Fundamentals and Exchange Rate Prediction Revisited

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Abstract:

This paper measures latent fundamental exchange rates with independent component-based rates constructed from a cross section of exchange rates and then uses their deviations from exchange rates to forecast. Empirical results indicate that the independent component-based model and its Taylor rule and purchasing power parity augmented models are superior to the random walk in predicting exchange rates. These results are robust to several scenarios and are likely to be observed if the US sources and the recursive scheme are applied. Our results reveal that information regarding the third moment of exchange rate changes is helpful to explain exchange rate movements.

JEL classification: F31, F47

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1. Introduction

This paper applies independent component analysis (ICA) to construct fundamental exchange rates from a panel of nominal exchange rates and then examines the superiority of independent component-based (IC-based) models in the out-of-sample prediction of nominal exchange rates. The IC-based fundamental exchange rate picks up information regarding the third moment of exchange rate changes, but such information is neglected by the principal component-based (PC-based) rates. Hence, the IC-based rate is less prone to measurement errors, which helps the IC-based model to predict exchange rates. Using the panel data of the U.S. plus seventeen other OECD countries over 1973-2011, we obtain three interesting results. First, the IC-based model rather than the PC-based model is superior to the driftless random walk in out-of-sample contests, supporting that the information on nonstandard fundamentals is crucial for exchange rate prediction, but extracting such information from observable fundamentals is difficult (Engel and West, 2005; Engel et al., 2012). Second, the Taylor rule (TR) and purchasing power parity (PPP) fundamental augmented IC-based models reveal even stronger evidence to beat the random walk at medium and long horizons, indicating the importance of standard and nonstandard fundamentals in predicting exchange rates. Finally, the above-mentioned results are robust to several scenarios under investigation, and the superiority of the IC method in out-of-sample prediction is more likely to be observed if the US sources and the recursive scheme are applied. Our empirical results shed light on solving the exchange-rate disconnect puzzle (Obstfeld and Rogoff, 2000).

The exchange-rate disconnect puzzle, indicating the failure of structural exchange rate models in the out-of-sample prediction of exchange rates, has been a well known puzzle in empirical international finance since the seminal paper by Meese and Rogoff (1983). Although many articles have found evidence of defeating the random walk in out-of-sample contests (Mark, 1995; Chinn and Meese, 1995, Killian and Taylor, 2003;

Molodtsova and Papell, 2009), these evidences are either too weak or not robust enough to forecast horizons and sample periods (Cheung et al., 2005).[1]

Two likely reasons for the failure of structural models in out-of-sample contests are examined in the literature. The first one is imprecise parameter estimates (Engel et al., 2007; Rapach and Wohar, 2004; Mark and Sul, 2001, 2011; Groen, 2005). Mark and Sul (2001) have shown that predictive accuracy can be significantly improved by pooling across currencies. The second one is the imperfect approximation of the true fundamental exchange rates (Engel et al., 2012; Engel and West, 2005; Groen, 2006). Stock and Watson (2002a, 2002b) find that common components from a large panel of economic data are good measures of fundamental drivers of economies. Groen (2006) estimates factor-based fundamental exchange rates based on a large panel of economic data but finds mixed results on the superiority of the factor-based model in out-of-sample contests.

Engel and West (2005) point out that exchange rates are the best proxy for measuring latent fundamental exchange rates. Engel et al. (2012) assume that exchange rates are a linear mixture of unknown factors and then estimate common factors from cross-sectional exchange rates by applying a classical factor analysis and the principal component analysis (PCA) proposed by Bai (2004). By treating the estimated common components as the factor-based fundamental exchange rates, they apply a panel error-correction model to examine the performance of the factor-based model in out-of-sample prediction. Although maximum likelihood estimators are consistent and are more efficient than those of PC-based estimators (Bai and Li, 2012), Engel et al. (2012) find that both estimators reveal only a weak improvement in the out-of-sample prediction of nominal exchange rates.

This paper applies the noisy ICA to model nominal exchange rates and hence

[1] Engel (2013) provides an interesting survey on the determination of nominal exchange rates since 1995.

assumes that they are a mixture of latent independent sources (factors) plus an additive Gaussian noise. Components such as noise trading, risk premiums, news on fundamentals, and exchange rate shocks are expected to have widespread effects on exchange rate changes (Balke et al., 2013). It seems reasonable to assume that these components are independent of each other. Moreover, the non-normality of exchange rate changes has received substantial support in the literature (Boothe and Glassman, 1987, Domowitz and Hakkio, 1985, Engel and Hamilton, 1990). The non-Gaussian nominal exchange rate changes imply that latent sources are non-Gaussian.[2] To estimate non-Gaussian independent sources, information on higher-order moments is needed. However, PCA constructs orthogonal factors using information only up to the second moment. Hence, a likely reason for Engel et al. (2012) to obtain weak improvement in out-of-sample contests could be that their factor-based fundamental exchange rates are not a good measure of the latent fundamental rates.

