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Asymmetric Roles of Macroeconomic Variables in the Real Exchange Rate: Insights from U.S.-Korea Data

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Asymmetric Roles of Macroeconomic Variables in the Real Exchange Rate: Insights from U.S.-Korea Data*

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Abstract

This paper investigates the asymmetric out-of-sample predictability of macroeconomic variables for the real exchange rate between the United States and Korea. While conventional models often suggest that the bilateral real exchange rate is primarily driven by the relative economic performance of the two countries, our research highlights the superior predictive power of latent factors obtained from U.S. economic variables, while Korean factors fail to enhance predictability and often act as noise. We attribute the strong predictability of U.S. factors to significant cross-correlations observed among a panel of bilateral real exchange rates *vis-à-vis* the U.S. dollar, indicating a limited role for idiosyncratic factors associated with smaller economies. Our major findings are based on data from the pre-COVID19 era. We further explore how economic crises disrupt this relationship, resulting in temporary yet persistent disconnects between the real exchange rate and macroeconomic fundamentals.

Keywords: Dollar/Won Real Exchange Rate; Asymmetric Predictability; 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 investigates the asymmetric predictability of macroeconomic variables for the real exchange rate between the United States and Korea. Employing a data-driven approach, we evaluate the out-of-sample forecastability of latent factors obtained from a large panel of macro predictors for each country. Our empirical results demonstrate that factor augmented forecasting models outperform commonly used benchmark models only when U.S. factors are utilized.

A substantial body of research demonstrates that exchange rate models often fail to outperform the random walk (RW) model in out-of-sample forecasting. Since the seminal work of Meese and Rogoff (1983), studies such as Cheung, Chinn, and Pascual (2005) confirmed the weak link between exchange rates and economic fundamentals. In a subsequent study, limited success has been reported by Engel and Hamilton (1990) and Cheung, Chinn, Pascual, and Zhang (2019). Some studies suggest that exchange rate models perform better over longer horizons. See, among others, Mark (1995), Chinn and Meese (1995), and Groen (2005). Using over two-centuries of data, Lothian and Taylor (1996) reported strong out-of-sample predictability of fundamentals for the real exchange rate. Engel, Mark, and West (2008) highlighted improved forecastability using panel techniques.[1] However, Engel and Wu (2023) showed challenges remain particularly when accounting for small-sample bias.[2]

The pioneering work of Stock and Watson (2002) initiated the use of latent common factors through principal components (PC) analysis for forecasting macroeconomic variables, including exchange rates. Researchers have leveraged large panels of time series data for deeper insights into exchange rate dynamics. For example, Engel, Mark, and West (2015) used cross-section information regarding the deviations of 17 bilateral exchange rates from fundamentals, and show that these factor-based forecasting models often outperformed the RW model, especially post-1999. Chen, Jackson, Kim, and Resiandini (2014) extracted PC factors from 50 commodity prices, linking the first factor to the dollar exchange rate, yielding superior out-of-sample predictions for the dollar exchange rate. Greenaway-McGrevy, Mark, Sul, and Wu (2018) showed exchange rates are driven by dollar and euro factors, with their model outperforming the RW model. Verdelhan (2018) used international currency portfolios to identify dollar and carry factors that effectively explained exchange rate dynamics, while Eichenbaum, Johannsen, and Rebelo (2021) highlighted foreign demand for dollar-denominated bonds as a key driver of exchange rate dynamics.

While principal component (PC) analysis is widely used in the forecasting and empirical macroeconomics literature, Boivin and Ng (2006) noted its limitations when relevant predictive information is dominated by other factors within the analysis. This is because PC extracts latent common

[1] Rapach and Wohar (2004), Groen (2000), and Mark and Sul (2001) also reported panel evidence that demonstrate a close link between monetary models and exchange rate dynamics.

[2] Incorporating Taylor Rule fundamentals has shown promise in understanding exchange rate dynamics. Notable contributions include 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) for improving forecast accuracy, while many studies report in-sample evidence that Taylor rule fundamentals enhance understanding of exchange rate dynamics. See among others, Mark (2009), Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008), Engel and West (2006), Clarida and Waldman (2008), and Kim, Fujiwara, Hansen, and Ogaki (2015).

factors without explicitly accounting for the relationship between predictors and the target variable. To overcome this, we explore alternative data dimensionality reduction methods such as partial least squares (PLS), introduced by Wold (1982). Unlike PC, PLS leverages the covariance structure between target and predictor variables to generate *target-specific* factors.[3] For further comparisons between PC and PLS approaches, see among others, Kelly and Pruitt (2015) and Groen and Kapetanios (2016). In line with Bai and Ng (2008) and Kelly and Pruitt (2015), the Least Absolute Shrinkage and Selection Operator (LASSO) technique is also employed to select target-specific groups of predictors from the full dataset, extracting more relevant factors for the target variable.

In this paper, we evaluate and compare the predictability of latent common factors for the dollar/won real exchange rate. Utilizing principal component (PC) analysis and partial least squares (PLS), and the LASSO method in combination with PC and PLS, we estimate common factors from 125 U.S. and 192 Korean monthly frequency time series variables. Our analysis primarily focuses on the pre-COVID19 sample period, followed by a discussion of the temporary yet persistent disconnect between the dollar/won real exchange rate and its underlying fundamentals.

We reveal asymmetric predictability of latent factors for the real exchange rate. Specifically, our factor-augmented forecasting models outperform benchmark models only when U.S. factors are utilized, while Korean factors yield limited predictive contents. These findings call into question the conventional assumption that bilateral real exchange rates are determined by the relative economic performance of the two countries. Our research suggests that this assumption may not hold in cases where the economies involved are asymmetrically sized, as with the U.S. and Korea. We attribute the superior predictability of U.S. factors to the strong cross-correlations observed between bilateral real exchange rates *vis-à-vis* the U.S. dollar.

Our findings also indicate that the models perform better at shorter horizons when incorporating U.S. nominal/financial market factors. Conversely, models that incorporate U.S. real activity factors outperform benchmark models at longer horizons. These results align with the findings of Boivin and Ng (2006), who emphasized the importance of extracting more informative content from subsets of predictors. Our approach also aligns with that of Ca' Zorzi and Rubaszek (2023) in the sense that we extract a smaller number of useful latent factors from a large panel of macro predictors.[4]

To the best of my knowledge, this paper presents the seminal attempt to evaluate the relative predictability by applying data dimensionality reduction methods to extensive panels of macroeconomic data for both the U.S. and Korea. Closely related studies include Engel, Mark, and West (2015), Ca' Zorzi and Rubaszek (2020), and Ca' Zorzi and Rubaszek (2023). However, these studies primarily utilize cross-sectional information derived from a small number of predictors across

[3] See Kim and Son (2024) and Kim and Ko (2020) for applications of PLS factors in out-of-sample forecasting for financial market vulnerability variables.

[4] Ca' Zorzi and Rubaszek (2023) challenged the recent tendency to increase the number of predictors, as seen in Cubeddu, Krogstrup, Adler, Rabanal, Dao, and Hannan (2019), demonstrating that a parsimonious forecasting model can outperform those models.

a broad panel of currencies, with the Korean won being one of them.[5] Furthermore, their work overlooks critical structural information regarding Korea's transition to a market based economy following the 1997-98 Asian Financial Crisis.[6] While their studies achieved statistically meaningful panel analyses, incorporating a robust case study with a more extensive dataset could provide useful insights.

The remainder of the paper is organized as follows. Section 2 provides a detailed explanation of the methodologies for estimating latent common factors using PC, PLS, and the LASSO, particularly when predictors follow an integrated process. Section 3 describes the data and presents preliminary statistical analysis, including an examination of the in-sample fit to identify the sources of latent common factors. Section 4 introduces the factor-augmented forecasting models and evaluates their out-of-sample forecasting performance. This section also discusses the performance of these data-driven factor models during periods of economic crisis. Finally, Section 5 concludes.

2 Methods of Estimating Latent Common Factors

This section describes how we estimate latent common factors via Principal Component (PC), Partial Least Squares (PLS), and the Least Absolute Shrinkage and Selection Operator (LASSO), applied to a large panel of macroeconomic predictors.

2.1 Principal Component Factors

Since the seminal work of Stock and Watson (2002), PC has been widely utilized in the forecasting literature. This section provides a brief overview of the procedure, addressing cases where predictors obey either an integrated $I(1)$ or a stationary $I(0)$ process.

