The Won/Dollar Exchange Rate Forecasting Models in the 1990s: Time Varying Coefficient Co-integrating Regression with Long Horizon Forecasting Models

by

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Abstract

This study is concerned with the prediction of the won/dollar exchange rate using a time varying coefficient co-integrating regression incorporated into long horizon forecasting models. The bootstrapping result shows some predictable components in the won/dollar exchange rate. As the forecast horizon is set at longer periods of time, the time varying coefficient exchange rate determination models generally yield better forecast performances than the fixed coefficient model, outperforming the random walk model. These results have been most apparent in the models composed only of Korea's macroeconomic variables, instead of the stylized monetary models composed of both US and Korean variables. However, including fixed exchange rate period data brings about a deterioration in forecast performance.

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Contents

I. Introduction

Since the breakdown of the Bretton Woods System in 1973, the generally unpredictable nature of exchange rates has been a continual source of embarrassment to international financial economists everywhere. Numerous attempts have been made to construct models of exchange rate prediction, vigorously attacking the widely acknowledged view that making accurate forecasts of exchange rate movements is just not possible. Efforts to this end can be traced back to Meese and Rogoff(1983) who formulated various structural exchange rate models, only to find that none of them consistently performed better than the random walk model in out-of-sample forecasting. Since Meese and Rogoff(1983), many others have also attempted to challenge the random walk hypothesis of exchange rates.

For example, Woo(1985) incorporated a money demand function with a partial adjustment mechanism, but his version of the monetary model is only very slightly more accurate than the random walk model in out-of-sample forecasting. Campbell and Clarida(1987) attempted to explain exchange rate movements with interest rate differentials, but found that there was no real significant correlation between them. Similarly, Meese and Rogoff(1988), in their investigation of the link between exchange rates and real interest differentials, discovered that no such stable relationship between the two existed. On a slightly different tack, Diebold and Nasan(1990) used non-parametric methods to estimate the conditional mean change in the log exchange rate, but they too could make no improvements on the random walk.

However, in the first half of the 1990s some researchers found a few systematic components in exchange rate movements that seemed to be exploitable in forecasting exchange rates. Cumby and Huizinga(1991) detected predictable movements in the real exchange rate by rejecting the hypothesis that the correlation between the expected changes in nominal exchange rates and the expected inflation differential is zero. Engel and Hamilton(1990) found that exchange rate movements are often characterized by long swings, and developed a model of exchange rate dynamics based on a sequence of stochastic segmented time trends. Abauf and Jorion(1991), Diebold, Husted, and Rush(1991), and Grilli and Kaminsky(1991) found favorable evidence to support the hypothesis that long run purchasing power parity holds in historical exchange rate data spanning a long period which includes a fixed exchange rate regime. Recently Mark(1995) applied the long horizon regression to the monetary model of exchange rate determination, showing that economic fundamentals have predictive power over exchange rate movements.

Mark(1995) projected the change in exchange rate onto the current deviation from its economic fundamental and found that out-of-sample forecasts by long horizon regression consistently out-performs the driftless random walk. Our study basically builds on Mark's findings(1995) and applies long horizon regression to the Korean won/dollar exchange rate prediction model. In Korea, however, many economically important institutional changes have occurred during its relatively short period of economic development. To account for this problem, we have introduced the time varying coefficient co-integrating models, developed by Park and Hahn(1995), to the won/dollar exchange rate determination models. We made forecasts under the assumption that coefficients of exchange rate determination models are time varying, and compared the forecast results with those implemented under the assumption that coefficients are constant.

As for the exchange rate determination models, we initially employed conventional monetary models such as the Frenkel(1976)-Bilson(1978), Dornbusch(1976)-Frankel(1979), and Hooper-Morton(1982). In addition to such stylized models, we have constructed four additional won/dollar exchange rate determination models that exclude U.S. variables from the monetary models. As Korea's share in U.S. trade is very small, the won/dollar exchange rate is more likely to be explained by Korean macroeconomic variables alone rather than by the differences between Korea and U.S. macro variables.

The main points we want to address in this paper can be summarized as follows: Does the random walk model outperform the structural models in the case of the won/dollar exchange rate? Can we improve forecast performance by incorporating time varying coefficients due to structural change? Does setting up a model with Korean macroeconomic variables only rather than focusing on the differences between Korea and U.S. variables improve exchange rate forecasting? What about the data drawn from before March 1980 - does including that information improve forecasting performance?

The paper is organized as follows: Section II describes the won/dollar exchange rate determination models and estimation methods. Section III presents in-sample explanatory power and out-of-sample forecasting performance of each model. Major findings of the paper are summarized in Section IV.

II. Won/dollar Exchange Rate Models and Estimation Methods

1. Exchange Rate Determination Models

The most popular model used in empirical exchange rate studies seems to be the monetary model. In this paper, we consider four different specifications of the monetary model, which are commonly employed in empirical literature. The general specifications of these four models can be subsumed as follows:

$$
\begin{aligned}
(1) \quad s_t = {} & \alpha + \beta_1(m_t - m_t^*) + \beta_2(y_t - y_t^*) + \beta_3(si_t - si_t^*) \\
& + \beta_4(\pi_t^e - \pi_t^{e*}) + \beta_5 ctb_t + \beta_6 ctb_t^* + \varepsilon_t .
\end{aligned}
$$

where, s_t denotes logarithm of the exchange rate, m_t logarithm of the money supply, y_t logarithm of the real national income, si_t short term interest rate, π_t^e expected inflation, ctb_t cumulative trade balance, superscript * foreign variables, superscript t time. If we impose restrictions on coefficients of the equation (1), we can obtain the following models.

Table 1. Monetary Models of the Exchange Rate

	β_1	β_2	β_3	β_4	β_5	β_6
Model 1 (Benchmark)	+	−	0	0	0	0
Model 2 (Frenkel-Bilson)	+	−	+	0	0	0
Model 3 (Dornbusch-Frankel)	+	−	−	+	0	0
Model 4 (Hooper-Morton)	+	−	−	+	−	+

According to the monetary approach, the exchange rate is determined by the differences between the macroeconomic variables of the two countries, such as relative money, relative income, interest rate differential, and expected inflation differential. However, compared with the size of the U.S. economy, Korea is very small.[1] Therefore, it is possible to conjecture that won/dollar exchange rate movements are more likely to be reliant on Korean economic variables rather than on the differences between the two sets of Korean and U.S.'s economic variables. That is to say, U.S. variables might have negligible effects on the won/dollar exchange rate when compared with the variables of Korea.

Moreover, we can imagine a situation where including U.S. variables in modelling the won/dollar exchange rate might give rise to mis-specification, leading in turn to a substantial deterioration in the forecasting performance of the model. In order to investigate whether this conjecture is valid, we have built additional models that employ only Korea's macroeconomic variables as in equation (2), excluding U.S. variables from the exchange rate determination equation altogether from equation (1). In short, we will use two kinds of models for the won/dollar exchange rate determination, one that includes both U.S. and Korean variables and the other one that includes only Korean variables.