The IC method can be formulated as the optimization of an objective function which minimizes the cross dependence among the components. The method is based on maximizing non-Gaussianity via a measure of the distance to normality, such as skewness, excess kurtosis, negentropy and others. After estimating the mixing coefficients (factor loadings) and independent sources from observed exchange rate changes, we construct the IC-based fundamental exchange rates by multiplying the estimated independent sources with mixing coefficients. Furthermore, we examine the superiority of the IC-based model and its fundamental augmented models in out-of-sample contests. To benefit from the gains in forecast accuracy, we impose the homogeneity restriction in the panel estimation of a predictive equation (Mark and Sul, 2001).

The remainder of the paper proceeds as follows. We present the empirical model,

[2] One can only estimate the independent component model of Gaussian data up to an orthogonal transformation, and the mixing matrix is not identifiable if there are more than two Gaussian independent components (Hyvärinen et al., 2001).

construct the sources-based fundamental exchange rates, and describe the strategy of out-of-sample prediction in section 2. In section 3, we describe the data, discuss the estimates of mixing coefficients and independent sources, and elucidate out-of-sample prediction results. Section 4 examines the robustness of our results. Section 5 proposes a simulation analysis to explain why IC-based models are better than PC-based models in out-of-sample prediction. Finally, section 6 concludes. The appendix describes the construction of the IC-based fundamental exchange rates.

2. The Empirical Model and its Estimation

We treat log nominal exchange rates as observed signal mixtures which are a linear combination of latent independent sources with unknown mixing coefficients:

$$e_{i,t} = c_i + \sum_{j=1}^{K} \delta_{i,j} f_{j,t} + u_{i,t} \equiv c_i + E_{i,t} + u_{i,t},\ i=1,\ldots,N,\ t=1,\ldots,T. \tag{1}$$

where $e_{i,t}$ indicates the log nominal exchange rate; $f_{j,t}$ is the jth source at time t and $\delta_{i,j}$ is the ith country's mixing coefficient on the jth source; $E_{i,t}$ denotes the latent fundamental exchange rate of country i at time t, which is constructed by multiplying K independent sources with mixing coefficients; $u_{i,t}$ is an identically, independently and normally distributed noise, i.e., $u_{i,t} \sim \text{i.i.d.} N(0, \sigma_{u_i}^2)$. Furthermore, we assume that the $f_{j,t}$ s are I(1) variables; hence, equation (1) implies that $e_{i,t}$ and the $f_{j,t}$ s are cointegrated. Our purpose is to estimate the latent non-Gaussian independent sources and mixing coefficients by using observed data, $e_{i,t}$, i=1,…, N, t=1,…,T.

Assuming cointegration between $e_{i,t}$ and the $f_{j,t}$s, Engel et al. (2012) extract the $f_{j,t}$s from a panel of nominal exchange rates using PCA (Bai, 2004). Although PCA is quite successful with multivariate Gaussian data, PCs could be far away from real ones when data are non-Gaussian (Särelä and Valpola, 2005). This paper applies ICA to estimate non-Gaussian independent sources and adopts skewness to measure the distance to normality. Hence, ICA picks up information regarding the third moment of exchange rate changes, which is ignored by PCA. The reason for measuring non-Gaussianity with skewness is that in our data, exchange rate changes reveal stronger evidence of skewness than kurtosis, a finding consistent with Brunnermeier et al. (2009) and Brunnermeier and Pedersen (2009). Next, using kurtosis as an objective function is notorious for being prone to overfitting and producing very spiky sources estimates (Särelä and Vigario, 2003; Hyvärinen et al., 2001). The de-noising source separation (DSS, 2005) algorithm provided by Särelä and Valpola (2005) is applied in estimation.[3] The stationarity of data is required for ICA. Hence, we adopt the two-step method of Bai and Ng (2004) to extract level sources ($\hat{f}_{j,t}$s). Their method extracts stationary sources ($\widehat{\Delta f}_{j,t}$s) from exchange rate changes in the first step and then cumulates them over time to obtain level sources ($\hat{f}_{j,t}=\sum_{s=2}^{t}\widehat{\Delta f}_{j,t}$) in the second step.