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

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

where $\mathbf{f}_t = \left[f_{1,t}^{PC}, f_{2,t}^{PC}, \cdots, f_{R,t}^{PC} \right]'$ is an $R \times 1$ vector of *latent* time-varying common factors at time t

[5] Engel, Mark, and West (2015) utilized latent factors derived from idiosyncratic deviations of a panel of bilateral exchange rates from their fundamentals to improve the forecastability. Ca' Zorzi and Rubaszek (2023) employed an unbalanced panel comprising 30 currencies, including the Korean Won, spanning the period from 1991 to 2018, while Ca' Zorzi and Rubaszek (2020) analyzed data spanning from 1975 to 2017, focusing on approximately 10 advanced economies (including the euro area as a single economy) and Korea.

[6] Korea underwent a rapid structural transformation following the 1997-98 foreign exchange crisis, under IMF guidance, transitioning to an advanced market economy by around 2000. This shift marked a successful progress from a developing to an advanced economy. Notably, during this period, there was a shift in the foreign exchange rate system from a controlled peg to a free float system. Furthermore, significant economic reforms and developments occurred from 1970s to the1990s, laying the foundation for this transition. Regarding out-of-sample forecasting exercises, Ca' Zorzi and Rubaszek (2023) relied on a limited number of test sets, ranging from 5 to 9 for each country, which appears to be insufficient for robust evaluation.

and $\boldsymbol{\lambda}_i = [\lambda_{i,1}, \lambda_{i,2}, \cdots, \lambda_{i,R}]'$ 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), we estimate latent common factors by applying the PC method to first-differenced data to obtain a consistent estimator of $\mathbf{f}_t^{PC}$.[7,8] Differencing both sides of (1), we obtain the following.

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

for $t = 2, \cdots, T$. We first normalize the data, $\Delta\tilde{\mathbf{x}} = [\Delta\tilde{\mathbf{x}}_1, \Delta\tilde{\mathbf{x}}_2, ..., \Delta\tilde{\mathbf{x}}_N]$, 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 $\hat{\boldsymbol{\lambda}}_i$.[9] Estimates of the idiosyncratic component are obtained by taking the residual, $\Delta\hat{\varepsilon}_{i,t} = \Delta\tilde{x}_{i,t} - \hat{\boldsymbol{\lambda}}_i' \Delta\hat{\mathbf{f}}_t^{PC}$.[10,11]

2.2 Partial Least Squares Factors

As Boivin and Ng (2006) pointed out, PC factors may not be effective for forecasting a variable when the predictive information for the target is concentrated in a specific factor that could be overshadowed by others. Acknowledging this limitation, we complement our factor estimation by employing PLS for a scalar target variable q_t, which has been somewhat overlooked in the current literature. Unlike PC, the method of PLS generates *target specific* latent common factors, which is an attractive feature.

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

$$q_t = \Delta\mathbf{x}_t' \boldsymbol{\beta} + e_t, \tag{3}$$

where $\Delta\mathbf{x}_t = [\Delta x_{1,t}, \Delta x_{2,t}, ..., \Delta x_{N,t}]'$ is an $N \times 1$ vector of predictor variables at time $t = 1, ..., T$, while $\boldsymbol{\beta}$ is an $N \times 1$ vector of coefficients. e_t is an error term. Note that the predictors are again first-differenced as in the previous section.

PLS is especially useful for regression models when N is large. To reduce the dimensionality of

[7] See also Bai and Ng (2010).

[8] 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.

[9] This step is necessary, because PC is not scale invariant. That is, we demean and standardize each time series prior to analysis.

[10] The level variables are subsequently recovered via cumulative summation, $\hat{\varepsilon}_{i,t} = \sum_{s=2}^{t} \Delta\hat{\varepsilon}_{i,s}$ and $\hat{\mathbf{f}}_t^{PC} = \sum_{s=2}^{t} \Delta\hat{\mathbf{f}}_s^{PC}$

[11] Note that this procedure yields consistent factor estimates even when $\mathbf{x}$ includes some stationary $I(0)$ variables. Alternatively, one may continue differencing each variable until the null of nonstationarity hypothesis is rejected via a unit root test. However, this approach may be less practical when unit root tests provide contradicting statistical inferences. See Cheung and Lai (1995) and Behera and Kim (2019) for related discussions. Nonetheless, the factor estimates obtained from this alternative approach are remarkably similar, largely because most predictors are filtered through either log-differencing or percent differences.

the data, rewrite (3) as follows,

$$\begin{aligned} q_t &= \Delta\mathbf{x}_t^{'}\mathbf{w}\boldsymbol{\theta} + u_t \\ &= \Delta\mathbf{f}_t^{PLS'}\boldsymbol{\theta} + u_t \end{aligned} \tag{4}$$

where $\Delta\mathbf{f}_t^{PLS} = \left[\Delta f_{1,t}^{PLS}, \Delta f_{2,t}^{PLS}, ..., \Delta f_{R,t}^{PLS}\right]^{'}$, $R < N$ 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,

$$\Delta\mathbf{f}_t^{PLS} = \mathbf{w}^{'}\Delta\mathbf{x}_t, \tag{5}$$

where $\mathbf{w} = [\mathbf{w}_1, \mathbf{w}_2, ..., \mathbf{w}_R]$ is an $N \times R$ weighting matrix. That is, $\mathbf{w}_r = [w_{1,r}, w_{2,r}, ..., w_{N,r}]^{'}$, $r = 1, ..., R$, 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, obtained from PLS regression that minimizes the sum of squared residuals from the equation (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 $\Delta\mathbf{x}_t$.

$$\Delta\hat{f}_{1,t}^{PLS} = \sum_{i=1}^{N} w_{i,1}\Delta x_{i,t}, \tag{6}$$

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 (6) 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.

2.3 Least Absolute Shrinkage and Selection Operator Factors

We employ the Least Absolute Shrinkage and Selection Operator (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. That is, the LASSO solves the following constrained minimization problem using L_1-norm penalty on β.

$$\min_{\boldsymbol{\beta}} \left\{ \frac{1}{T} \sum_{t=1}^{T} (q_t - \Delta \mathbf{x}_t' \boldsymbol{\beta})^2 \right\}, \text{ s.t. } \sum_{j=1}^{N} |\beta_j| \leq \tau \tag{7}$$

where $\Delta \mathbf{x}_t = [\Delta x_{1,t}, \Delta x_{2,t}, ..., \Delta x_{N,t}]'$ is an $N \times 1$ vector of predictor variables at time $t = 1, ..., T$, $\boldsymbol{\beta}$ 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.

3 In-Sample Analysis

3.1 Data Descriptions

We employ two sets of large panel macroeconomic data from the U.S. and Korea to assess and compare their predictability for the real dollar/won exchange rate. The U.S. dataset includes 126 macroeconomic time series variables from the FRED-MD database, while the Korean dataset consists of 192 macroeconomic time series data from the Bank of Korea. Korea maintained a largely fixed exchange rate regime for the dollar/won exchange rate until around 1980, after which it switched to a heavily managed floating regime. Following the Asian Financial Crisis in 1997, Korea began transitions to a market-based exchange rate system.

Our analysis focuses on the free-floating exchange rate regime beginning in the 2000s, after Korea's recovery from the Asian Financial Crisis. The dataset spans from October 2000 to August 2023, providing rich monthly observations of macroeconomic predictors relevant to the Korean context.[12] We adjusted the nominal exchange rate using the consumer price index (CPI) to obtain the real exchange rate. Our primary empirical results are based on pre-COVID-19 data (ending in 2019), as the COVID-19 crisis caused significant disconnect between the real exchange rate and its latent factors. In the subsequent discussion, we explore how out-of-sample predictability evolves during economic crises, highlighting the temporary yet persistent disconnect from underlying fundamentals.

The 126 U.S. predictors are categorized into nine groups: Groups #1 through #4 cover real activity variables, such as industrial production and labor market indicators, while Groups #5 through #9 include nominal and financial market variables such as interest rates and prices. Similarly, the 192 Korean predictors are divided into 13 groups: Groups #1 through #6 include real activity variables, such as inventories and industrial production, while Groups #7 through #13

[12] The sample period begins in October 2000, matching the availability of key Korean interest rate data, such as the 10-year Government Bond yield and the BBB- Corporate Bond yield, which commenced in October 2000. Also, 18 housing price variables became available starting in August 2000.

cover nominal and financial market variables. Detailed information on these categorizations is provided in Table 1. All variables, except those expressed as percentages (e.g., interest rates and unemployment rates), were log-transformed before estimation.

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 (4) and (7) as well as standard monetary models in international macroeconomics.[13]

Next, we implement a panel unit root test for predictors 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 ($f_{r,t}^{PC}, r = 1, 2, .., R$) utilizing PC as explained in the previous section, then it tests 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.

