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Superior Predictability of American Factors of the Won/Dollar Real Exchange Rate*

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Abstract

Utilizing an array of data dimensionality reduction methods, we estimate latent common factors for the Won/Dollar real exchange rate from a large panel of economic predictors of the U.S. and Korea. We demonstrate superior out-of-sample predictability of our factor augmented forecasting models relative to conventional models when we utilize factors obtained from U.S. economic variables, while the Korean factors fail to enhance predictability. Our models perform better at longer horizons when the American real activity factors are employed, whereas the American nominal/financial market factors help improve short-run prediction accuracy. The UIP-based global factors with the dollar as numéraire overall perform well, while the PPP and RIRP factors play a limited role in forecasting the Won/Dollar exchange rate.

Keywords: Won/Dollar Real Exchange Rate; Principal Component Analysis; Partial Least Squares; LASSO; Out-of-Sample Forecast

JEL Classification: C38; C53; C55; F31; G17

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1 Introduction

This paper presents factor-augmented forecasting models for the real exchange rate between Korea and the U.S. We demonstrate superior out-of-sample prediction performance of our models over commonly used benchmark models when we employ latent factors that are extracted from a large panel of macroeconomic time series data in the U.S. On the other hand, we report a very limited role of factors from Korean macroeconomic variables in predicting the real exchange rate. We interpret such superb forecastability exclusive to American factors as a consequence of high degree of cross-correlations between bilateral real exchange rates *vis-à-vis* the U.S. dollar.

In their seminal work, Meese and Rogoff (1983) demonstrate that the random walk (RW) model performs well in forecasting exchange rates in comparison with the models that are motivated by exchange rate determination theories. Cheung, Chinn, and Pascual (2005) add more evidence of such a disconnect between the exchange rate and economic fundamentals, showing that exchange rate models still do not consistently outperform the RW model in out-of-sample forecasting.¹ In a related work, Engel and West (2005) provide an interesting point that asset prices such as the exchange rate can show a near unit root process, though these prices are still consistent with asset pricing models as the discount factor approaches one.²

However, a group of researchers demonstrated that exchange rate models could outperform the RW model at longer horizons. For example, Mark (1995) used a regression model of multiple-period changes (long-differenced) in the nominal exchange rate on the deviation of the exchange rate from its fundamentals, then reported overall superior long-horizon predictability of fundamentals for the exchange rate. Chinn and Meese (1995) also report similar long-horizon evidence of greater predictability of exchange rate models relative to the RW. Using over two century-long annual frequency data, Lothian and Taylor (1996) report good out-of-sample predictability of fundamentals for the *real* exchange rate. Groen (2005) reports some long-horizon evidence of superior predictability of monetary fundamentals employing a vector autoregressive (VAR) model framework.³ Also, Engel, Mark, and West (2008) show

¹However, Engel and Hamilton (1990) report some evidence that their nonlinear models outperform the RW. But their findings are still at odds with uncovered interest parity (UIP).

²Many researchers provide panel evidence of a close link between monetary models and exchange rate dynamics. See for example, Rapach and Wohar (2004), Groen (2000), and Mark and Sul (2001).

³They demonstrate that the monetary fundamentals-based *common* long-run model tends to outperform the RW model as well as the standard cointegrated vector autoregressive (VAR) model

that out-of-sample predictability can be enhanced by focusing on panel estimation and long-horizon forecasts.

Another group of researchers started using Taylor Rule fundamentals in addition to conventional monetary fundamentals. See among others, Engel, Mark, and West (2008), Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008), Molodtsova and Papell (2009), Molodtsova and Papell (2013), and Ince, Molodtsova, and Papell (2016). They show that models with Taylor Rule fundamentals tend to perform well in forecasting the exchange rate. See Rossi (2013) for a survey of research work that demonstrates the importance of Taylor Rule fundamentals in understanding exchange rate dynamics.⁴

We note that the pioneering work of Stock and Watson (2002) has initiated an influx of papers that utilize latent common factors in forecasting macroeconomic variables via principal components (PC) analysis. The current exchange rate literature is not an exception. A number of researchers began using large panels of time series data to better understand exchange rate dynamics. For instance, Engel, Mark, and West (2015) use cross-section information (PC factors) that are obtained from a panel of 17 bilateral exchange rates relative to the US dollar, then demonstrate that factor based forecasting models often outperform the RW model during the post-1999 sample period. They also report good forecasting performance of the dollar factor in combination with Purchasing Power Parity (PPP) factors. Chen, Jackson, Kim, and Resiandini (2014) used PC to extract latent common factors from 50 world commodity prices. Their first common factor turns out to be closely related with the dollar exchange rate, which is consistent with an observation that world commodities are priced in U.S. dollars. They show that this first common factor yields superior out-of-sample predictive contents for the dollar exchange rate.

Greenaway-McGrevy, Mark, Sul, and Wu (2018) demonstrate that exchange rates are mainly driven by a dollar and an euro factor. They show that their dollar-euro factor model dominates the RW model in the out-of-sample prediction performance. Verdelhan (2018) uses portfolios of international currencies to extract the two risk factors (dollar factor and carry factor), which successfully explain exchange rate dynam-

at 2 to 4 year horizons.

⁴In a related work, Wang and Wu (2012) show the superior out-of-sample interval predictability of the Taylor Rule fundamentals at longer horizons. Also, many researchers report in-sample evidence that Taylor rule fundamentals help understanding exchange rate dynamics. See among others, Mark (2009), Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008), Engel and West (2006), and Clarida and Waldman (2008).

ics. Ca' Zorzi, Kociecki, and Rubaszek (2015) demonstrate that structural Bayesian vector autoregression (SBVAR) models with a Dornbusch prior tend to outperform the RW model at medium horizons, although it is still difficult to beat the RW model in the short-run.

PC has been widely used in the current forecasting and empirical macroeconomics literature. However, it extracts latent common factors from predictors without considering the relationship between predictors and the target variable. As shown by Boivin and Ng (2006), its performance may be poor in forecasting the target variable if useful predictive contents are in a certain factor that is dominated by other factors. Recognizing this potential problem, we employ an alternative data dimensionality reduction method such as the partial least squares (PLS) method proposed by Wold (1982). This method utilizes the covariance between the target and predictor variables to generate *target-specific* factors. See Kelly and Pruitt (2015) and Groen and Kapetanios (2016) for some comparisons between the PC and PLS approaches. Similar to Bai and Ng (2008) and Kelly and Pruitt (2015), we also use the Least Absolute Shrinkage and Selection Operator (LASSO) to select target-specific *groups* of the predictors among the full dataset to extract more relevant factors for the target.

In this paper, we suggest factor-augmented forecasting models for the KRW/USD real exchange rate. We employ PC and PLS as well as the LASSO in combination with PC and PLS to estimate common factors using large panels of 125 American and 192 Korean monthly frequency macroeconomic time series data from October 2000 to March 2019. Since most macroeconomic data are better approximated by a nonstationary integrated process (Nelson and Plosser, 1982), we extract common factors by applying these methods to first differenced predictors to consistently estimate factors (Bai and Ng, 2004). We also extract common factors from country-level global data using up to 43 country-level data for prices and interest rates, motivated by exchange rate determination theories such as Purchasing Power Parity (PPP), Uncovered Interest Parity (UIP), and Real Uncovered Interest Parity (RIRP). We then implement an array of out-of-sample forecasting exercises utilizing these factor estimates, and investigate what factors help improve the prediction accuracy for the exchange rate. We evaluate the out-of-sample predictability of our factor models via the ratio of the root mean squared prediction error (RRMSPE) criteria.

Our major findings are as follows. First, our factor-augmented forecasting models outperform the random walk (RW) and autoregressive AR(1) type benchmark models only when they utilize American factors. Korean factor-augmented models overall got

dominated by the AR model, although they still outperform the RW model when the forecast horizon is one-year or longer. It is well known that bilateral exchange rates relative to the U.S. dollar tend to exhibit high cross-correlations. That is, U.S. common factors are likely to dominate dynamics of these exchange rates *vis-à-vis* dollars over idiosyncratic components in each country such as Korea. Combining Korean (idiosyncratic) factors with American factors slightly improves the forecasting performance but failed to observe sufficiently large improvement enough to outperform the AR model.

Second, our models tend to perform better in short horizons when they are combined with nominal/financial market factors in the U.S. On the other hand, American real activity factor models outperform both the RW and AR models at longer horizons. Put it differently, good short-run prediction performance of our models with the total factors seems to inherit the superior performance of our models with financial market factors, while superior long-run predictability seems to stem from information from real activity factors. These results are consistent with the work of Boivin and Ng (2006) in the sense that one may extract more useful information from subsets of predictors.

Third, forecasting models with UIP motivated factors perform well when the U.S. serves as the reference country. However, PPP and RIRP based factor models are dominated by the AR model whichever country serves as the reference. Overall, data-driven factor models seem to perform better than these proposition-based factor models.

The rest of the paper is organized as follows. Section 2 carefully describes how we estimate latent common factors via PC, PLS, and the LASSO for the real exchange rate when predictors obey an integrated process. Section 3 presents data descriptions and preliminary statistical analysis. We also report some in-sample fit analysis to investigate the source of latent common factors. In Section 4, we introduce our factor-augmented forecasting models and evaluation schemes. Then, we present and interpret our out-of-sample forecasting exercise results. We also report results with alternative identification approaches, proposition-based models and nonstationary forecasting models, in comparison with the data-driven factor forecasting models. Section 5 concludes.

2 Methods of Estimating Latent Common Factors

This section explains how we estimate latent common factors by applying Principal Component (PC), Partial Least Squares (PLS), and the Least Absolute Shrinkage and Selection Operator (LASSO) to a large panel of *nonstationary* predictors.

2.1 Principal Component Factors

Since the seminal work of Stock and Watson (2002), PC has been popularly used in the current forecasting literature. We begin with this approach to show how to estimate latent common factors when predictors obey an integrated $I(1)$ process, largely based on the work of Bai and Ng (2004, 2010).

Consider a panel of N macroeconomic $T \times 1$ time series predictors/variables, $\mathbf{x} = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N]$, where $\mathbf{x}_i = [x_{i,1}, x_{i,2}, \dots, x_{i,T}]'$, $i = 1, \dots, N$. We assume that each predictor \mathbf{x}_i has the following factor structure. Abstracting from deterministic terms,

$$x_{i,t} = \boldsymbol{\lambda}_i' \mathbf{f}_t^{PC} + \varepsilon_{i,t}, \quad (1)$$

where $\mathbf{f}_t = [f_{1,t}^{PC}, f_{2,t}^{PC}, \dots, f_{R,t}^{PC}]'$ is an $R \times 1$ vector of *latent* time-varying common factors at time t and $\boldsymbol{\lambda}_i = [\lambda_{i,1}, \lambda_{i,2}, \dots, \lambda_{i,R}]'$ denotes an $R \times 1$ vector of time-invariant idiosyncratic factor loading coefficients for \mathbf{x}_i . $\varepsilon_{i,t}$ is the idiosyncratic error term.

