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Are exchange rates disconnected from macroeconomic variables? Evidence from the factor approach

Yunjung Kim[1] · Cheolbeom Park[1]

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Abstract
We use factor-augmented predictive regressions to analyze the relation between nominal exchange rates and macroeconomic variables. Using a panel of 121 US macroeconomic time series, we estimate eight factors through principal component analysis. Those estimated factors have significant predictive power and can substantially improve the predictive power of purchasing power parity through both in-sample and out-of-sample analyses. The estimated macroeconomic factor, which co-moves with US stock market variables, has strong predictive power for nominal exchange rate fluctuations in the short run, while estimated factors, co-moving with interest rate spreads, government-issued bond yields and employment variables, have strong predictive power in the long run. Moreover, optimal factors selected by the BIC in the out-of-sample analysis differ greatly depending on the time points when forecasts are made. Finally, we show that factors extracted from a panel of 121 US time series data and those extracted from a panel of 215 Korean macroeconomic series together can predict a substantial portion of movements in the Korea–US bilateral exchange rate.

Keywords Exchange rate · Macroeconomic variables · Factor approach · Predictive regression

JEL Classification F31 · F37 · F47

1 Introduction

Since Meese and Rogoff (1983) questioned the ability of macroeconomic variables to forecast exchange rates, many economists have investigated this issue. Although

✉ Cheolbeom Park
cbpark_kjs@korea.ac.kr

Yunjung Kim
kimyjh@korea.ac.kr

[1] Department of Economics, Korea University, 145 Anamro, Seongbuk-gu, Seoul 02841, Korea

numerous macroeconomic models have been proposed and examined empirically, the empirical findings on the relation between exchange rates and macroeconomic variables differ greatly depending on the selected macroeconomic variables, sample periods, countries, length of forecast horizons, econometric methodologies, and other factors. For example, while Mark (1995) and Chinn and Meese (1995) report that variables based on the monetary model with flexible prices have significant predictive power for future exchange rate changes, Kilian (1999) and Berkowitz and Giorgianni (2001) show that those results are not robust for extended sample periods. Later, however, Park and Park (2013) argue that those variables have strong ability to predict future exchange rate movements through the time-varying cointegration approach.

We address the literature's inconsistent and controversial results on the forecasting ability of macroeconomic variables by employing the factor-augmented predictive regression framework. Specifically, we use a panel of 121 monthly macroeconomic variables in the USA to determine the relation between exchange rates and macroeconomic variables. The factor approach, developed by Stock and Watson (2002) and Bai and Ng (2002, 2006), enables us to extract latent factors from the underlying panel of variables and test whether those latent factors have significant predictive power for future exchange rate movements. This factor approach can be particularly effective in examining the relation between exchange rates and macroeconomic data in several ways. First, previous studies have used a few selected macroeconomic variables and reported controversial results, but the factor approach enables us to avoid arbitrary decisions on the selection of macroeconomic variables. Instead, we can utilize information contained among the large number of macroeconomic data without causing a dimension problem due to a large number of predictors. Second, factors estimated from a large number of macroeconomic data are less noisy and have better explanatory power than individual time series data. [See Stock and Watson (2002) and Moench (2008)].

Using the advantages of the factor approach, we apply the factor-augmented predictive regression framework to 26 economies' bilateral US dollar exchange rates.[1] We find that estimated factors from a panel of US macroeconomic data have significant predictive power for future nominal exchange rate changes, even without accounting for non-US counterpart economies. The predictive power of those factors is particularly pronounced when the estimated factors are combined with the real exchange rate in both in-sample and out-of-sample analyses. Moreover, we show that individual factors' predictive powers differ over forecasting horizons, implying that different macroeconomic information is needed to forecast nominal exchange rate changes over different forecast horizons. After identifying the US macroeconomic variables co-moving with those estimated factors, we find that the factor co-moving with US stock market variables has greater predictive power for nominal exchange rate changes over short horizons, whereas the factors covarying with interest rate spreads, government-issued bond yields, and employment variables in the USA are selected more frequently as significant factors over long horizons. Moreover, the optimal factors selected by the BIC in the out-of-sample analysis differ greatly depending on the time points when forecasts are made. These findings echo Cheung and Chinn (2001),

[1] Exchange rates are defined as the amount of local currency needed to purchase one US dollar.

who report that the list of important macroeconomic variables and models in currency traders' mind to understand movements in exchange rates shifts over time. Moreover, the findings can explain why previous studies provide conflicting results, even when a large panel of macroeconomic variables is stably related with exchange rate fluctuations. Finally, we add estimated factors from a panel of Korean time series variables as well as estimated US factors in the predictive regression and show that factors from Korea and USA together predict a substantial portion of movements in the Korea–USA bilateral exchange rate, confirming the connection between macroeconomic variables and exchange rates.

Our study is similar to Ludvigson and Ng (2009, 2010) and Jurado, Ludvigson, and Ng (2015) in the sense that latent factors are extracted from a large number of macroeconomic variables, but it is also different in the sense that those factors are used to forecast bilateral US dollar exchange rate changes instead of bond returns or to measure uncertainty. Similarly to Engel, Mark, and West (2014) and Greenway-McGrevy et al. (2018), we apply the factor approach in predicting exchange rates. Unlike those studies, however, we estimate factors from a panel of US macroeconomic data and/or a panel of Korean macroeconomic series instead of a panel of exchange rate data.

The rest of this paper is organized as follows: Section 2 presents our econometric methodology. Data sources and estimated factors from a large set of macroeconomic series are presented in Sect. 3. The results of an in-sample analysis are shown in Sect. 4. Section 5 provides evidence from an out-of-sample analysis. Section 6 presents the results of the predictive regression with factors estimated from a panel of Korean time series as well as estimated US factors. Finally, concluding remarks are offered in Sect. 7.

2 Econometric methodology

Although the exchange rate is a macroeconomic variable monitored by policymakers and economists, its movements are not well explained by other macroeconomic variables, and its impact on other macroeconomic variables also seems limited. This phenomenon has been reported by many studies since Meese and Rogoff (1983) and is named the "exchange-rate disconnect puzzle" by Obstfeld and Rogoff (2001). In this literature, a standard approach to assessing whether nominal exchange rate changes are predictable by macroeconomic variables uses the following predictive regression:

$$\Delta^h s_{i,t+h} = \beta_{0,i} + \beta_{i,h}' X_t + \varepsilon_{i,t+h} \tag{1}$$

where $s_{i,t}$ denotes the log of the nominal exchange rate between the currency of country i and US dollars, $\Delta^h s_{i,t+h} \equiv s_{i,t+h} - s_{i,t}$, and X_t denotes a vector of macroeconomic predictors.

X_t in Eq. (1) usually consists of a few macroeconomic variables, depending on the underlying model. However, this approach could be restrictive because the relation between exchange rates and macroeconomic variables depends on the selected macroeconomic variables, sample periods, forecast horizons, and other decisions. Furthermore, Cheung and Chinn (2001) find from a survey of US foreign exchange traders that the importance foreign exchange traders attach to macroeconomic fundamentals varies over time. Observing the unstable relation between exchange rates and a few selected macroeconomic series, we seek to address whether macroeconomic series have significant predictive power for future exchange rate changes utilizing a large number of macroeconomic variables together. However, when the number of macroeconomic series (denoted by N) is greater than the number of time periods (denoted by T), this approach with a large number of variables is not feasible in the conventional regression approach.[2] To overcome this problem, we assume the following factor structure for US macroeconomic variables:

$$x_{j,t} = \lambda_j' F_t + e_{j,t} \tag{2}$$

where $x_{j,t}$ is an individual series contained in X_t, F_t is a $r \times 1$ vector of common factors, λ_j is a corresponding $r \times 1$ vector of factor loadings, and $e_{j,t}$ is an idiosyncratic error. $e_{j,t}$ can be serially correlated and weakly correlated across series, as in Stock and Watson (2002).

We estimate F_t using the principal component analysis (PCA). Bai and Ng (2002) and Stock and Watson (2002) show that the space spanned by F_t can be consistently estimated by $\hat{F}_t$ (an estimate of F_t by PCA) as both N and $T \to \infty$. We employ the information criterion (IC_2) developed in Bai and Ng (2002) to determine the number of factors. When we apply IC_2 to the panel of 121 macroeconomic series, we find eight factors over the full sample.[3] Having obtained these factors, we run the following predictive regressions for 26 economies to check whether the estimated factors from US macroeconomic data are helpful in forecasting nominal exchange rates:

$$\Delta^h s_{i,t+h} = \alpha_{0,i} + \alpha_{F,i,h}' \hat{f}_t + \alpha_{Z,i,h}' Z_t + \varepsilon_{i,t+h} \tag{3}$$

where $\hat{f}_t$ denotes an estimate of f_t, a subset of F_t, and Z_t is a vector of the observable predictor. We run regression Eq. (3) both without Z_t and with Z_t in the empirical analysis. When we include Z_t, we use the real exchange rate to represent Purchasing Power Parity (PPP) fundamentals, which are reported to have the strongest predictive power among macroeconomic models in Engel, Mark, and West (2008). Moreover, PPP fundamentals are also expected to reflect the relative macroeconomic conditions between US and non-US economies. Since the factors that are pervasive in the panel of US macroeconomic series are not necessarily important for forecasting $\Delta^h s_{i,t+h}$, $f_t \subset F_t$. Although we use $\hat{f}_t$ instead of true f_t in Regression (3), Bai and Ng (2006) show that the bias arising from the error-in-variable problem disappears asymptoti-

[2] When $N > T$, the Least Absolute Shrinkage and Selection Operator (LASSO) approach, proposed by Tibshirani (1996), may be considered. The LASSO approach achieves the improvement of the prediction accuracy by forcing the sum of absolute value of the regression coefficients to be less than a fixed value, which forces certain coefficients to be set to zero and results in a simpler and interpretable model. In contrast, our approach assumes the factor structure for the U.S macroeconomic series and focuses on the predictability of common components they share, not individual series with noises.

[3] Since we examine whether factors estimated from the large number of macroeconomic variables can forecast exchange rate changes, exchange rates are not included in the panel of 121 macroeconomic series.

cally and that (up to a rotation) the least squares (LS) estimate of $\alpha'_{F,i,h}$ is consistent and asymptotically normal as $N, T \to \infty$ and $\sqrt{T}/N \to 0$. Hence, we apply the LS estimation to Eq. (3) to examine the predictive power of factors from the US macroeconomic variables on a panel of bilateral US dollar rates.