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

where $pv_{\hat{e}_i}$ denotes the p-value of the ADF statistic with no deterministic terms for de-factored $\Delta x_{i,t}$.[14]

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 U.S. real activity factors ($f_{r,t}^{PC,R}$) include more long-run predictive contents, while its financial market factors ($f_{r,t}^{PC,F}$) 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.[15] However, nonstationary common factors eventually dominate stationary dynamics of de-factored idiosyncratic

[13] For instance, 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.

[14] $P_{\hat{e}}$ 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.

[15] The alternative hypothesis is that there is at least one stationary variable.

components.[16] 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

3.3 Factor Model In-Sample Analysis

This section reports the in-sample properties of the latent factors estimated using the full sample data.

3.3.1 In-Sample Fit Analysis

In Figure 1, we present cumulative R^2 statistics of the latent factors for the dollar/won real exchange rate. The three figures in the top panel show the cumulative R^2 statistics of PC (solid lines) and PLS factors (dashed lines), obtained from all predictors, real activity predictors, and financial sector predictors in the US. The bottom row figures display the cumulative R^2 statistics of Korean factors obtained in a similar manner. Some interesting findings are as follows.

First, the PLS factors provide a notably better in-sample fit in comparison with the performance of PC factors. This is because PLS utilizes the covariance information between the target and the predictor variables, while PC factors are extracted solely from the predictor variables. 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 primarily 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 independent of the target variable, hence the additional contribution of PC factors does not necessarily decrease.

Second, U.S. factors greatly outperform Korean factors in terms of in-sample fit. The cumulative R^2 values of U.S. 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, close to zero. These findings imply that Korean macroeconomic variables may not be an important driver of the dollar/won real exchange rate dynamics, while U.S. predictors contain substantial predictive contents for it. Also, we note that the contribution of PLS Korean factors mostly stem from that of PLS Korean financial sector factors. PLS real Korean factors explain less than 10% of variations jointly even when 12 factors are utilized.

Figure 1 around here

[16] See Kim and Kim (2018) for a simulation study that shows the dominance of stationary components over non-stationary components in small samples.

3.3.2 Cross-Section Correlations of the Dollar/Won Rate with Other Exchange Rates

We investigate the source of this asymmetric explanatory power by examining the co-movement behavior between bilateral exchange rates relative to the US dollar. We conjecture that U.S. factors are the dominant drivers of exchange rates *vis-à-vis* the U.S. dollar, rather than the idiosyncratic factors of small open economies like Korea. For this purpose, we implement a formal test by Pesaran (2021) for cross-section dependence in 36 bilateral real exchange rates against the U.S. dollar, including 16 euro-zone countries, using the following test statistics.[17]

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

where $\hat{\rho}_{i,j}$ is the pair-wise correlation coefficients from the residuals of the ADF regressions for each real exchange rate.[18]

The CD statistic was 176.748 ($pv = 0.000$), indicating strong empirical evidence of cross-section dependence at any conventional significance level. The heat map in Figure 2 clearly demonstrates these strong cross-correlations in the real exchange rates relative to the U.S. dollar. With some exceptions, such as China, which often employs a 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 excluding 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

3.3.3 Marginal R^2 Analysis

Next, we investigate the source of these common factor estimates via the marginal R^2 analysis, following the approach suggested by Ludvigson and Ng (2009). For this purpose, 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 all predictors, real activity variables, and nominal/financial market variables, respectively.

[17] We obtained all nominal exchange rates and CPIs from the IFS for the sample period from September 2000 to December 2019. 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.

[18] We 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.

As shown in Figure 3, the marginal R^2 statistics of the first U.S. PC factor (solid lines) are very similar to those of the first U.S. PLS factor (bar graphs). In contrast, the marginal R^2 statistics of the first Korean PC factor differ significantly from those of the first Korean PLS factor. Specifically, the marginal R^2 statistics of the Korean PLS factor are negligibly low compared with those of the PC factor.

Since PC factors are obtained solely from the predictors without reference to the target variable, the marginal R^2 values of the PC factor are expected to be high. However, because PLS factors are estimated using the covariance between the target variable and the predictors, the low R^2 statistics of the Korean PLS factor imply that Korean predictors are largely disconnected from the dollar/won real exchange rate.

Note also that PLS U.S. factors are more closely connected with Groups #1 (industrial production) and #2 (labor market) than with other groups. Putting it differently, the first PLS U.S. factor appears to be strongly driven by these real activity variables rather than by financial market variables or other real activity variables. We also point out that these two groups include key variables that influence the Fed's decision making process regarding the U.S. monetary policy stance under its dual mandate, which in turn affects the dollar exchange rate.

Figure 3 around here

We investigate the source of the common factors at a more disaggregated level, examining the marginal R^2 statistics of the real and financial market factors. Figure 4 reports the marginal R^2 statistics of the first U.S. real activity factor. Again, the PLS and PC factors explain the variations in real activity variables similarly well. We also note that the U.S. 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 U.S. 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 dollar/won 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,

$$q_{t+j} = \alpha_j q_t + u_{t+j}, \; j = 1, 2, .., k, \tag{8}$$

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,

$$\widehat{q}^{AR}_{t+j|t} = \hat{\alpha}_j q_t, \tag{9}$$

where $\hat{\alpha}_j$ is the least squares (LS) estimate of α_j in (8).

We augment (8) by adding factor estimates. That is, our factor augmented stationary $AR(1)$-type forecasting model is the following.

$$q_{t+j} = \alpha_j q_t + \boldsymbol{\beta}_j' \boldsymbol{\Delta} \hat{\mathbf{f}}_t + u_{t+j}, \; j = 1, 2, .., k \tag{10}$$

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 (10) coincides with an exact $AR(1)$ process when $j = 1$, but extended by the factor covariates $\Delta \hat{\mathbf{f}}_t$. Note also that (10) nests the stationary benchmark model (8) when $\boldsymbol{\Delta} \hat{\mathbf{f}}_t$ does not contain any useful predictive contents for q_{t+j}, that is, $\boldsymbol{\beta}_j = 0$. (10) yields the following j-period ahead forecast,

$$\widehat{q}^{F_{AR}}_{t+j|t} = \hat{\alpha}_j q_t + \hat{\boldsymbol{\beta}}_j' \Delta \hat{\mathbf{f}}_t, \tag{11}$$

where $\hat{\alpha}_j$ and $\hat{\boldsymbol{\beta}}_j$ are the LS coefficient estimates from (10).

We evaluate the out-of-sample predictability of our factor-augmented forecasting model $\widehat{q}^{F_{AR}}_{t+j|t}$ using a recursive window scheme.[19] We employ the AR benchmark forecast $\widehat{q}^{AR}_{t+j|t}$ in (9) in addition to the no-change Random Walk (RW) benchmark $\widehat{q}^{RW}_{t+j|t} = q_t$. The evaluation criterion is the ratio of the root mean square prediction error ($RRMSPE$),

$$RRMSPE(j) = \frac{\sqrt{\frac{1}{T-T_0-j} \sum_{t=T_0+j}^{T} \left(\varepsilon^{F_{AR}}_{t+j|t} \right)^2}}{\sqrt{\frac{1}{T-T_0-j} \sum_{t=T_0+j}^{T} \left(\varepsilon^{BM}_{t+j|t} \right)^2}}, \tag{12}$$

where

$$\varepsilon^{BM}_{t+j|t} = q_{t+j} - \widehat{q}^{BM}_{t+j|t}, \; \varepsilon^{F}_{t+j|t} = q_{t+j} - \widehat{q}^{F_{AR}}_{t+j|t}, \; BM = AR, RW \tag{13}$$

[19] We use initial $T_0 < T$ observations, $\{q_t, \Delta x_{i,t}\}_{t=1}^{T_0}$, $i = 1, 2, ..., N$ to estimate the first set of factors $\left\{ \Delta \hat{\mathbf{f}}_t \right\}_{t=1}^{T_0}$ using one of our data dimensionality reduction methods. We formulate the first forecast $\widehat{q}^{F_{AR}}_{T_0+j|T_0}$ by (11), then calculate and keep the forecast error ($\varepsilon^{F_{AR}}_{T_0+j|T_0}$). Next, we add one observation ($t = T_0 + 1$) for the second round forecasting, then re-estimate $\left\{ \Delta \hat{\mathbf{f}}_t \right\}_{t=1}^{T_0+1}$ using $\{q_t, \Delta x_{i,t}\}_{t=1}^{T_0+1}$, $i = 1, 2, ..., N$ to formulate the second round forecast, $\hat{q}^{F_{AR}}_{T_0+j+1|T_0+1}$, and its resulting forecast error $\varepsilon^{F_{AR}}_{T_0+j+1|T_0+1}$. We repeat this process until we forecast the last observation, q_T.