Following Bai and Ng (2004, 2010), we estimate latent common factors by applying the PC method to first-differenced data. This is because, as shown by Nelson and Plosser (1982), most macroeconomic time series variables are better approximated by an integrated nonstationary stochastic process. Note that the PC estimator of \mathbf{f}_t would be inconsistent if $\varepsilon_{i,t}$ is an integrated process. Differencing both sides of (1), we obtain the following.

$$\Delta x_{i,t} = \boldsymbol{\lambda}_i' \Delta \mathbf{f}_t^{PC} + \Delta \varepsilon_{i,t} \quad (2)$$

for $t = 2, \dots, T$. We first normalize the data, $\Delta \tilde{\mathbf{x}} = [\Delta \tilde{\mathbf{x}}_1, \Delta \tilde{\mathbf{x}}_2, \dots, \Delta \tilde{\mathbf{x}}_N]$, then apply PC to $\Delta \tilde{\mathbf{x}} \Delta \tilde{\mathbf{x}}'$ to obtain the factor estimates $\Delta \hat{\mathbf{f}}_t^{PC}$ along with their associated factor loading coefficients $\hat{\boldsymbol{\lambda}}_i$.⁵ Naturally, estimates of the idiosyncratic component are obtained by taking the residual, $\Delta \hat{\varepsilon}_{i,t} = \Delta \tilde{x}_{i,t} - \hat{\boldsymbol{\lambda}}_i' \Delta \hat{\mathbf{f}}_t^{PC}$. The level variable

⁵This is because PC is not scale invariant. We demean and standardize each time series.

estimates are then recovered via cumulative summation as follows.

$$\hat{\varepsilon}_{i,t} = \sum_{s=2}^t \Delta \hat{\varepsilon}_{i,s}, \quad \hat{\mathbf{f}}_t^{PC} = \sum_{s=2}^t \Delta \hat{\mathbf{f}}_s^{PC} \quad (3)$$

It should be noted that this procedure yields consistent factor estimates even when \mathbf{x} includes some stationary $I(0)$ variables. For example, assume that \mathbf{x}_j , $j \in \{1, \dots, N\}$ is $I(0)$. Differencing it once results in $\Delta \mathbf{x}_j$, which is still a stationary $I(-1)$ process. Therefore the PC estimator remains consistent. Alternatively, one may continue to difference the variables until the null of nonstationarity hypothesis is rejected via a unit root test.⁶ However, this may not be practically useful when unit root tests provides contradicting statistical inferences under alternative test specifications (i.e., number of lags, number of observations) in finite samples. See Cheung and Lai (1995) for related discussions.

2.2 Partial Least Squares Factors

We employ PLS for a scalar target variable q_t , which is a somewhat overlooked estimator in the current literature. Unlike PC, the method of PLS generates *target specific* latent common factors, which is an attractive feature. As Boivin and Ng (2006) pointed out, PC factors might not be useful in forecasting the target variable when useful predictive contents are in a certain factor that may be dominated by other factors.

PLS is motivated by the following linear regression model. Abstracting from deterministic terms,

$$q_t = \Delta \mathbf{x}_t' \boldsymbol{\beta} + e_t, \quad (4)$$

where $\Delta \mathbf{x}_t = [\Delta x_{1,t}, \Delta x_{2,t}, \dots, \Delta x_{N,t}]'$ is an $N \times 1$ vector of predictor variables at time $t = 1, \dots, T$, while $\boldsymbol{\beta}$ is an $N \times 1$ vector of coefficients. e_t is an error term. Again, we first-difference the predictor variables assuming that \mathbf{x}_t is a vector of $I(1)$ variables..

PLS is especially useful for regression models that have many predictors, that is,

⁶This approach is used to construct the Fred-MD database. The Fred-MD is available at <https://research.stlouisfed.org/econ/mccracken/fred-databases/>.

when N is large.⁷ To reduce the dimensionality, rewrite (4) as follows,

$$\begin{aligned} q_t &= \Delta \mathbf{x}_t' \mathbf{w} \boldsymbol{\theta} + u_t \\ &= \Delta \mathbf{f}_t^{PLS'} \boldsymbol{\theta} + u_t \end{aligned} \quad (5)$$

where $\Delta \mathbf{f}_t^{PLS} = [\Delta f_{1,t}^{PLS}, \Delta f_{2,t}^{PLS}, \dots, \Delta f_{R,t}^{PLS}]'$, $R < N$ is an $R \times 1$ vector of PLS factors.

Note that $\Delta \mathbf{f}_t^{PLS}$ is a linear combination of *all* predictor variables, similar to ridge regression, that is,

$$\Delta \mathbf{f}_t^{PLS} = \mathbf{w}' \Delta \mathbf{x}_t, \quad (6)$$

where $\mathbf{w} = [\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_R]$ is an $N \times R$ weighting matrix. That is, $\mathbf{w}_r = [w_{1,r}, w_{2,r}, \dots, w_{N,r}]'$, $r = 1, \dots, R$, is an $N \times 1$ vector of weights on predictor variables for the r^{th} PLS factor, $\Delta f_{r,t}^{PLS}$. $\boldsymbol{\theta}$ is an $R \times 1$ vector of PLS regression coefficients. PLS regression minimizes the sum of squared residuals from the equation (5) for $\boldsymbol{\theta}$ instead of $\boldsymbol{\beta}$ in (4).

It should be noted that we do not utilize $\boldsymbol{\theta}$ for our out-of-sample forecasting exercises in the present paper. To make it comparable to PC factors, we utilize PLS factors $\Delta \mathbf{f}_t^{PLS}$, then augment the benchmark forecasting model with estimated PLS factors $\Delta \hat{\mathbf{f}}_t^{PLS}$.

Among available PLS algorithms, see Andersson (2009) for a brief survey, we use the one proposed by Helland (1990) that is intuitively appealing. Helland's algorithm to estimate PLS factors for a scalar target variable q_t is as follows.

First, $\Delta \hat{f}_{1,t}^{PLS}$ is pinned down by the linear combinations of the predictors in $\Delta \mathbf{x}_t$.

$$\Delta \hat{f}_{1,t}^{PLS} = \sum_{i=1}^N w_{i,1} \Delta x_{i,t}, \quad (7)$$

where the loading (weight) $w_{i,1}$ is given by $Cov(q_t, \Delta x_{i,t})$. Second, we regress q_t and $\Delta x_{i,t}$ on $\Delta \hat{f}_{1,t}^{PLS}$ then get residuals, \tilde{q}_t and $\Delta \tilde{x}_{i,t}$, respectively, to remove the explained component by the first factor $\Delta \hat{f}_{1,t}^{PLS}$. Next, the second factor estimate $\Delta \hat{f}_{2,t}^{PLS}$ is obtained similarly as in (7) with $w_{i,2} = Cov(\tilde{q}_t, \Delta \tilde{x}_{i,t})$. We repeat until the R^{th} factor $\Delta \hat{f}_{R,t}^{PLS}$ is obtained. Note that this algorithm generates mutually orthogonal factors.

⁷For example, the least squares estimator is not even feasible when N is greater than T .

2.3 Least Absolute Shrinkage and Selection Operator Factors

We employ a shrinkage and selection method for linear regression models, the LASSO, which is often used for sparse regression. Unlike ridge regression, the LASSO selects a subset (\mathbf{x}^s) of predictor variables from \mathbf{x} by assigning 0 coefficient to the variables that are relatively less important in explaining the target variable. Putting it differently, we implement the *feature selection* task using the LASSO.

The LASSO puts a cap on the size of the estimated coefficients for the ordinary least squares (LS) driving the coefficient down to zero for some predictors. The LASSO solves the following constrained minimization problem using L_1 -norm penalty on β .

$$\min_{\beta} \left\{ \frac{1}{T} \sum_{t=1}^T (q_t - \Delta \mathbf{x}'_t \beta)^2 \right\}, \text{ s.t. } \sum_{j=1}^N |\beta_j| \leq \tau \quad (8)$$

where $\Delta \mathbf{x}_t = [\Delta x_{1,t}, \Delta x_{2,t}, \dots, \Delta x_{N,t}]'$ is an $N \times 1$ vector of predictor variables at time $t = 1, \dots, T$, β is an $N \times 1$ vector of associated coefficients. As the value of tuning (penalty) parameter τ decreases, the LASSO returns a smaller subset of \mathbf{x} , setting more coefficients to zero.

Following Kelly and Pruitt (2015), we choose the value of τ to generate a certain number of predictors by applying the LASSO to $\Delta \mathbf{x}$. We then employ the PC and PLS approaches to extract common factors, $\Delta \mathbf{f}_t^{PC/L}$ or $\Delta \mathbf{f}_t^{PLS/L}$, out of the predictor variables that are chosen by the LASSO regression. The variables selected from the regression were based on the entire period and the tuning parameter was selected accordingly. Similar to our PLS approach, we use the LASSO method only to obtain the subset of predictors that are closely related to the target. Having obtained them, we use a rolling window approach to extract the common factors using PC and PLS methods described above.

3 In-Sample Analysis

3.1 Data Descriptions

We employ two sets of large panel macroeconomic data in the U.S. and Korea to assess and compare the predictability of these dataset for the real dollar/won exchange rate. For this purpose, we obtained a panel of 126 American macroeconomic time

series variables from the FRED-MD database. We also obtained 192 Korean macroeconomic time series data from the Bank of Korea. Korea has maintained a largely fixed exchange rate regime for the dollar-won exchange rate until around 1980, then switched to a heavily managed floating exchange rate regime. Korea continued such dirty float or managed float until they were forced to adopt a market based exchange rate regime after they got hit by the Asian Financial Crisis in 1997.

We focus on the free floating exchange rate regime in 2000's after the Korean economy fully recovered from the crisis. Observations are monthly and span from October 2000 to March 2019 to utilize reasonably many monthly predictors in Korea. We use the consumer price index (CPI) to transform the nominal KRW/USD exchange rate to the real exchange rate.

We categorized 126 American predictors into 9 groups. Groups #1 through #4 include real activity variables that include industrial productions and labor market variables, while groups #5 to #9 are nominal/financial market variables such as interest rates and prices in the U.S. Similarly, we categorized 192 Korean predictors into 13 groups. Groups #1 through #6 include real activity variables that include inventories and industrial productions, while groups #7 to #13 are nominal/financial market variables such as interest rates and monetary aggregates. See Table 1 for more detailed information. We log-transformed all quantity variables prior to estimations other than those expressed in percent (e.g., interest rates and unemployment rates).

Table 1 around here

3.2 Unit Root Tests

We first implement some specification tests for our analysis. Table 2 presents the augmented Dickey Fuller (ADF) test results for the log real exchange rate ($q_t = s_t + p_t^{US} - p_t^{KR}$) and the log nominal exchange rate (s_t). The ADF test rejects the null of nonstationarity for q_t at the 5% significance level, while it fails to reject the null hypothesis for s_t at any conventional level. Note that these results are consistent with standard monetary models in international macroeconomics. Recall, for example, that purchasing power parity (PPP) is consistent with stationary q_t and nonstationary s_t , because PPP implies a cointegrating relationship [1, 1] between s_t and the relative price ($relp_t = p_t^{US} - p_t^{KR}$) for the real exchange rate q_t in the long-run.