1). For example, Korea's trade volume, which is the sum of all exports and imports between the two countries, is 54,975 million dollars in 1996, which forms 19.6% of Korea's total volume of trade (280,054 million dollars in 1996), while it takes only 3.8% of the U.S. total trade volume (1,442,323 million dollars in 1996). This data is taken from the Monthly Bulletin of the Bank of Korea, September 1997.

(2) $s_t = \alpha + \beta_1 m_t + \beta_2 y_t + \beta_3 si_t + \beta_4 \pi^e_t + \beta_5 ctb_t + \varepsilon_t.$

Table 2. Monetary Models Based on Domestic Variables

classification	β_1	β_2	β_3	β_4	β_5
Model 5	+	−	0	0	0
Model 6	+	−	+	0	0
Model 7	+	−	−	+	0
Model 8	+	−	−	+	−

2. Time Varying Coefficient (TVC) Models of Exchange Rate Determination

In the above exchange rate determination models shown in equation (1) and equation (2), the coefficients βs are assumed to be constant during the estimation period. However, during Korea's short history of rapid economic development, she has undergone too many institutional and structural changes to build exchange rate determination models with constant coefficients.

Looking at the transition of the exchange rate system, Korea had shifted from a fixed exchange rate system to a multi-currency basket system in February 1980, and shifted to the market average rate system in March 1990. The daily foreign exchange fluctuation band has been expanded gradually, and the capital market of Korea has been gradually opened up since January 1992. In addition, deregulation on interest rates of banks and other depository financial institutions have been implemented by the third round schedule, step by step.

All of these above mentioned facts move us to conjecture that there has been a gradual change in Korea's exchange rate determination mechanism. Therefore, it might be necessary to apply a time varying coefficient model to improve the forecast performance. On these grounds, we have considered the time varying coefficient co-integration model developed by Park and Hahn (1995) in exchange rate determination modeling in equations (1) and (2).

The time varying coefficient (TVC) co-integration model can be written as follows. Let us assume some series y_t and x_t as m-dimensional integrated process of order one and the errors μ_t to be stationary.

(3) $y_t = x_t' \alpha_t + u_t.$

The main point of Park and Hahn(1995)'s time varying coefficient co-integrating regression is that in regressing y_t on x_t, they may not be co-integrated with the estimated fixed coefficient $\bar{\alpha}$. But x_t and y_t are more likely to be co-integrated if the coefficients α_t are allowed to vary along with time.

The problem that we may encounter in this process lies in estimating the coefficient α along with time. Park and Hahn(1995) show that we can approximate and estimate α by building up an estimator constructed with time polynomial and trigonometric functions. They also show that the estimator devised in that way has nice property with asymptotic normality.

To look at Park and Hahn's(1995) TVC method in detail, let's assume the coefficient α_t to be an m-vector of parameters changing over time. Also let's assume n to be the sample size and define $\alpha_t = \alpha\left(\frac{t}{n}\right)$, which is a smooth function defined on [0, 1]. What we want is to estimate a general function $\Pi(\alpha)$ of α, which approximates α.

For the estimation of $\Pi(\alpha)$, we need to consider the pth order finite series expansion which approximates α. This approximation can be done by a series of time polynomial and trigonometric function f_is,[2)]

$$(4) \quad \alpha_p = \sum_{i=1}^{p} \beta_{p_i} f_i .$$

It makes sense to estimate $\Pi(\alpha)$ by $\Pi(\hat{\alpha}_p)$ using the estimated values of $\hat{\beta}_{p_i}$s.

$$(5) \quad \hat{\alpha}_p = \sum_{i=1}^{p} \hat{\beta}_{p_i} f_i.$$

To estimate $\hat{\beta}_{p_i}$s, let the vector of series function $f_i\ s$ as $g_p = (f_1,\ f_2,\ \cdots,\ f_p)'$. Then we may consider a regression,

$$(6) \quad y_t = z_{pt}'\beta_p + v_{pt},$$

where $z_{pt} = g_p(\frac{t}{n}) \otimes x_t$, and $v_{pt} = u_t + (\alpha - \alpha_p)\left(\frac{t}{n}\right)' x_t$.

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2). The actual form of the pth order series function f_i s are

$(\frac{t}{n}), (\frac{t}{n})^2, \cdots, (\frac{t}{n})^{p_1}$, $\cos\frac{2\pi t}{n}$, $\sin\frac{2\pi t}{n}$, $\cos\frac{4\pi t}{n}$, $\sin\frac{4\pi t}{n}$, $\cdots$, $\cos\frac{2\pi p_2 t}{n}$, $\sin\frac{2\pi p_2 t}{n}$,
where $p = p_1 + 2p_2$.

Let the $mp \times 1$ coefficients β_p of new regressor z_{pt} as $\beta_p = (\beta'_{p1}, \beta'_{p2}, \ldots\ldots, \beta'_{pp})$, and $Z = (z_{p1}, \ldots\ldots\ldots, z_{pn})'$, $y = (y_1, \ldots\ldots, y_n)'$. Let us define the OLS estimator $\hat{\beta}_p$ for β_p by $\hat{\beta}_p = (Z'Z)^{-1}Z'y$

Then the estimate $\hat{\alpha}_p$ can be obtained from equation (5) by using the OLS estimate of $\hat{\beta}_p$ of β_p, and we may write as $\Pi(\hat{\alpha}_p) = \Phi\hat{\beta}_p$. Park and Hahn(1995) show that the estimator $\Pi(\hat{\alpha}_p)$ obtained by the above process is an asymptotically normal estimator of $\Pi(\alpha)$ as

$$(7) \quad V^{-\frac{1}{2}}\left(\Pi(\hat{\alpha}_p) - \Pi(\alpha)\right) \xrightarrow{d} N(0, \omega^2 I),$$

where $V = \Phi(Z'Z)^{-1}\Phi'$ and ω^2 is the long run variance of the errors $\{u_t\}$.[3)]

But asymptotic normality of the estimator $\Pi(\hat{\alpha}_p)$ holds under the condition that $\{x_t\}$ are generated independently of the regression errors $\{u_t\}$. If the regressor $\{x_t\}$ and the errors term $\{u_t\}$ are correlated, it leads to the asymptotic bias of the estimator and invalidity of standard testing procedure. However, some degree of correlation between the regressor $\{x_t\}$ and the errors term $\{u_t\}$ exist in general.

Park (1992) has worked out this problem of correlation between the regressor and error term by transforming the variables by CCR procedure The main point of Park's(1992) CCR transformation is to make the regressor $\{x_t\}$ and the errors term $\{u_t\}$ asymptotically independent by transforming $\{x_t\}$ and $\{y_t\}$ by the stationary components. In order to do that, a new regressor $\{x_t^*\}$ and regressand $\{y_t^*\}$ are created by filtering the original regressor $\{x_t\}$ and regressand $\{y_t\}$, using the stationary component obtained from the model.