3 Data and latent factors from US macroeconomic series

3.1 Data

Nominal exchange rate data for 26 countries are obtained from International Financial Statistics (IFS).[4] Nine currencies that switched to the euro at the beginning of 1999 are rescaled using bilateral euro rates to avoid discontinuity for those currencies. The consumer price indices (CPI) of the associated countries are also taken from IFS. After removing bilateral US dollar rates, 121 macroeconomic series are obtained from Federal Reserve Economic Data-Monthly Databases (FRED-MD), a macroeconomic dataset managed by the Federal Reserve Bank of St. Louis.[5] This dataset mimics the coverage of the "Stock–Watson dataset" which is constructed primarily from Global Insights Basic Economics Database and used in many studies such as Stock and Watson (2002, 2006), Ludvigson and Ng (2009) and Jurado, Ludvigson, and Ng (2015). The advantage of FRED-MD database is that the large macroeconomic panel dataset is publically accessible and updated in real time. The database contains information about various aspects of the US economy, such as real output, income, employment, consumer spending, housing market condition, inventories, money stock, interest rates and spreads, stock market indicators, and price indices. This database shares the same predictive content as that in the so-called Stock–Watson dataset as demonstrated by McCracken and Ng (2016). For those reasons, we use the FRED-MD database excepting for exchange rate variables. All of the macroeconomic data are standardized prior to estimation. The sample period covers January 1973 to December 2015, which is dictated by the availability of the panel of macroeconomic variables.

3.2 Latent factors from US macroeconomic series

We apply PCA to 121 macroeconomic series to estimate the latent factors, the number of which is determined by IC_2. This criterion selects eight factors from the series under investigation, consistent with the results in Ludvigson and Ng (2009) and Jurado, Ludvigson and Ng (2015). The factors that are pervasive in the panel of US macroeconomic series are not necessarily selected by the BIC in the predictive regression of exchange rate changes. Because of this possibility, we should favor a conservative approach in selecting the number of factors, in the sense of including possibly more factors than the

[4] The 26 countries examined in this study are Australia, Austria, Belgium, Canada, Chile, Colombia, Denmark, Finland, France, Germany, Iceland, Italy, Japan, Korea, Netherlands, New Zealand, Norway, the Philippines, Portugal, Singapore, South Africa, Spain, Sweden, Switzerland, Thailand, and the United Kingdom.

[5] FRED-MD can be downloaded from the website: http://research.stlouisfed.org/econ/mccracken/.

Table 1 Descriptive statistics for estimated factors

	AR(1) coefficient	Cumulative R-squared
$\hat{F}_{1t}$	0.75	0.17
$\hat{F}_{2t}$	0.77	0.25
$\hat{F}_{3t}$	− 0.10	0.32
$\hat{F}_{4t}$	0.44	0.38
$\hat{F}_{5t}$	0.60	0.42
$\hat{F}_{6t}$	0.33	0.46
$\hat{F}_{7t}$	0.21	0.49
$\hat{F}_{8t}$	− 0.24	0.52

$\hat{F}_{it}$ are factors found by IC_2 criterion applied to 121 US macroeconomic series

true number of pervasive factors but not fewer. The factors in excess will be trimmed by the BIC in the predictive regression. Hence, we check the number of factors using alternative criteria such as IC_1 in Bai and Ng (2002), edge distribution (ED) in Onatski (2010), and eigenvalue Ratio (ER) in Ahn and Horenstein (2013). The number of factors estimated by IC_1 is also eight, whereas ED and ER indicate that the number of factors is six and three, respectively. These pieces of evidence suggest that the number of factors selected by IC_2 is not too few but satisfies the conservative approach.

Autocorrelation coefficients and cumulative R^2s for these eight factors are reported in Table 1. The factors exhibit some, but not extreme, persistence. $\hat{F}_{2t}$ exhibits the highest autocorrelation (0.77) among the eight factors. $\hat{F}_{1t}$ explains 17%, the largest fraction, of the total variation in the macroeconomic dataset. The eight factors together can explain more than 52% of the total variation in the 121 macroeconomic series.

Factor analysis is often criticized for making it difficult to give an economic meaning to the estimated factors. To mitigate this problem, we regress each of the 121 US macroeconomic series on each of those eight factors and obtain R^2s. Based on the obtained R^2s, we identify which macroeconomic variables are closely related with those factors. Figures 1 and 2 plot each of the eight factors together with those closely related macroeconomic series. As shown in the top panel of Fig. 1, $\hat{F}_{1t}$ moves closely with various measures indicating US employment conditions, while $\hat{F}_{2t}$ varies tightly with interest rate spreads (both credit spreads and long-run term spreads). $\hat{F}_{3t}$ and $\hat{F}_{4t}$ are related with prices and government-issued bond yields (i.e., interest rates), respectively. $\hat{F}_{5t}$ shares components with short-term interest rate term spreads. Although it is difficult to relate one economic sector to $\hat{F}_{6t}$, $\hat{F}_{6t}$ seems to covary with stock market variables and investment variables. $\hat{F}_{7t}$ co-moves with stock market variables, and $\hat{F}_{8t}$ is generally correlated with measures of money supply.

4 Predictive regression: in-sample analysis

4.1 Optimal factors versus PPP

Utilizing the estimated factors from the panel of US macroeconomic series, we first run a predictive regression (3) without including any observable predictor (i.e., without

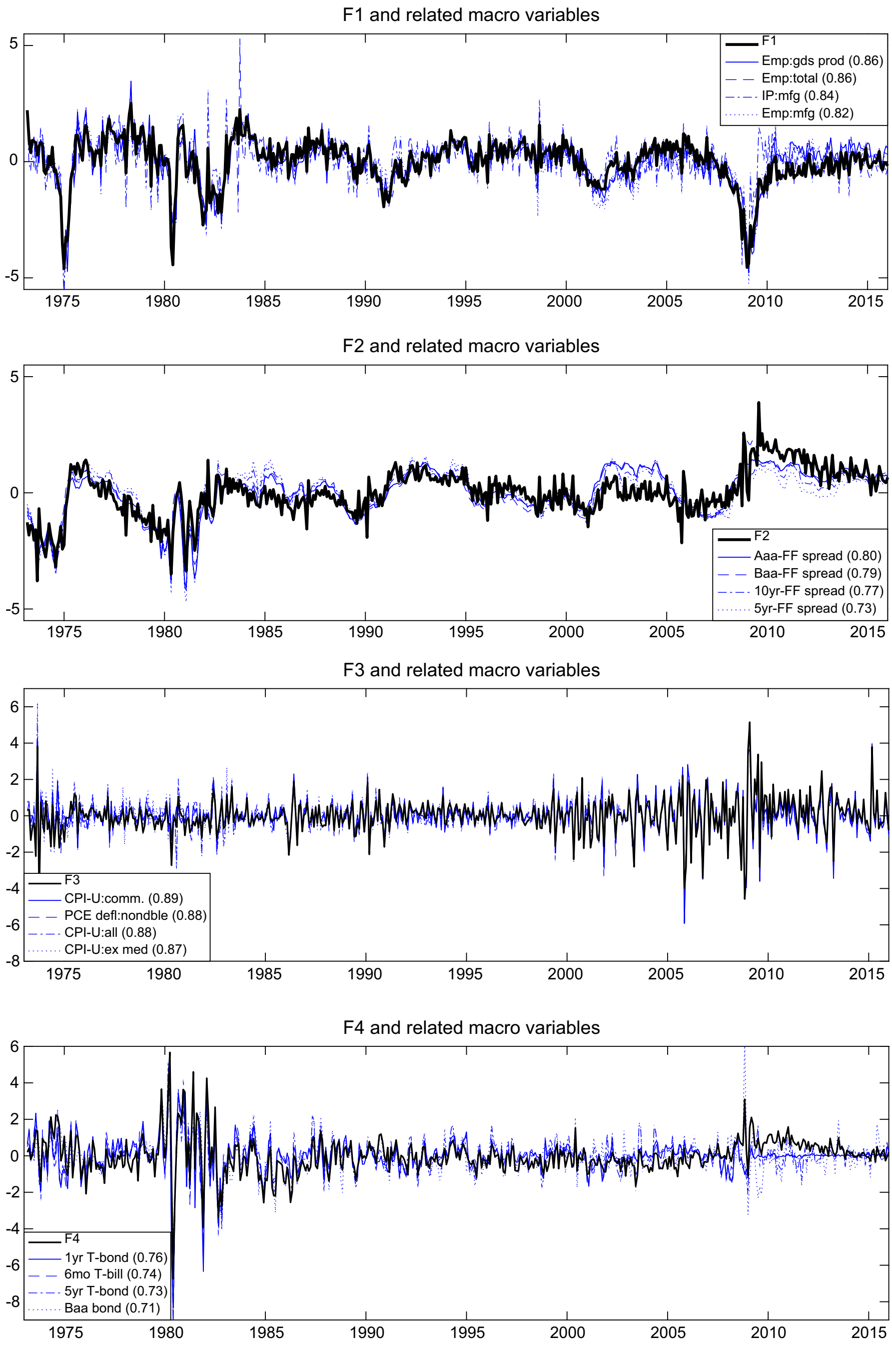

Fig. 1 Estimated factors and related macroeconomic series: $\hat{F}_{1t}$–$\hat{F}_{4t}$