Next, we implement a panel unit root test for predictor variables in the US (\mathbf{x}_t^{US}) and in Korea (\mathbf{x}_t^{KR}) via the Panel Analysis of Nonstationarity in Idiosyncratic and Common components (PANIC) analysis by Bai and Ng (2004, 2010). The PANIC procedure estimates common factors ($f_{r,t}^{PC}, r = 1, 2, \dots, R$) via PC as explained in the previous section, then test the null of nonstationarity for common factors via the ADF test with an intercept. It also implements a panel unit root test for de-factored idiosyncratic components of the data by the following statistic.

$$P_{\hat{e}} = \frac{-2 \sum_{i=1}^N \ln p_{\hat{e}_i} - 2N}{2N^{1/2}},$$

where $p_{\hat{e}_i}$ denotes the p -value of the ADF statistic with no deterministic terms for de-factored $\Delta x_{i,t}$.⁸

Note that we also test the null hypothesis for the common factors of subsets of \mathbf{x}_t , that is, real and financial sector variables separately. This is because we are interested in the out-of-sample predictability of the common factors from these subsets of the data. In what follows, we show American real activity factors ($f_{r,t}^{PC,R}, r = 1, 2, \dots, R$) include more long-run predictive contents, whereas American financial market factors ($f_{r,t}^{PC,F}, r = 1, 2, \dots, R$) yield superior predictability in the short-run, which is consistent with the implications of Boivin and Ng (2006).

The PANIC test fails to reject the null of nonstationarity for all common factor estimates at the 5% significance level with an exception of the second financial factor in the US. Its panel unit root test rejects the null hypothesis that states all variables are $I(1)$ processes for all cases.⁹ However, nonstationary common factors eventually dominate stationary dynamics of de-factored idiosyncratic components.¹⁰ Hence, test results in Table 2 provide strong evidence in favor of nonstationarity in the predictor variables \mathbf{x}_t , which is consistent with Nelson and Plosser (1982).

Table 2 around here

⁸ $P_{\hat{e}}$ statistic has an asymptotic standard normal distribution. The panel test utilizes the p -value of the ADF statistics with no deterministic terms, because defactored variables are mean-zero residuals.

⁹The alternative hypothesis is that there is at least one stationary variable.

¹⁰See Kim and Kim (2018) for a simulation study that shows the dominance of stationary components over nonstationary components in small samples.

3.3 Factor Model In-Sample Analysis

This section describes some in-sample properties of the factor estimates we discussed in previous section. The in-sample factors are estimated based on the entire available data, and therefore these factors will be different that of the *out-of-sample* factors obtained in the next section. Figure 1 presents in-sample fit analysis for the KRW/USD real exchange rate. Three figures in top row report cumulative R^2 statistics of PC and PLS factors obtained from all predictors, real activity predictors, and financial sector predictors in the US, respectively from left to right. Three figures in bottom row provide cumulative R^2 values of Korean factors similarly. Some interesting findings are as follows.

First, the PLS factors (dashed lines) provide a notably better in-sample fit in comparison with the performance of PC factors (solid lines). This is because PLS utilizes the covariance between the target and the predictor variables, while PC factors are extracted from the predictor variables only. It is also interesting to see that the cumulative R^2 statistics of PLS factors overall exhibit a positive slope at a decreasing rate as the number of factors increases, whereas additional contributions of PC factors show no such patterns. This is mainly due to the fact that our PLS algorithm sequentially estimates orthogonalized common factors after removing explanatory power of previously estimated factors. The PC method extracts common factors without considering the target variable, hence the additional contribution of PC factors does not necessarily decrease.

Second, American factors greatly outperform Korean factors. Cumulative R^2 values of American PLS factors reach well above 60%, while Korean PLS factors cumulatively explain less than 40% of variations in the real exchange rate. Note that Korean PC factors yield virtually no explanatory power. These findings imply that Korean macroeconomic variables might not play an important role in explaining the Won/Dollar real exchange rate dynamics, while American predictors contain substantial predictive contents for it.

Figure 1 around here

We relate such findings with a strong degree of cross-correlations of many bilateral exchange rates relative to the US dollars, implying that American factors better explain dynamics of exchange rates *vis-à-vis* the U.S. dollar than idiosyncratic factors

in local countries such as Korea. To see this, we implement a formal test by Pesaran (2021) for the cross-section dependence in 36 bilateral real exchange rates against the U.S. dollar including 16 euro-zone countries.¹¹

Consider the following test statistic.

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{i,j} \right) \longrightarrow^d N(0,1)$$

where $\hat{\rho}_{i,j}$ is the pair-wise correlation coefficients from the residuals of the ADF regressions for each real exchange rate.¹² The CD statistic was 176.748 ($pv = 0.000$) implying strong empirical evidence of cross-section dependence at any conventional significance level.

The heat map in Figure 2 clearly demonstrates such strong cross-correlations in the real exchange rate relative to the U.S. dollar. With some exceptions such as China that often employs managed float, most real exchange rates exhibit highly correlated contemporaneous relations. The average $\hat{\rho}_{i,Korea}$ was 0.446, while the average $\hat{\rho}_{i,j}$ of all countries was 0.481.

We obtained similar results even when we exclude all euro-zone countries. The CD statistic was 59.019 ($pv = 0.000$) and the average $\hat{\rho}_{i,j}$ was 0.293. Such strong cross-correlations of many bilateral real exchange rates imply a dominant role of the reference country, that is, the U.S. in determining the dynamics of these bilateral exchange rates.

Figure 2 around here

Third, PLS factors from American real activity groups and financial variable groups explain variations in the KRW/USD real exchange rate similarly well. On the other hand, the contribution of PLS Korean factors mostly stem from that of

¹¹We obtained all nominal exchange rates and CPIs from the IFS for the sample period from September 2000 to December 2018. 16 eurozone countries that are included are Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Portugal, Slovakia, Slovenia, and Spain. We were able to retrieve 20 non-eurozone countries including Brazil, Canada, Chile, China, Colombia, Czech Republic, Denmark, Hungary, India, Indonesia, Israel, Japan, Korea, Mexico, Poland, Russia, Singapore, Switzerland, Sweden, and the UK. We obtained the Singapore CPI from the Department of Statistics of Singapore.

¹²We implemented the ADF regression for each real exchange rate relative to the U.S. dollar via the general-to-specific rule with maximum 6 lags, then calculated pair-wise correlation coefficients using the ADF regression residuals of 35 real exchange rates.

PLS Korean financial sector factors. PLS real Korean factors explain less than 10% of variations jointly even when 12 factors are utilized.

Next, we investigate the source of these common factor estimates via the marginal R^2 analysis. That is, we regress each predictor onto the common factor and record what proportion of the variation can be explained by the common factor. Results are reported in Figures 3 to 5 for the first common factor from the entire predictors, real activity variables, and nominal/financial market variables, respectively.

As can be seen in Figure 3, we note that the marginal R^2 statistics of the first American PC factor (solid lines) are very similar to those of the first PLS American factor (bar graphs). On the other hand, the marginal R^2 statistics of the first Korean PC factor is quite different from the PLS factor. More specifically, the marginal R^2 statistics of the Korean PLS factor are negligibly low in comparison with those of the PC factor. Since PC factors are obtained only from the predictors with no reference on the target variable, the marginal R^2 values of the PC factor are expected to be high. However, since PLS factors are estimated using the covariance of the target variable and the predictor, low R^2 statistics of the Korean PLS factor imply that Korean predictors are largely disconnected from the KRW/USD real exchange rate. This is consistent with negligibly low cumulative R^2 statistics in Figure 1.

Note also that PLS American factors are more closely connected with groups #1 (industrial production) and #2 (labor market) than other groups. Put it differently, the first PLS American factor seems to be strongly driven by these real activity variables rather than financial market variables and other real activity variables. We also point out that these two groups include key variables that influence the Fed's decision making process of U.S. monetary policy stance under its dual mandate. That is, they are potentially useful predictors of financial market conditions.

Figure 3 around here

We investigate the source of the common factors in a more disaggregated level, looking at the marginal R^2 statistics of the real and financial market factors. Figure 4 reports the R^2 statistics of the first American real activity factor. Again, the PLS and PC factors turn out to explain the variations in real activity variables similarly well. We also note that the American real activity factor is mainly driven by industrial production (Group #1) and labor market (Group #2) variables. However, the

PLS Korean real activity factor explains negligible variations in Korean real activity variables, while the first PC factor exhibits reasonably high R^2 statistics. This again confirms our previous findings. Similar results were observed from the marginal R^2 analysis for the first financial market PLS and PC factors in Figure 5. The American PLS and PC nominal/financial market factors seem to be driven mostly by CPIs and PPIs in the US.

Figures 4 and 5 around here

4 Out-of-Sample Prediction Performance

4.1 Factor-Augmented Forecasting Models

This section reports our out-of-sample forecast exercise results using factor-augmented forecasting models for the KRW/USD real exchange rate. Based on the ADF test results in Table 2, we employ the following *stationary AR(1)*-type stochastic process for the real exchange rate q_t . Abstracting from an intercept,

$$q_{t+j} = \alpha_j q_t + u_{t+j}, \quad j = 1, 2, \dots, k, \quad (9)$$

where α_j is less than one in absolute value for stationarity. Note that we regress the j -period ahead target variable (q_{t+j}) *directly* on the current period target variable (q_t) instead of using a *recursive* forecasting approach with an AR(1) model, $q_{t+1} = \alpha q_t + \varepsilon_{t+1}$, which implies $\alpha_j = \alpha^j$ under that approach. With this specification, the j -period ahead forecast is,

$$\widehat{q}_{t+j|t}^{AR} = \hat{\alpha}_j q_t, \quad (10)$$

where $\hat{\alpha}_j$ is the least squares (LS) estimate of α_j in (9).

We augment (9) by adding factor estimates. That is, our factor augmented stationary *AR(1)*-type forecasting model is the following.

$$q_{t+j} = \alpha_j q_t + \beta_j' \Delta \hat{\mathbf{f}}_t + u_{t+j}, \quad j = 1, 2, \dots, k \quad (11)$$

We again employ a *direct* forecasting approach by regressing q_{t+j} directly on q_t and the estimated factors ($\Delta \hat{\mathbf{f}}_t$). Note that (11) coincides with an exact *AR(1)* process

when $j = 1$, but extended by the factor covariates $\Delta\hat{\mathbf{f}}_t$. Note also that (11) nests the stationary benchmark model (9) when $\Delta\hat{\mathbf{f}}_t$ does not contain any useful predictive contents for q_{t+j} , that is, $\beta_j = 0$. We obtain the following j -period ahead forecast for q_{t+j} ,

$$\hat{q}_{t+j|t}^{FAR} = \hat{\alpha}_j q_t + \hat{\beta}'_j \Delta\hat{\mathbf{f}}_t, \quad (12)$$

where $\hat{\alpha}_j$ and $\hat{\beta}_j$ are the LS coefficient estimates from (11).