It may be worth mentioning that as the CCR transformation is done by subtracting the stationary component from the non-stationary variables, the long run relationship between the non-stationary variables $\{x_t\}$ and $\{y_t\}$ are not changed by this transformation. By carrying out the CCR transformation, we can get the OLS estimator which is asymptotically unbiased as well as more efficient, and also we can use standard testing procedures.

After estimating the coefficient β_p, the remaining problem is testing whether co-integrating regression with time varying coefficient specification is correct or not.

First of all, to test the null hypothesis of fixed coefficient specification against the

3). The long run variance means the summed autocovariance of a stationary process.

alternative of time varying coefficient specification, we use the variable addition approach developed by Park (1990).[4] In performing Park's (1990) variable addition test in our context, we have used 4th degree of time polynomials t, t^2, t^3, t^4 as superfluous regressors s_t to the fixed coefficient regression in equation (8).

$$(8) \quad y_t = x_t' \bar{\alpha} + s_t' \varphi + v_t.$$

Then we have constructed the test statistic as

$$(9) \quad \tau_1 = \frac{RSS_{fc} - RSS_{fc}^s}{\bar{\omega}^2}.$$

where RSS_{fc}^s and RSS_{fc} are the residual sum of squares from the regressions in equation(8) with and without the augmented regressors s_t respectively, and $\bar{\omega}^2$ is the consistent estimate of long run variance of regression errors obtained without s_t.

Another approach in testing the validity of the specification of co-integrating regression with TVC is to test the null hypothesis of TVC specification against the alternative of a spurious regression with non-stationary errors having a unit root.

In doing so, we construct the statistic τ_2 as

$$(10) \quad \tau_2 = \frac{RSS_{tvc} - RSS_{tvc}^s}{\bar{\omega}_p^2}.$$

where RSS_{tvc} is the RSS of TVC co-integration regression in equation (6), RSS_{tvc}^s the RSS of the regression that incorporates the time polynomials t, t^2, t^3, t^4 as explanatory variables in regression equation in equation (6). Then as the number of superfluously added variables (time polynomials) is four, τ_1 and τ_2 both follow $\chi^2(4)$ distribution.

4). Park's (1990) variable addition approach exploits the fact that if the specification is correct, the regression errors will be stationary. Therefore, even if we include some more regressors which are independent of the error term to the original regression, the standard test on the coefficients of the added regressors will show the superfluousness of the added regressors. Park (1990) has shown that using time polynomials as added regressors behaves reasonably well in finite samples.

3. Forecasting by Long Horizon Regression

After estimating exchange rate determination models in equations (1) and (2) by both of the fixed and time varying coefficient models, we obtain the deviation of current exchange rate from the fundamental value by subtracting the estimated fundamental value from the current exchange rate. With these estimated deviation of current exchange rate, we perform the forecasts.

For the forecasting method, we use the long horizon regression.[5)] The long horizon regression is based upon the notion that asset returns are more predictable when they are measured over multiple periods rather than over one period.

In long horizon regression, the regressand is generally an asset return over a longer time period than the sampling interval and the regressor is the economic fundamental that is believed to force those asset returns. In this paper, we performed the long-horizon regression by projecting the k-period change in the exchange rate onto the current deviation of the exchange rate from its fundamental by a two step OLS procedure.

In detail, as a first step, we regress current exchange rate onto the economic fundamentals by OLS in both of the fixed and time varying coefficient specification of exchange rate determination models. Then after getting the coefficients of exchange rate determination models, we obtain the deviation of current exchange from its fundamental value as

$$(11) \quad z_t \equiv \bar{s}_t - s_t,$$

where $\bar{s}_t$ is the logarithm of the estimated equilibrium exchange rate, and s_t is the actual value of the exchange rate.

As a second step, we project k period exchange rate change onto the previously obtained deviation from its fundamental value z_t by OLS again as

$$(12) \quad s_{t+k} - s_t = \alpha_k + \beta_k z_t + \varepsilon_{t+k,k},$$

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5). The long horizon regression was originally introduced by financial economists. For example, Fama and French(1988) regressed stock returns on lagged stock returns, and Kim, M.J., Charles Nelson, and Richard Starts(1991) have found out mean reverting behavior in stock prices. It has been widely used during the last decade and macro economists have also used long-horizon regressions to detect predictable components in nominal interest rates, real interest rates, and inflation (Campbell and Shiller 1991, Mishikin 1990). More recently Mark (1995) and Mark and Choi (1997), Choi and Sul(1997a,b) applied long horizon regression in uncovering long-run relationship between economic fundamental and exchange rate.

where β_k denotes the adjustment speed toward equilibrium, ε_{t+k} forecasting error. If the slope coefficient β_k has a positive and statistically significant value, then we can interpret it as the evidence of reverting behavior of the actual exchange rate to its equilibrium level that is determined by economic fundamentals.

4. Bootstrapping

In applying asymptotic statistical inference to the estimated coefficient $\hat{\beta}_k$ in equation (12), we encounter two econometric problems. One is the serial correlation in the error terms of the regression equation (12) and the other is the small sample bias in estimating $\hat{\beta}_k$, which is caused by the stochastic character of equation (12).

The first problem is caused by overlapping observations in the regressand in equation (12). In equation (12), the change in exchange rate extends over horizons, exceeding the sampling period of the error terms. These overlapping observations in the regressand lead to the serial correlation of the error terms, and they result in incorrect standard errors of the standard OLS coefficient estimates of equation (12).

To account for this problem, we estimate the asymptotically consistent covariance matrix using the Newey and West's(1987) heteroskedasticity and autocorrelation consistent covariance matrix estimation method. We use two ways in setting the truncation lag for the Bartlett window of the Newey and West's estimation method. The first way arbitrarily sets the truncation lag at 20, and the second way uses the lag determined by the Andrews'(1991) AR(1) lag truncation.

Another problem is the small sample bias resulting from the endogenous and stochastic nature of the regressors in equation (12). Stambaugh(1986) has shown that the OLS estimate of β_k in equation(12) is biased in finite samples. He investigated a regression in our context as

$$(13) \quad s_{t+1} - s_t = \alpha(1) + \beta(1)\, z_t + \varepsilon_{1t+1}.$$

$$(14) \quad z_{t+1} = \mu + \psi\, z_t + \varepsilon_{2t+1}.$$

where $(\varepsilon_{1,t}, \varepsilon_{2,t})'$ is an *i.i.d* vector sequence and $Cov(\varepsilon_{1,t}, \varepsilon_{2,t+1}) \neq 0$. The regressor z_t and residual term $\varepsilon_{1,t+1}$ are contemporaneously uncorrelated, but z_t is correlated with the lags of ε_{t+k}. Stambaugh(1986) showed that the bias of the OLS estimate of $\beta(1)$ in equation (13) is proportional to the bias of the OLS estimate ψ in equation(14), and to the correlation between $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ as

$$(15) \quad E(\bar{\beta}-\beta) = \frac{Cov(\varepsilon_{1,t}, \ \varepsilon_{2,t})}{Var(\varepsilon_{2,t})} E(\bar{\psi}-\psi).$$

He also showed that the amount of bias in the least squares estimates of ψ in equation (15) is disproportional to the sample size n as

$$(16) \quad E(\bar{\psi}-\psi) \simeq -\left(\frac{1+3\psi}{n}\right).$$

This means that asymptotic test based on the biased estimate $\beta(1)$ is likely to reject the true null hypothesis that $\beta(1)=0$ too often and z_t may appear to be a predictor of $s_{t+1}-s_t$ even though it has no predictive power. Even though the bias in Stambaugh's(1986) regression is for AR(1) regressor and $k=1$ case, the same intuition can be expanded for more complex and $k>1$ cases.