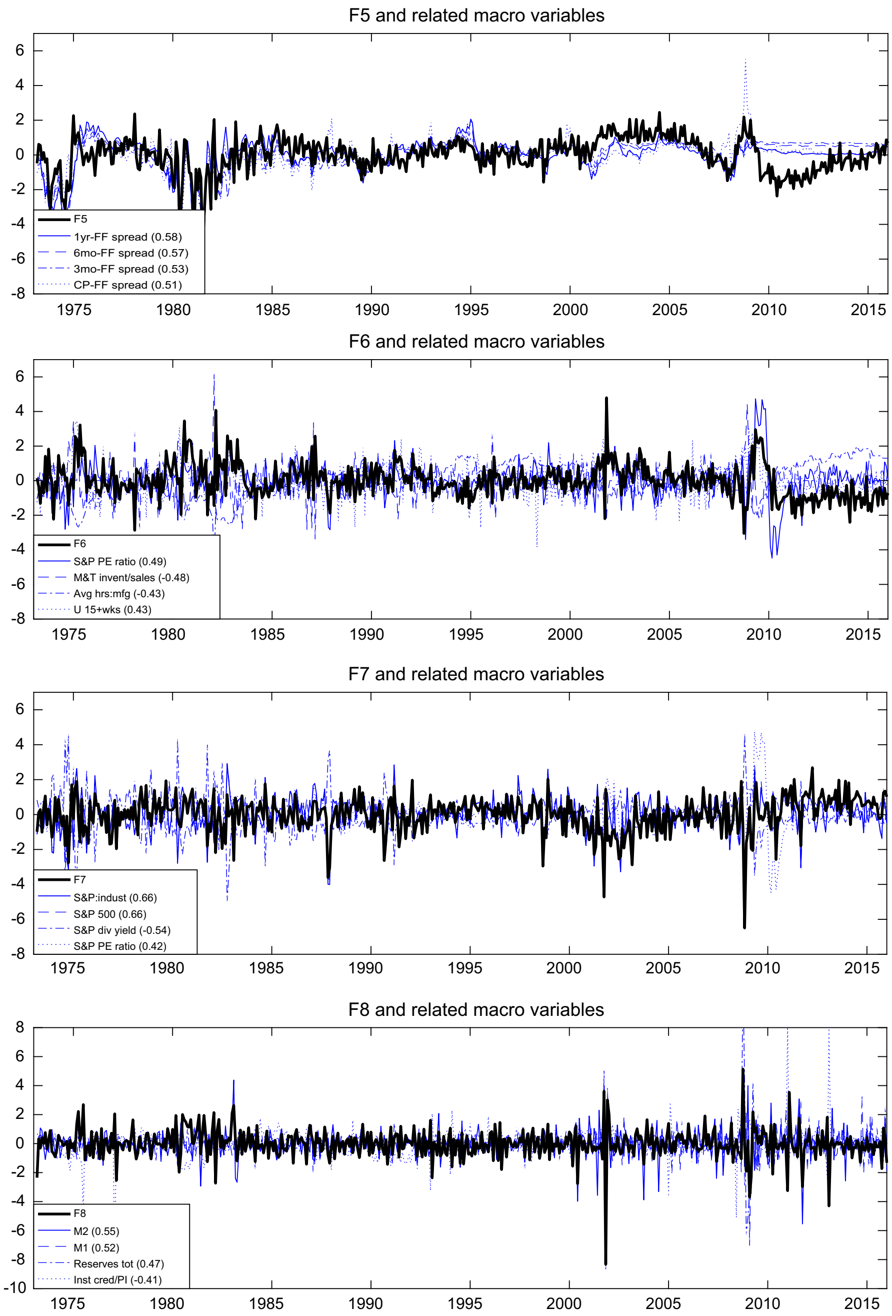

Fig. 2 Estimated factors and related macroeconomic series: $\hat{F}_{5t}$–$\hat{F}_{8t}$

Z_t). For each country and for each horizon (1 month, 3 months, 6 months, 12 months, and 24 months), we select the subset of eight factors that minimizes the BIC criterion and regress nominal exchange rate changes on those selected factors. Note that the factors that are important for the total variation of a macroeconomic series do not necessarily have the best ability to forecast $\Delta^h s_{i,t+h}$. Hence, the factors selected by the BIC criterion do not need to be $\hat{F}_{1t}$ or $\hat{F}_{2t}$. Figure 3 shows the frequencies at which each factor has been selected for each horizon. $\hat{F}_{7t}$, which is closely related with US stock market variables, is selected at overwhelming frequencies for the 1-month horizon, In addition, $\hat{F}_{8t}$ co-moving with US money supply measures is quite frequently chosen for the 1-month horizon, but other factors are selected more frequently as the horizon increases. This pattern suggests that factors with strong predictive power for nominal exchange rate movements differ across horizons. $\hat{F}_{7t}$ and $\hat{F}_{8t}$ play an important role in predicting exchange rates in the short run. For longer horizons such as 1 and 2 years, however, $\hat{F}_{1t}$, $\hat{F}_{4t}$, $\hat{F}_{5t}$ and $\hat{F}_{7t}$ which are related to US real economic activity such as employment conditions, interest rate spreads and stock market variables, become important in explaining exchange rate changes.[6] In contrast with $\hat{F}_{1t}$, $\hat{F}_{4t}$, $\hat{F}_{5t}$, $\hat{F}_{7t}$ and $\hat{F}_{8t}$, $\hat{F}_{3t}$, related to the price sector, is rarely selected as an optimal factor in the predictive regression. Table 2 shows adjusted R^2 from $\Delta^h s_{i,t+h} = \alpha_{0,i} + \alpha'_{F,i,h} \hat{f}_t + \varepsilon_{i,t+h}$. Although the predictive power of the factors estimated from the US macroeconomic series to explain bilateral exchange rate movements differ greatly across counterpart countries, the predictive power as measured by adjusted R^2 generally increases with the forecast horizon. The magnitude of the predictive power is substantial: the average adjusted R^2 ranges from 1.1% at a 1-month horizon to 20% at a 2-year horizon.

To compare the predictive power of the optimal factors chosen by the BIC with that of PPP, the following predictive regression, with only the real exchange rate, is run:

$$\Delta^h s_{i,t+h} = \gamma_{0,i} + \gamma_{0,i,h} q_{i,t} + \varepsilon_{i,t+h} \tag{4}$$

where $q_{i,t}$ is the real exchange rate between country i and USA. Comparing Table 2 with the PPP columns in Table 3, we note that the optimal factors selected by the BIC show much better forecasting ability than PPP shows at a 1-month horizon in terms of adjusted R^2. For a 1-month horizon, adjusted R^2s improve in 20 out of 26 countries when the optimal factors from the US macroeconomic series (instead of the real exchange rate) are used in the predictive regression. This result is notable because we use factors from the US macroeconomic variables only, without considering any of the variables from counterpart countries. Possibly due to this limit, however, PPP shows better performance in predicting nominal exchange rate changes at three- and 6-month horizons. The gap in adjusted R^2s between PPP and the optimal factors becomes smaller as the horizon grows, and the optimal factors show almost equal predictive power when the horizon reaches the 2-year threshold.

4.2 Optimal factors and PPP

Next, we run the predictive regression (3) with optimal factors and an observable predictor. The chosen Z_t in regression (3) is $q_{i,t}$. We select $q_{i,t}$ as the observable

[6] Our finding that factors co-moving with interest rate term spreads ($\hat{F}_{5t}$ and $\hat{F}_{2t}$) are often selected in the predictive regressions is similar to Chen and Tsang (2013) who show that information contained in the yield curve has predictive power for nominal exchange rate movements.

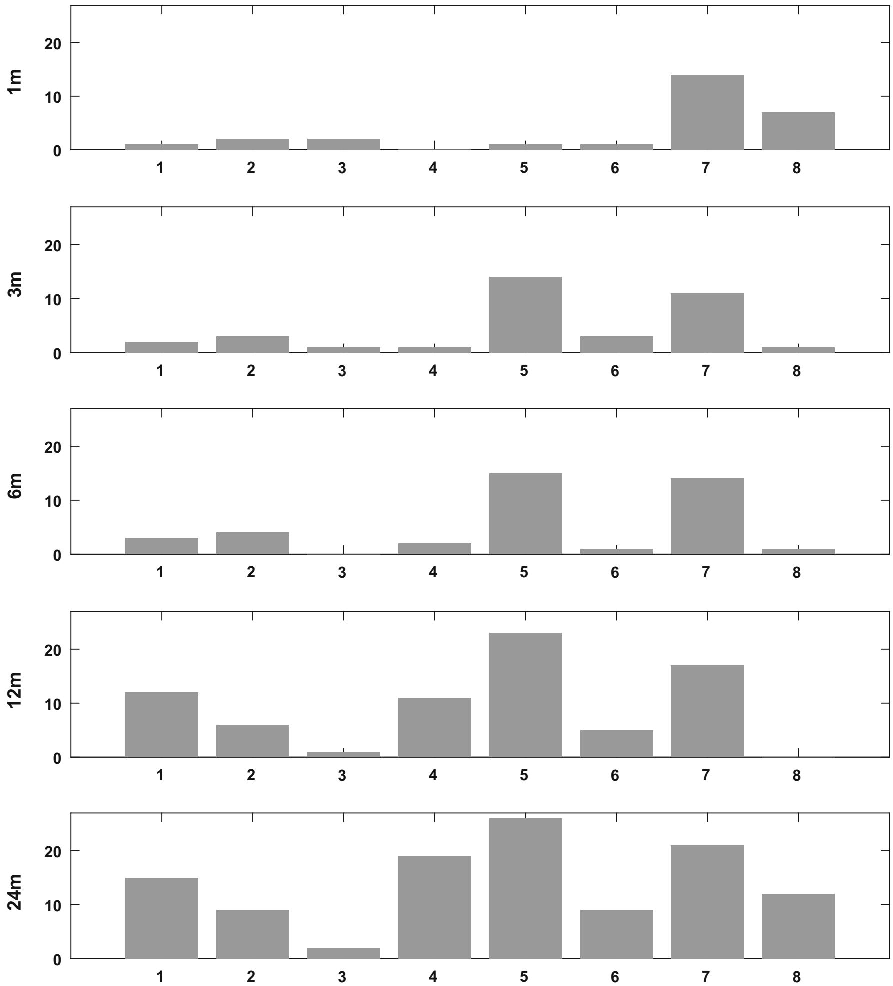

Fig. 3 Selected frequencies of macroeconomic factors in predictive regressions with macroeconomic factors only. This figure shows the selected frequencies of macroeconomic factors when the predictive regression has estimated macroeconomic factors only

predictor for several reasons. Engel, Mark, and West (2008) report that PPP has the strongest ability to forecast exchange rate changes among alternative models. We also intend to check whether the optimal factors from the US macroeconomic series have additional predictive power for nominal exchange rate movements after controlling for $q_{i,t}$ as well as a synergy effect with $q_{i,t}$ in forecasting nominal exchange rate fluctuations. Finally, the real exchange rate might account for the economic status of non-US counterpart countries in bilateral exchange rates.