We evaluate the out-of-sample predictability of our factor-augmented forecasting model $\hat{q}_{t+j|t}^{FAR}$ using a fixed-size rolling window scheme as follows.¹³ We use initial $T_0 < T$ observations, $\{q_t, \Delta x_{i,t}\}_{t=1}^{T_0}$, $i = 1, 2, \dots, N$ to estimate the first set of factors $\{\Delta\hat{\mathbf{f}}_t\}_{t=1}^{T_0}$ using one of our data dimensionality reduction methods. We formulate the first forecast $\hat{q}_{T_0+j|T_0}^{FAR}$ by (12), then calculate and keep the forecast error ($\varepsilon_{T_0+j|T_0}^{FAR}$). Next, we add one observation ($t = T_0 + 1$) but drop one earliest observation ($t = 2$) for the second round forecasting. That is, we re-estimate $\{\Delta\hat{\mathbf{f}}_t\}_{t=2}^{T_0+1}$ using $\{q_t, \Delta x_{i,t}\}_{t=2}^{T_0+1}$, $i = 1, 2, \dots, N$, maintaining the same number of observations (T_0) in order to formulate the second round forecast, $\hat{q}_{T_0+j+1|T_0+1}^{FAR}$, and its resulting forecast error $\varepsilon_{T_0+j+1|T_0+1}^{FAR}$. We repeat until we forecast the last observation, q_T . We implement the same procedure for the benchmark forecast $\hat{q}_{t+j|t}^{AR}$ by (10) in addition to the no-change Random Walk (RW) benchmark $\hat{q}_{t+j|t}^{RW} = q_t$.¹⁴

We employ the ratio of the root mean square prediction error (*RRMSPE*) to evaluate the j -period ahead out-of-sample prediction accuracy of our factor augmented models relative to the benchmark. That is,

$$RRMSPE(j) = \frac{\sqrt{\frac{1}{T-j-T_0+1} \sum_{t=T_0}^{T-j} \left(\varepsilon_{t+j|t}^{BM}\right)^2}}{\sqrt{\frac{1}{T-j-T_0+1} \sum_{t=T_0}^{T-j} \left(\varepsilon_{t+j|t}^{FAR}\right)^2}}, \quad (13)$$

where

$$\varepsilon_{t+j|t}^{BM} = q_{t+j} - \hat{q}_{t+j|t}^{BM}, \quad \varepsilon_{t+j|t}^F = q_{t+j} - \hat{q}_{t+j|t}^{FAR}, \quad BM = AR, RW \quad (14)$$

Note that $RRMSPE(j) > 1$ indicates that our factor models outperform the benchmark models.¹⁵

¹³Rolling window schemes tend to perform better than the recursive method in the presence of structural breaks. However, results with recursive approaches were qualitatively similar.

¹⁴Consider a random walk model, $q_{t+1}^{BMRW} = q_t + \eta_{t+1}$, where η_{t+1} is a white noise process. Therefore, j -period ahead forecast from this benchmark RW model is simply q_t .

¹⁵Alternatively, one may employ the ratio of the root mean absolute prediction error (*RRMAPE*).

4.2 Prediction Accuracy Evaluations for the Real Exchange Rate

We implement out-of-sample forecast exercises using a fixed-size (50% split point, that is, $T_0 = T/2$) rolling window method with up to 3 (k) latent factor estimates.¹⁶ Latent common factors are acquired via the PLS, PC, and LASSO methods for large panels of macroeconomic data of the U.S. and Korea.

Table 3 reports the *RRMSPE* statistics of our forecasting model $\hat{q}_{t+j|t}^{FAR}$ relative to $\hat{q}_{t+j|t}^{RW}$. Recall that our models outperform the RW benchmark when the *RRMSPE* is greater than one. We also obtained the *RRMSPE* statistics of $\hat{q}_{t+j|t}^{FAR}$ relative to $\hat{q}_{t+j|t}^{AR}$ (not reported to save space), and the superscript * indicates that $\hat{q}_{t+j|t}^{FAR}$ outperforms $\hat{q}_{t+j|t}^{AR}$. In fact, since the AR benchmark performs better than the RW model, it implies that $\hat{q}_{t+j|t}^{FAR}$ outperforms both the benchmarks $\hat{q}_{t+j|t}^{RW}$ and $\hat{q}_{t+j|t}^{AR}$. Our major findings are as follows.

First, the American predictors yield superior predictive contents for the KRW/USD real exchange rate, while the Korean factor models perform relatively poorly. That is, our factor models outperform both the RW and AR models only when the American factors are employed. The models with the Korean factors overall got dominated by the AR model although they still outperform the RW model when the forecast horizon is one-year or longer. Recall that these empirical findings are consistent with our in-sample fit analysis shown in the previous section. Interestingly, when we combine the American factors with equal numbers of the Korean factors, the performance tends to deteriorate. That is, the *RRMSPE* often decreases in comparison with those of the American factor augmented models implying that the Korean factors may add noise in our combined models.

Second, we observe that our American factor models tend to perform better at short horizons when combined with nominal/financial market factors, while real activity factors improve the predictability at longer horizons. That is, the good prediction performance of our models with the total factors, $\Delta \hat{\mathbf{f}}_t^{PLS}$ or $\Delta \hat{\mathbf{f}}_t^{PC}$, at 1-period horizon seem to inherit the superior performance of our models with financial market factors, $\Delta \hat{\mathbf{f}}_t^{PLS,F}$ or $\Delta \hat{\mathbf{f}}_t^{PC,F}$, while superior long-run predictability seems to stem from predictive contents of real activity factors, $\Delta \hat{\mathbf{f}}_t^{PLS,R}$ or $\Delta \hat{\mathbf{f}}_t^{PC,R}$. These results imply that factors obtained from subsets may provide more useful information than factors from

Results are overall qualitatively similar.

¹⁶We obtained qualitatively similar results with a 70% sample split point.

the entire predictor variables, which is consistent with Boivin and Ng (2006).

Table 3 around here

We also employ the LASSO approach to select the subsets of the predictor variables that are useful to explain the target variable. The idea behind that is to estimate the factors using fewer but more informative predictor variables as discussed by Bai and Ng (2008). Following Kelly and Pruitt (2015), we adjust the tuning parameter τ in (8) to choose a group of 30 predictors from each panel of macroeconomic variables in the US and in Korea, while 20 predictors were chosen from each of the real activity and the financial market variable groups. Then, we employed PLS and PC to estimate up to 3 common factors to augment the benchmark AR model.

As we can see in Table 4, results are qualitatively similar to previous ones. The financial factor augmented forecasting models tend to perform better for the 1-period ahead forecasts, while real factors provide superior predictive contents for the real exchange rate at longer horizons. The Korean factor-augmented models perform overall poorly relative to the AR model, although they still outperform the RW model when the forecast horizon is 1-year or longer.

Table 4 around here

4.3 Model Predictability with Proposition Based Global Factors

This section implements out-of-sample forecast exercises using the models that are augmented by global factors, motivated by three exchange rate determination theories: Purchasing Power Parity (PPP); Uncovered Interest Parity (UIP); Real Interest Rate Parity (RIRP).

4.3.1 Purchasing Power Parity: Relative Price Factors

We first employ PPP to identify common global factors. Under PPP, the real exchange rate $q_t (= s_t + relp_t)$ is stationary, while the log nominal exchange rate s_t and the log

relative price $relp_t (= p_t - p_t^*)$ are nonstationary $I(1)$ processes. Put it differently, there exists a cointegrating vector $[1, 1]$ for s_t (foreign currency price of 1 USD) and $relp_t$, where p_t and p_t^* are the log prices in the U.S. and in the foreign country, respectively. Recall that our unit root test results in Table 2 are consistent with PPP.

We obtained the Consumer Price Index (CPI) of 43 countries from the IFS database including 18 euro-zone countries. Assuming that the U.S. is the home/reference country, we constructed 42 relative prices $(p_t - p_t^*)$, then estimated the first common factor from these relative prices after taking the first difference $(\Delta p_t - \Delta p_t^*)$, or $(\pi_t - \pi_t^*)$, since the relative price is an integrated process. Also, we extracted the common factors from the 42 relative prices with Korea as the reference country.^{17,18}

We report j -period ahead out-of-sample predictability exercise results (50% split point) for the Won-Dollar real exchange rate using one factor models when the U.S. or Korea serves as the reference country in Table 5. Results imply overall poor performance of PPP motivated factor models irrespective of the choice of the numéraire currency.

Our factor models overall outperform the RW model when the forecast horizon is 1-year or longer, which is consistent with the view that PPP is a long-run proposition. However, our PPP factor models rarely beat the AR benchmark model nor our data-driven macroeconomic factor models presented in the previous section. It is not surprising to find similar performance of the Korean reference factor model as the American factor model, since they include fundamentally similar information of CPIs in 43 countries.

Table 5 around here

¹⁷For the group of developed countries, we include 11 euro-zone countries (Austria, Belgium, Finland, France, Germany, Greece, Italy, Luxembourg, Netherlands, Portugal, Spain) and 8 non-euro-zone countries (Canada, Denmark, Japan, Singapore, Switzerland, Sweden, United Kingdom, United States). All data are obtained from the IFS database with an exception of Singapore. We obtained the Singapore CPI from the Department of Statistics of Singapore. In addition to the group of 19 developed countries, we added 7 the rest of euro-zone countries (Cyprus, Estonia, Ireland, Latvia, Lithuania, Slovakia, Slovenia) except Malta, and 17 non-euro-zone countries (Brazil, China, Chile, Colombia, Czech Republic, Hong Kong, Hungary, India, Indonesia, Israel, Korea, Malaysia, Mexico, Poland, Romania, Russia, Saudi Arabia).

¹⁸We focus on the relative price factor because of lack of available nominal exchange rates in the presence of euro-zone countries.

4.3.2 Uncovered Interest Parity: Interest Rate Spread

The second proposition we adopt is Uncovered Interest Parity (UIP). Abstracting from risk premium, UIP states the following.

$$\Delta s_{t+1} = i_t^* - i_t + \varepsilon_{t+1}, \quad (15)$$

where Δs_{t+1} is the nominal exchange rate return, that is, appreciation (depreciation) rate of the home (foreign) currency, while i_t and i_t^* are nominal short-run interest rates in the home and foreign countries, respectively. $\varepsilon_{t+1} = \Delta s_{t+1} - E_t \Delta s_{t+1}$ is the mean-zero ($E_t \varepsilon_{t+1} = 0$) rational expectation error term.

Motivated by (15), we obtained 18 international short-term interest rates from the FRED and the OECD database to construct nominal interest rate spreads by subtracting US interest rate (i_t) from the national interest rate (i_t^*).¹⁹ We estimate the first common factor via PLS and PC from the balanced panel of 17 interest rate spreads relative to American interest rate. We took the first difference of the spreads to make sure we estimate factors consistently.²⁰ Similarly, we estimated the first common factor from 17 interest rate spreads relative to Korean interest rate.

We also employ a similar factor model as (9) but for the nominal exchange rate return Δs_t . Since s_t is an integrated process, we employ the following $AR(1)$ -type model for Δs_t . Abstracting from an intercept,

$$\Delta s_{t+j} = \alpha_j \Delta s_t + u_{t+j}, \quad j = 1, 2, \dots, k, \quad (16)$$

where α_j is less than one in absolute value for stationarity.²¹ Note that we regress the j -period ahead target variable (Δs_{t+j}) *directly* on the current period exchange rate return (Δs_t). Then, the j -period ahead forecast is,

$$\Delta \hat{s}_{t+j}^{AR} = \hat{\alpha}_j \Delta s_t, \quad (17)$$

¹⁹For the group of developed countries, we include 11 euro-zone countries (Austria, Belgium, Finland, France, Germany, Greece, Italy, Luxembourg, Netherlands, Portugal, Spain) and 7 non-euro-zone countries (Canada, Denmark, Japan, Switzerland, Sweden, United Kingdom, United States). All data are obtained from the OECD database and the FRED.

²⁰The PANIC test provides strong evidence of nonstationarity for the interest rate spreads.

²¹That is, we assume that there are two eigenvalues for the level exchange rate, 1 and α_1 .

while the corresponding factor augmented forecasting model is given as follows.

$$\Delta s_{t+j} = \alpha_j \Delta s_t + \beta_j' \Delta \hat{\mathbf{f}}_t + u_{t+j}, \quad j = 1, 2, \dots, k \quad (18)$$

which augment (16) by adding factor estimates ($\Delta \hat{\mathbf{f}}_t$). The j -period ahead forecast for the exchange rate return is,

$$\Delta \hat{s}_{t+j|t}^{FAR} = \hat{\alpha}_j \Delta s_t + \hat{\beta}_j' \Delta \hat{\mathbf{f}}_t, \quad (19)$$

where $\hat{\alpha}_j$ and $\hat{\beta}_j$ are the LS coefficient estimates.