This problem of small sample bias and size distortion in asymptotic distribution of the OLS estimates of β_k in equation (12) motivates us to draw the approximate exact small sample distribution, and work out the statistical inference based upon that. To get this approximated exact small sample distribution, we have performed Gaussian bootstrapping under the null hypothesis that the exchange rate is unpredictable.

In doing the Gaussian bootstrapping, we have assumed that the error terms are normally distributed, and specified the data generating process under the null hypothesis that exchange rate is unpredictable as:

$$(17) \quad \triangle q_t = a + \varepsilon_{1,t}.$$

$$(18) \quad z_t = b_0 + \sum_{j=1}^{4} b_j z_{t-j} + \varepsilon_{2,t}.$$

Let $\underline{\varepsilon_t}=(\varepsilon_{1,t}, \varepsilon_{2,t})'$ and error covariance matrix $V=E(\underline{\varepsilon_t \varepsilon_t'})$. Then the Gaussian bootstrap distribution has been obtained by 2,000 trials where each trial ($i=1,..,2000$) has been performed following below steps.

1st step : Get the OLS estimates $\bar{a}, \bar{b}_0, \bar{b}_1, \bar{b}_2, \bar{b}_3, \bar{b}_4$ and residuals $\{\underline{\bar{\varepsilon}_t}\}_{t=1}^{T}$ of the data generating process (DGP) specified as equation(17) and (18).

2nd step : Estimate the error covariance matrix V from $\{\underline{\bar{\varepsilon}_t}\}_{t=1}^{T}$ and generate the pseudo-error terms $\{\underline{e_t^i}\}_{t=1}^{T}$ from a bi-variate normal distribution with mean 0 and covariance matrix V.

3rd step : With the generated pseudo-error terms $\{\underline{e_t^i}\}_{t=1}^{T}$ and the estimated coefficients, construct the artificial data series $\{(s_{t+k}-s_t)^i\}_{t=1}^{n+T}$ and $\{z_t^i\}_{t=1}^{n+T}$ of length $n+T$ as[6)]

$$\triangle q_t^i = \bar{a} + e_{1t}^i$$

$$z_t^i = \bar{b}_0 + \sum_{j=1}^{4} \bar{b}_j z_{t-j}^i + e_{2t}^i$$

4th step : Do the regression with the obtained artificial observation set and get the estimates of slope coefficient β, R^2, and t values.

5th step : Repeat the above procedure for 2,000 times and get the distribution of the statistic.

In addition, we have performed non-parametric bootstrapping in obtaining the distribution of the Theils' U statistic. Theil's U statistic is the ratio between the Root Mean Square Error(RMSE) of the out-of-sample forecast and that of the random walk(here after U). If Theil's U statistic is less than one, then out-of-sample forecast is better than that of the random walk. The process of non parametric bootstrapping is very similar to the Gaussian bootstrapping except for the 2nd step.

1st step : The same as Gaussian bootstrapping.

2nd step : Generate the pseudo error terms $\{\underline{e_t^i}\}_{t=1}^{T}$ by re-sampling the residuals randomly with replacement from the single set of estimated OLS residuals $\{\underline{\bar{\varepsilon}_t}\}_{t=1}^{T}$,obtained from the 1st step.

3rd step : The same as Gaussian bootstrapping.

4th step : With the artificial observation set in the 3rd step, conduct the regression to get the estimate of Theil's U value.

5th step : Repeat these non parametric bootstrapping for 2,000 times to get the distribution of Theil's U value.

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6). In constructing $\{z_t^i\}$ series, we have used the initial values of z_t as $z_0 = z_{-1} = z_{-2} = z_{-3} = z_{-4} = 0$. To reduce the effects of these initial values to the subsequent data points, we have generated more data points ($n+T$), and dropped the first n data points.

III. Empirical Results

The data is taken from monthly recordings for Korea and the United States. The sample consists of 190 observations ranging from March 1980 to December 1995. The exchange rate is Korean won price of the U.S. dollar. The monetary variables used are M1 at the end of period and other variables are used for average data. Industrial production index and the long term interest rate differential are used as proxies for real income and the expected inflation differential, respectively.

1. Unit Root and Co-integration Test

We first test for unit root and the long run equilibrium relation between the exchange rate and the macro economic variables. Table 5 reports the results of Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Stock-Watson (SW) unit root tests. The number of lags in ADF is selected by Akaike and Schwarz information criterion.[7] PP and SW tests use 8 lags.

Table 3. Unit Root Test (1980:3 ~ 1995:12)

	ADF		PP		SW	
	τ_μ	τ_τ	$Z(t_{\alpha*})$	$Z(t_{\tilde{\alpha}})$	Q^μ	Q^τ
s_t	-1.85	-1.87	-1.41	-2.17	-6.4	-5.2
$m_t - m_t^*$	0.56	-1.51	0.36	-3.10	0.6	-17.4
$y_t - y_t^*$	-1.35	-2.64	-0.96	-6.80	-0.9	-67.6
$si_t - si_t^*$	-1.76	-2.18	-2.88	-2.87	-9.1	-8.7
$li_t - li_t^*$	-4.47	-4.43	-3.77	-3.67	-9.8	-8.6
ctb_t	-2.63	-2.95	-0.93	-1.19	-4.5	-5.7
ctb_t^*	0.86	-3.47	3.91	-2.88	0.5	-2.6
m_t	0.34	-1.71	-2.34	-2.37	0.1	-24.5
ip_t	-1.19	-1.33	-2.00	-1.98	-0.4	-55.9
si_t	-3.70	-3.41	-1.30	-1.76	-7.3	-7.2
li_t	-3.90	-3.55	-1.43	-1.60	-8.2	-8.5
critical values						
1%	-3.46	-3.99	-3.46	-3.99	-20.6	-29.2
5%	-2.88	-3.43	-2.88	-3.43	-14.1	-21.7

7). The test results are not substantially different according to the number of lags, so, table 5 reports only the results with Akaike criterion.

All six statistics reveal that all the series, save relative long-term interest differential, Korean short-term and long-term interest rates, industrial production indices, fail to reject null hypothesis of the presence of unit root. In the case of relative long term interest rate differential, the ADF and PP tests reject the null of unit root at the 1% and 5% significance level, but SW test fails to reject the null. In the case of Korean short term and long term interest rates, the ADF rejects the null at the 5% significance level, but SW test fails to reject the null. In the case of relative industrial production index, Korean money and industrial production index, the SW's Q^{τ} rejects the null, but the remaining five statistics fail to reject the null hypothesis of unit root.