Again, optimal factors are determined by the BIC criterion; the frequencies selected are shown in Fig. 4 for each horizon. The pattern is quite similar to that in Fig. 3. $\hat{F}_{7t}$ (co-moving with US stock market variables) is overwhelmingly the most frequently

Table 2 Adjusted R^2 from factor-augmented predictive regressions: optimal macroeconomic factors only

Horizon	Optimal macroeconomic factors only				
	1 month	3 months	6 months	12 months	24 months
1. Australia	0.005	0.013	0.017	0.097	0.224
2. Austria	0.012	0.023	0.033	0.099	0.192
3. Belgium	0.012	0.026	0.039	0.133	0.257
4. Canada	0.018	0.043	0.060	0.133	0.237
5. Chile	0.049	0.069	0.083	0.145	0.196
6. Colombia	0.010	0.015	0.035	0.083	0.143
7. Denmark	0.013	0.028	0.042	0.115	0.230
8. Finland	0.009	0.008	0.018	0.090	0.226
9. France	0.012	0.030	0.046	0.098	0.251
10. Germany	0.014	0.025	0.037	0.109	0.199
11. Iceland	0.016	0.110	0.156	0.256	0.392
12. Italy	0.009	0.017	0.029	0.091	0.258
13. Japan	0.011	0.016	0.023	0.085	0.120
14. Korea	0.005	0.007	0.057	0.113	0.185
15. Netherlands	0.014	0.026	0.036	0.100	0.198
16. New Zealand	0.005	0.006	0.037	0.106	0.280
17. Norway	0.007	0.010	0.023	0.070	0.213
18. Philippines	0.001	0.001	0.005	0.004	0.059
19. Portugal	0.025	0.015	0.017	0.060	0.171
20. Singapore	0.004	0.013	0.006	0.008	0.035
21. South Africa	0.008	0.015	0.028	0.111	0.206
22. Spain	0.007	0.011	0.024	0.079	0.248
23. Sweden	0.006	0.006	0.010	0.058	0.206
24. Switzerland	0.005	0.003	0.007	0.014	0.069
25. Thailand	−0.001	0.005	0.008	0.029	0.079
26. UK	0.003	0.010	0.023	0.088	0.318
Average	0.011	0.021	0.035	0.091	0.200

The table shows adjusted R^2 from the regression of $\Delta^h s_{i,t+h} = \alpha_{0,i} + \alpha'_{F,i,h}\hat{f}_t + \varepsilon_{i,t+h}$ where $\hat{f}_t$ denotes estimated US macroeconomic factors

chosen at the 1-month horizon. However, $\hat{F}_{5t}$ (co-moving with US interest rate short-term spread variables), $\hat{F}_{4t}$ (covarying with US interest rates), and $\hat{F}_{1t}$ (correlated with US employment conditions) become more frequently chosen at 1- and 2-year horizons. Moreover, $\hat{F}_{3t}$ (related to US price indices) is rarely selected at any horizon, implying that US price sectors have limited relationships with exchange rate fluctuations.

The adjusted R^2s of the predictive regression with optimal factors and $q_{i,t}$ are presented in Table 3, along with those of the predictive regression with $q_{i,t}$ only. As

Table 3 Adjusted R^2 from factor-augmented predictive regressions: PPP only and PPP and optimal factors

Horizons	1 month		3 months		6 months		12 months		24 months	
Predictive regression	PPP	PPP and US Factors	PPP	PPP and US Factors	PPP	PPP and US Factors	PPP	PPP and US Factors	PPP	PPP and US Factors
1. Australia	0.005	0.018	0.021	0.028	0.046	0.055	0.097	0.142	0.185	0.283
2. Austria	0.007	0.016	0.028	0.034	0.056	0.064	0.119	0.161	0.252	0.358
3. Belgium	0.002	0.012	0.013	0.022	0.031	0.044	0.075	0.142	0.195	0.345
4. Canada	0.004	0.020	0.016	0.048	0.038	0.077	0.089	0.156	0.202	0.304
5. Chile	0.053	0.085	0.168	0.207	0.245	0.288	0.253	0.316	0.228	0.312
6. Colombia	−0.002	0.008	0.000	0.025	0.005	0.041	0.015	0.091	0.041	0.155
7. Denmark	0.004	0.015	0.017	0.028	0.040	0.065	0.093	0.148	0.209	0.355
8. Finland	0.007	0.014	0.025	0.031	0.056	0.064	0.122	0.172	0.272	0.367
9. France	0.005	0.014	0.020	0.032	0.051	0.066	0.115	0.152	0.256	0.383
10. Germany	0.005	0.017	0.022	0.029	0.050	0.060	0.112	0.165	0.260	0.351
11. Iceland	0.009	0.030	0.031	0.119	0.058	0.182	0.131	0.299	0.213	0.448
12. Italy	0.002	0.009	0.011	0.023	0.029	0.048	0.070	0.111	0.146	0.333
13. Japan	0.001	0.011	0.009	0.038	0.024	0.071	0.059	0.148	0.184	0.311
14. Korea	0.017	0.021	0.058	0.068	0.119	0.144	0.241	0.290	0.444	0.493
15. Netherlands	0.005	0.017	0.022	0.030	0.049	0.059	0.110	0.150	0.250	0.341
16. New Zealand	0.000	0.005	0.005	0.011	0.018	0.030	0.048	0.120	0.100	0.334
17. Norway	0.004	0.009	0.020	0.025	0.046	0.059	0.096	0.124	0.173	0.270
18. Philippines	0.001	0.002	0.007	0.008	0.018	0.024	0.049	0.071	0.126	0.203

Table 3 continued

Horizons	1 month		3 months		6 months		12 months		24 months	
Predictive regression	PPP	PPP and US Factors	PPP	PPP and US Factors	PPP	PPP and US Factors	PPP	PPP and US Factors	PPP	PPP and US Factors
19. Portugal	−0.001	0.025	−0.001	0.027	0.000	0.030	0.001	0.066	−0.001	0.176
20. Singapore	0.009	0.014	0.031	0.056	0.065	0.114	0.121	0.168	0.233	0.262
21. South Africa	0.001	0.008	0.010	0.027	0.029	0.048	0.074	0.133	0.200	0.284
22. Spain	0.000	0.006	0.005	0.013	0.015	0.032	0.043	0.088	0.110	0.283
23. Sweden	0.004	0.009	0.018	0.022	0.045	0.050	0.103	0.120	0.254	0.344
24. Switzerland	0.009	0.014	0.033	0.038	0.064	0.069	0.133	0.144	0.264	0.363
25. Thailand	0.004	0.004	0.018	0.019	0.038	0.040	0.084	0.094	0.160	0.180
26. UK	0.011	0.014	0.042	0.046	0.088	0.095	0.169	0.211	0.306	0.481
Average	0.006	0.016	0.025	0.041	0.051	0.074	0.101	0.153	0.202	0.320

The table compares adjusted R^2s from the regression of $\Delta^h s_{i,t+h} = \alpha_{0,i} + \alpha'_{Z,i,h} q_{it} + \varepsilon_{i,t+h}$ and from the regression of $\Delta^h s_{i,t+h} = \alpha_{0,i} + \alpha'_{F,i,h} \hat{f}_t + \alpha'_{Z,i,h} q_{it} + \varepsilon_{i,t+h}$ where $\hat{f}_t$ is estimated US macroeconomic factors

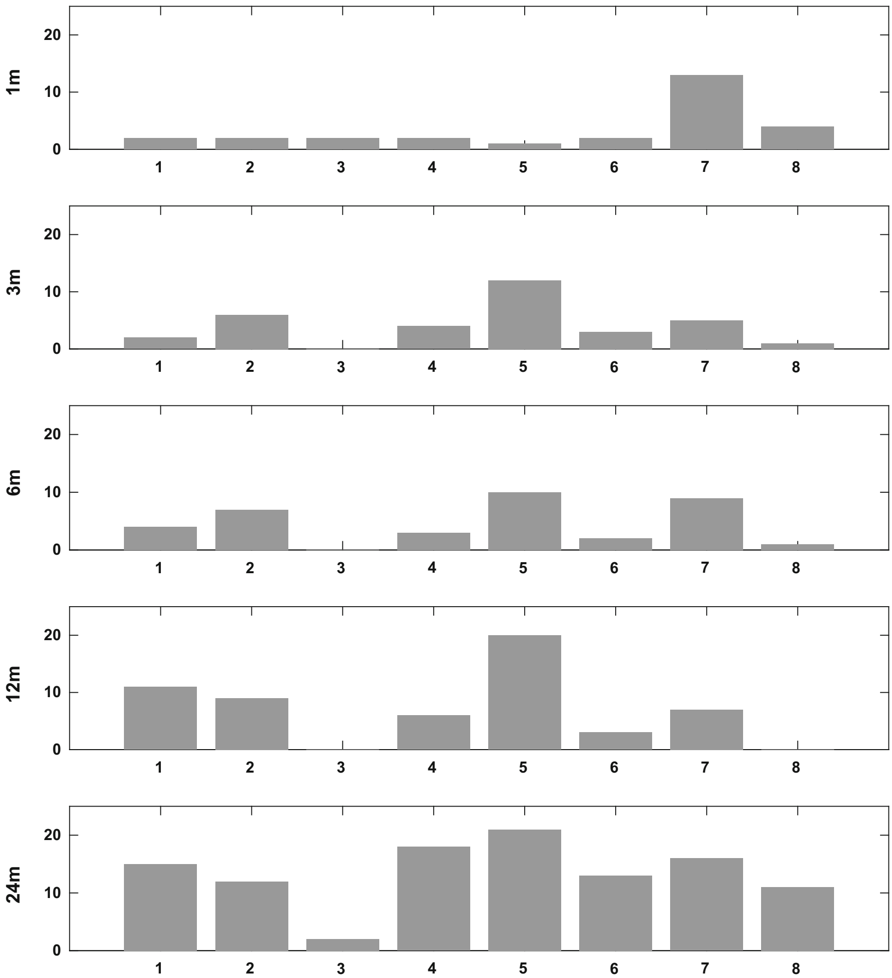

Fig. 4 Selected frequencies of macroeconomic factors in predictive regressions with macroeconomic factors and PPP. This figure shows the selected frequencies of macroeconomic factors when the predictive regression has estimated macroeconomic factors and the real exchange rate

shown in Table 3, the optimally chosen factors improve the adjusted R^2s substantially. The adjusted R^2s from all countries examined except Thailand improve with the inclusion of the optimal factors at a 1-month horizon. At a 2-year horizon, improvement in the adjusted R^2 can be observed in all countries: adjusted R^2 increases an average of 20–32% at this horizon. Switzerland shows a remarkable improvement in adjusted R^2 in Table 3 when US macroeconomic factors are combined with PPP in the predictive regression compared with the adjusted R^2 of the predictive regression with factors only in Table 2. This might imply that the relative economic condition between Switzerland and the US captured by PPP as well as the US macroeconomic factors are important in forecasting the dynamics of the bilateral exchange rate between Switzerland and the US. Overall, the results in Table 3 suggest that US macroeconomic variables have substantial predictive power for future nominal exchange rate movements in addition to the PPP relation.