The first 2 columns of Table 6 reports the *RRMSPE* statistics of the 1-period ahead out-of-sample forecasts for the nominal exchange rate return (Δs_t) using the UIP motivated factors. The American UIP-PLS factor forecasting models perform well relative to both benchmark models. The American macroeconomic data driven PLS models perform similarly well. The Korean UIP factor models overall performed poorly except when we included two UIP factors. However, they perform better than the Korean macroeconomic factor augmented models, highlighting marginal but potentially important contributions of the UIP global factors.

Table 6 around here

4.3.3 Real Interest Rate Parity: Real Interest Rate Spread

The last proposition we employ is Real Interest Rate Parity (RIRP), which combines PPP with UIP. Taking the first difference to the PPP equation ($q_t = s_t + p_t - p_t^*$) at time $t + 1$,

$$\Delta q_{t+1} = \Delta s_{t+1} + \pi_{t+1} - \pi_{t+1}^* \quad (20)$$

Combining (15) and (20), we obtain the following expression for RIRP.

$$\Delta q_{t+1} = r_t^* - r_t + \varepsilon_{t+1}, \quad (21)$$

where $r_t = i_t - \pi_{t+1}$ and $r_t^* = i_t^* - \pi_{t+1}^*$ are the *ex post* real interest rates in the home and foreign country, respectively. Note that this specification is inconsistent with the ADF test results in Table 2 that provides strong empirical evidence in favor of the

stationarity of the real KRW/USD exchange rate, although it shows highly persistent dynamics similar to that of the nominal exchange rate.

Using international CPIs and short-run interest rates we used, we estimated the first common factors by applying PLS and PC to a panel of 17 real interest rate spreads ($r_t^* - r_t$) without taking differences. This is because we obtained very strong evidence in favor of stationarity for real interest rate spreads.²²

Similar to the previous section, we estimate the common factors from the macroeconomic data for Δq_t to compare the results with the RIRP based models. Results are reported in Table 7.

RRMSPE statistics in the first two columns demonstrate the RIRP global common factors are not useful whichever country serves as the reference country. However, our macroeconomic data driven PLS factor models outperform both benchmark models when the American factors are employed. Again, the Korean factor models perform quite poorly relative to both benchmark models.

Table 7 around here

5 Concluding Remarks

In this paper, we propose parsimonious factor-augmented forecasting models for the Won/Dollar real exchange rate in a data rich environment. We apply an array of data dimensionality reduction methods to large panels of 125 American and 192 Korean monthly frequency macroeconomic time series data from October 2000 to March 2019. In addition to Principal Component (PC) analysis that has been frequently used in the current literature, we employ the Partial Least Squares (PLS) approach and the Least Absolute Shrinkage and Selection Operator (LASSO) combined with PC and PLS to extract target-specific common factors for the KRW/USD exchange rate.

We augment benchmark forecasting models with estimated common factors to formulate out-of-sample forecasts. Then, using the ratio of the root mean squared prediction error (*RRMSPE*) criteria, we evaluate the prediction accuracy of our proposed models for the real exchange rate (or returns) relative to the random walk (RW) and the stationary autoregressive (AR) models.

²²The PANIC test results are available upon request.

Our forecasting models consistently outperform both the RW and the AR benchmark models only when we utilize latent common factors from the American predictors. In particular, our models that utilize the American real activity factors perform well at longer horizons, while the American nominal/financial market factors help improve the prediction performance at short horizons. The superior performance with factors from subset of predictors is in line with the work of Boivin and Ng (2006) who demonstrated the importance of relevant common factors for the target variable. Models with the Korean factors overall perform poorly relative to the AR model, while they still outperform the RW model when the forecast horizon is 1-year or longer.

We also implement forecasting exercises using global common factors that are motivated by exchange rate determination theories such as Purchasing Power Parity (PPP), Uncovered Interest Parity (UIP), and Real Uncovered Interest Parity (RIRP). Forecasting models with UIP common factors turn out to perform fairly well when the US serves as the reference country, while models with PPP or RIRP factors perform overall poorly whichever country is used for the reference country.

References

- ANDERSSON, M. (2009): “A Comparison of Nine PLS1 Algorithms,” *Journal of Chemometrics*, 23, 518–529.
- BAI, J., AND S. NG (2002): “Determining the Number of Factors in Approximate Factor Models,” *Econometrica*, 70(1), 191–221.
- (2004): “A PANIC Attack on Unit Roots and Cointegration,” *Econometrica*, 72(4), 1127–1177.
- (2008): “Forecasting Economic Time Series Using Targeted Predictors,” *Journal of Econometrics*, 146(2), 304–317.
- (2010): “Panel Unit Root Tests With Cross-Section Dependence: A Further Investigation,” *Econometric Theory*, 26(4), 1088–1114.
- BOIVIN, J., AND S. NG (2006): “Are More Data Always Better for Factor Analysis?,” *Journal of Econometrics*, 132(1), 169–194.
- CA’ ZORZI, M., A. KOCIECKI, AND M. RUBASZEK (2015): “Bayesian Forecasting of Real Exchange Rates with a Dornbusch Prior,” *Economic Modelling*, 46(C), 53–60.
- CHEN, S.-L., J. JACKSON, H. KIM, AND P. RESIANDINI (2014): “What Drives Commodity Prices?,” *American Journal of Agricultural Economics*, 96(5), 1455–1468.
- CHEUNG, Y.-W., M. CHINN, AND A. G. PASCUAL (2005): “Empirical Exchange Rate Models of The Nineties: Are Any Fit to Survive?,” *Journal of International Money and Finance*, 24(7), 1150–1175.
- CHEUNG, Y.-W., AND K. S. LAI (1995): “Lag Order and Critical Values of the Augmented Dickey-Fuller Test,” *Journal of Business & Economic Statistics*, 13(3), 277–80.
- CHINN, M., AND R. MEESE (1995): “Banking on Currency Forecasts: How Predictable is Change in Money?,” *Journal of International Economics*, 38(1-2), 161–178.

- CLARIDA, R. H., AND D. WALDMAN (2008): “Is Bad News About Inflation Good News for the Exchange Rate? And, If So, Can That Tell Us Anything about the Conduct of Monetary Policy?,” in *Asset Prices and Monetary Policy*, NBER Chapters, pp. 371–396. National Bureau of Economic Research, Inc.
- ENGEL, C., AND J. HAMILTON (1990): “Long Swings in the Dollar: Are They in the Data and Do Markets Know It?,” *American Economic Review*, 80(4), 689–713.
- ENGEL, C., N. C. MARK, AND K. D. WEST (2008): “Exchange Rate Models Are Not As Bad As You Think,” in *NBER Macroeconomics Annual 2007, Volume 22*, NBER Chapters, pp. 381–441. National Bureau of Economic Research, Inc.
- (2015): “Factor Model Forecasts of Exchange Rates,” *Econometric Reviews*, 34(1-2), 32–55.
- ENGEL, C., AND K. D. WEST (2005): “Exchange Rates and Fundamentals,” *Journal of Political Economy*, 113(3), 485–517.
- (2006): “Taylor Rules and the Deutschmark: Dollar Real Exchange Rate,” *Journal of Money, Credit and Banking*, 38(5), 1175–1194.
- GREENAWAY-MCGREY, R., N. C. MARK, D. SUL, AND J.-L. WU (2018): “Identifying Exchange Rate Common Factors,” *International Economic Review*, 59(4), 2193–2218.
- GROEN, J. (2005): “Exchange Rate Predictability and Monetary Fundamentals in a Small Multi-country Panel,” *Journal of Money, Credit and Banking*, 37(3), 495–516.
- GROEN, J., AND G. KAPETANIOS (2016): “Revisiting Useful Approaches to Data-Rich Macroeconomic Forecasting,” *Computational Statistics and Data Analysis*, 100, 221–239.
- GROEN, J. J. J. (2000): “The monetary exchange rate model as a long-run phenomenon,” *Journal of International Economics*, 52(2), 299–319.
- HELLAND, I. S. (1990): “Partial Least Squares Regression and Statistical Models,” *Scandinavian Journal of Statistics*, 17, 97–114.

- INCE, O., T. MOLODTSOVA, AND D. H. PAPELL (2016): “Taylor rule deviations and out-of-sample exchange rate predictability,” *Journal of International Money and Finance*, 69(C), 22–44.
- KELLY, B., AND S. PRUITT (2015): “The Three-Pass Regression Filter: A New Approach to Forecasting Using Many Predictors,” *Journal of Econometrics*, 186(2), 294–316.
- KIM, H., AND J. KIM (2018): “London calling: Nonlinear mean reversion across national stock markets,” *The North American Journal of Economics and Finance*, 44(C), 265–277.
- LOTHIAN, J. R., AND M. P. TAYLOR (1996): “Real Exchange Rate Behavior: The Recent Float from the Perspective of the Past Two Centuries,” *Journal of Political Economy*, 104(3), 488–509.
- MARK, N. (1995): “Exchange Rates and Fundamentals: Evidence on Long-Horizon Predictability,” *American Economic Review*, 85(1), 201–18.
- MARK, N., AND D. SUL (2001): “Nominal Exchange Rates and Monetary Fundamentals: Evidence From a Small Post-Bretton Woods Panel,” *Journal of International Economics*, 53(1), 29–52.
- MARK, N. C. (2009): “Changing Monetary Policy Rules, Learning, and Real Exchange Rate Dynamics,” *Journal of Money, Credit and Banking*, 41(6), 1047–1070.
- MEESE, R. A., AND K. ROGOFF (1983): “Empirical Exchange Rate Models of The Seventies: Do They Fit Out of Sample?,” *Journal of International Economics*, 14(1), 3 – 24.
- MOLODTSOVA, T., A. NIKOLSKO-RZHEVSKYY, AND D. PAPELL (2008): “Taylor Rules With Real-Time Data: A Tale of Two Countries And One Exchange Rate,” *Journal of Monetary Economics*, 55(Supplement 1), S63–S79.
- MOLODTSOVA, T., AND D. PAPELL (2009): “Out-of-Sample Exchange Rate Predictability With Taylor Rule Fundamentals,” *Journal of International Economics*, 77(2), 167 – 180.

- MOLODTSOVA, T., AND D. H. PAPELL (2013): “Taylor Rule Exchange Rate Forecasting during the Financial Crisis,” *NBER International Seminar on Macroeconomics*, 9(1), 55–97.
- NELSON, C. R., AND C. I. PLOSSER (1982): “Trends and Random Walks in Macroeconomic Time Series : Some Evidence And Implications,” *Journal of Monetary Economics*, 10(2), 139–162.
- PESARAN, M. H. (2021): “General Diagnostic Tests for Cross-Sectional Dependence in Panels,” *Empirical Economics*, 60, 13–50.
- RAPACH, D. E., AND M. WOCHAR (2004): “Testing the Monetary Model of Exchange Rate Determination: A Closer Look at Panels,” *Journal of International Money and Finance*, 23(6), 867–895.
- ROSSI, B. (2013): “Exchange Rate Predictability,” *Journal of Economic Literature*, 51(4), 1063–1119.
- STOCK, J. H., AND M. W. WATSON (2002): “Macroeconomic Forecasting using Diffusion Indexes,” *Journal of Business and Economic Statistics*, 20(2), 147–162.
- VERDELHAN, A. (2018): “The Share of Systematic Variation in Bilateral Exchange Rates,” *Journal of Finance*, 73(1), 375–418.
- WANG, J., AND J. J. WU (2012): “The Taylor Rule and Forecast Intervals for Exchange Rates,” *Journal of Money, Credit and Banking*, 44(1), 103–144.
- WOLD, H. (1982): *Soft Modelling: The Basic Design and Some Extensions*, vol. 1 of *Systems under indirect observation, Part II*. North-Holland, Amsterdam.