Stock and Watson (2002a, 2002b) point out that the scale effect may contaminate the estimation of factors. We therefore construct the normalized nominal exchange rate ($e^{n}_{i,t}$) and then calculate its changes.[4] After estimating mixing coefficients and level sources, we construct the IC-based fundamental exchange rate ($\hat{E}^{I}_{i,t}$) accordingly (see the appendix for details). The deviation of the exchange rate from its IC-based fundamental rate is measured by $\hat{E}^{I}_{i,t}-e^{n}_{i,t}$.[5]

To construct PC- and IC-based fundamental exchange rates, we need to specify the number of sources. The number of principal components is estimated by the information

[3]The DSS algorithm can be justified as an expectation-maximization (EM) algorithm that proceeds by alternating between the E-step and the M-step. In the E-step, the posterior distribution of sources is computed based on the known data and the current estimates of mixing vectors using Bayes' theorem. In the M-step, the posterior distribution of the sources is used to compute new maximum likelihood estimates of mixing vectors and sources. The detailed discussion of the algorithm is given in Särelä and Valpola (2005) and the code of the DSS (2005) is available from Professor Valpola's webpage.

[4] $e^{n}_{i,t}=[e_{i,t}-\mu_{e,i}]/\sigma_{e,i}$, where $\mu_{e,i}$ and $\sigma_{e,i}$ are the mean and standard deviation of $e_{i,t}$.

[5] We apply normalized exchange rates to estimate $\hat{E}^{I}_{i,t}$; hence, it matches with $e^{n}_{i,t}$ instead of $e_{i,t}$.

criterion of IC_{p2} provided by Bai and Ng (2002), and the estimated number of sources is three.[6] The finding of three estimated sources is consistent with Bai and Ng (2007) who point out three primitive shocks in 132 monthly US variables. It also agrees with Eickmeier (2009) pointing out that two to six latent common factors are sufficient to explain variations in most macroeconomic variables, and it agrees with Greenaway-McGrevy et al. (2014) indicating three factors in 27 monthly exchange rates. Since no article discusses the criterion of selecting the number of independent sources, to the best of our knowledge, we assume that it is the same as the number of principal components determined by IC_{p2}.[7]

The assumptions that nominal exchange rates cointegrate with latent fundamental rates and that exchange rates are not weakly exogenous imply that the deviations of the exchange rate from its latent fundamental rate are helpful to predict future exchange rate changes. Several articles have pointed out that the fundamental exchange rates implied by a flexible price monetary (M) model (Mark, 1995; Groen, 2000, 2005; Mark and Sul, 2001), a Taylor rule (TR) model (Molodtsova and Papell, 2009) and the PPP model (Kilian and Taylor, 2003; Engel et al., 2007) are helpful to forecast exchange rates. The long-horizon predictive equation for a fundamental augmented source-based model is:

$$e_{i,t} - e_{i,t-h} = \beta^{d}_{k,h}(\hat{E}^{d}_{i,t-h} - e^{n}_{i,t-h}) + \gamma^{d}_{k,h}(z_{i,k,t-h} - e_{i,t-h}) + \upsilon^{d}_{i,k,h,t}, \tag{2}$$

$$\upsilon^{d}_{i,k,h,t} = c^{d}_{i,k,h} + u^{d}_{i,k,h,t}, \quad k=TR, M, PPP;\ h=1, 4, 8, 12;\ i=1,\ldots,N;\ d=I, P,$$

where h is the forecast horizon and is set to one, four, eight and twelve quarters, $z_{i,k,t}$ is the kth model-based fundamental exchange rate for country i, and the regression error

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6 The estimated source number is also three if IC_{p1} or IC_{p3} is applied. The accuracy of IC_{p} is good, relative to other criterions, even though the cross-sectional size is small (Bai and Ng, 2002).

7 For noisy ICA models, the algorithm using only second-order moments of the data in the pre-whitening step is able to consistently estimate the mixing matrix if the number of common sources is less than the Ledermann bound: LB=(2N+1- $\sqrt{8\text{N}+1}$)/2 (Bonhomme and Robin, 2009). Our empirical analysis in section 3 is based on the number of sources up to three that is less than the Ledermann bound which is 11.65 for the period before the launch of the euro and 5.23 for the period after the Bretton Woods system ended.

$\upsilon^{d}_{i,k,h,t}$ includes an individual specific effect, $c^{d}_{i,k,h}$.