When $\sqrt{T}$ is comparable to N, a bias may appear for the slope coefficients in the predictive regression, as discussed in Bai and Ng (2006). Hence, bias-corrected slope coefficients for the real exchange rate and optimal factors in predictive regressions for the 1-month horizon are provided in Appendix Table 9.[7] Consistent with the finding in Ludvigson and Ng (2010) that the bias is quite small for large N and T, the bias-corrected slope coefficients and t-statistics are slightly changed. We also report test results for the hypothesis that all coefficients of macroeconomic factors in the predictive regressions are zero. As shown in Table 4, the null hypothesis is generally rejected at the conventional significance level; for example, the null hypothesis is rejected at the 5% significance level for 20 countries at 2-year horizons. These results suggest that US macroeconomic factors are generally significant predictors of nominal exchange rates.[8,9]

5 Predictive regression: out-of-sample analysis

In addition to the in-sample analysis, we conduct an out-of-sample analysis, a standard way to evaluate forecasting ability since Meese and Rogoff (1983). The initial sample period for the first forecast covers January 1973 to December 1987 where 1 = January 1973 and t_0 = December 1987. The out-of-sample analysis is conducted as follows. First, we estimate US macroeconomic factors and factor loadings during the initial period using the panel of macroeconomic variables for $t = 1, 2 \ldots t_0 - h$. Then, we select optimal factors in the predictive regression using the BIC criterion for the initial period. With the optimal factors and the real exchange rate, we make a forecast for $s_{t_0+h} - s_{t_0}$, and calculate a forecast error. We repeat these steps to predict $s_{t_0+1+h} - s_{t_0+1}$ recursively after adding the next one-period observations of the real exchange rate and US macroeconomic data to our dataset at $t_0 + 1$. That is, factors are estimated again from PCA using series for $t = 1, 2, \ldots, t_0 + 1 - h$, optimal factors are selected by the BIC criterion, and forecasts are made with selected optimal factors and the real exchange rate at $t_0 + 1$ for $s_{t_0+1+h} - s_{t_0+1}$. This process continues until the end of the sample period. Forecast horizons are the same as those for the in-sample analyses.

The optimal factors selected by the BIC differ not only across horizons but also across time points when the forecasts are made. The finding that optimal factors vary across time points is similar to the report in Cheung and Chinn (2001) that foreign exchange traders' ranking of important macroeconomic variables shifts over time. Consistent with the results of the in-sample analysis, Fig. 5 also shows that $\hat{F}_{7t}$ is the factor selected most frequently at a 1-month horizon. As the forecast horizon increases, however, the frequency of the selection of $\hat{F}_{7t}$ decreases, and $\hat{F}_{1t}$ and $\hat{F}_{2t}$ are the factors

7 The bias-corrected slope coefficients for other horizons are available upon request.

8 The Philippines, Sweden and Thailand are the only exceptions; in their cases, $H_0 : \alpha_{F,i,h} = 0$ has never been rejected for any horizon at the 5% level.

9 The Newey–West standard errors are used for all in-sample predictive regressions in Tables 2, 3, 4, and 7 to correct for possible heteroskedastic and autocorrelation problems.

Table 4 Joint test results of macro factors in factor-augmented PPP model

	1 month		3 months		6 months		12 months		24 months	
	Wald Stat	*p* value	Wald Stat	*p* value	Wald Stat	*p* value	Wald Stat	*p* value	Wald Stat	*p* value
1. Australia	5.91	0.0151	2.48	0.1151	2.43	0.1191	6.44	0.0920	16.87	0.0020
2. Austria	4.97	0.0258	2.54	0.1112	4.33	0.0375	8.27	0.0160	17.69	0.0034
3. Belgium	5.39	0.0203	3.23	0.0723	3.35	0.0671	9.03	0.0109	18.30	0.0055
4. Canada	4.55	0.0329	10.47	0.0053	10.35	0.0057	9.66	0.0216	13.05	0.0110
5. Chile	5.25	0.0723	7.85	0.0198	5.95	0.0509	2.65	0.1038	1.90	0.1677
6. Colombia	5.90	0.0152	6.99	0.0303	6.34	0.0421	8.14	0.0432	7.53	0.0568
7. Denmark	6.06	0.0139	3.41	0.0649	7.35	0.0253	9.84	0.0073	21.42	0.0015
8. Finland	4.74	0.0295	2.22	0.1360	2.18	0.1398	8.54	0.0360	16.91	0.0007
9. France	5.08	0.0242	3.63	0.0567	3.58	0.0585	5.38	0.0204	13.80	0.0319
10. Germany	6.22	0.0126	5.77	0.0163	5.22	0.0224	11.89	0.0078	16.32	0.0026
11. Iceland	4.89	0.0270	38.23	0.0000	31.07	0.0000	36.03	0.0000	28.89	0.0001
12. Italy	4.59	0.0322	4.08	0.0435	4.91	0.0267	7.19	0.0073	47.88	0.0000
13. Japan	7.11	0.0077	12.12	0.0023	12.12	0.0023	23.10	0.0001	22.03	0.0002
14. Korea	1.09	0.2961	2.46	0.1165	7.31	0.0259	10.10	0.0177	9.54	0.0085
15. Netherlands	6.27	0.0123	2.60	0.1069	5.12	0.0236	7.85	0.0198	18.09	0.0012
16. New Zealand	3.11	0.0779	4.04	0.0445	3.14	0.0764	17.18	0.0002	109.01	0.0000
17. Norway	2.58	0.1085	3.53	0.0604	5.51	0.0189	6.68	0.0355	15.29	0.0016
18. Philippines	1.98	0.1593	1.45	0.2281	1.21	0.2715	3.42	0.1808	7.17	0.1270

Table 4 continued

	1 month		3 months		6 months		12 months		24 months	
	Wald Stat	p value	Wald Stat	p value	Wald Stat	p value	Wald Stat	p value	Wald Stat	p value
19. Portugal	12.63	0.0018	11.40	0.0033	8.15	0.0170	8.52	0.0141	12.63	0.0272
20. Singapore	3.52	0.0607	10.15	0.0014	8.33	0.0155	10.69	0.0048	3.26	0.1960
21. South Africa	2.95	0.0861	5.90	0.0152	5.83	0.0158	9.68	0.0215	18.16	0.0011
22. Spain	4.47	0.0345	3.96	0.0465	4.79	0.0286	7.79	0.0053	27.01	0.0001
23. Sweden	2.83	0.0923	1.37	0.2419	2.99	0.0837	2.43	0.1188	10.33	0.0664
24. Switzerland	3.51	0.0609	2.33	0.1267	3.53	0.0603	1.60	0.2062	31.84	0.0000
25. Thailand	1.66	0.1976	1.59	0.2073	3.29	0.0699	3.14	0.0765	3.07	0.0799
26. UK	2.69	0.1007	1.84	0.1752	0.93	0.3338	9.24	0.0098	18.15	0.0012

This table shows test results for $H_0 : \alpha_{F,i,h} = 0$ in the regression of $\Delta^h s_{i,t+h} = \alpha_{0,i} + \alpha'_{F,i,h} \hat{f}_t + \alpha'_{Z,i,h} q_{it} + \varepsilon_{i,t+h}$ where $\hat{f}_t$ denotes estimated US macroeconomic factors

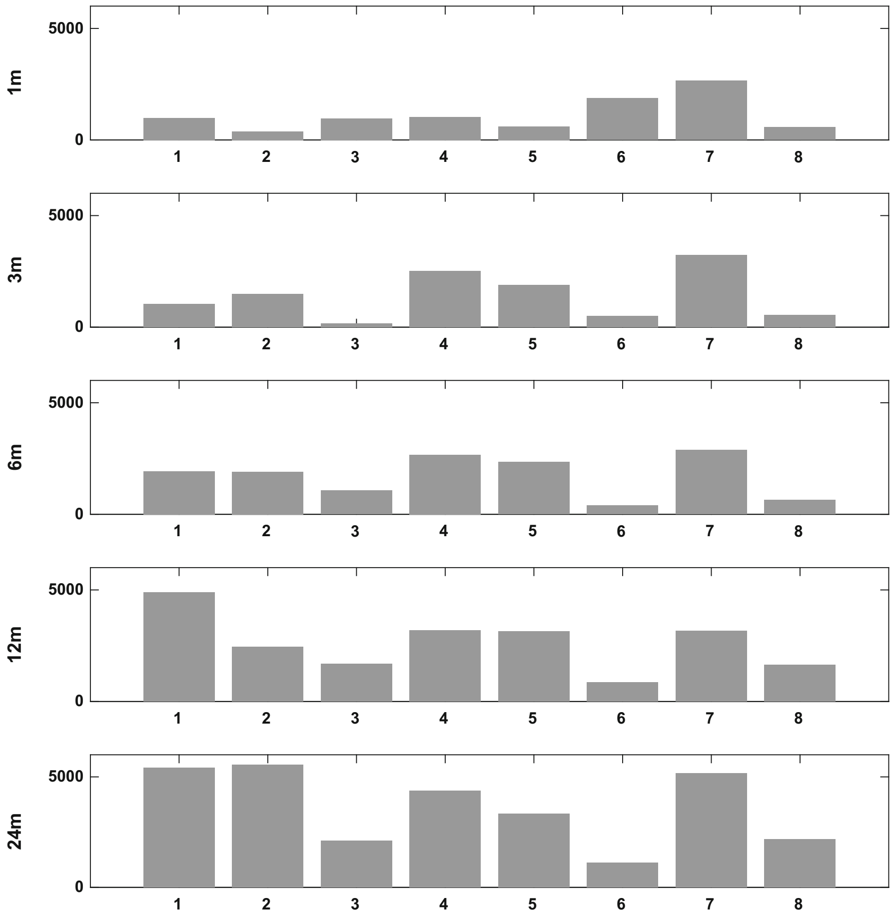

Fig. 5 Selected frequencies of macroeconomic factors in out-of-sample predictive regressions with PPP. This figure shows the selected frequencies of macroeconomic factors by the BIC when the predictive regression has estimated macroeconomic factors and the real exchange rate in the out-of-sample analysis

chosen most frequently at a 2-year horizon. Unlike the results of the in-sample analysis, $\hat{F}_{3t}$ is also selected with some frequency in the out-of-sample analysis. This result also implies that US stock market variables are important in forecasting exchange rate changes in the short run, while variables indicating employment conditions and interest rate spreads make greater contributions in long-run predictions.