Note that $RRMSPE(j) < 1$ indicates that our factor models outperform the benchmark models.[20]

4.2 Evaluation of Factor-Augmented Models

We implement out-of-sample forecast exercises using a fixed-size (50% split point, that is, $T_0 = T/2$) recursive window method with up to 3 (k) latent factor estimates.[21] 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 $\widehat{q}^{F_{AR}}_{t+j|t}$ relative to $\widehat{q}^{RW}_{t+j|t}$. Recall that our models outperform the RW benchmark when the $RRMSPE$ is less than one. We also obtained the $RRMSPE$ statistics of $\widehat{q}^{F_{AR}}_{t+j|t}$ relative to $\widehat{q}^{AR}_{t+j|t}$ (not reported to save space). The superscript $*$ denotes cases where $\widehat{q}^{F_{AR}}_{t+j|t}$ outperforms $\widehat{q}^{AR}_{t+j|t}$. Since the AR benchmark consistently outperformed the RW model across all cases, the superscript $*$ indicates that $\widehat{q}^{F_{AR}}_{t+j|t}$ outperforms both benchmarks: $\widehat{q}^{RW}_{t+j|t}$ and $\widehat{q}^{AR}_{t+j|t}$. Our major findings are as follows.

First, the U.S. predictors demonstrate superior predictive power for the dollar/won real exchange rate, while the Korean factor models perform relatively poorly compared to their U.S. counterparts. More specifically, our factor models consistently outperform both the RW and AR models only when the U.S. factors are utilized. In contrast, models incorporating Korean factors are generally outperformed by the AR model, though they still outperform the RW model when the forecast horizon extends to one year or longer. These empirical findings are consistent with our in-sample fit analysis presented in the previous section. Interestingly, the performance of our factor models tends to deteriorate when U.S. factors are combined with Korean factors, implying that the inclusion of Korean factors may add noise in predicting the dollar/won real exchange rate.

Second, our U.S. factor models tend to perform better at shorter horizons when nominal/financial market factors are included, while real activity factors enhance predictability at longer horizons. Specifically, the strong predictive performance of models with the total factors, $\Delta\hat{\mathbf{f}}_t^{PLS}$ or $\Delta\hat{\mathbf{f}}_t^{PC}$, at the 1-period horizon seem to inherit the superior performance of models with financial market factors, $\Delta\hat{\mathbf{f}}_t^{PLS,F}$ or $\Delta\hat{\mathbf{f}}_t^{PC,F}$. In contrast, superior longer horizon predictability is primarily driven by the contributions of real activity factors, $\Delta\hat{\mathbf{f}}_t^{PLS,R}$ or $\Delta\hat{\mathbf{f}}_t^{PC,R}$. These findings imply that factors obtained from specific subsets of predictors can provide more useful information than those derived from the full set of variables, consistent with the insights of Boivin and Ng (2006).

Table 3 around here

We also employ the LASSO approach to identify subsets of predictors that are most relevant for explaining the target variable. The idea behind that is to estimate factors using fewer, but more informative predictors, as discussed by Bai and Ng (2008). Following Kelly and Pruitt (2015), we

[20] Alternatively, one may employ the ratio of the root mean absolute prediction error ($RRMAPE$). Results are overall qualitatively similar.

[21] We obtained qualitatively similar results with a 70% sample split point.

adjusted the tuning parameter τ in (7) to choose 30 predictors from each panel of macroeconomic variables in the U.S. and Korea, while 20 predictors were selected from each of the real activity and the financial market variable groups. Using these subsets, we employed PLS and PC to estimate up to three common factors, which were then used to augment the benchmark AR model. The results, consistent with those in Table 3, are presented in Table A1 in the Appendix.

4.3 Diebold-Mariano-West Test Results

We extend our previous analyses by conducting the Diebold-Mariano-West (DMW) test, by Diebold and Mariano (1995) and West (1996), to directly assess the statistical significance of the U.S. factor models relative to the Korean factor models. For this purpose, we define the following loss differential function,

$$d_t = (\varepsilon_{t+j|t}^{F_{Korea}})^2 - (\varepsilon_{t+j|t}^{F_{U.S.}})^2, \tag{14}$$

where

$$\varepsilon_{t+j|t}^{F_{Korea}} = q_{t+j} - \widehat{q}_{t+j|t}^{F_{Korea}},\ \varepsilon_{t+j|t}^{F_{U.S.}} = q_{t+j} - \widehat{q}_{t+j|t}^{F_{U.S.}}$$

The DMW test statistic is defined as follows to test the null hypothesis of equal predictive accuracy, that is, $H_0 : Ed_t = 0$,

$$DMW(j) = \frac{\bar{d}}{\sqrt{\widehat{Avar}(\bar{d})}}, \tag{15}$$

where $\bar{d}$ is the sample average, $\bar{d} = \frac{1}{T-T_0-j}\sum_{t=T_0+j}^{T} d_t$, and the long-run variance of $\bar{d}$ is $\widehat{Avar}(\bar{d}) = \frac{1}{T-T_0}\sum_{i=-q}^{q} k(i,q)\hat{\mathbf{\Gamma}}_i$.[22]

The DMW test statistics in (15) obeys the standard normal distribution under the null hypothesis. The results, presented in Table 4, show that $RRMSPE$ values are below one in all 18 cases, consistent with the findings in Table 3. That is, U.S. factors yield superior predictive content compared to Korean factors. The overall DMW test results reject the null hypothesis of equal predictability in 11 out of 18 cases at the 10% significance level. Notably, for all one-year ahead forecasts, the U.S. factor models significantly outperform the Korean factor models at the 5% significance level.[23]

Table 4 around here

We also conducted the DMW test on our factor models, comparing them to the benchmark RW and AR models. Since the benchmark models are nested within our factor models, asymptotic

[22] T_0 is the number of initial observations that are used to formulate the first out-of-sample forecast. Following Andrews and Monahan (1992), we use the quadratic spectral kernel ($k(\cdot)$) with automatic bandwidth (q) selection for our analysis. And $\hat{\Gamma}_i$ is the i^{th} autocovariance function estimate.

[23] Results from alternative specifications corroborate the findings presented in Table 3. U.S. factor models consistently outperform Korean factor models when total or real activity factors are employed. However, results become mixed when financial factors are used.

critical values are not suitable. To address this, we employed the approach of McCracken (2007), which adjusts the test statistics by re-centering them to account for nuisance parameters. Consistent with the findings in Table 3, the results favor again favor the U.S. factor augmented models.[24]

4.4 Deviations from Fundamentals after Crises

Our primary findings were based on pre-COVID-19 era data, excluding the significant outlier effects associated with the COVID-19 crisis. In this section, we examine how economic crises influence the predictive power of macroeconomic variables, highlighting a temporary yet persistent disconnect between the real exchange rate and the underlying fundamentals captured by latent factors.

Figure 6 displays the $RRMSPE$ statistics using the recursive window scheme, with a specific focus on two significant economic crises: the Subprime Mortgage Crisis (2007-2008) in the top panel and the COVID-19 Pandemic Crisis (2020) in the bottom panel.

It should be noted that we observe a rapid rise in the $RRMSPE$ statistic for one-year ahead forecasts following the onset of the COVID-19 pandemic. Such increases eventually lead to the loss of superior predictability of U.S. factor models when compared to both the benchmark RW model and Korean factor models. Although our factor-augmented forecasting models exhibit overall weak performance for one-month ahead forecasts, a similar reduction in predictability is evident. Korean factor models experience a gradual loss of predictability, ultimately being surpassed by the benchmark model, mirroring the trend observed in U.S. factor models. Putting it differently, we report a deviation from the fundamentals following the onset of the pandemic.

Likewise, we identify a similar pattern during a preceding crisis in the top panel, although caution is necessary when analyzing the $RRMSPE$ statistics during the Great Recession era due to the limited training sample period.[25] The $RRMSPE$ statistics of all factor models show a gradual increase (loss of predictability) following the onset of the subprime mortgage market crisis, irrespective of whether U.S. or Korean factors were employed.

Figure 6 around here

It should be also noted that the U.S. PLS-AR and PC-AR models exhibit sudden drops in 1-year ahead predictability (increases in $RRMSPE$ values) around March 2021. This is attributed to the models utilizing data up to March 2020, a period when U.S. activity nearly halted due to the pandemic, for forecasting March 2021. Similarly, another abrupt decline is observed around April 2020 for 1-month ahead predictability. These sudden changes in U.S. macroeconomic activity, highlighted in Figure 7, stand in contrast to Korean macroeconomic data that exhibit a gradual decline in real activity.

[24] Detailed results are available upon request.