Table 6 reports the results of Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF), Johansen (JH), Park (TVC) co-integration tests in equation(1) and (2).[8] It is not clear whether or not some variables have unit roots. However, the co-integration results are not altered when stationary variables are added to non-stationary variables.

Table 4. Co-integration Test (1980:3 ~ 1995:12)

	DF	ADF	JH	TVC	
				τ_1	τ_2
Model 1	-2.98	-2.26	2	322.28	20.66
Model 2	-1.55	-2.33	3	214.49	5.68
Model 3	-1.55	-1.68	3	11.40	5.32
Model 4	-2.13	-1.76	6	7.22	0.69
Model 5	-2.13	-1.95	2	46.51	11.05
Model 6	-2.83	-2.66	4	1.99	6.48
Model 7	-1.70	-3.30	5	9.80	2.94
Model 8	-1.78	-3.61	6	56.47	9.58

Notes: DF and ADF denote t values of the Dickey-Fuller and the Augmented Dickey-Fuller test. JH denotes the number of co-integration vectors resulting from Johansen λ_{max} and the trace statistics.

Co-integration test results are different depending upon test methodologies. In the case of fixed coefficient models, the DF and ADF statistics fail to reject the null of no co-integration at the 10% significance level. On the other hand, the JH test reveals that except for Model 6, Model 7 and Model 8 all Models appear to have co-integration.

To test the validity of time varying coefficient co-integrating specification, we use Park's (1990) variable addition tests that have been devised in equation(9) and (10). Those tests show that Model 2, Model 3, and Model 7 have time varying coefficients

8). The number of lags in the ADF test is selected by minimizing the Akaike and Schwarz information criterion, and the JH test employes minimum lags such that the residuals follow the normal distribution. In Park's test, t, t^2, t^3, t^4 are added so that τ_1 and τ_2 follow $\chi^2(4)$ distribution, critical values of which are 9.49 and 7.78 at the 5% and 10% level.

co-integration according to τ_1 and τ_2. However, in other models τ_1 and τ_2 exhibit conflicting results. In the cases of Model 1, Model 5, and Model 8, τ_1 implies time varying coefficients co-integration, but τ_2 implies no co-integration. In the case of Model 4 and Model 6, τ_1 implies fixed coefficients co-integration, but τ_2 implies time varying coefficients co-integration.

2. In-sample Explanatory Power

We have tested the null hypothesis that the exchange rate is unpredictable by a one tail test that β_k is zero. Table 7 reports the estimated slope coefficients, asymptotic t ratios, and R^2's of the fixed coefficient models along with the marginal significance levels which have been obtained by the parametric bootstrapping, For comparison, we also provide bias-adjusted results, which are obtained by subtracting the 50 percentile value of the bootstrap distribution which was obtained under the null hypothesis that exchange rate is unpredictable.

When we look at table 7, we can see that with the exception of the one-month forecasts in Models 4 and 8, all β's have positive values, and are significant at the 5% level. In most cases, lengthening the forecast horizon results in rising values of β, t, and R^2. For example, the bias-adjusted β of Model 1 are 0.014, 0.304, 0.745, 1.157, 1.344 at one, twelve, twenty four, thirty six, forty eight month horizon, and t-values are 0.648, 2.005, 3.128, 5.553, 10.107, and R^2 are 0.046, 0.213, 0.429, 0.626, 0.715, increasing as the horizon grows. These results suggest that in exchange rate movements noise factors dominate in the short run, but in the long run systematic movements become more apparent.

Next let us compare the estimation results of the fixed and TVC coefficients models. We have selected Model 1 and Model 6 for comparison. As will be shown later from the table 8 to table 11, Model 1 exhibits the best forecasting performance among fixed coefficients models, and Model 6 shows the best forecast performance among the TVC models. The estimated result of Model 1 with fixed coefficients shows wrong sign in the coefficient of relative money from the view point of monetary model.

(Model 1 - FC) $s_t = 6.630 + 0.006(m_t - m_t^*) + 0.061(y_t - y_t^*)$.

Next let us consider the Model 6. With fixed coefficients, Model 6 had a rather mediocre forecast record. However, by allowing the coefficient on the interest rate to time vary, it gave the best forecasting performance of all the eight models. The estimation results between fixed and time varying coefficients models are also quite different. A fixed coefficient on the interest rate means that an increase in Korean national income and interest rate decreases the won/dollar exchange rate. In contrast, with a time varying coefficient on the interest rate, a rise in Korean national income and interest rate makes the won/dollar exchange rate go up.

(Model 6 - FC) $s_t = 6.928 + 0.052 m_t - 0.115 y_t - 0.017 si_t$

(Model 6 - TVC) $s_t = 0.012 m_t + 0.293 y_t + \alpha_t si_t$

In performing a regression with TVC in Model 6, we have detrended m_t and y_t series which show monotone increasing tendency. For the order of the approximation function f_is in equation (4)., we have roughly selected 2 for the time polynomials, and 2 for the trigonometric functions respectively. The time varying coefficients of the short term interest rate in Model 6 are plotted in Figure 1. The coefficient of short term interest rate assumes positive value until June 1987, but turns to negative values after that time. The coefficient increases in the early 1980s, reaching a peak 0.013 in December 1984. After that, it decreases until April 1990 to -0.0141 and then rises to -0.0087 in December 1992. However, the coefficient decreases after January 1993, reaching -0.0231 in December 1995, implying that the influence of short term interest on the exchange rate has been growing recently.