We compare the predictive power of the predictive regression augmented with the factors and PPP with that of the random walk model or PPP only. Clark and West (2007) statistics are employed for the evaluation of the predictive powers of the competing models. When the random walk model is compared, for example, the Clark–West adjusted U-statistics can be written as follows:

$$\tilde{U}_{i,h}^{(F,R)} = \frac{P^{-1}\sum_{t=1}^{P}\left(\Delta^{\hat{h}} s_{i,t+h}^{F} - \Delta^{h} s_{i,t+h}\right)^2 - P^{-1}\sum_{t=1}^{P}\left(\Delta^{\hat{h}} s_{i,t+h}^{F} - \Delta^{\hat{h}} s_{i,t+h}^{R}\right)^2}{P^{-1}\sum_{t=1}^{P}\left(\Delta^{\hat{h}} s_{i,t+h}^{R} - \Delta^{h} s_{i,t+h}\right)^2} \tag{5}$$

where superscript F indicates the factor-PPP augmented model, superscript R is a random walk model, and P is the number of forecasts. The null hypothesis is that the two competing forecasting models have an equal mean squared prediction error, whereas the alternative hypothesis is that the larger model (the factor-PPP augmented model) has a smaller mean squared prediction error. Due to the possible serial correlation among forecast errors, Newey–West standard errors are employed for the test. According to Bai and Ng (2006), factor estimation yields a contribution at order N^{-1} to the variance of the prediction error. It means that a large N allows better estimation of the factors, which would result in smaller prediction uncertainty. Since we use a large panel of macroeconomic variables, we conjecture that the prediction uncertainty arising from the factor estimation would be small.

Table 5 shows the Clark–West adjusted U-statistics against the random walk model. Bold font numbers indicate that the null hypothesis of the equal mean squared prediction error is rejected at a 10% or higher significance level. The factor-PPP augmented model shows a smaller mean squared prediction error than the random walk model in all countries except Thailand at a 1-month horizon. Moreover, the difference is significant in 20 out of 26 countries. As the horizon increases, a similar pattern continues, and the factor-PPP augmented model has a significantly smaller mean squared prediction error than the random walk model in all countries but Portugal at a 2-year horizon.

We also test the equal predictive accuracy between the factor-PPP augmented model and the PPP model in Table 6. As shown in the first column of Table 6, the factor-PPP augmented model outperforms the PPP model in 23 countries out of 26 at a 1-month forecast horizon. Among those 23 countries, the adjusted Clark–West adjusted U-statistics is significant in 18 countries. At three- and 6-month horizons, the adjusted Clark–West U statistics are significantly smaller than one in approximately half the countries. However, the rejection rate increases with the horizon again, and the null hypothesis is rejected at a 10% or higher level in 18 countries at a 2-year horizon.

6 Forecasting exchange rate with US macroeconomic factors and domestic macroeconomic factors

We have shown that US macroeconomic factors have substantial predictive power for bilateral exchange rates with or without conditioning on PPP. In examining the predictive ability of US macroeconomic factors, we have not considered the economic conditions of counterpart economies. It would be interesting to evaluate the forecast ability of macroeconomic factors extracted not only from a panel of US macroeconomic series but also from a panel of a counterpart economy's macroeconomic series

Table 5 Out-of-sample analysis: optimal factors and PPP versus random walk

	1 month	3 months	6 months	12 months	24 months
1. Australia	**0.962**	**0.948**	**0.926**	**0.826**	**0.742**
2. Austria	**0.97**	**0.958**	**0.882**	**0.688**	**0.321**
3. Belgium	**0.974**	0.995	**0.936**	**0.782**	**0.486**
4. Canada	**0.96**	**0.953**	**0.935**	**0.849**	**0.717**
5. Chile	**0.519**	**− 0.015**	**− 0.27**	**− 0.084**	**− 0.087**
6. Colombia	**0.982**	**0.967**	**0.961**	**0.935**	**0.956**
7. Denmark	**0.974**	**0.98**	**0.918**	**0.776**	**0.529**
8. Finland	**0.971**	**0.96**	**0.9**	**0.757**	**0.355**
9. France	**0.992**	**0.975**	**0.924**	**0.756**	**0.464**
10. Germany	**0.971**	**0.976**	**0.896**	**0.739**	**0.406**
11. Iceland	**0.941**	**0.874**	**0.82**	**0.7**	**0.585**
12. Italy	0.992	1.008	**0.979**	**0.829**	**0.748**
13. Japan	**0.99**	**0.987**	**0.949**	**0.867**	**0.66**
14. Korea	0.978	**0.923**	**0.826**	**0.641**	**0.081**
15. Netherlands	**0.967**	**0.968**	**0.902**	**0.747**	**0.439**
16. New Zealand	0.999	1	0.982	**0.936**	**0.792**
17. Norway	**0.984**	**0.978**	**0.926**	**0.85**	**0.682**
18. Philippines	0.994	0.991	0.981	**0.935**	**0.678**
19. Portugal	0.998	1.019	1.022	**0.984**	1.065
20. Singapore	**0.945**	**0.883**	**0.794**	**0.78**	**0.651**
21. South Africa	**0.962**	**0.969**	**0.962**	**0.964**	**0.732**
22. Spain	**0.988**	1.003	0.999	**0.92**	**0.781**
23. Sweden	**0.977**	0.992	**0.951**	**0.883**	**0.612**
24. Switzerland	**0.958**	**0.937**	**0.83**	**0.653**	**0.263**
25. Thailand	1.034	1.023	**0.945**	**0.858**	**0.737**
26. UK	**0.969**	**0.937**	**0.855**	**0.658**	**0.416**
Average	0.960	0.930	0.874	0.778	0.570

This table shows the Clark–West corrected U-statistics to compare out-of-sample predictive power between the random walk model and predictive regression with optimal US factors and PPP. The Clark–West U-statistics are greater than one when the random walk model shows superior out-of-sample forecasting ability. Bold fonts indicate the rejection of equal predictive power between the random walk model and predictive regression with optimal US factors and PPP at the 10% level

to examine the connection between the exchange rate and macroeconomic variables. We thus run the following regression:

$$\Delta^h s_{i,t+h} = \alpha_{0,i} + \alpha'_{F,h}\hat{f}_t + \alpha'_{dF,i,h}\widehat{df}_{i,t} + \varepsilon_{i,t+h} \tag{6}$$

where $\widehat{df}_{i,t}$ denotes an estimate of the macroeconomic factors from a large panel of time series data for the counterpart economy.

Table 6 Out-of-sample analysis: optimal factors and PPP versus PPP

	1 month	3 months	6 months	12 months	24 months
1. Australia	**0.97**	**0.981**	0.991	**0.949**	1.078
2. Austria	**0.989**	1.014	1.006	0.987	**0.95**
3. Belgium	**0.983**	1.022	1.008	**0.965**	**0.972**
4. Canada	**0.963**	**0.969**	**0.973**	**0.939**	1.015
5. Chile	**0.921**	**0.752**	**0.59**	**0.537**	**0.395**
6. Colombia	**0.985**	**0.974**	**0.965**	**0.928**	**0.909**
7. Denmark	**0.986**	1.015	1.01	0.992	**0.916**
8. Finland	**0.982**	0.993	**0.979**	**0.915**	**0.814**
9. France	1.005	1.012	1.022	0.986	0.981
10. Germany	**0.984**	1.018	**0.99**	**0.963**	**0.951**
11. Iceland	**0.953**	**0.907**	**0.861**	**0.777**	**0.679**
12. Italy	0.996	1.019	1.025	**0.969**	**0.897**
13. Japan	**0.986**	**0.987**	**0.97**	**0.923**	**0.928**
14. Korea	0.985	0.991	0.971	0.966	**0.879**
15. Netherlands	**0.981**	1.01	0.996	**0.976**	0.994
16. New Zealand	1	0.998	0.993	**0.983**	**0.81**
17. Norway	0.996	1.012	1.002	1.015	1.022
18. Philippines	0.994	0.994	0.995	0.994	**0.895**
19. Portugal	0.994	1.001	0.993	**0.934**	**0.924**
20. Singapore	**0.959**	**0.942**	**0.881**	**0.943**	**0.947**
21. South Africa	**0.96**	**0.967**	**0.965**	**0.953**	**0.889**
22. Spain	**0.988**	0.999	1.012	1	**0.944**
23. Sweden	**0.985**	1.019	1.015	1.013	1.016
24. Switzerland	**0.98**	1.011	1.001	1.037	1.015
25. Thailand	1	0.995	0.994	0.992	0.986
26. UK	**0.987**	0.996	0.996	**0.877**	**0.419**
Average	0.981	0.985	0.969	0.943	0.893

This table shows the Clark–West corrected U-statistics to compare out-of-sample predictive power between the PPP model and predictive regression with optimal factors and PPP. The Clark–West U-statistics are greater than one when the PPP model shows superior out-of-sample forecasting ability. Bold fonts indicate the rejection of equal predictive power between the PPP model and predictive regression with optimal US factors and PPP at the 10% level

Due to data accessibility issues, we examine regression (6) using the Korea–US bilateral exchange rate, a panel of macroeconomic data for Korea, and a panel of macroeconomic data for the US. A total of 215 macroeconomic series of Korea are obtained from the dataset managed by the Bank of Korea (BOK) and the National Statistical Office.[10] The large macroeconomic dataset constructed for Korea contains

[10] The dataset managed by the BOK can be found at http://ecos.bok.or.kr/. The dataset managed by the National Statistical Office can be found at http://kosis.kr/. The panel of Korean macroeconomic series does not include exchange rates, in accordance with that for the US.

information on various aspects of the Korean economy, such as domestic construction, industry production, inventory, sales, unemployment, housing market, export, import, monetary base, interest rates, price indices, and stock market indices. The list of 215 macroeconomic variables in Korea is provided in Table 10 in Appendix.