Table 1. Macroeconomic Data Descriptions

<i>American Data</i>		
Group ID	Data ID	Data Description
#1	1-16	Industrial Production Indices
#2	17-47	Labor Market Variables
#3	48-57	Housing Inventories
#4	58-65	Manufacturers' Consumption/ New Orders
#5	66-79	Monetary Aggregates
#6	80-96	Domestic Interest Rates
#7	97-116	Producer/Consumer Prices
#8	117-121	Stock Indices
#9	122-126	Exchange Rates

<i>Korean Data</i>		
Group ID	Data ID	Data Description
#1	1-27	New Orders
#2	28-34	Inventory
#3	35-52	Housing
#4	53-74	Retails/Manufacturing
#5	75-87	Labor
#6	88-98	Industrial Production
#7	99-102	Business Condition
#8	103-114	Stock Indices
#9	115-127	Interest Rates
#10	128-145	Exports/Imports Prices
#11	146-163	Prices
#12	164-180	Money
#13	181-192	Exchange Rates

Note: We obtained the American data from the FRED-MD website. The Korean Data was obtained from the Bank of Korea.

Table 2. Unit Root Test Results

<i>ADF Test</i>			
q_t	-2.966 [†] (0.038)	s_t	-1.953 (0.308)
<i>PANIC Test</i>			
\mathbf{x}_t^{US}		\mathbf{x}_t^{KR}	
$f_{1,t}^{PC}$	-2.519 (0.100)	$f_{1,t}^{PC}$	1.186 (0.998)
$f_{2,t}^{PC}$	-1.270 (0.641)	$f_{2,t}^{PC}$	-2.085 (0.237)
$P_{\hat{\epsilon}}$	11.341 [‡] (0.000)	$P_{\hat{\epsilon}}$	16.667 [‡] (0.000)
$f_{1,t}^{PC,R}$	-2.443 (0.124)	$f_{1,t}^{PC,R}$	-0.634 (0.868)
$f_{2,t}^{PC,R}$	-2.393 (0.133)	$f_{2,t}^{PC,R}$	-2.057 (0.254)
$P_{\hat{\epsilon}}$	5.763 [‡] (0.000)	$P_{\hat{\epsilon}}$	15.552 [‡] (0.000)
$f_{1,t}^{PC,F}$	-1.888 (0.326)	$f_{1,t}^{PC,F}$	1.250 (0.999)
$f_{2,t}^{PC,F}$	-3.437 [‡] (0.009)	$f_{2,t}^{PC,F}$	-1.544 (0.512)
$P_{\hat{\epsilon}}$	6.425 [‡] (0.000)	$P_{\hat{\epsilon}}$	8.711 [‡] (0.000)

Note: q_t and s_t are the CPI-based real and the nominal bilateral Won/Dollar exchange rate, respectively. PLS estimates target specific factors for q_t and s_t separately, while PC yields common factors independent on the target variable. Real variables are from group #1 through #4 for American factors and groups #1 through #7 for Korean factors, while financial variables include group #5 through #9 for American factors and groups #8 through #13 for Korean factors. The augmented Dickey-Fuller (ADF) test reports the ADF t -statistics when an intercept is included. P -values are in parenthesis. For the PANIC test results, we report the ADF t -statistics with an intercept for each common factor estimate. $P_{\hat{\epsilon}}$ denotes the panel test statistics from the de-factored idiosyncratic components. [‡] and [†] denote a rejection of the null hypothesis at the 1% and 5% level, respectively.

Table 3. Out-of-Sample Predictability for the Real Exchange Rate

<i>American Factors</i>							
j	#Factors	$\Delta \mathbf{f}_t^{PLS}$	$\Delta \mathbf{f}_t^{PLS,R}$	$\Delta \mathbf{f}_t^{PLS,F}$	$\Delta \mathbf{f}_t^{PC}$	$\Delta \mathbf{f}_t^{PC,R}$	$\Delta \mathbf{f}_t^{PC,F}$
1	1	1.0115*	1.0077	1.0074	1.0251*	1.0088*	1.0144*
	2	1.0355*	0.9971	1.0198*	1.0148*	1.0023	1.0155*
	3	1.0266*	0.9941	1.0223*	1.0142*	0.9680	1.0223*
12	1	1.3440*	1.3611*	1.2499*	1.3194*	1.3375*	1.2380
	2	1.3389*	1.3469*	1.0965	1.2573*	1.3375*	1.2352
	3	1.2421*	1.2246	1.0243	1.2572*	1.3308*	1.1217
36	1	1.4269*	1.4466*	1.2710	1.3742*	1.4271*	1.2409
	2	1.2736	1.3948*	1.2316	1.3142	1.3980*	1.2585
	3	1.2232	1.4229*	1.2715	1.3225	1.3882*	1.2300
<i>Korean Factors</i>							
j	#Factors	$\Delta \mathbf{f}_t^{PLS}$	$\Delta \mathbf{f}_t^{PLS,R}$	$\Delta \mathbf{f}_t^{PLS,F}$	$\Delta \mathbf{f}_t^{PC}$	$\Delta \mathbf{f}_t^{PC,R}$	$\Delta \mathbf{f}_t^{PC,F}$
1	1	0.9006	1.0029	0.9382	0.6836	0.8443	0.9646
	2	0.6329	0.9441	0.9450	0.4931	0.8644	0.2871
	3	0.4880	0.8965	0.5315	0.2348	0.7819	0.1707
12	1	1.2607*	1.2162	1.2698*	1.2381	1.2422*	1.2074
	2	1.2431*	1.1635	1.2362	1.2067	1.2433*	1.1877
	3	1.2380	1.0719	1.2288	1.2159	1.2298	1.2485*
36	1	1.3737*	1.3787*	1.3883*	1.3752*	1.3652	1.3797*
	2	1.3498	1.2832	1.3850*	1.3843*	1.3425	1.3809*
	3	1.1916	1.1056	1.3377	1.3847*	1.3435	1.3687
<i>American and Korean Factors</i>							
j	#Factors	$\Delta \mathbf{f}_t^{PLS}$	$\Delta \mathbf{f}_t^{PLS,R}$	$\Delta \mathbf{f}_t^{PLS,F}$	$\Delta \mathbf{f}_t^{PC}$	$\Delta \mathbf{f}_t^{PC,R}$	$\Delta \mathbf{f}_t^{PC,F}$
1	2	0.9469	1.0082*	0.9542	0.8242	0.8925	0.9781
	4	0.9441	0.9419	0.8800	0.4030	0.8900	0.2400
	6	0.5604	0.8730	0.5753	0.2230	0.7975	0.1871
12	2	1.3503*	1.3203*	1.2704*	1.3054*	1.3351*	1.1799
	4	1.3055*	1.2448*	1.0548	1.1873	1.3342*	1.1753
	6	1.1377	1.0888	0.9167	1.1621	1.3277*	1.1377
36	2	1.4278*	1.4534*	1.2882	1.3655	1.4190*	1.2216
	4	1.2430	1.3358	1.2300	1.2845	1.3804*	1.2352
	6	1.1017	1.1954	1.2246	1.2733	1.3578	1.2321

Note: We report the *RRMSPE* statistics employing a rolling window scheme with a 50% sample split point. *RRMSPE* denotes the mean squared prediction error (*RMSPE*) from the benchmark random walk (RW) model divided by the *RMSPE* from each competing model with k factors. Superscript *R* and *F* mean that factors were estimated from real and financial variables, respectively. *RRMSPE* statistics that are greater than 1 indicate that the competing model outperforms the benchmark RW model. * denotes the cases that the competing model outperforms the benchmark AR model as well as the RW model.

Table 4. Out-of-Sample Predictability with LASSO for the Real Exchange Rate

<i>American Factors</i>							
j	#Factors	$\Delta \mathbf{f}_t^{PLS}$	$\Delta \mathbf{f}_t^{PLS,R}$	$\Delta \mathbf{f}_t^{PLS,F}$	$\Delta \mathbf{f}_t^{PC}$	$\Delta \mathbf{f}_t^{PC,R}$	$\Delta \mathbf{f}_t^{PC,F}$
1	1	1.0162*	1.0218*	1.0188*	1.0392*	1.0184*	1.0329*
	2	1.0388*	0.9849	1.0261*	1.0451*	1.0160	1.0520*
	3	1.0387*	0.9807	1.0379*	1.0419*	1.0278*	1.0474*
12	1	1.2145	1.3792*	1.1614	1.2515*	1.3354*	1.2413
	2	1.1729	1.3456*	1.1068	1.2305	1.3549*	1.1742
	3	1.1734	1.3395*	1.1350	1.0718	1.3060*	1.1282
36	1	1.2970	1.5208*	1.2753	1.3555	1.4750*	1.3515
	2	1.3264	1.4849*	1.3718	1.2840	1.4654*	1.3337
	3	1.2664	1.4729*	1.3596	1.3029	1.4816*	1.3415
<i>Korean Factors</i>							
j	#Factors	$\Delta \mathbf{f}_t^{PLS}$	$\Delta \mathbf{f}_t^{PLS,R}$	$\Delta \mathbf{f}_t^{PLS,F}$	$\Delta \mathbf{f}_t^{PC}$	$\Delta \mathbf{f}_t^{PC,R}$	$\Delta \mathbf{f}_t^{PC,F}$
1	1	0.9735	1.0022	0.9773	0.5423	0.9743	0.5820
	2	0.4596	0.9929	0.6262	0.5492	0.9646	0.3462
	3	0.5694	0.9760	0.6352	0.3133	0.9632	0.2832
12	1	1.2271	1.2144	1.2199	1.1532	1.2434*	1.1571
	2	1.1769	1.2247	1.1618	1.1656	1.2418*	1.1594
	3	1.1812	1.2154	1.1611	1.1720	1.2274	1.1600
36	1	1.3667	1.2937	1.3728	1.3919*	1.3654	1.3920*
	2	1.3624	1.3071	1.3783*	1.3936*	1.3648	1.3919*
	3	1.3794*	1.2798	1.2943	1.4058*	1.3316	1.3155
<i>American and Korean Factors</i>							
j	#Factors	$\Delta \mathbf{f}_t^{PLS}$	$\Delta \mathbf{f}_t^{PLS,R}$	$\Delta \mathbf{f}_t^{PLS,F}$	$\Delta \mathbf{f}_t^{PC}$	$\Delta \mathbf{f}_t^{PC,R}$	$\Delta \mathbf{f}_t^{PC,F}$
1	2	0.9954	1.0169*	0.9854	0.5882	0.9919	0.6359
	4	0.5416	0.9679	0.7121	0.6120	0.9696	0.4283
	6	0.6234	0.9530	0.6667	0.3999	0.9695	0.3120
12	2	1.2325	1.3289*	1.1751	1.1768	1.3298*	1.1787
	4	1.0980	1.3127*	1.0330	1.1387	1.3483*	1.0954
	6	1.0936	1.2745*	1.0212	1.0291	1.2780*	1.0795
36	2	1.2664	1.4650*	1.2462	1.3389	1.4520*	1.3508
	4	1.2798	1.4418*	1.3483	1.2810	1.4358*	1.3306
	6	1.2135	1.3949*	1.2337	1.2589	1.4167*	1.3051

Note: We report the *RRMSPE* statistics employing a rolling window scheme with a 50% sample split point. *RRMSPE* denotes the mean squared prediction error (*RMSPE*) from the benchmark random walk (RW) model divided by the *RMSPE* from each competing model with k factors. Superscript *R* and *F* mean that factors were estimated from real and financial variables, respectively. *RRMSPE* statistics that are greater than 1 indicate that the competing model outperforms the benchmark RW model. * denotes the cases that the competing model outperforms the benchmark AR model as well as the RW model.