Equation (2) degenerates to a source-based model if $\gamma^{d}_{k,h}=0$, to a fundamental-based model if $\beta^{d}_{k,h}=0$, to the random walk with drift if $\gamma^{d}_{k,h}=\beta^{d}_{k,h}=0$, and to the driftless random walk if $c^{d}_{i,k,h}=\beta^{d}_{k,h}=\gamma^{d}_{k,h}=0$. Engel et al. (2007) and Mark and Sul (2001) include a time-specific effect in (2) and use the recursively-estimated time average as a projection of the future time effect. We simply set the future time effect to zero since the average time effect in exchange rate changes is zero. Equation (2) should reveal impressive evidence in out-of-sample contests if the IC-based fundamental exchange rate is a good measure of the latent fundamental rate. In addition, if $\hat{E}^{I}_{i,t}$ is better than $\hat{E}^{P}_{i,t}$ in measuring the ith country's latent fundamental exchange rate, equation (2) should produce stronger evidence of defeating the random walk than when $\hat{E}^{I}_{i,t}-e^{n}_{i,t}$ in equation (2) is replaced with $\hat{E}^{P}_{i,t}-e^{n}_{i,t}$. The information on nonstandard fundamentals is helpful for predicting exchange rates if the model based on equation (2) with $\gamma^{d}_{k,h}=0$ defeats the random walk in out-of-sample contests. The information on standard and nonstandard fundamentals is helpful for exchange rate prediction if a fundamental augmented source-based model reveals stronger evidence of defeating the random walk than the source-based model itself.

Following Engel et al. (2012), the TR-based fundamental exchange rate is:

$$z_{i,TR,t}=1.5(\pi_{i,t}-\pi_{*,t})+0.5(y^{gap}_{i,t}-y^{gap}_{*,t})+e_{i,t},$$

where $y^{gap}_{i,t}$ and $\pi_{i,t}$ are the output gap and inflation rate of country *i*, respectively, and the subscript "*" denotes the United States. The M-based fundamental exchange rate is:

$$z_{i,M,t}=(m_{i,t}-m_{*,t})-(y_{i,t}-y_{*,t}),$$

where $m_{i,t}$ and $y_{i,t}$ are the log money supply and log output of country *i*, respectively.

Finally, the PPP-based fundamental exchange rate is:

$$z_{i,PPP,t} = p_{i,t} - p_{*,t} ,$$

where $p_{i,t}$ is the log price level of country *i*.

Out-of-sample Prediction

After estimating equation (2) with the least squares dummy variable (Mark and Sul, 2001), the forecasts of nominal exchange rate changes are constructed as follows:

$$\hat{e}_{i,t+h} - e_{i,t} = \hat{c}^{d}_{i,k,h} + \hat{\beta}^{d}_{k,h}(\hat{E}^{d}_{i,t} - e^{n}_{i,t}) + \hat{\gamma}^{d}_{k,h}(z_{i,k,t} - e_{i,t}),\ t = T_0, T_0 + 1, ..., T - h, \qquad (3)$$

where T_0 is the last period of time in the in-sample period. The recursive scheme with the initial estimation window being fourteen years is applied in out-of-sample contests (Engel et al., 2012).[8] The number of out-of-sample forecasts decreases with the forecast horizon, *h*. The source number in each recursive sample is determined by IC_{p2}. After conducting out-of-sample forecasts, we add the recent observations to the in-sample data and then re-estimate the output gaps, the number of sources, mixing coefficients and latent sources; re-calculate source-based fundamental exchange rates; and re-construct forecasts. In other words, the output gap, the number of sources, and the source-based fundamental exchange rate are constructed based on in-sample data and they are re-constructed when the in-sample data are expanded. No future information is used in conducting out-of-sample forecasts. Hence the forecasts from equation (3) and the random walk are both ex-ante forecasts.

The benchmark model is the driftless random walk since it is more difficult to be defeated than the random walk with drift in out-of-sample contests (Mark, 1995, Engel et

[8] Exchange rates reveal a significant common break at 1985 in the Early sample and two significant common breaks at 1985 and 2002 in the Long sample. If data are characterized by structural changes, the rolling scheme has the advantage of using only those data relevant to the present data generating process in estimation. However, if the amount of data is not large, reducing the sample in estimation to reduce heterogeneity increases the variance of the parameter estimates, causing the mean square forecast error to increase (Clark and McCracken, 2004). This could be the reason why it is more common to construct forecasts with a recursive scheme in the macroeconomic literature (Mark, 1995; Kilian and Taylor, 2003; Engle et al., 2007, 2012; Stock and Watson, 2003).

al., 2012). The superiority of a model relative to the benchmark model is evaluated based on the Theil-U (TU) statistic and the *CW*-statistic of Clark and West (2006, 2007).[9] We conclude that the model is superior to the driftless random walk if the *TU*-statistic is less than one or the *CW*-statistic is less than -1.282.