[25] Our sample begins in October 2000. Therefore, in the initial out-of-sample (OOS) analysis in 2006, we base our assessment on approximately a 3-year period for both the training and the test sets. Notably, RRMSPE statistics demonstrate gradual improvement, indicating the incremental addition of predictability from macro factors until the onset of the crisis around 2007, leading to a subsequent decline in predictability.

For instance, U.S. Industrial Production declined from 101.6 in February to 84.6 in April, while the unemployment rate rose from 3.5% to 14.8% during the same period. U.S. latent factor estimates also show similar abrupt declines, suggesting that these movements describe overall U.S. activity. In contrast, Korean data showed much more gradual declines followed by a slow recovery. Ultimately, macroeconomic factors lose predictability after the pandemic crisis, with an expectation of recovery based on the earlier episode of a rebound after the Great Recession.

Despite the limitation imposed by the short sample period, these findings appear to represent a temporary departure from the fundamentals, which one would expect to recover slowly, as observed after the Great Recession until the COVID-19 pandemic. In this current study, hence, we have chosen to concentrate on forecasting exercises during the tranquil period using pre-COVID observations.[26]

Figure 7 around here

5 Concluding Remarks

In this paper, we propose parsimonious factor-augmented forecasting models for the real exchange rate within a data-rich environment. We leverage various data dimensionality reduction techniques on extensive panels of macroeconomic time series data, consisting of 125 American and 192 Korean monthly frequency variables. Unlike other research that utilizes cross-section information from many exchange rates, our approach utilizes many country-level macroeconomic variables in the U.S. and Korea for the dollar/won real exchange rate.

Our proposed forecasting models consistently demonstrate superior performance compared to both the random walk (RW) and autoregressive (AR) benchmark models, but this is only achieved when utilizing latent common factors derived from the U.S. predictors. Specifically, models incorporating U.S. real activity factors exhibit strong performance at longer horizons, while U.S. nominal/financial market factors enhance prediction accuracy at shorter horizons. These findings align with the research of Boivin and Ng (2006), who emphasized the importance of identifying relevant common factors for the target variable. In contrast, models incorporating Korean factors generally underperform compared to the AR model, although they still outperform the RW model for forecast horizons of 1 year or longer. We interpret this phenomenon as being related to the high cross-correlations of dollar exchange rates, which result in a weak influence from idiosyncratic small open economies.

We report temporary yet persistent disconnects between the real exchange rate and its underlying fundamentals during economic turmoils such as the COVID-19 Pandemic Crisis. We suspect such deviations might occur in the presence of elevated uncertainty. What triggered such anomalies

[26] A thorough examination of this topic can be addressed in a separate project, incorporating other exchange rates with longer sample periods.

and how persistent the deviations last are intriguing questions that can be investigated utilizing long-horizon data that allows sufficiently many events to be used in order to answer these questions.

In a nation where economic prosperity heavily relies on exports and imports, the significance of effectively monitoring and forecasting real exchange dynamics cannot be overstated. This manuscript provides insights into the practical and efficient utilization of extensive data, offering valuable guidance not only for entrepreneurs but also for policy-makers.

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Table 1. Macroeconomic Data Descriptions

U.S. Macroeconomic Data

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

Korean Macroeconomic Data

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: Macroeconomic data for the U.S. and Korea were obtained from FRED-MD and the Bank of Korea, respectively.

Table 2. Unit Root Test Results

ADF Test

q_t	$-2.966^{\dagger}$ (0.038)	s_t	-1.953 (0.308)

PANIC Test

$\mathbf{x}_t^{US}$		$\mathbf{x}_t^{KR}$	
$f_{1,t}^{PC}$	-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)
$P_{\hat{e}}$	$11.341^{\ddagger}$ (0.000)	$P_{\hat{e}}$	$16.667^{\ddagger}$ (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)
$P_{\hat{e}}$	$5.763^{\ddagger}$ (0.000)	$P_{\hat{e}}$	$15.552^{\ddagger}$ (0.000)
$f_{1,t}^{PC,F}$	-1.888 (0.326)	$f_{1,t}^{PC,F}$	1.250 (0.999)
$f_{2,t}^{PC,F}$	$-3.437^{\ddagger}$ (0.009)	$f_{2,t}^{PC,F}$	-1.544 (0.512)
$P_{\hat{e}}$	$6.425^{\ddagger}$ (0.000)	$P_{\hat{e}}$	$8.711^{\ddagger}$ (0.000)

Note: q_t and s_t are the CPI-based real and nominal bilateral dollar/won exchange rates, respectively. PLS estimates target specific factors for q_t and s_t separately, while PC yields common factors independent of the target variable. Real variables are from Groups #1 through #4 for U.S. factors and Groups #1 through #7 for Korean factors, while financial variables include Groups #5 through #9 for U.S. 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, with P-values in parentheses. For the PANIC test results, we report the ADF t-statistics with an intercept for each common factor estimate. $P_{\hat{e}}$ 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. j-Period Ahead Out-of-Sample Predictability for the Real Exchange Rate

				U.S. Factors			
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	0.9886*	0.9924	0.9927	0.9755*	0.9913*	0.9858*
	2	0.9657*	1.0029	0.9806*	0.9854*	0.9977	0.9847*
	3	0.9741*	1.0059	0.9782*	0.9860*	1.0331	0.9782*
12	1	0.7440*	0.7347*	0.8001*	0.7579*	0.7477*	0.8078
	2	0.7469*	0.7424*	0.9120	0.7954*	0.7477*	0.8096
	3	0.8051*	0.8166	0.9763	0.7954*	0.7514*	0.8915
36	1	0.7008*	0.6913*	0.7868	0.7277*	0.7007*	0.8059
	2	0.7852	0.7169*	0.8120	0.7609	0.7153*	0.7946
	3	0.8175	0.7028*	0.7865	0.7561	0.7204*	0.8130
				Korean Factors			
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	1.1104	0.9971	1.0659	1.4628	1.1844	1.0367
	2	1.5800	1.0592	1.0582	2.0280	1.1569	3.4831
	3	2.0492	1.1154	1.8815	4.2589	1.2789	5.8582
12	1	0.7932*	0.8222	0.7875*	0.8077	0.8050*	0.8282
	2	0.8044*	0.8595	0.8089	0.8287	0.8043*	0.8420
	3	0.8078	0.9329	0.8138	0.8224	0.8131	0.8010*
36	1	0.7280*	0.7253*	0.7203*	0.7272*	0.7325	0.7248*
	2	0.7409	0.7793	0.7220*	0.7224*	0.7449	0.7242*
	3	0.8392	0.9045	0.7476	0.7222*	0.7443	0.7306
				American and Korean Factors			
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	1.0561	0.9919*	1.0480	1.2133	1.1204	1.0224
	4	1.0592	1.0617	1.1364	2.4814	1.1236	4.1667
	6	1.7844	1.1455	1.7382	4.4843	1.2539	5.3447
12	2	0.7406*	0.7574*	0.7872*	0.7660*	0.7490*	0.8475
	4	0.7660*	0.8033*	0.9480	0.8422	0.7495*	0.8508
	6	0.8790	0.9184	1.0909	0.8605	0.7532*	0.8790
36	2	0.7004*	0.6880*	0.7763	0.7323	0.7047*	0.8186
	4	0.8045	0.7486	0.8130	0.7785	0.7244*	0.8096
	6	0.9077	0.8365	0.8166	0.7854	0.7365	0.8116

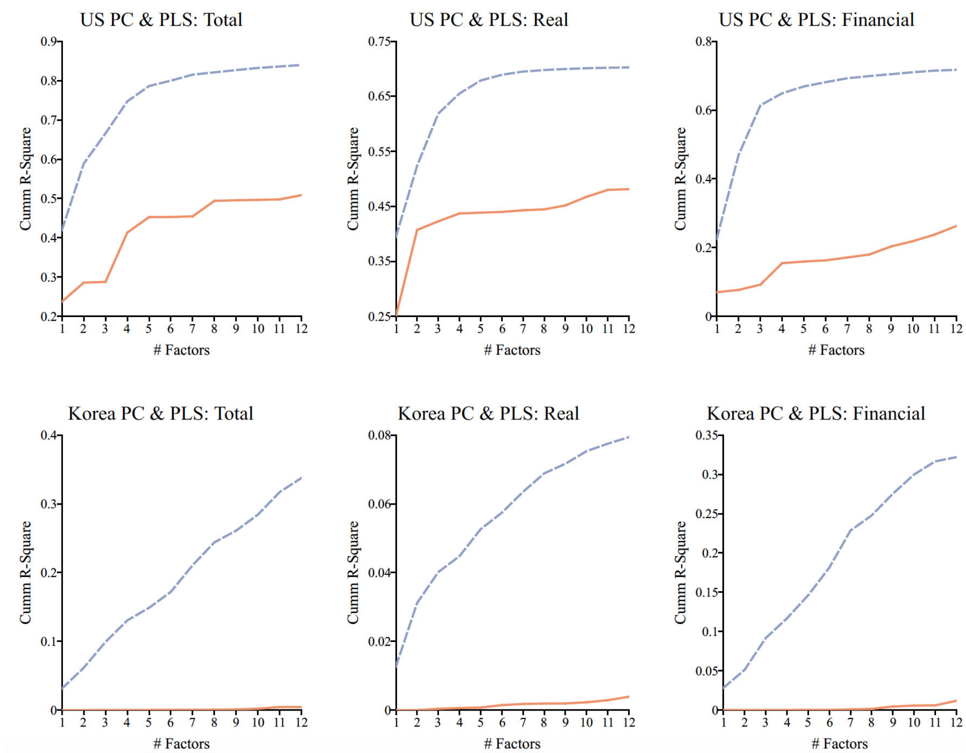
Note: We report the *RRMSPE* statistics employing a recursive window scheme with a 50% sample split point. *RRMSPE* denotes the ratio of the mean squared prediction error (*RMSPE*) from the benchmark random walk (RW) model to the *RMSPE* from each competing model with k factors. Superscript R and F mean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