Figure 1. The Coefficient of Short Term Interest Rate

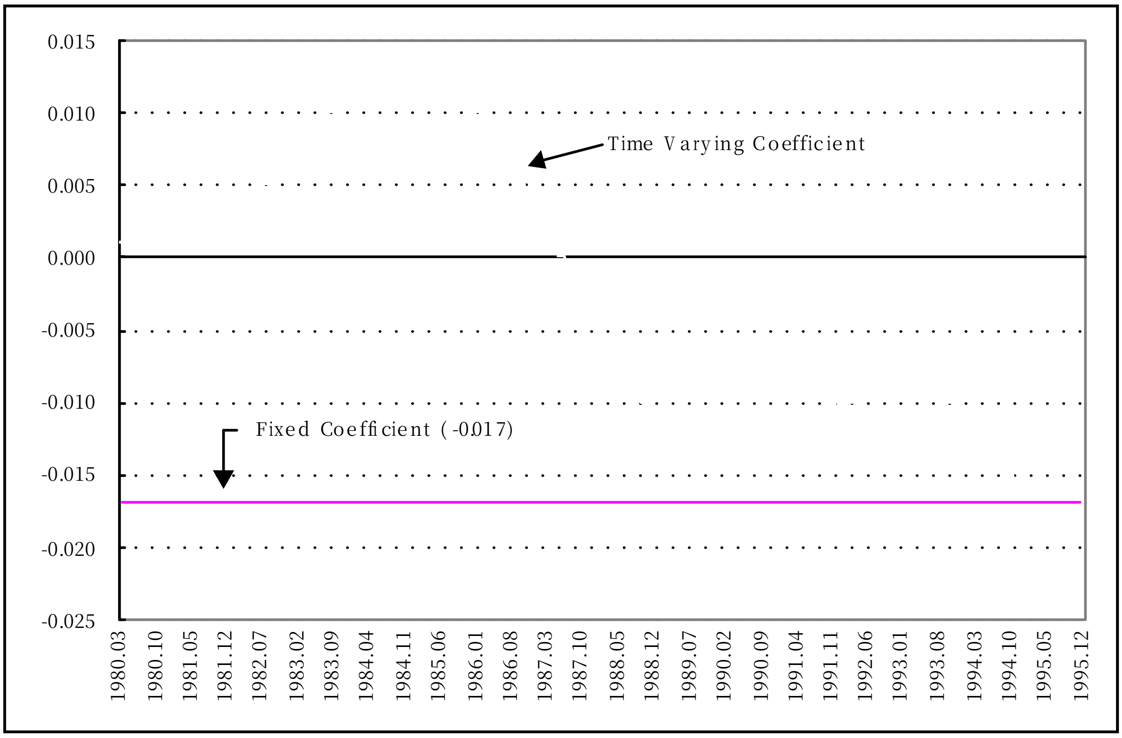

Table 5. In-Sample Fit Results of Fixed Coefficient Model: 1980:3~1995:12

	k	bias unadjusted/bias adjusted					p-value			
		β_k	R^2	$t_r(20)$	$t_r(A)$	A	β_k	R^2	$t_r(20)$	$t_r(A)$
Model 1	1	0.019	0.050	1.240	1.283					
		0.014	0.046	0.648	0.800	12	0.132	0.003	0.288	0.230
	12	0.355	0.252	2.732	6.374					
		0.304	0.213	2.005	5.625	142	0.018	0.053	0.118	0.004
	24	0.843	0.497	3.991	14.888					
		0.745	0.429	3.128	13.943	263	0.000	0.020	0.072	0.000
	36	1.294	0.721	6.547	18.483					
		1.157	0.626	5.553	17.337	171	0.000	0.002	0.024	0.000
	48	1.522	0.840	11.366	15.441					
		1.344	0.715	10.107	13.996	124	0.000	0.000	0.005	0.003
Model 2	1	0.009	0.007	0.546	0.528					
		0.006	0.004	0.185	0.233	12	0.260	0.269	0.433	0.412
	12	0.325	0.149	2.404	4.310					
		0.295	0.117	1.934	3.835	97	0.008	0.130	0.119	0.022
	24	0.910	0.411	3.343	5.496					
		1.582	0.594	5.130	4.554	95	0.000	0.033	0.087	0.024
	36	1.458	0.643	4.460	5.068					
		0.850	0.349	2.768	4.861	58	0.000	0.004	0.060	0.054
	48	1.684	0.697	5.918	5.448					
		1.377	0.558	3.805	4.325	49	0.000	0.006	0.039	0.072
Model 3	1	0.007	0.003	0.314	0.308					
		0.005	0.000	0.146	0.172	12	0.337	0.488	0.459	0.446
	12	0.373	0.135	2.076	4.058					
		0.351	0.106	1.785	3.756	67	0.002	0.124	0.132	0.020
	24	1.121	0.424	3.857	5.475					
		1.078	0.370	3.494	5.066	44	0.000	0.015	0.046	0.014
	36	1.690	0.577	5.025	5.066					
		1.632	0.505	4.597	4.603	29	0.000	0.006	0.031	0.038
	48	1.754	0.516	6.135	6.150					
		1.676	0.430	5.602	5.541	32	0.000	0.028	0.019	0.027
Model 4	1	−0.004	0.000	−0.164	−0.172					
		−0.007	−0.002	−0.393	−0.373	12	0.696	0.774	0.629	0.637
	12	0.495	0.065	1.343	1.536					
		0.455	0.036	0.948	1.130	80	0.004	0.301	0.272	0.250
	24	1.626	0.235	2.569	2.776					
		1.549	0.184	2.056	2.228	56	0.000	0.114	0.142	0.139
	36	2.632	0.347	2.670	2.648					
		2.524	0.278	2.059	1.977	39	0.000	0.081	0.164	0.195
	48	2.811	0.329	2.931	2.938					
		2.666	0.248	2.185	2.095	40	0.000	0.133	0.168	0.200

Table 5. (continued)

	k	bias unadjusted/bias adjusted					p-value			
		β_k	R^2	$t_r(20)$	$t_r(A)$	A	β_k	R^2	$t_r(20)$	$t_r(A)$
Model 5	1	0.024	0.077	1.579	1.645					
		0.020	0.074	1.063	1.200	12	0.072	0.000	0.203	0.001
	12	0.405	0.317	3.130	7.967					
		0.354	0.280	2.477	7.280	150	0.008	0.025	0.083	0.000
	24	0.919	0.576	4.661	13.949					
		0.825	0.509	3.861	13.080	197	0.000	0.008	0.042	0.001
	36	1.368	0.790	8.375	15.714					
		1.236	0.697	7.467	14.650	101	0.000	0.001	0.010	0.007
	48	1.567	0.872	13.072	13.123					
		1.395	0.753	11.932	11.799	70	0.000	0.000	0.003	0.005
Model 6	1	0.005	0.001	0.250	0.236	12				
		0.003	-0.001	0.040	0.057		0.406	0.643	0.488	0.481
	12	0.322	0.086	1.958	3.714	87				
		0.296	0.057	1.630	3.380		0.009	0.243	0.149	0.034
	24	0.969	0.274	2.678	3.824	85				
		0.918	0.222	2.256	3.358		0.000	0.080	0.121	0.061
	36	1.653	0.491	3.543	3.635	53				
		1.582	0.423	3.043	3.080		0.000	0.019	0.087	0.103
	48	1.799	0.472	4.128	4.174	54				
		1.704	0.390	3.508	3.468		0.000	0.036	0.073	0.094
Model 7	1	0.003	0.001	0.153	0.145	12				
		0.001	-0.002	-0.055	-0.030		0.455	0.764	0.520	0.516
	12	0.302	0.073	1.685	3.628	83				
		0.275	0.045	1.360	3.293		0.017	0.278	0.194	0.040
	24	0.983	0.271	2.676	3.722	74				
		0.929	0.221	2.265	3.279		0.000	0.087	0.122	0.068
	36	1.669	0.483	3.606	3.745	46				
		1.601	0.413	3.111	3.194		0.000	0.022	0.084	0.090
	48	1.841	0.474	4.213	4.014	44				
		1.747	0.388	3.592	3.303		0.000	0.040	0.073	0.102
Model 8	1	-0.010	0.002	-0.356	-0.365	12				
		-0.015	-0.001	-0.782	-0.736		0.858	0.596	0.732	0.747
	12	0.512	0.052	1.319	1.432	97				
		0.449	0.019	0.741	0.837		0.012	0.395	0.311	0.306
	24	1.719	0.202	2.358	2.537	87				
		1.600	0.138	1.621	1.729		0.000	0.192	0.200	0.201
	36	2.859	0.328	2.636	2.767	63				
		2.695	0.239	1.778	1.782		0.000	0.143	0.213	0.221
	48	3.050	0.300	2.684	3.384	67				
		2.837	0.190	1.675	2.236		0.000	0.217	0.245	0.206

Notes: A is the number of Andrews's AR(1) truncation lags, and tr(20) and tr(A) respectively the t values of β with 20 and A lags estimated by the Newey and West method.