3. Empirical Investigations

3.1. Data Description

Quarterly data for end-of-period nominal exchange rates (foreign currency per US dollar, code line ae), the seasonally-adjusted industrial production index (IPI, code line 66), money supply[10] and the consumer price index (CPI, code line 64) over the period from 1973Q1 to 2011Q2 are obtained from the IMF's IFS CD-ROM. Money supply and CPI are seasonally adjusted by taking a four-quarter average of the log levels. The inflation rate, π_t, is constructed from log CPI: $\pi_t = p_t - p_{t-1}$. The output gap is the deviation of log output from potential log output measured by the Hodrick-Prescott (HP) filter. The U.S. plus seventeen other OECD countries are considered. The seventeen other countries are Australia (AUT), Austria (AUS), Belgium (BEL), Canada (CAN), Denmark (DEN), Finland (FIN), France (FRN), Germany (GER), Japan (JAP), Italy (ITA), Korea (KOR), the Netherlands (NET), Norway (NOR), Spain (SPN), Sweden (SWD), Switzerland (SWZ), and the United Kingdom (UK). The United States is treated as the base country. Due to the launch of the Euro in January 1999, Euro-zone countries do not have a nominal exchange rate for their local currency after December 1998. We therefore consider two sample periods: the period after the Bretton Woods system ended (1973Q1-

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[9] Though no article has formally discussed whether the CW test works satisfactorily in a panel setting, we do believe that the CW test should work fine if the number of observations is much larger than the number of countries in the panel. We thank Professor Kenneth West's comment.

[10] The data on money supply deserve some description. Due to the lack of consistent data among countries, different definitions of money are used. Money supply is basically defined as M1 if it is available. Otherwise, for a given country, the definition of money that has the longest run of available data will be used. There are eight countries with M1, two with M2, one with M3, five with currency in circulation, one with quasi money, and one with money plus quasi money. The sample period for the monetary-based and Taylor-rule-based fundamentals end at 2009Q2 and 2011Q1, respectively, due to data availability.

2011Q2, Long) and the period before the appearance of the Euro (1973Q1-1998Q4, Early).[11] Data are available in the Early sample for all seventeen countries, but are available for only nine countries in the long sample.

3.2. The estimates of mixing coefficients and latent sources

Before estimating the mixing matrix and latent sources, we examine the normality of nominal exchange rate changes. Table 1 reports summary statistics of exchange rate changes for the Early and Long samples. The skewness is significantly different from zero, at the 5% level, for six out of nine (six out of seventeen) countries in the Long (Early) sample. The kurtosis is significantly greater than three for six out of nine (three out of seventeen) countries in the Long (Early) sample. The Jarque-Bera normality test rejects the normality hypothesis for six out of nine (five out of seventeen) countries in the Long (Early) sample. These results indicate that nominal exchange rate changes do not appear to be jointly and normally distributed, and hence the information regarding the higher-order moments of exchange rate changes are helpful for estimating the mixing matrix and non-Gaussian independent sources.

In Figure 1, we plot the first, second and third independent and principal components constructed from both samples, and they appear to follow a unit-root process. Except for the second independent component in the Early sample, ICs are more volatile than PCs, especially in the Long sample. The mixing coefficients of ICs and PCs ($\hat{\delta}^{I}_{i,j}$, $\hat{\delta}^{P}_{i,j}$, i=1,…,N, j=1, 2, 3) for both periods are reported in Table 2, of which we will make a few observations. First, mixing coefficients measure a currency's sensitivity to sources, and these estimates are generally less than 0.4 regardless of the sample periods. In particular, the mixing coefficient estimates of the third source are generally small relative to those of the first and second sources. Second, the estimated mixing coefficients of the

[11] The forecast results for the period beginning in 1999 (Late) are examined in the robustness section.

first source, the $\hat{\delta}^I_{i,1}$ s, are larger than those of the second source, the $\hat{\delta}^I_{i,2}$ s, for sixteen out of seventeen countries in the Early sample and for six out of nine countries in the Long sample. Similar results are also observed for the estimated mixing coefficients of PCs. This implies that the first source reflects the major tendency regardless of the sample periods. Third, PCs and ICs are literally a weighted average of the log exchange rates of other countries since none of the mixing coefficient estimates are zero (Stock and Watson, 2006; Engel et al. 2012). Furthermore, the mixing coefficient estimates differ across countries, indicating that currencies are not treated equally in estimating latent sources. Fourth, the absolute values of the mixing coefficient estimates from ICA are generally smaller than those from PCA ($\hat{\delta}^I_{i,j} < \hat{\delta}^P_{i,j}$) regardless of the sources and samples.

If the estimated sources and mixing coefficients from ICA are closer to the true ones than those from PCA, the IC-based fundamental exchange rate should be a better measure of the true latent fundamental rate than the PC-based rate. The exchange rate will move in a reverse direction and toward its IC-based rate when both rates deviate.[12] This implies that $\hat{E}^I_{i,t} - e^n_{i,t}$ contains more helpful information than $\hat{E}^P_{i,t} - e^n_{i,t}$ in predicting exchange rates, which will be examined in the next section.