Because exchange rates in Korea became completely floating from January 1998, we focus on the period between January 1998 and December 2015. Over this period, four macroeconomic factors are estimated from the 215 macroeconomic series for Korea. $\widehat{DF}_{i,t1t}$ has a high correlation, at almost one, with the export value index; $\widehat{DF}_{2t}$ is positively correlated with domestic construction orders; $\widehat{DF}_{3t}$ has a positive correlation with the market interest rate (the yield on CD); and $\widehat{DF}_{4t}$ co-moves with the shipment index by industry and the index of mining and manufacturing industrial products.

Optimal factors among the estimated Korean and US factors are selected by the BIC in the predictive regression. Table 7 compares the results from the predictive regressions with the real exchange rate only, with US macroeconomic factors, and with US and Korean macroeconomic factors. As shown in Table 7, the predictive regressions with US macroeconomic factors have lower adjusted R^2 than in the PPP model at all horizons. When Korean macroeconomic factors are added, however, the adjusted R^2 improves substantially for all horizons, implying that the macroeconomic variables from both economies have significant predictive power for movements in the bilateral exchange rate. Similar to the results in previous sections, the factors chosen by the BIC differ across horizons. For example, $\widehat{DF}_{4t}$, co-moving with the shipment index by industry and the index of mining and manufacturing industrial products in Korea, is often selected over short horizons, while $\widehat{DF}_{3t}$, related to the market interest rate, replaces $\widehat{DF}_{4t}$ at long horizons. Consistent with Chen and Tsang (2013) who show that yield curves have good predictive power for nominal exchange rate movements, factors related with US interest rates and Korean interest rates ($\hat{F}_{2t}$, $\hat{F}_{5t}$, and $\widehat{DF}_{4t}$) have significant coefficients from the 6-month horizon and on.

Finally, we compare the out-of-sample performance of Eq. (6) with that of the random walk model and the PPP in Table 8. We employ the Clark–West adjusted U-statistics to test the null hypothesis of the equal predictability between Eq. (6) and the random walk model and the Diebold–Mariano test statistics to test the same null hypothesis between Eq. (6) and PPP.[11] As shown in Table 8, Eq. (6) shows more accurate predictability than the random walk at all horizons, and those differences are significant at the 5% level. In the comparison between Eq. (6) and PPP, Eq. (6) shows slightly better performance at 1-month, 3-month, and 2-year horizons, although the null of equal forecast ability cannot be rejected. We then add the real exchange rate to Eq. (6) and compare out-of-sample predictive power between Eq. (6) augmented with the real exchange rate and the random walk model and PPP. As shown in the

[11] Since PPP is not nested with Eq. (6), we use the Diebold–Mariano test statistics instead of the Clark–West U-statistics for the comparison.

Table 7 Predictive regression with macroeconomic factors from Korea and the US: in-sample analysis

	1 month			3 months			6 months			12 months			24 months		
	PPP	US factors	US and Korean factors	PPP	US factors	US and Korean factors	PPP	US factors	US and Korean factors	PPP	US factors	US and Korean factors	PPP	US factors	US and Korean factors
q_{it}	−0.051			**−0.128**			**−0.261**			**−0.508**			**−0.815**		
$\hat{F}_{1t}$					−0.010			−0.021	−0.024		−0.027	−0.032			
$\hat{F}_{2t}$								**−0.036**	**−0.040**		**−0.072**	**−0.079**		**−0.129**	**−0.130**
$\hat{F}_{3t}$								**−0.012**	**−0.012**		**−0.022**	**−0.022**		**−0.028**	**−0.027**
$\hat{F}_{4t}$														**0.081**	**0.069**
$\hat{F}_{5t}$								**−0.033**	**−0.035**		**−0.077**	**−0.081**		**−0.100**	**−0.096**
$\hat{F}_{6t}$		**−0.005**			**−0.013**										
$\hat{F}_{7t}$															**0.019**
$\widehat{DF}_{1t}$			−0.006												
$\widehat{DF}_{2t}$						**0.012**									
$\widehat{DF}_{3t}$									**0.021**			**0.033**			**0.051**
$\widehat{DF}_{4t}$						**−0.014**			**−0.017**			**−0.018**			
$\overline{R}^2$	0.024	0.015	0.022	0.067	0.066	0.097	0.136	0.094	0.197	0.258	0.230	0.330	0.396	0.347	0.476
Wald test		3.465	2.614		12.396	18.420		10.625	24.460		10.310	30.067		13.997	41.702
p value		0.063	0.106		0.002	0.000		0.031	0.000		0.036	0.000		0.007	0.000

PPP shows the results of $\Delta^h s_{i,t+h} = \alpha_{0,i} + \alpha'_{Z,i,h} q_{i,t} + \varepsilon_{i,t+h}$, US factors show the results of $\Delta^h s_{i,t+h} = \alpha_{0,i} + \alpha'_{F,h} \hat{f}_t + \varepsilon_{i,t+h}$, and US and Korean factors show the results of $\Delta^h s_{i,t+h} = \alpha_{0,i} + \alpha'_{F,h} \hat{f}_t + \alpha'_{dF,i,h} \widehat{df}_{i,t} + \varepsilon_{i,t+h}$, where $\hat{f}_t$ denotes estimated US macroeconomic factors and $\widehat{df}_{i,t}$ denotes estimated Korean macroeconomic factors. The Wald test and p value for US Factors and US and Korean Factors are the joint test results for $H_0 : \alpha_{F,h} = 0$ and $H_0 : \alpha_{dF,i,h} = 0$, respectively. Bold fonts indicate the rejection of equal predictive power at the 5% level

Table 8 Predictive regression with macroeconomic factors from Korea and the US: out-of-sample analysis

Horizons	1-month	3-months	6-months	12-months	24-months
	Random walk versus predictive regression with macroeconomic factors from Korea and the US				
Clark-West U-statistics	**0.8937**	**0.6347**	**0.7166**	**0.6276**	**0.2124**
	PPP versus predictive regression with macroeconomic factors from Korea and the US				
Diebold–Mariano statistics	– 0.2476	– 0.2845	0.2518	0.1624	– 0.2121
	Random walk versus predictive regression with macroeconomic factors from Korea and the USA and real exchange rate				
Clark-West U-statistics	**0.8976**	**0.6836**	**0.7165**	**0.3121**	**– 0.1147**
	PPP versus predictive regression with macroeconomic factors from Korea and the USA and real exchange rate				
Clark-West U-statistics	**0.9042**	**0.7171**	**0.7601**	**0.4386**	**0.2983**

The predictive regression with macroeconomic factors from Korea and the USA is $\Delta^h s_{i,t+h} = \alpha_{0,i} + \alpha'_{F,h}\hat{f}_t + \alpha'_{dF,i,h}\widehat{df}_{i,t} + \varepsilon_{i,t+h}$, and the predictive regression with macroeconomic factors from Korea and the USA and real exchange rate is $\Delta^h s_{i,t+h} = \alpha_{0,i} + \alpha'_{F,h}\hat{f}_t + \alpha'_{dF,i,h}\widehat{df}_{i,t} + \alpha'_{Z,i,h}q_{i,t} + \varepsilon_{i,t+h}$. The Clark–West U-statistics are greater than one when the first model shows superior out-of-sample forecasting ability to the second one. The Diebold–Mariano test statistic is positive when the first model shows superior out-of-sample forecasting ability to the second one. Bold fonts indicate the rejection of equal predictive power at the 10% level

last two panels of Table 8, the addition of the real exchange rate greatly enhances the predictive power of Eq. (6). As a result, Eq. (6) augmented with the real exchange rate shows significantly more precise out-of-sample predictive power than the random walk model or the PPP at all horizons according to the Clark–West adjusted U-statistics.

7 Conclusion

Many studies in international finance have tried to relate exchange rates to macroeconomic variables. Some have succeeded in finding a significant relation between the two, whereas others have not. We use a large panel of US macroeconomic series to see whether bilateral US dollar exchange rates are explained by US macroeconomic variables. Utilizing the factor-augmented predictive regression, we find that factors extracted from US macroeconomic data have significant predictive power for fluctuations in the nominal exchange rate and can substantially improve the predictive power of the PPP through both in-sample and out-of-sample analyses. Furthermore, factors estimated from the large panels of Korean and US macroeconomic variables show excellent predictive power for movements in the Korea–US bilateral exchange rate. Overall, this evidence strongly suggests that the exchange rate is not disconnected from a large panel of macroeconomic variables.

Moreover, we find that the factors frequently chosen to predict short-run movements in the exchange rate are not necessarily the factors most often selected to predict long-run movements in the exchange rate and that optimal factors selected by the BIC in the out-of-sample analysis differ greatly depending on the time points when the forecasts are made. These findings can explain why the few macroeconomic variables selected in previous studies have sensitive forecast abilities depending on the sample period, forecast horizon, and other conditions. The findings suggest that, even if there is a stable relation between the exchange rate and a large panel of macroeconomic variables, that relation cannot be clearly seen between the exchange rate and a few selected variables as the sample period or forecast horizon changes. This might be due to the finding in Cheung and Chinn (2001) that currency traders use different models and macroeconomic variables over time to understand exchange rate movements, or due to the consequence of the scapegoat effect described in Bacchetta and Van Wincoop (2013). Further investigation in this direction would be an interesting future research project.

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Appendix

See Tables 9 and 10.

