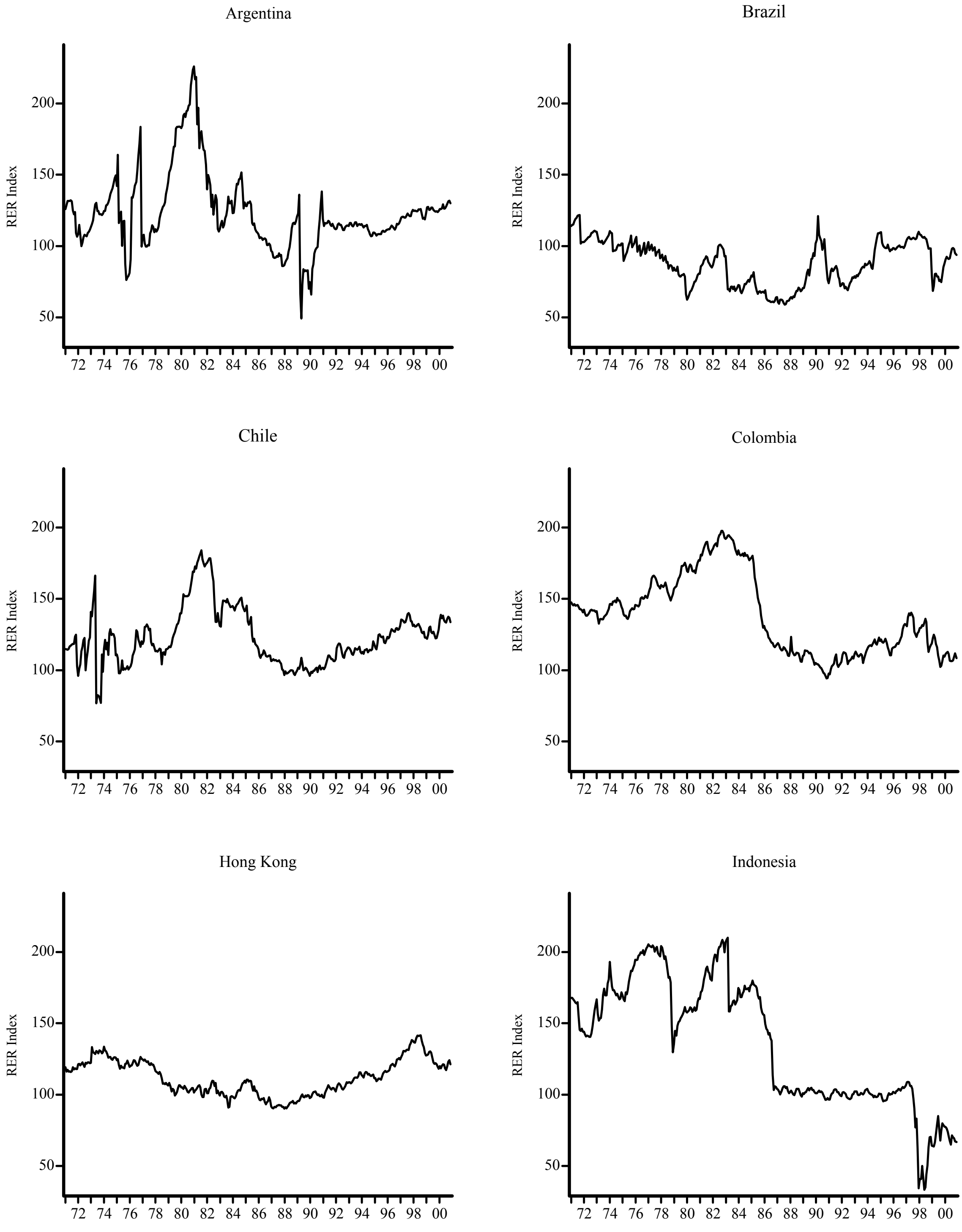


Figure 1 continued: Real Exchange Rate Indices for the 14 Sample Countries

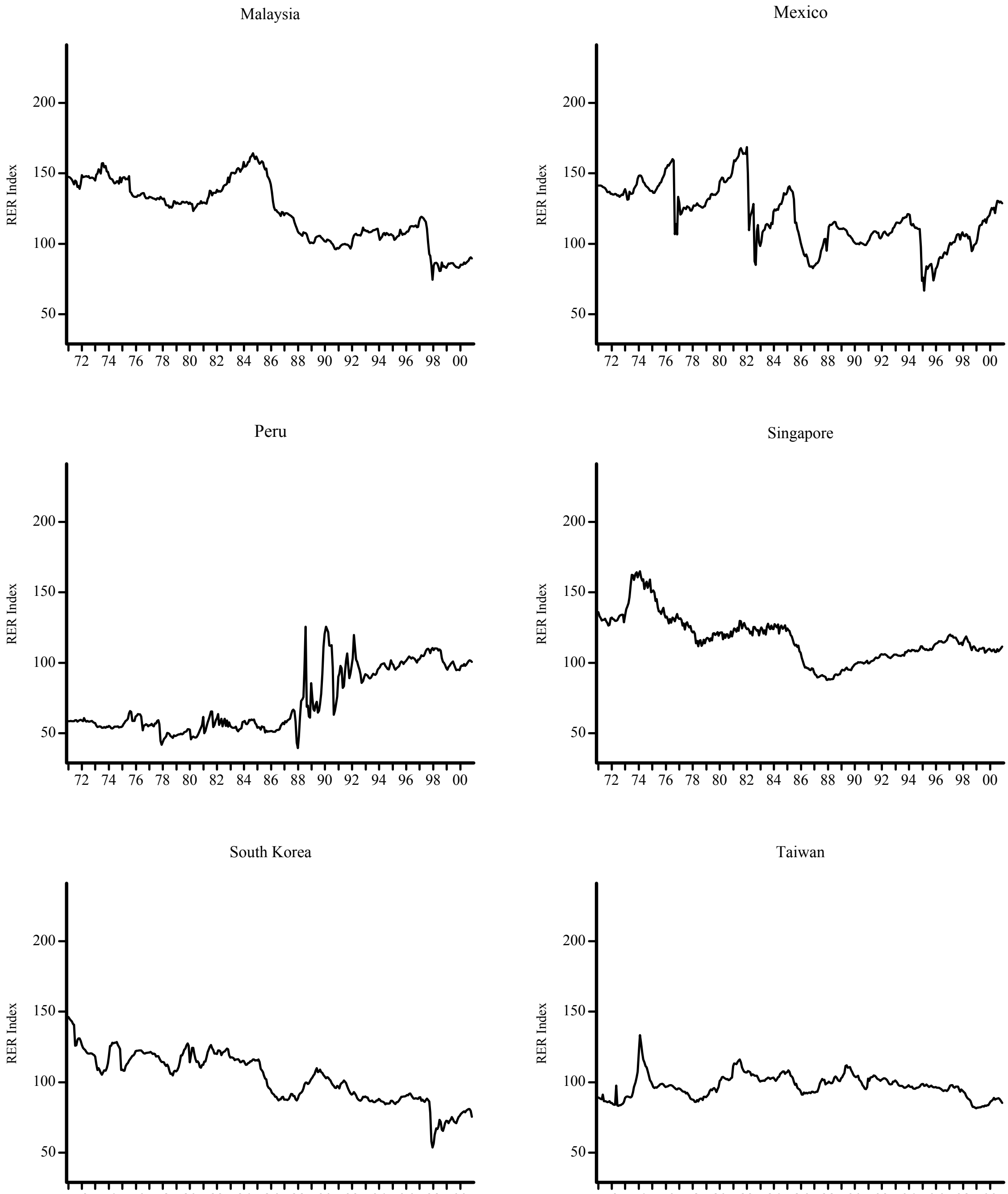
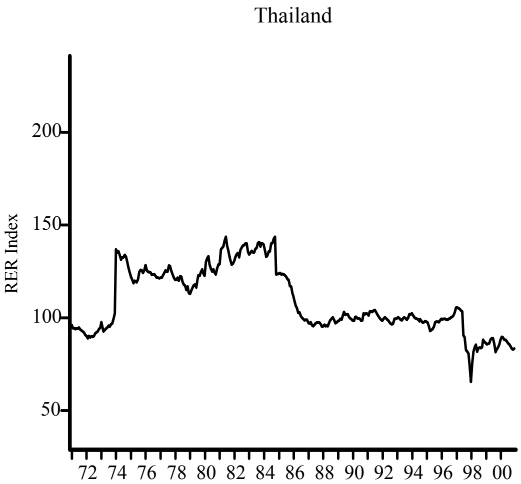
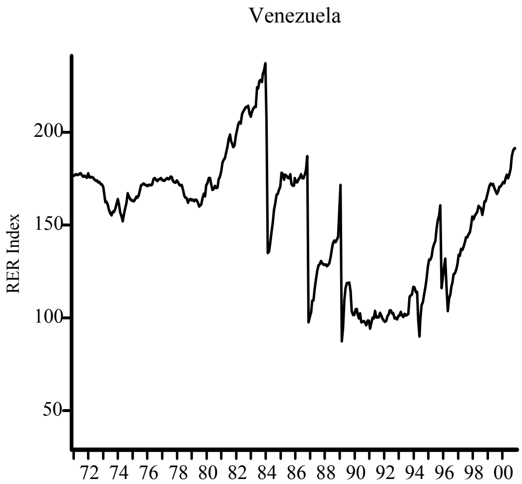


Figure 1 continued: Real Exchange Rate Indices for the 14 Sample Countries





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Notes

1. See Arize (1993), Cottani et.al. (1990), Kroner & Lastrapes (1993), and Maloney & Azevedo (1995).

2. The assumption of an infinite cost of devaluing is extreme and not necessary to the argument. It is simply a convenient way to have a model where the two policymakers have different costs of intervention.