Table 5. PPP Based Models for the Real Exchange Rate

j	#Factors	<i>American Reference</i>		<i>Korean Reference</i>	
		$\Delta \mathbf{f}_t^{PPP,PLS}$	$\Delta \mathbf{f}_t^{PPP,PC}$	$\Delta \mathbf{f}_t^{PPP,PLS}$	$\Delta \mathbf{f}_t^{PPP,PC}$
1	1	1.0061	1.0057	0.9678	0.9670
	2	0.9905	0.9866	0.9639	0.9710
	3	0.9831	0.9697	0.9566	0.9636
12	1	1.2381*	1.2372	1.2422*	1.2441*
	2	1.1760	1.2265	1.2108	1.2153
	3	1.1868	1.1836	1.0970	1.1617
36	1	1.3415	1.3364	1.4172*	1.4151*
	2	1.3406	1.3401	1.3710	1.2233
	3	1.3167	1.3140	1.0971	1.2321

Note: We report the *RRMSPE* statistics employing a rolling window scheme with a 50% sample split point. *RRMSPE* denotes the mean squared prediction error (*RMSPE*) from the benchmark random walk (RW) model divided by the *RMSPE* from each competing model with k factors. *RRMSPE* statistics that are greater than 1 indicate that the competing model outperforms the benchmark RW model. *denotes the cases that the competing model outperforms the benchmark AR model as well as the RW model. $\Delta f_t^{PPP,PLS(PC)}$ denotes PLS (or PC) factors based on PPP.

Table 6. UIP Based Models for the Nominal Exchange Rate Returns

<i>American Factors</i>				
#Factors	$\Delta \mathbf{f}_t^{UIP,PLS}$	$\Delta \mathbf{f}_t^{UIP,PC}$	$\Delta \mathbf{f}_t^{PLS}$	$\Delta \mathbf{f}_t^{PC}$
1	1.0357*	1.0317*	1.0371*	1.0281*
2	1.0529*	1.0258	1.0455*	1.0154
3	1.0261*	1.0237	1.0703*	1.0158

<i>Korean Factors</i>				
#Factors	$\Delta \mathbf{f}_t^{UIP,PLS}$	$\Delta \mathbf{f}_t^{UIP,PC}$	$\Delta \mathbf{f}_t^{PLS}$	$\Delta \mathbf{f}_t^{PC}$
1	1.0161	1.0121	0.9191	0.5361
2	1.0334*	1.0264*	0.7552	0.5829
3	1.0166	1.0250	0.5044	0.2566

Note: We report the *RRMSPE* statistics for the one-period ahead forecast employing a rolling window scheme with a 50% sample split point. *RRMSPE* denotes the mean squared prediction error (*RMSPE*) from the benchmark random walk (RW) model divided by the *RMSPE* from each competing model with k factors. *RRMSPE* statistics that are greater than 1 indicate that the competing model outperforms the benchmark RW model. * denotes the cases that the competing model outperforms the benchmark AR model as well as the RW model. $\Delta \mathbf{f}_t^{UIP,PLS(PC)}$ denotes PLS (or PC) factors based on the UIP condition, whereas $\Delta \mathbf{f}_t^{PLS(PC)}$ denotes PLS (or PC) factors based on data-driven macroeconomic factors for the nominal exchange rate return.

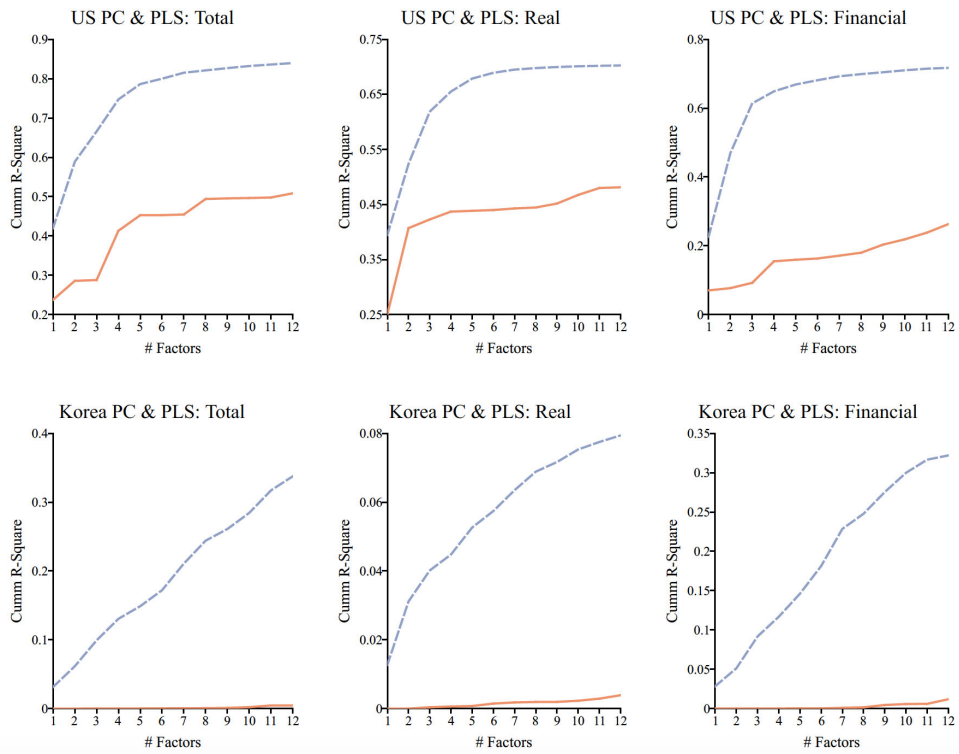
Table 7. RIRP Based Models for the Real Exchange Rate Return

#Factors	$\Delta \mathbf{f}_t^{RIRP,PLS}$	<i>American Factors</i>		
		$\Delta \mathbf{f}_t^{RIRP,PC}$	$\Delta \mathbf{f}_t^{PLS}$	$\Delta \mathbf{f}_t^{PC}$
1	1.0057	1.0066	1.0290*	1.0198*
2	1.0042	0.9882	1.0358*	1.0061
3	0.9924	0.9754	1.0598*	1.0061

#Factors	$\Delta \mathbf{f}_t^{RIRP,PLS}$	<i>Korean Factors</i>		
		$\Delta \mathbf{f}_t^{RIRP,PC}$	$\Delta \mathbf{f}_t^{PLS}$	$\Delta \mathbf{f}_t^{PC}$
1	0.9833	0.9792	0.9191	0.6676
2	0.9742	0.9836	0.7552	0.4295
3	0.9697	0.9631	0.5044	0.2443

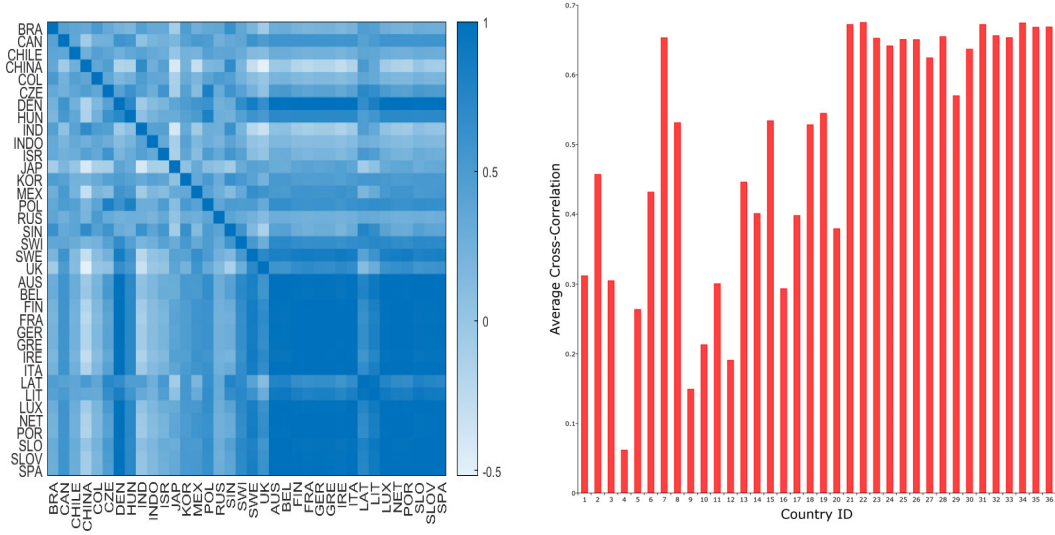
Note: We report the *RRMSPE* statistics for the one-period ahead forecast employing a rolling window scheme with a 50% sample split point. *RRMSPE* denotes the mean squared prediction error (*RMSPE*) from the benchmark random walk (RW) model divided by the *RMSPE* from each competing model with *k* factors. *RRMSPE* statistics that are greater than 1 indicate that the competing model outperforms the benchmark RW model. * denotes the cases that the competing model outperforms the benchmark AR model as well as the RW model. $\Delta \mathbf{f}_t^{RIRP,PLS(PC)}$ denotes PLS (or PC) factors based on RIRP, whereas $\Delta \mathbf{f}_t^{PLS(PC)}$ denotes PLS (or PC) factors based on data-driven macroeconomic factors for the real exchange rate return.

Figure 1. Cumulative R^2 Analysis



Note: We regress the real exchange rate on each factor and obtain the R^2 statistics. Since we use orthogonalized factors, we report the cumulative R^2 statistics. Dotted lines are for PLS factors and solid lines are for PC factors.