3. Out-of-Sample Forecasting

As the predictive power of the model can vary according to the estimation period and forecast horizon used, we have performed out of sample forecasting over two different sample periods. For one, we have taken the data from March 1980, when the multi-basket exchange rate system was introduced to allow the exchange rate to fluctuate relatively freely. For the other, we have extended the sample period as far back as possible (see Appendix 1) including even the pre-floating period data (March 1980). However, as including pre-floating data has generally deteriorated prediction results for all eight of the models, we report only the out-of-sample forecast result based on the former data period.

This implies that in the Korean case, fixed exchange rate period information is of no help in predicting flexible exchange rate movements. These results are opposed to those of Mark and Choi(1997) who, using the data of the UK, Canada, Germany and Japan, found that flexible exchange rate period prediction accuracy generally improves when additional data is exploited by extending the sample back towards the fixed exchange rate period.

The reasoning which can support Mark and Choi's(1997) findings may be that to maintain the fixed exchange rate system, the central bank needs to intervene in the foreign exchange market. In the process of central bank intervention money supplies are changed, resulting in the changes in the other macro economic variables. Therefore, this may be attributed to some structural inconsistency rather than an actual structural break in the coefficients of macroeconomic variables throughout the fixed and flexible exchange rate period. This may go some way towards explaining how the fixed exchange rate period data aids exchange rate forecasting in UK, Canada, Germany and Japan during periods of flexible exchange rates.

If we look at the Korean case, a substantial part of Korea's economic variables have been determined by government control. That is to say, there has been a wide range of government repression in most of economic sectors so that the economic indicators do not represent the market value.[9] That may contribute to the occurrence of structural break in the coefficients of economic variables after the introduction of multi-basket exchange rate determination system in 1980, so that pre-float data is of little help to the exchange rate forecasting in float exchange rate period of Korea.

In out-of-sample forecasting we use the rolling regression, which adds one observation as the forecast proceeds one step forward. Forecasting begins at three different points of time, March 1990, January 1991, and January 1992 and ends with

9). As has been already mentioned previously, most of Korea's interest rate have been determined by the government until the first round of interest rate liberalization in 1991.

December 1995. All of these three forecasting periods include important turning points that occurred in 1993 and 1995. The won depreciated during the early 1990's, reaching a nadir in 1993. From that point, the won appreciated until 1994, whereupon it began to depreciate once again, and has continued to do so up until the present day.

To facilitate comparison of the forecasting accuracy of each model, we report the Theils' U's and the ratio of RMSE of each model to that of the driftless random walk in Table 8 through Table 13. In the case of fixed coefficient models, to test whether the U statistics are truly different from 1, we obtain the distribution of the U statistics and significance levels by non-parametric bootstrapping.

From Table 8 to Table 13, k means forecast horizon, FC fixed coefficient model, TVC time varying coefficient model, and # the number of forecasts made. In the case of TVC models, the reported U's are minimized values obtained by changing the coefficients of the model in various combinations.

A. Fixed Coefficient Models

We report the forecast results from January 1991 to December 1995, since this period gives the best performance of the three starting points mentioned above. Model 1 and Model 8 out-perform the random walk model up to the 36 month and 24 month forecast horizons. For example, the U statistics of Model 1 are 0.969, 0.817, 0.536, 0.373 at 1, 12, 24, and 36 month forecast horizons with a minimum value of 0.297 at the 33 month forecast horizon. But the rest of the models fail to beat the driftless random walk model at forecast horizons longer than one month. Even in these cases, as the U statistic at one month forecast is bigger than 0.9, it may be difficult to assert that the forecasts are any better than the random walk model.

In most of the fixed coefficients models, leaving out the U.S. variables fails to significantly improve forecasting performance. The only exception to this is Model 8. When both U.S. and Korean variables are included, the U statistic displays 0.937, 1.153, 1.311 2.085, and 1.385 at the 1, 12, 24, 36, and 48 month forecast horizon. However, using the Korean variables alone as explanatory variables improves the U statistic of 1, 12, 24, 36, 48 month's forecast horizon to 0.971, 0.982, 0.836, 1.146, 1.301 respectively.

B. Time Varying Coefficient Models

Tables 8 through 13 contain the estimated U values of TVC models. Among other things, Model 6 which consists of Korean money, income, and short term interest rate, exhibits the best forecast performance out of all eight models. The values of U at 1, 12, 24, 36, 48 month forecast horizon show 0.899, 0.622, 0.713, 0.795, 0.260, respectively. Model 7 shows next best forecast performance, which is comprised of Korean money, income, short term interest rate, and long term interest rate as explanatory variables. The U values of Model 7 are 0.949, 0.727, 0.683, 0.743, 0.389 respectively. Model 5, which is constructed from Korean money and income also performs well with the U values of 0.981, 0.778, 0.826, 0.732, 0.537.

Table 6. Benchmark Model (1991:1 ~ 1995:12)

k	Model 1		Model 5		#
	FC	TVC	FC	TVC	
1	0.969(0.18)	0.979	0.969(0.17)	0.981	59
12	0.817(0.32)	0.817	0.822(0.32)	0.778	48
24	0.536(0.18)	0.878	0.710(0.35)	0.826	36
36	0.373(0.15)	0.876	1.168(0.67)	0.732	24
48	1.685(0.77)	0.718	2.511(0.83)	0.537	12

Notes: The U statistics of TVC Model 1 and Model 5 are obtained by varying the coefficients of money. The numbers in parentheses are the marginal significance levels of the U statistics obtained from non-parametric bootstrapping.

Table 7. Bilson-Frenkel Model (1991:1 ~ 1995:12)

k	Model 2		Model 6		#
	FC	TVC	FC	TVC	
1	0.998(0.55)	0.942	0.973(0.21)	0.899	59
12	1.269(0.84)	0.769	1.321(0.88)	0.622	48
24	1.685(0.84)	0.739	1.986(0.90)	0.713	36
36	2.335(0.85)	0.770	3.049(0.91)	0.795	24
48	3.314(0.88)	0.708	4.427(0.92)	0.260	12

Notes: The U statistics of TVC Model 2 and Model 6 are obtained by varying the coefficients of short term interest rate.