Table 4. Diebold-Mariano-West Test: U.S. vs. Korean Real Factor Models

		PLS Factors		*PC Factors*	
j	#Factors	*RRMSPE*	*DMW*	*RRMSPE*	*DMW*
1	1	**0.9952**	0.200	**0.8370**	1.125
	2	**0.9468**	0.762	**0.8624**	$2.012^{\dagger}$
	3	**0.9018**	1.266	**0.8078**	$2.270^{\dagger}$
12	1	**0.8935**	$3.370^{\ddagger}$	**0.9287**	$2.348^{\ddagger}$
	2	**0.8638**	$3.261^{\ddagger}$	**0.9295**	$2.591^{\ddagger}$
	3	**0.8753**	$2.184^{\dagger}$	**0.9242**	$2.573^{\ddagger}$
36	1	**0.9530**	1.479^{*}	**0.9566**	1.057
	2	**0.9200**	1.383^{*}	**0.9603**	0.858
	3	**0.7770**	$3.842^{\ddagger}$	**0.9678**	0.702

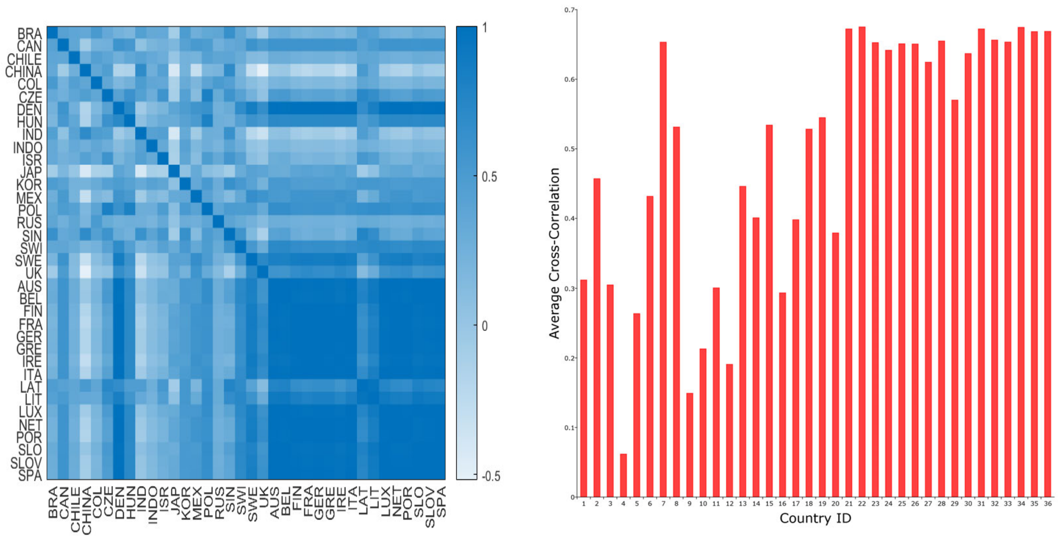
Note: We report the *RRMSPE* statistics comparing the predictability of the U.S. real factor model to the Korean real factor model. *RRMSPE* values that are less than 1 indicate that the U.S. factor model outperforms the Korean factor model. *DMW* denotes the Diebold-Mariano-West statistics, which are asymptotically normally distributed under the null hypothesis of equal predictability. ‡, †, and * denote a rejection of the null hypothesis at the 1%, 5%, and 10% level, respectively.

Figure 1. Cumulative R^2 Analysis



Note: We regress the real exchange rate on each factor, up to 12, and then cumulatively obtain the R^2 statistics. Dotted lines represent PLS factors, while solid lines are for PC factors.

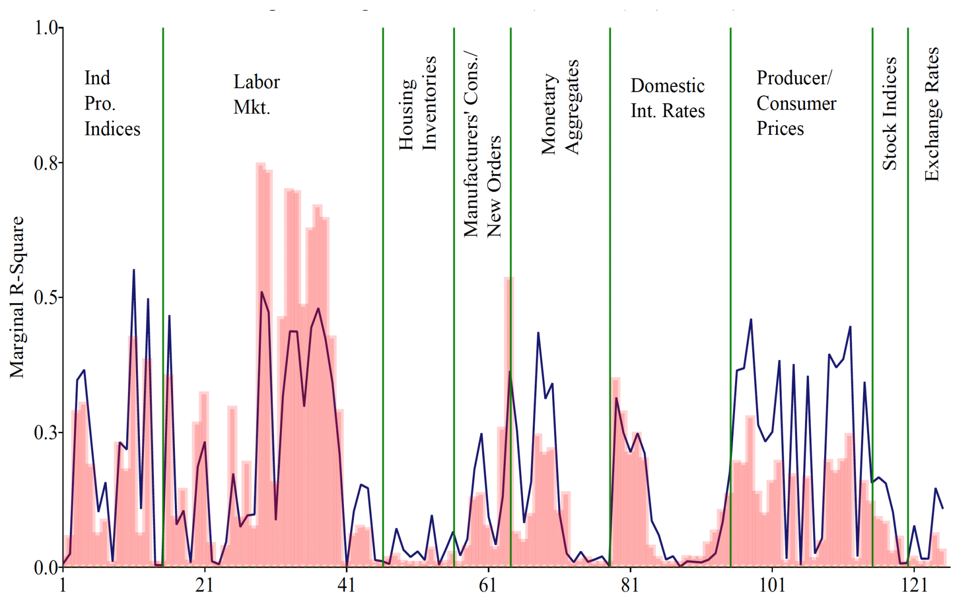
Figure 2. Cross-Section Dependence across Dollar Real Exchange Rates



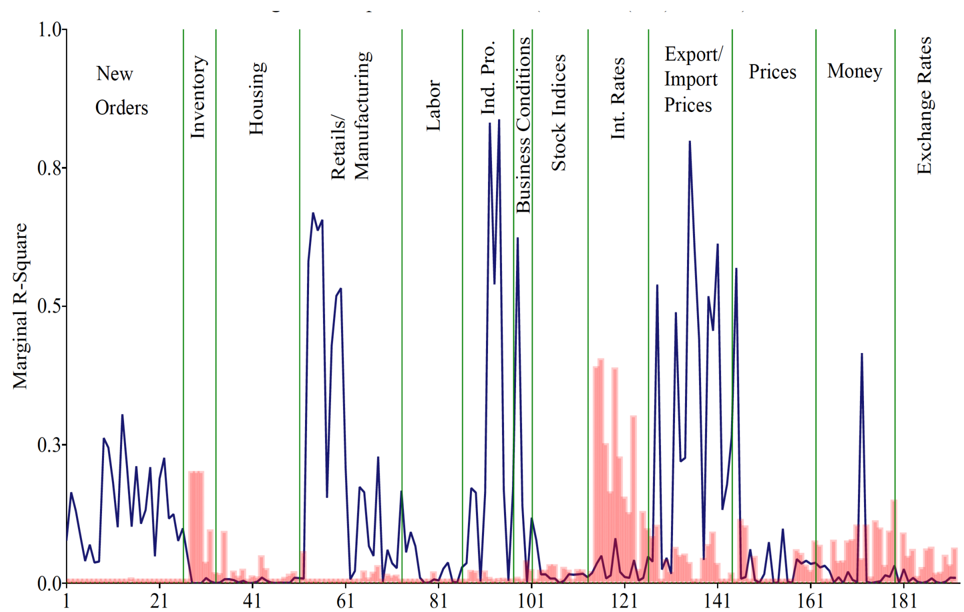
Note: The heat map on the left shows the cross-correlations of the ADF regression residuals for 36 real exchange rates relative to the U.S. dollar. The figure on the right reports the average cross-correlations for each real exchange rate in the figure on the right. The country ID is in the same order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