3. Flood & Marion (1997) make a detailed set of assumptions and prove that a one-sided Ss rule is optimal in their set up. For a related contribution, see Ozkan & Sutherland (1998). In both of these cases, there is a single policymaker, so interventions are predictable by rational agents.

4. V will be equal to S*-s* whenever the pragmatic policymaker intervenes to reset the real exchange rate and otherwise equal to zero.

5. Ss pricing rules are not generally optimal policy rules, though Sheshenski & Weiss (1983) prove the optimality of the one sided Ss rule for a particular set of assumptions. However, Blanchard & Fischer (1989, p. 405) note that, "in many cases, a simple Ss rule may still be a good approximation to the optimal rule". Since our main goal is empirical, choosing an explicit loss function and deriving the optimal Ss type rule is beyond the scope of this paper. All we really need is a world where heterogeneous policymakers sometimes will all undertake the same action and sometimes will not, along with uncertainty about the type of next period's policymaker.

6. For some arguments about the superiority of the conditional variance to a rolling standard deviation approach to measuring uncertainty, see Grier & Perry (2000).

7. In that sense, the paper most directly related to ours is Grier & Hernandez-Trillo (2004) who estimate a bivariate GARCH-M model of the RER and industrial production for Mexico.

8. On the development of GARCH modelling, see Engle (1983) and Bollerslev (1990).

9. This type of model was first proposed by Cermeño & Grier (2002), who also present simulation evidence on the small sample properties of the estimator we employ here.

10. www.jpmorgan.com/MarketDataInd/Forex/currIndex.html. Data retrieved 4/16/01.

11. The 14 countries in the sample are: Argentina, Brazil, Chile, Colombia, Hong Kong, Indonesia, Malaysia, Mexico, Peru, Singapore, South Korea, Taiwan, Thailand and Venezuela.

12. In fact, in the large set of real appreciations studied by Goldfajn & Valdés (1999), between 38 - 40 percent of them occurred in countries that were not officially pegging their exchange rates (see their Table 3 on p. 243). They go on to show that only 8 percent of significant appreciations are reversed smoothly, which indicates that a large number of the non-pegged regime appreciations were reversed abruptly via nominal devaluations.

13. Many papers in empirical finance dealing with exchange rate uncertainty assume that the exchange rate is a pure random walk and therefore do not model the mean of the process at all. In contrast we find that the rate of change of the real exchange rate can be partially predicted by a set of autoregressive terms. In this respect, our model of the RER "fits" better than the standard pure random walk model used in the literature.

14. LM tests of autocorrelation in the residuals were never significant. The calculated statistics for AR(1), AR(5), AR(10), and AR(15) were 0.02, 0.16, 0.31, and 11.5. The critical values of the Chi-square statistic at the .1 level with 1, 5, 10, and 15 degrees of freedom are 2.71, 9.24, 15.99, and 22.31, respectively

15. Specifically we use a Gauss code that utilizes the OPTMUM module. This code is available from the authors upon request.

16. According to World Political Leaders, 1945-2001, Latin American countries averaged 12.1 chief executives in the 1960-2000 period, while the East Asian countries had an average of 6.4. In addition, many authors (see Birdsall & Jaspersen (eds) (1997), World Bank (1993), Stiglitz (1996), Sachs (1985), Page (1994), and Meier (1990)) have noted that public support of export policy promotion (after initial attempts at import substitution policies in the 1950s) has been broad and consistent in East Asia and not in Latin America.

17. Pesaran, Smith & Im (1996) show via simulations that the Mean Group Estimator performs well in samples where T is large, which is exactly our case with T = 360.

18. Industrial production data is available from 1994.1-2000.12 for Argentina, 1978.2-2000.12 for Brazil (with a gap from 1986.10-1987.5), 1970.1-2000.12 for Chile, 1980.1-2000.12 for Colombia (with a gap from 1992.2-1992.7), 1970.1-2000.12 for Korea, 1971.1-200.12 for Malaysia, 1970.1-2000.12 for Mexico, 1979.1-2000.12 for Peru, and 1975.1-2000.12 for Taiwan. All data is from the IMF International Financial Statistics, except Taiwanese data, which is from the Monthly Bulletin of Statistics of the Republic of China, and Brazilian data before 1991, which is from the UN's Monthly Bulletin of Statistics. For the Brazilian cast, we spliced the two data sets (in growth rates) at August 1991 because they had almost identical growth rates for that month (4.4% & 3.7%). The correlation coefficient for industrial production in the two different data sets in 1991 was .97.