Table 8. Dornbusch-Frankel Model (1991:1 ~ 1995:12)

k	Model 3		Model 7		#
	FC	TVC	FC	TVC	
1	0.970(0.18)	0.986	0.964(0.15)	0.949	59
12	1.027(0.64)	0.925	1.205(0.82)	0.727	48
24	1.301(0.75)	0.934	1.858(0.88)	0.683	36
36	1.500(0.75)	0.940	2.767(0.89)	0.743	24
48	1.522(0.74)	0.924	4.001(0.91)	0.389	12

Notes: The U statistics of TVC Model 3 are obtained by varying the coefficient of money, and those of TVC Model 7 are obtained by varying the coefficient of short term interest rate.

Table 9. Hooper-Morton Model (1991:1 ~ 1995:12)

k	Model 4		Model 8		#
	FC	TVC	FC	TVC	
1	0.937(0.03)	1.053	0.971(0.20)	1.042	59
12	1.153(0.78)	1.197	0.982(0.57)	0.950	48
24	1.311(0.76)	1.008	0.836(0.49)	0.890	36
36	2.085(0.84)	1.219	1.146(0.68)	0.825	24
48	1.385(0.73)	1.692	1.301(0.72)	0.694	12

Notes: The U statistics of TVC Model 4 are obtained by varying the coefficient of the cumulated trade balance of the U.S., and those of TVC Model 8 are obtained by varying the coefficient of money.

There are several noteworthy points in comparison to the fixed coefficient models. First, there is no fixed coefficient model which shows less than 1 U values at all the 5 forecast horizons. However, in the case of TVC models, six models (except for Model 4 and Model 8) show values of Us that are less than one at all forecast horizons. In the case of Model 8, the values of U are less than one except for one month forecasts.

Second, in the case of fixed coefficient models, forecast performance generally declines as the forecast horizon lengthens. However, for TVC models, forecast performance generally improves as the forecast horizon grows. In the case of TVC models (except for Model 4), all models show the lowest U value at the 48 month forecast horizon. Even in Model 4, the U value at the 48 month forecast horizon shows almost no difference from the lowest U value.

Third, in many cases permitting a time varying coefficient substantially improves forecast accuracy when comparing to fixed coefficient models. The improvement in forecast performance becomes more evident as the forecast horizon lengthens. Except for the cases of Model 1, 4, 5, and 8, forecast performance improves remarkably at all of the forecast horizons as the coefficients are allowed to time vary. Even in the cases of Models 1, 5, and 8, the forecast performance at longer than 36 month forecast horizon improves as the coefficients are allowed to time vary. This phenomenon is especially evident at the 48 month forecast horizon, where the forecast performance of time varying coefficient models regularly out-performs that of fixed coefficient models.

Fourth, introducing time varying coefficient models means quite a bit of shuffling in the rankings of forecast performance. Fixed coefficient models generally give the top two places to Model 1 and Model 5. However, in the cases of TVC models, gold, silver and bronze are distributed to Model 6, Model 7, and Model 5 respectively with Model 1 nowhere to be seen.

IV. Conclusions

This paper investigates the extent to which deviations of the won/dollar exchange rate from its fundamental value implied by economic theory are useful in predicting the exchange rate changes over long horizons. The major conclusions can be summarized as follows. First, if we fix the coefficients of the exchange rate determination models, the predictive power of the models is generally much weaker than that of the random walk model in most of forecast horizons. Only in exceptional cases do fixed coefficient models show better forecast performance than the random walk model. However, if we allow the coefficients of the models to vary over time, then the forecast performance improves remarkably and most of the models display a better forecast performance than the random walk model. With the exceptions of Model 4 and Model 8, all six other models out-performed the random walk model particularly well in every forecast horizon.

Second, if we allow the coefficients to vary with the lapse of time, the forecast performance improves to a greater extent as the forecast horizon becomes longer. This phenomenon is most apparent in the case of Model 6. Fixing the coefficients yields the U value as 0.973, 1.321, 1.986, 3.049, 4.427 at the 1, 12, 24, 36, 48 month forecast horizons. But allowing the coefficients to time vary improves the U value remarkably to 0.899, 0.622, 0.713, 0.705, 0.206 at the same forecast horizons.

Third, in the case of fixed coefficient models, Benchmark, Frenkel-Bilson, and Dornbusch-Frankel Model, using relative differences of the U.S. and Korea's macroeconomic variables give a better forecast performance than when using only Korea's macroeconomic variables. But in the Hooper-Morton Model, using Korea's macro economic variables alone offers considerably better forecasting.

However, in the case of all TVC models (Benchmark, Frenkel-Bilson, Dornbusch-Frankel and Hooper-Morton Model), using Korea's macroeconomic variables alone yields better forecasts than when using the relative differences of the U.S. and Korea's macro economic variables. As an example, at the 48 month forecast horizon, the U values of Benchmark, Frenkel-Bilson, Dornbusch-Frankel and Hooper-Morton Model obtained by using relative differences of the U.S. and Korea's economic variables are 0.718, 0.708, 0.924, 1.692 respectively, while the U values obtained by using Korea's economic variables alone through the same models display far lower values as 0.537, 0.260, 0.389, 0.694 respectively.

Fourth, when we allow the coefficients to vary with the lapse of time, then the order of the forecast ability changes significantly. Generally in the case of fixed coefficient models, with exceptions on some forecast horizons, the forecast ability of models are in the order of Model 1 and Model 8. However, in TVC cases, the forecast ability of models ranks in the order of Model 6 and Model 7.

Fifth, including the fixed exchange rate period data before March 1980 deteriorates the forecast ability of the models. The reason that the inclusion of fixed exchange rate data limits the forecasting ability in a flexible exchange rate period seems to be linked to the prolonged governmental repression in most of Korea's economic sectors.

Appendix 1. Contents of Data

Variable	Contents of Data	Sources
Korea		
s_t	Won/Dollar Exchange Rate, Average, (60:1~96:1)	BOK
m_t	M1, End of Period, Million Won, NSA, (60:1~96:1)	BOK
y_t	Industrial Production Index, 1990=100, SA, (60:1~96:1)	BOK
si_t	3 year Corporate Bond Yield, average, %, (72:1~96:2)	BOK
li_t	5 year National Housing Bond Yield, average, %, (70:1~96:2)	BOK
ctb_t	Cumulative Trade Balance, Million dollar, (65:1~95:12)	BOK
USA		
m_t^*	M1, End of Period, Million dollar, SA (60:1~95:12)	DS
y_t^*	Industrial Production Index, 1990=100, SA, (60:1~95:12)	IFS
si_t^*	3 month Treasury Bill Rate, average, % (60:1~96:1)	DS
li_t^*	10 year Government Bond Yield, average, % (60:1~96:1)	IFS
ctb_t^*	Cumulative Trade Balance, Million dollar, FAS-CIF (60:1~95:12)	DS

Notes: BOK means Bank of Korea, KSE Korean Stock Exchange,
IFS International Financial Statistics, DS Data Stream,
SA seasonally adjusted, NSA not seasonally adjusted

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