Figure 3. Marginal R^2 Analysis: Total Factors

U.S. Factor #1



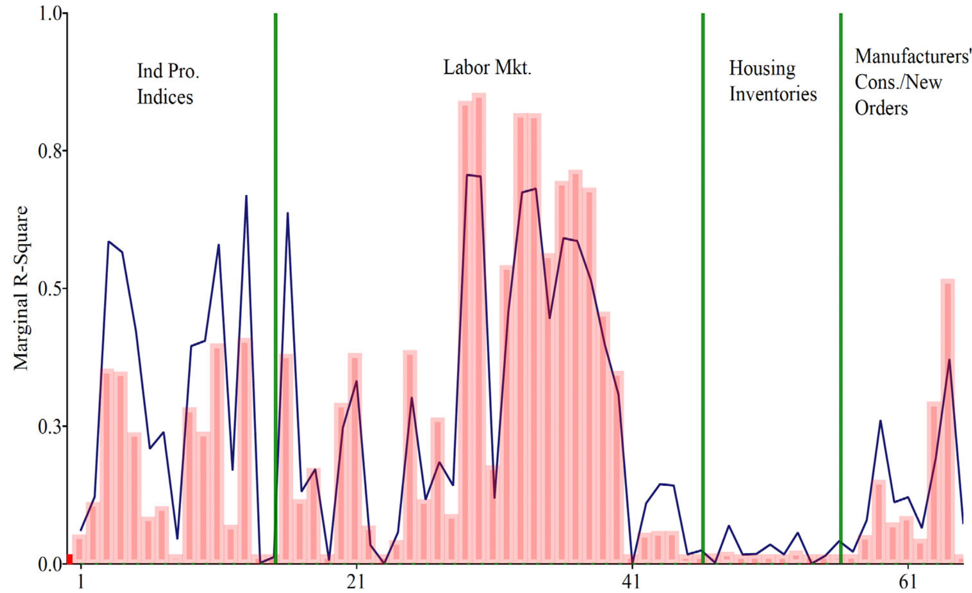
Korean Factor #1



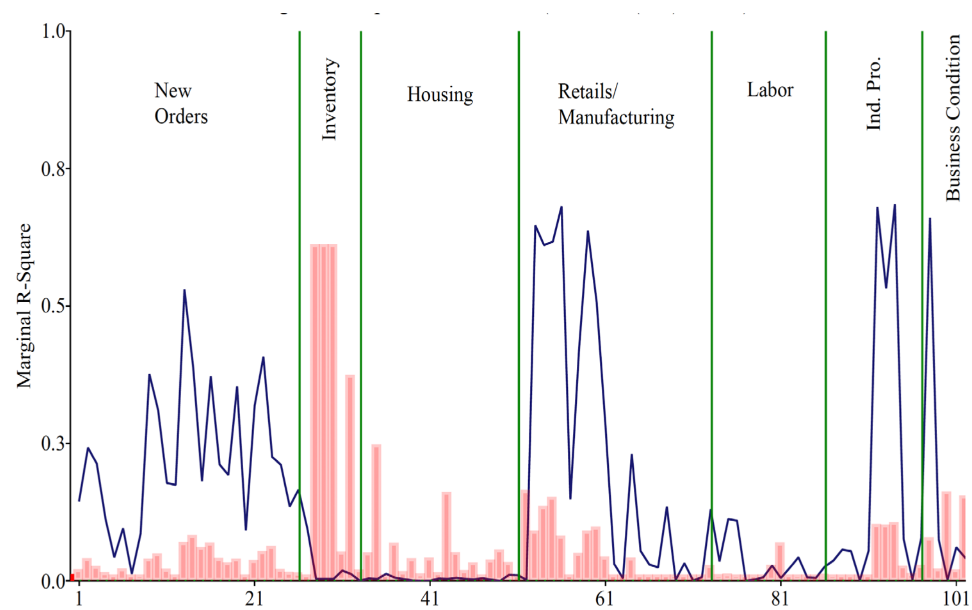
Note: We report the R^2 statistics that were obtained by regressing each predictor on the first common factor estimate. The horizontal axis represent the predictor IDs. Solid indicate the PC factor, while bar graphs represent the PLS factor.

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

U.S. Real Factor #1



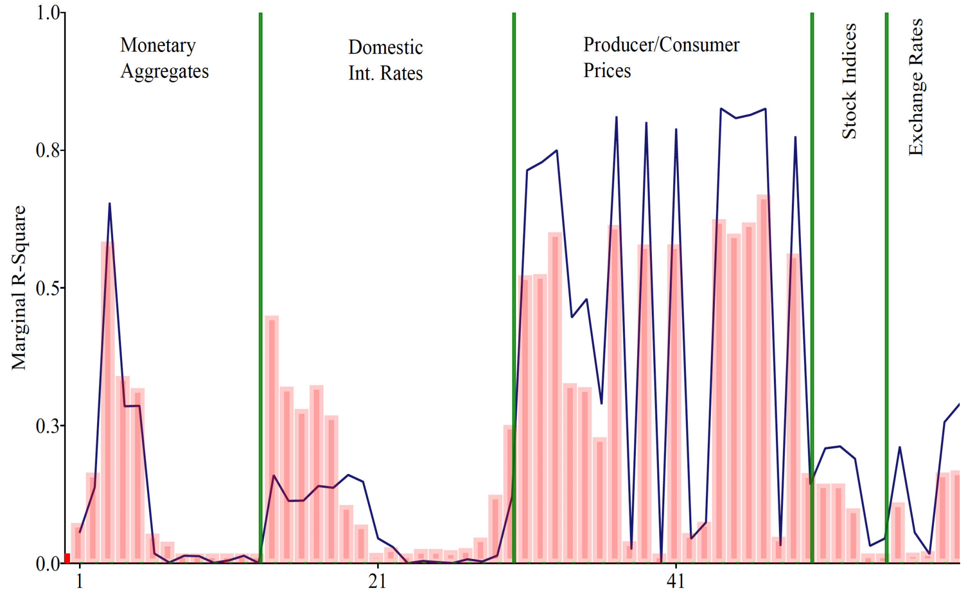
Korean Real Factor #1



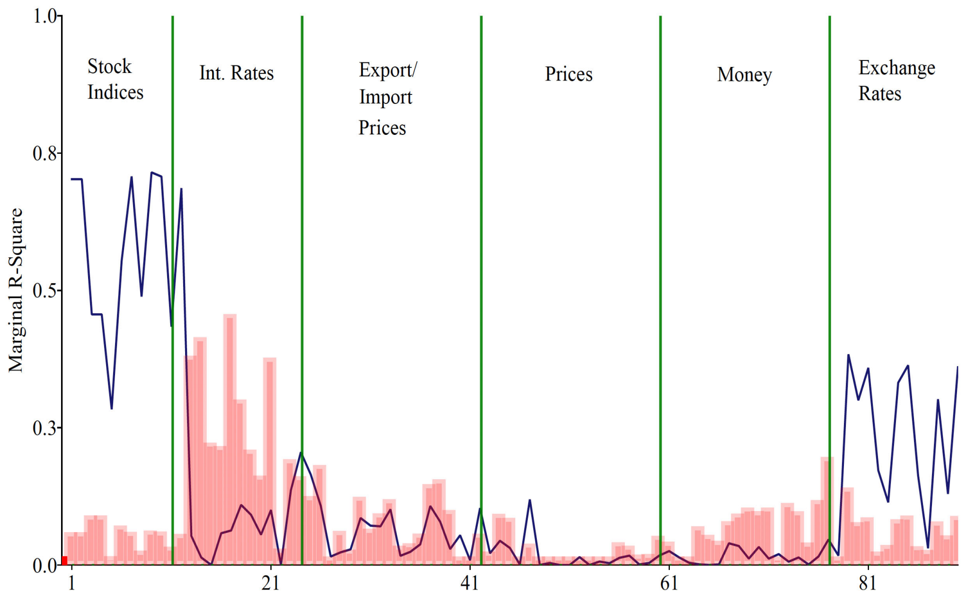
Note: We report the R^2 statistics obtained by regressing each predictor on the first common factor estimate. The horizontal axis represents the predictor IDs. Solid lines indicate the PC factor, while bar graphs represent the PLS factor.