3.3. Out-of-Sample Contests

We first examine the out-of-sample predictability of the IC- and PC-based models over the Early and Long samples, respectively, and the number of sources is determined by IC_{p2}. Table 3 reports the medians (across N) of the *TU*-statistic for different forecast

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[12] We assume cointegration between sources and exchange rates; hence, $\hat{E}^I_{i,t} - e^n_{i,t}$ in (2) is stationary. The superiority of the IC method in out-of-sample contests could be spurious if $\hat{E}^I_{i,t} - e^n_{i,t}$ is highly persistent (Rossi, 2005). We apply Pesaran's (2007) CIPS statistic to test the unit-root hypothesis of $\hat{E}^I_{i,t} - e^n_{i,t}$ where $\hat{E}^I_{i,t}$ is constructed with the number of sources being determined by IC_{p2}. The model with an intercept is applied and the lag order of the model is set to 4. The *CIPS* statistic rejects the unit-root hypothesis of $\hat{E}^I_{i,t} - e^n_{i,t}$ for the Early sample, but fails to reject the hypothesis for the Long sample. The reason could be due to the small panel size for the Long sample (N=9) that reduces the power of the test. Given the rejection of the unit-root hypothesis for the Early sample, we therefore assume that $\hat{E}^I_{i,t} - e^n_{i,t}$ is stationary.

horizons (the first line in each row under columns 3 - 6), the number of countries having the *TU*-statistic less than 1.0 for different forecast horizons (the left number on the second line of each row under columns 3 - 6), the number of countries for which the *CW*-statistic rejects the hypothesis of equal forecast accuracy at the 10% level for different horizons (numbers in parentheses), the percentage of the *TU*-statistics that are less than 1.0 over all horizons ($\overline{TU}$), and the percentage of the *CW*-statistics rejecting the null of equal accuracy at the 10% level over all horizons ($\overline{CW1}$) and over medium and long horizons ($\overline{CW2}$). The *TU*-statistic is the ratio of the root mean square error from a model and the root mean square error from the driftless random walk. The model is superior to the driftless random walk if the *TU*-statistic is less than one. The *CW*-statistic examines if the two models have the same mean square prediction errors, and the hypothesis of equal accuracy is rejected if the *CW*-statistic is less than -1.282. The median of the *TU*-statistic appears in bold if it is less than 1.0. The numbers in the last three columns are boldfaced if they are greater than or equal to 0.5. We conclude that a model is helpful to improve the out-of-sample predictability of exchange rates if some of these percentages are boldfaced.

The results from the bottom panel of Table 3 indicate that the out-of-sample predictability is limited for the PC-based model but is impressive for the IC-based model. The medians of the *TU* ratios under different horizons are smaller than 1.0 for the IC-based model if the forecast horizon is greater than one quarter. $\overline{TU}$ and $\overline{CW2}$ are 0.59 and 0.47 for the Early sample, and they are 0.61 and 0.44 for the Long sample. Similar results are obtained if the IC-based fundamental exchange rates are constructed with the number of sources being determined by the cumulative percentage of total variance (*CPV*) rule (Jackson, 1993) and the Bayesian information criterion (BIC_3, Bai and Ng, 2002).[13] The above results support that information regarding standard fundamentals is important in explaining exchange rate movements, but extracting such information from observable fundamentals is difficult (Engel and West, 2005; Engel et al., 2012).

Table 4 reports the out-of-sample predictability of fundamental-augmented models defined by equation (2). For the Early sample, a fundamental-augmented IC-based model is superior to the random walk and the fundamental-augmented PC-based model in out-of-sample forecasts. As for the Long sample, the TR- and PPP-augmented IC-based models and the PPP-augmented PC-based model reveal significant evidence to beat the random walk. The results from Table 4 indicate that information regarding both standard and nonstandard fundamentals is helpful for exchange rate prediction (Engel et al., 2012).

The major difference between PCA and ICA is that the former uses information only up to the second moment of data, but the latter adopts information on higher-order moments when data are non-Gaussian. The skewness is adopted to measure non-Gaussianity in our paper. Thus, in addition to the information in PCA, the estimated sources from ICA pick up additional information regarding the third moment of exchange rate changes.[14] Hence, the IC-based fundamental exchange rates are less prone to measurement errors than the PC-based rate, which helps the IC-based model to predict exchange rates.

To further examine that the good performance of the IC method is mostly due to non-normality in data, we first exclude the five currencies rejecting normality form the Early panel: AUT, ITA, KOR, NOR and SWD. If the non-normality of exchange rate changes is crucial for the IC method, then removing the above five currencies should

[13] The criterion of *CPV* is to determine the number of factors by calculating the sum of the first m eigenvalues to exceed 50% of the total variance.