Table 9 Results of factor-augmented predictive regression: 1-month horizon

One month horizon	Bias-corrected coefficients									adj_ R^2
	q_{it}	$\hat{F}_{1t}$	$\hat{F}_{2t}$	$\hat{F}_{3t}$	$\hat{F}_{4t}$	$\hat{F}_{5t}$	$\hat{F}_{6t}$	$\hat{F}_{7t}$	$\hat{F}_{8t}$	
1. Australia	**− 0.027**					**0.005**				0.018
2. Austria	− 0.015							**0.004**		0.016
3. Belgium	− 0.009							**0.004**		0.012
4. Canada	− 0.010						**− 0.003**			0.020
5. Chile	− 0.056		**− 0.009**	− 0.013						0.085
6. Colombia	− 0.001		**− 0.003**							0.008
7. Denmark	− 0.011							**0.004**		0.015
8. Finland	− 0.016							**0.004**		0.014
9. France	− 0.014							**0.004**		0.014
10. Germany	− 0.014							**0.005**		0.017
11. Iceland	**− 0.032**	**− 0.006**								0.030
12. Italy	− 0.010							**0.004**		0.009
13. Japan	− 0.007							**0.004**		0.011
14. Korea	**− 0.037**	− 0.003								0.021
15. Nether-lands	− 0.014							**0.005**		0.017
16. New Zealand	− 0.009								**0.004**	0.005

Table 9 continued

One month horizon	Bias-corrected coefficients									adj_ R^2
	q_{it}	$\hat{F}_{1t}$	$\hat{F}_{2t}$	$\hat{F}_{3t}$	$\hat{F}_{4t}$	$\hat{F}_{5t}$	$\hat{F}_{6t}$	$\hat{F}_{7t}$	$\hat{F}_{8t}$	
17. Norway	−0.016							**0.003**		0.009
18. Philippines	−0.008								0.002	0.002
19. Portugal	0.007							**0.005**	**0.005**	0.025
20. Singapore	**−0.017**				**−0.002**					0.014
21. South Africa	−0.010						**−0.005**			0.008
22. Spain	−0.005							**0.003**		0.006
23. Sweden	−0.012							**0.003**		0.009
24. Switzerland	**−0.022**								0.004	0.014
25. Thailand	−0.011				−0.001					0.004
26. UK	−0.030			−0.002						0.014

This table shows the results of $\Delta^h s_{i,t+h} = \alpha_{0,i} + \alpha'_{F,i,h}\hat{f}_t + \alpha'_{Z,i,h}q_{it} + \varepsilon_{i,t+h}$ where $\hat{f}_t$ denotes estimated US macroeconomic factors. Coefficients are bias-corrected. The results for other forecast horizons (3-month, 6-month, 12-month, and 24-month horizons) are available upon request

Table 10 List of Korean macroeconomic variables

Number	Sector	Variable name
1	Market interest rates	Uncollateralized Call Rates (Overnight)
2		Uncollateralized Call Rates (Overnight, Direct Interbank Transactions)
3		Uncollateralized Call Rates (Overnight, Intermediated Transactions)
4		Yields on CD (91-day)
5		Yields on CP (91-day)
6		Yields of National Housing Bonds Type 1 (5-year)
7		Yields of Treasury Bonds (3-year)
8		Yields of Treasury Bonds (5-year)
9		Yields of Financial Debentures (1-year)
10		Yields of Monetary Stab. Bonds(364-day)
11		Yields of Corporate Bonds: O.T.C. (3-year, AA-)
12	Market interest rate spreads	CP-Call spread
13		CD-Call spread
14		TB (5-year)-Call spread
15		CP (AA-)-Call spread
16	Import value indexes	All items
17		Agricultural, forestry & marine products
18		Mining products
19		Manufacturing products
20		Food products & beverages
21		Fiber products & leather products
22		Wood & paper products
23		Coal products & petroleum products
24		Chemical products
25		Nonmetallic mineral products
26		Basic metal products
27		Metal products
28		General machinery
29		Electrical & electronic equipment
30		Precision equipment
31		Transport equipment
32		Other manufacturing products
33	Export value indexes	All items
34		Agricultural, forestry & marine products
35	Export value indexes	Manufacturing products
36		Food products & beverages
37		Fiber products & leather products
38		Wood & paper products

Table 10 continued

Number	Sector	Variable name
39		Coal products & petroleum products
40		Chemical products
41		Nonmetallic mineral products
42		Basic metal products
43		Metal products
44		General machinery
45		Electrical & electronic equipment
46		Precision equipment
47		Transport equipment
48		Other manufacturing products
49	Producer price indexes (basic groups)	All items
50		Goods
51		Agricultural, forestry & marine products
52		Services
53		Transportation
54		Financial & insurance activities
55		Real estate activities
56	Consumer price indexes (2010 = 100; all cities)	Total item
57		Food and non-alcoholic beverages
58		Housing, water, electricity, gas and other fuels
59		Furnishings, household equipment and routine household maintenance
60		Recreation and culture
61		Restaurants and hotels
62		Miscellaneous goods and services
63	Housing purchase price index	All Groups
64		All Groups (Seoul)
65		Detached Dwelling
66		Row House
67		Apartment
68		Apartment (Seoul)
69	Money and banking (monetary aggregates, deposits, loans and discounts, etc.)	Bank Notes and Coins in Circulation (End Of)
70		Monetary Base (End Of)
71		M1 (Narrow Money, End Of)
72		M1-MMF (End of)
73		M2 (Broad Money, End Of)
74		Lf (End Of)
75		L (End of)
76		Seasonally Adjusted M1 (End of)

Table 10 continued

Number	Sector	Variable name
77		Seasonally Adjusted M2 (End of)
78		Seasonally Adjusted Lf (End Of)
79		Total Deposits of CBs & SBs (End Of)
80		Time & Savings Deposits of CBs & SBs (End Of)
81		Loans of CBs & SBs (End Of)
82		Turnover Ratio of Demand Deposits, CBs & SBs
83	Loans & discounts by fund (CBs & SBs, End of)	Total Loans (CBs & SBs)
84		Equipment
85		Operation
86		Loans With Banking Funds
87		Loans With Gov't Funds
88	Loans and discounts of the Bank of Korea	TOTAL
89	Value of machinery orders received	Total Value Ordered
90		Domestic Demand
91		Government and Public
92		Private Demand
93		Manufacturing
94		Non-manufacturing
95		Agencies
96		Overseas Demand
97		Engines
98		Special Purpose Machinery
99		Metal Cutting and Forming
100		General Purpose Machinery
101		Communication Equipment
102		Electrical Machinery
103		Motor Vehicles
104		Total Value Ordered (Excluding Vessels)
105	Value of machinery orders received	Domestic Demand (Excluding Vessels)
106		Government and Public (Excluding Vessels)
107		Private Demand (Excluding Vessels)
108		Overseas Demand (Excluding Vessels)
109	Value of domestic construction orders received	Total Orders Received
110		Public
111		Central Government
112		Local Government

Table 10 continued

Number	Sector	Variable name
113		Public Corporation
114		Other Public Body
115		Private
116		Manufacturing
117		Non-manufacturing
118		Building
119		Dwellings
120		Offices and Stores
121		Factory and Storage
122		Public Offices
123		Others
124		Civil Engineering
125		Roads and Bridges
126		Water Supply and Sewerage
127		Generation of Electricity
128		Land Development
129		Installation of Machinery
130	Inventory index by industry	All Groups
131		Mining & Manufacturing
132		Mining and quarrying
133		Mining of Coal, Crude Petroleum and Natural Gas
134		Mining of Nonmetallic Minerals, Except Fuel
135		Manufacturing
136		Manufacture of Food Products
137		Manufacture of Beverages
138		Manufacture of Tobacco Products
139		Manufacture of Textiles, Except Apparel
140		Manufacture of wearing apparel, Clothing Accessories and Fur Articles
141	Inventory index by industry	Tanning and Dressing of Leather, Manufacture of Luggage and Footwear
142		Manufacture of Wood and of Products of Wood and Cork; Except Furniture
143		Manufacture of Pulp, Paper and Paper Products
144		Manufacture of Coke, Hard-coal and Lignite Fuel Briquettes and Refining
145		Manufacture of Chemicals and Chemical Products (Except Pharmaceuticals
146		Manufacture of Rubber and Plastic Products
147		Manufacture of Other Nonmetallic Mineral Products

Table 10 continued

Number	Sector	Variable name
148		Manufacture of Basic Metal Products
149		Manufacture of Fabricated Metal Products, Except Machinery and Furniture
150		Manufacture of Electronic Components, Computer, Radio, Television and
151		Manufacture of Medical, Precision and Optical Instruments, Watches and
152		Manufacture of Electrical Equipment
153		Manufacture of Other Machinery and Equipment
154		Manufacture of Motor Vehicles, Trailers and Semitrailers
155		Manufacture of Other Transport Equipment
156		Manufacture of Furniture
157		Other Manufacturing
158	Manufacturing production index by special classification	All Items
159		Capital Goods
160		Manufacturing Equipment
161		Electricity
162		Communication
163		Transportation Equipment
164		Agriculture
165		Construction
166		Office
167		Others
168		Intermediate Goods
169		Manufacturing
170		Construction
171		Fuel and Electricity
172	Manufacturing production index by special classification	Others
173		Consumer Goods
174		Durable Consumer Goods
175		Non-Durable Consumer Goods
176	Manufacturing operation ratio index	Manufacture
177		Food Products
178		Beverages Products
179		Tobacco Products
180		Petroleum Products

Table 10 continued

Number	Sector	Variable name
181		Manufacture of Apparel, Accessories, and Fur Articles
182		Tanning and Dressing of Leather, Luggage, and Footwear
183		Manufacture of Wood and of Wood and Cork Products
184		Pulp, Paper, and Paper Products
185		Coke, hard-coal and Lignite Fuel Briquettes and Refined Petroleum Products
186		Chemicals and Chemical Products
187		Rubber and Plastic Products
188		Nonmetallic Mineral Products
189		Basic Metal Products
190		Fabricated Metal Products
191		Electronic Components, Computer, Radio, Television and Communication Equipment and Apparatuses
192		Medical, Precision and Optical Instruments, Watches
193		Electrical Equipment
194		Other Machinery and Equipment
195		Motor Vehicles, Trailers and Semitrailers
196		Other Transport Equipment
197		Other Manufacturing
198	Index of mining and manufacturing industrial products	All Groups
199		Mining & Manufacturing
200		Mining
201		Manufacturing
202	Shipment index by industry	All Groups
203		Mining and Manufacturing
204		Mining
205		Manufacturing
206		Electricity, gas
207	estimation index of equipment investment	Total Equipment Index (S.A.)
208	Composite index of business indicators	Leading Composite Index
209		Coincident Composite Index
210		Lagging Composite Index
211		Cycle of Coincident Composite Index
212		Cycle of Leading Composite Index

Table 10 continued

Number	Sector	Variable name
213	Transactions in securities and stock price index	KOSPI (End Of)
214		Weighted Average of Dividend Yield
215		Price Earnings Ratio

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