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

U.S. Financial Factor #1

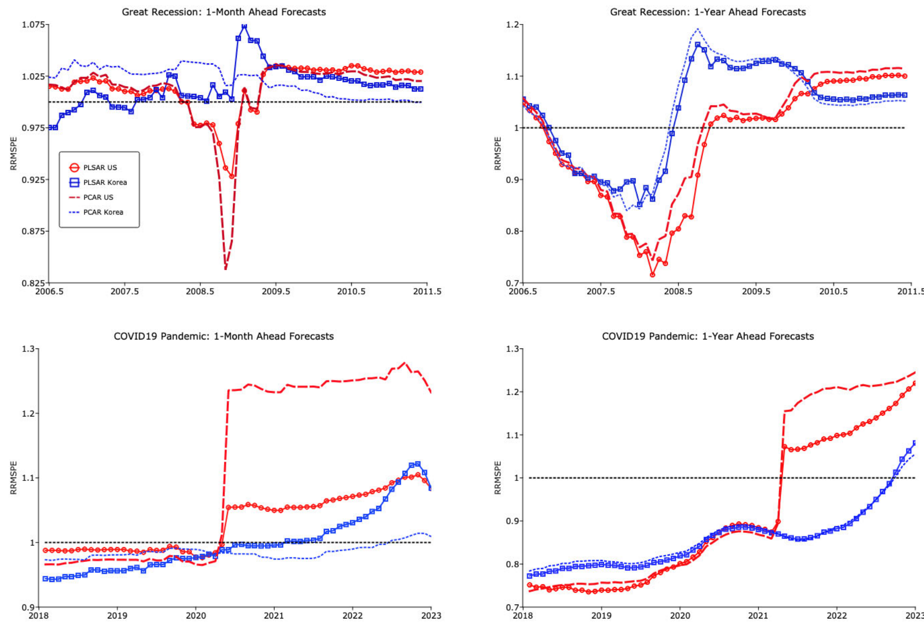


Korean Financial Factor #1



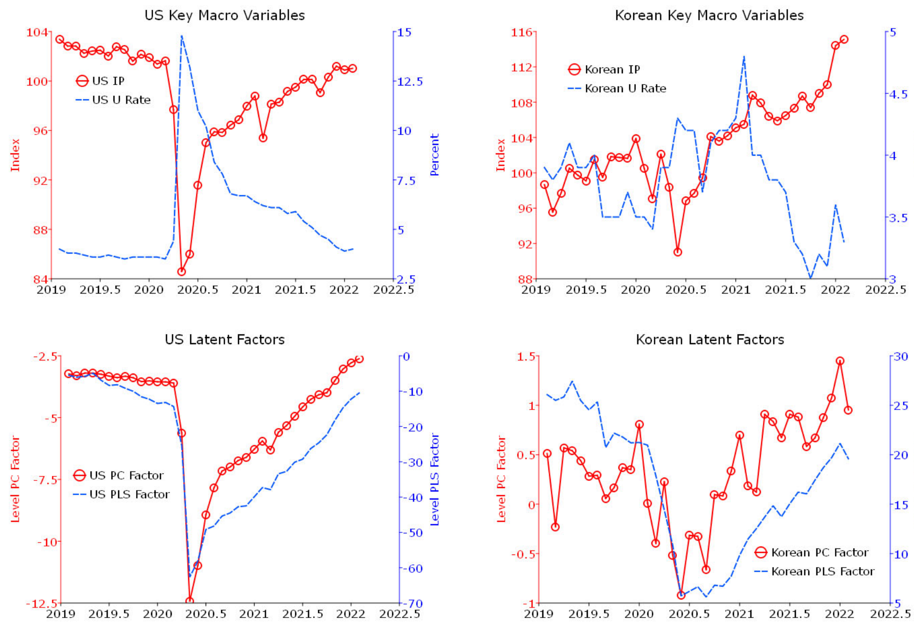
Note: We report the R^2 statistics obtained by regressing each predictor on the first common factor estimate. The horizontal axis represents the predictor IDs. Solid lines indicate the PC factor, while bar graphs represent the PLS factor.

Figure 6. Recursive Window RRMSPE Estimations near the Economic Crises



Note: The *RRMSPE* statistics, calculated using the recursive window scheme, are reported in proximity to two significant economic crises: the Subprime Mortgage Crisis in the top panel and the COVID-19 Pandemic Crisis in the bottom panel. The estimation was conducted using total factor models.

Figure 7. COVID-19 Pandemic Macroeconomic Variables



Note: The top panel presents two key macroeconomic activity variables for each country, namely industrial production and the unemployment rate, during the COVID-19 Pandemic Crisis. The bottom panel displays the latent total factor estimates.

Appendix

Table A1. j-Period Ahead Out-of-Sample Predictability with LASSO

				U.S. Factors			
j	#Factors	$\Delta \mathbf{f}_t^{PLS/L}$	$\Delta \mathbf{f}_t^{PLS,R/L}$	$\Delta \mathbf{f}_t^{PLS,F/L}$	$\Delta \mathbf{f}_t^{PC/L}$	$\Delta \mathbf{f}_t^{PC,R/L}$	$\Delta \mathbf{f}_t^{PC,F/L}$
1	1	0.9841*	0.9787*	0.9815*	0.9623*	0.9819*	0.9681*
	2	0.9626*	1.0153	0.9746*	0.9568*	0.9843	0.9506*
	3	0.9627*	1.0197	0.9635*	0.9598*	0.9730*	0.9547*
12	1	0.8234	0.7251*	0.8610	0.7990*	0.7488*	0.8056
	2	0.8526	0.7432*	0.9035	0.8127	0.7381*	0.8516
	3	0.8522	0.7465*	0.8811	0.9330	0.7657*	0.8864
36	1	0.7710	0.6575*	0.7841	0.7377	0.6780*	0.7399
	2	0.7539	0.6734*	0.7290	0.7788	0.6824*	0.7498
	3	0.7896	0.6789*	0.7355	0.7675	0.6749*	0.7454
				Korean Factors			
j	#Factors	$\Delta \mathbf{f}_t^{PLS/L}$	$\Delta \mathbf{f}_t^{PLS,R/L}$	$\Delta \mathbf{f}_t^{PLS,F/L}$	$\Delta \mathbf{f}_t^{PC/L}$	$\Delta \mathbf{f}_t^{PC,R/L}$	$\Delta \mathbf{f}_t^{PC,F/L}$
1	1	1.0272	0.9978	1.0232	1.8440	1.0264	1.7182
	2	2.1758	1.0072	1.5969	1.8208	1.0367	2.8885
	3	1.7562	1.0246	1.5743	3.1918	1.0382	3.5311
12	1	0.8149	0.8235	0.8197	0.8672	0.8042*	0.8642
	2	0.8497	0.8165	0.8607	0.8579	0.8053*	0.8625
	3	0.8466	0.8228	0.8613	0.8532	0.8147	0.8621
36	1	0.7317	0.7730	0.7284	0.7184*	0.7324	0.7184*
	2	0.7340	0.7651	0.7255*	0.7176*	0.7327	0.7184*
	3	0.7250*	0.7814	0.7726	0.7113*	0.7510	0.7602
				American and Korean Factors			
j	#Factors	$\Delta \mathbf{f}_t^{PLS/L}$	$\Delta \mathbf{f}_t^{PLS,R/L}$	$\Delta \mathbf{f}_t^{PLS,F/L}$	$\Delta \mathbf{f}_t^{PC/L}$	$\Delta \mathbf{f}_t^{PC,R/L}$	$\Delta \mathbf{f}_t^{PC,F/L}$
1	2	1.0046	0.9834*	1.0148	1.7001	1.0082	1.5726
	4	1.8464	1.0332	1.4043	1.6340	1.0314	2.3348
	6	1.6041	1.0493	1.4999	2.5006	1.0315	3.2051
12	2	0.8114	0.7525*	0.8510	0.8498	0.7520*	0.8484
	4	0.9107	0.7618*	0.9681	0.8782	0.7417*	0.9129
	6	0.9144	0.7846*	0.9792	0.9717	0.7825*	0.9264
36	2	0.7896	0.6826*	0.8024	0.7469	0.6887*	0.7403
	4	0.7814	0.6936*	0.7417	0.7806	0.6965*	0.7515
	6	0.8241	0.7169*	0.8106	0.7943	0.7059*	0.7662

Note: We report the *RRMSPE* statistics employing a recursive window scheme with a 50% sample split point. *RRMSPE* denotes the ratio of the mean squared prediction error (*RMSPE*) from the benchmark random walk (RW) model to the *RMSPE* from each competing model with k factors. Superscript R and F indicate that factors were estimated from real and financial variables, respectively. *RRMSPE* statistics less than 1 indicate that the competing model outperforms the benchmark RW model. $*$ denotes cases where the competing model outperforms both the benchmark AR model and the RW model.