[14] Data are pre-whitened before estimating the mixing matrix and independent sources in ICA. The pre-whiten step is similar to PCA and catches the information up to the second moment.

weaken the forecast accuracy of the IC-based model. The results from the top panel of Table 5 indicate that the evidence to beat the random walk is weak for the PC method and is also less impressive than the results revealed in Tables 3 and 4 for the IC method. PC and IC methods are more comparable if data are less non-Gaussian. Next, we include only the above five currencies in the Early panel and expect to find that the performance of the IC method is better for the five countries than for the other twelve. Indeed, the results from the bottom panel of Table 5 indicate that the evidence of beating the random walk is very impressive and is much stronger than the results revealed in the top panel. These results justify the importance of non-Gaussian data in ICA.[15]

4. Robustness[16]

The stability of our results reported in Tables 3 and 4 is examined by different scenarios. We first consider the Late (1999Q1-2010Q2) and P90 (1990Q1-2010Q2) periods and find that the superiority of the IC method is impressive for both periods. Second, changing the criterion of determining the source number from IC_{p2} to CPV and BIC_3 does not significantly affect the superiority of the IC method. Third, note that the random walk, the IC-based model and its fundamentals augmented models are nested models. This paper therefore applies the Max *t*-statistic (adj.) of Hubrich and West (2010) to evaluate the forecast accuracy of a small set of nested models.[17] The results indicate that the evidence of defeating the random walk is impressive for the Early sample even when the forecast horizon is one quarter. Similar results are observed for the Long sample. Fourth, we change the initial estimation window from fourteen years to both

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[15] We appreciate a reviewer's comment on this point.

[16] Empirical results in this section are available from the authors upon request.

[17] The critical values of the Max *t*-statistic (adj.) are simulated based on 1,000 bootstraps for constructing the sample correlation matrix between the adjusted difference in MSPEs across models and the random walk and on 10,000 Monte-Carlo simulations for obtaining critical values of the test statistic. The data generating processes (DGP) include N random walk processes for log nominal exchange rates and $3N$ equations for deviations from macroeconomic fundamentals, assumed to follow an AR(p) process. The lag order of the AR(p) process is determined by the BIC rule with 4 being the maximum lag setting. The DGP includes 68 (17×4) equations for the Early sample and 36 (9×4) equations for the Long sample. The long-horizon predictive equation is estimated using the method provided by Mark and Sul (2001).

sixteen years and twelve years and find that the results in Tables 3 and 4 are not qualitatively affected by these changes. Fifth, we treat Korea as an outlier and remove it from the panel since its exchange rate change is the most abnormal one based on the normality test in Table 1. The superiority of the IC-method is not qualitatively affected, although the $\overline{TU}$ statistics for the IC-based model and its TR augmented model are slightly less than 0.5.

Sixth, we apply the two-step method to construct PCs and ICs and find that the main results of the paper are not significantly affected. Seventh, we apply kurtosis to measure non-Gaussianity and find that the results from Tables 3 and 4 are not significantly affected for the Long sample. As for the Early sample, the kurtosis measure results in weaker superiority of the IC method than the skewness measure. The reason could be that exchange rate changes reveal weaker kurtosis (3/17) than skewness (6/17) in the Early sample. Eighth, we change the benchmark model to the random walk with drift. Both the IC and PC methods beat the random walk, indicating that driftless random walk is more difficult to be defeated than the random walk with drift.

Ninth, the sources extracted from the US-based exchange rates can be interpreted as the "US sources". How important are the US sources in the out-of-sample prediction of nominal exchange rates? This paper first re-examines the out-of-sample contests by setting the UK as the base country. The results from the Early sample, but not the Long sample, are generally similar to those reported in Tables 3 and 4. Next, JAP is treated as the base country. Only the M-augmented IC-based model defeats the random walk at the Early sample. Additionally, the PPP-augmented (M-augmented) PC-based model beats the random walk for both (Long) samples. In short, the US sources are important for the superiority of the IC method in the out-of-sample prediction of exchange rates. Finally, we re-examine the out-of-sample contests by using the rolling scheme with the rolling window being ten years as suggested by Clark and McCracken (2004). Only the TR-augmented IC-based model defeats the random walk at the eight-quarter horizon, for both samples, based on the $\overline{CW2}$ statistic. The above results are not significantly affected if we change the rolling window to fourteen years. The reason for the rolling scheme to have poor out-of-sample performance could be due to time-varying features in the data.[18]

The above results indicate that the good performance of the IC method is robust to sample periods, the criterions of source determination, the tests of evaluating forecast accuracy, initial estimation windows, outliers, the methods of constructing PCs, the measures of non-Gaussianity, and benchmark models. Second, the superiority of the IC method in out-of-sample prediction is more likely to be observed if the US sources and the recursive scheme are applied.