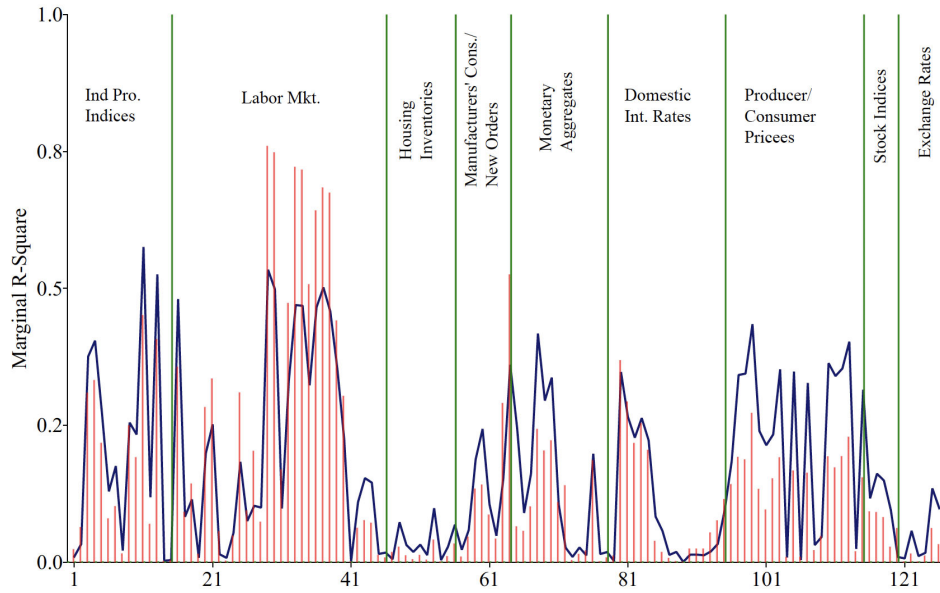
Figure 2. Cross-Section Dependence of the Real Exchange Rates relative to the Dollar



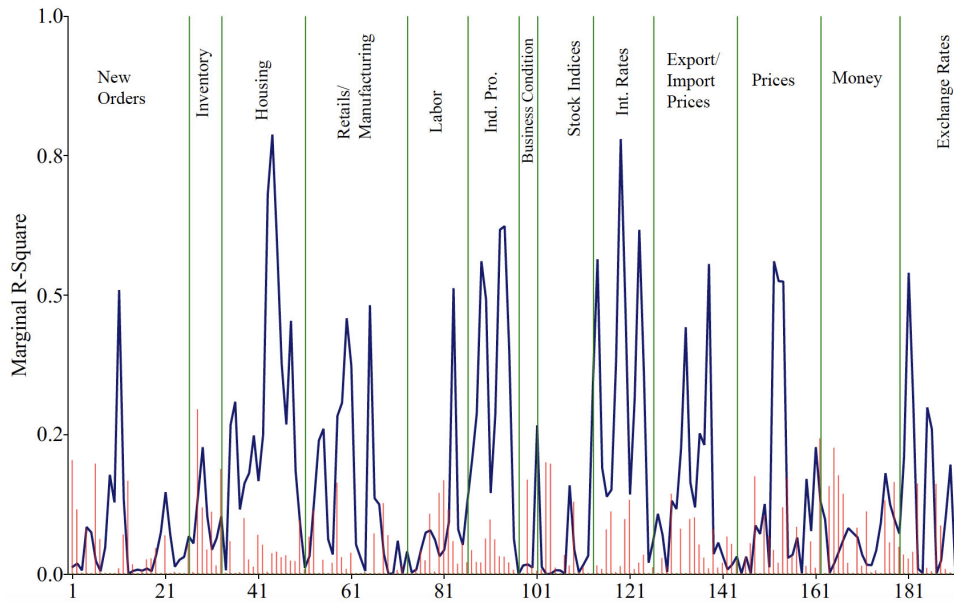
Note: The heat map on the left shows the cross-correlations of the ADF regression residuals of 36 real exchange rate relative to the U.S. dollar. We report the average cross-correlations of each real exchange rate in the figure on the right. The country ID is of the same order as in the heat map on the left. For example, Korea's ID 13.

Figure 3. Marginal R^2 Analysis: Total Factors

American Factor #1



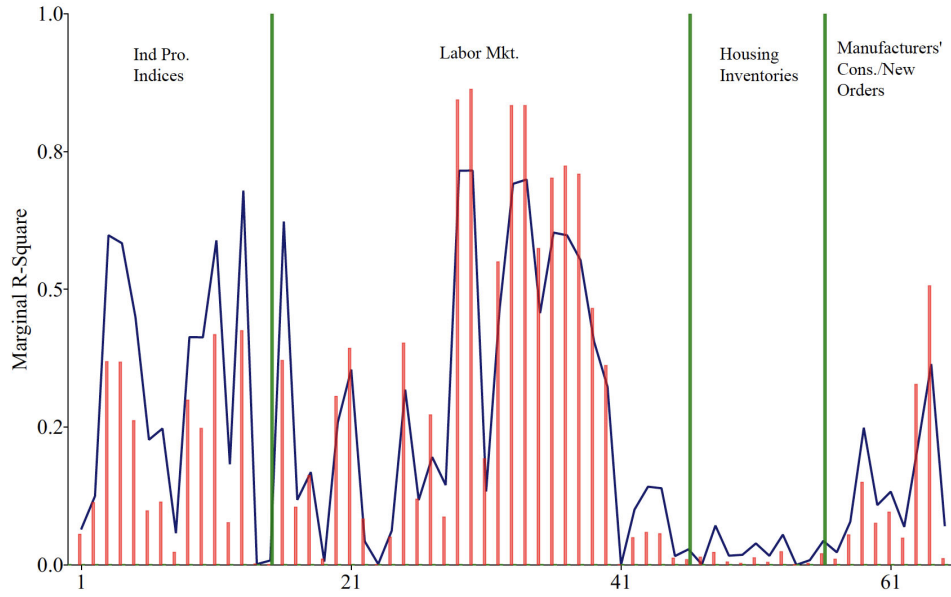
Korean Factor #1



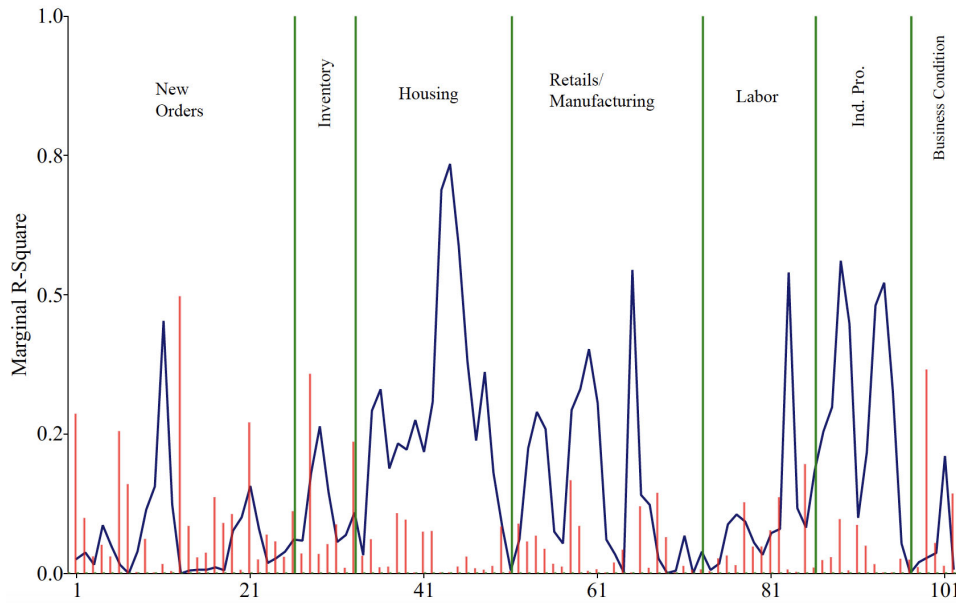
Note: We report the R^2 statistics that were obtained by regressing each predictor on the first common factor estimate. That is, the horizontal axis is the predictor IDs. Solid lines are for the PC factor, while bar graphs are for the PLS factor.

Figure 4. Marginal R^2 Analysis: Real Activity Factors

American Factor #1

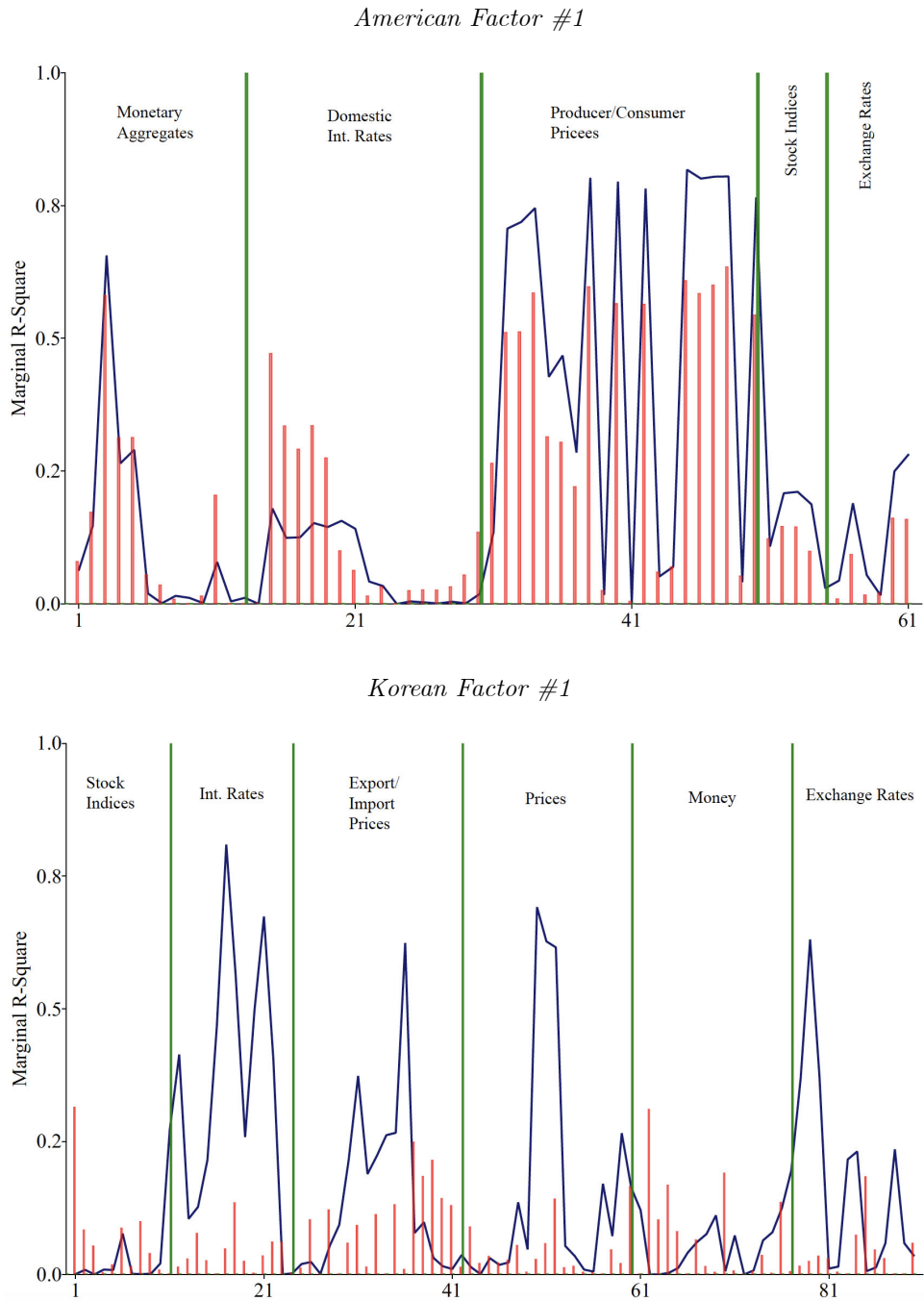


Korean Factor #1



Note: We report the R^2 statistics that were obtained by regressing each predictor on the first common factor estimate. That is, the horizontal axis is the predictor IDs. Solid lines are for the PC factor, while bar graphs are for the PLS factor.

Figure 5. Marginal R^2 Analysis: Nominal/Financial Factors



Note: We report the R^2 statistics that were obtained by regressing each predictor on the first common factor estimate. That is, the horizontal axis is the predictor IDs. Solid lines are for the PC factor, while bar graphs are for the PLS factor.