5. The Simulation Analysis

We argue that if exchange rate changes are non-Gaussian and are a linear combination of latent independent sources, ICA gives better results than PCA. To justify the above argument, we provide a simulation analysis that utilizes the following data generating process (DGP):

$$e^*_{i,t} = E^{*I}_{i,t} + \varepsilon_{i,t} \equiv \sum_{j=1}^{K} \hat{\delta}_{ij} f^{*I}_{j,t} + \varepsilon^*_{i,t},\ i=1,\ldots, N,\ t=1,\ldots, T,\ j=1,\ldots,K,\ K=1, 2, 3, \quad (4)$$

$$\varepsilon^*_{i,t} \sim \text{i.i.d.} N(0, \sigma_i^2),\quad \sigma_i^2 \sim \text{i.i.d.} U(0.9, 1.1),$$

where the $\hat{\delta}_{ij}$s are estimated mixing coefficients reported in Table 2; $f^{*I}_{j,t}$ is the jth non-Gaussian independent source bootstrapped from the jth estimated source ($\hat{f}^{I}_{j,t}$) reported in Figure 1; $\varepsilon^*_{i,t}$ is an idiosyncratic error that is identically, independently and

[18] Our simulation results (available from the authors upon request) indicate that the superiority of the IC method to the PC method in out-of-sample forecasts is stronger under the recursive scheme when structural changes appear in the data.

normally distributed with a zero mean, and its variance is identically, independently and uniformly distributed between 0.9 and 1.1. The DGP in (4) indicates that nominal exchange rates have an independent component structure and that the ith nominal exchange rate cointegrates with its latent fundamental exchange rate.

After generating $e^{*}_{i,t}$, we construct IC- and PC-based fundamental exchange rates and compare the out-of-sample predictive accuracy of IC- and PC-based models under the recursive scheme with the initial estimation window being fourteen years. The IC-based model is better than the PC-based model if the *TU*-statistic is less than one. Repeating the previous procedures 200 times, we report the average number of countries (across 200 replications) having the *TU*-statistic below one at different forecast horizons. The simulation results, reported in Table 6, indicate that the average number of countries having $TU < 1$ is above 12 (6.8) for all forecast horizons in the Early (Long) sample.[19] These results indicate that if nominal exchange rates are the mixture of non-Gaussian independent sources and the ith nominal exchange rate cointegrates with its latent fundamental rate, the IC-based model is better than the PC-based model in out-of-sample prediction.

6. Conclusions

The major reason for Engel et al. (2012) to find weak evidence to defeat the random walk in out-of-sample contests could be their inappropriate measure of the latent fundamental exchange rate with the PC-based rate. We measure the latent fundamental rate with the IC-based rate since it adopts information regarding the third moment of exchange rate changes, but such information is neglected by the PC-based rate. Hence, the IC-based fundamental exchange rate is less prone to measurement errors, which helps the IC-based model to predict exchange rates. Using the data of the U.S. plus seventeen

[19] Simulation results are not affected if $f^{*I}_{j,t}$ is replaced by $\hat{f}^{I}_{j,t}$ in each replication, or if $\sigma_i^2 \sim$ i.i.d.U(0.5, 1.5) in (4), or if a rolling scheme is applied.

other OECD countries over 1973-2011, we find that the IC-based model and its fundamental-augmented models are superior to the random walk, indicating that information regarding standard and nonstandard fundamentals is important in explaining exchange rate movements. Furthermore, our results are robust to several scenarios under investigation and are more likely to be observed if the US sources and the recursive scheme are applied. Our results support the predictability of nominal exchange rates and hence shed light on solving the exchange-rate disconnect puzzle.

Evans (2012) examines exchange-rate dark matter and shows that it accounts for 87 percent of the variance of real depreciation rates for G-7 countries at the five-year horizon. He suggests that exchange rates appearing disconnected from traditional fundamentals reflects the importance of dark matter. Therefore, interesting problems for future research are to address how are the deviations of nominal exchange rates away from IC-based fundamental rates related with dark matter and to determine the dominant factors in the deviations.

Appendix: Constructing IC-based Fundamental Exchange Rates

This appendix describes the construction of source-based fundamental exchange rates under a specific in-sample period, $[1, T_0]$.

1. Centering. Let $\mathbf{Z}^{o}$ be the $N \times T_0$ data matrix of $e_{i,t}$. After constructing the normalized exchange rates ($e_{i,t}^{n}$) and computing its changes, we let **Z** be the data matrix of $\Delta e_{i,t}^{n}$ $(= e_{i,t}^{n} - e_{i,t-1}^{n})$, i=1,…,N, t=1,…,$T_0 - 1$. Let **Y** be the matrix that subtracts the mean vector of $\mathbf{Z}$ from $\mathbf{Z}$, $\mathbf{Y} = \mathbf{Z} - \mathbf{E(Z)}$.

2. Whitening. Transform the data matrix ($\mathbf{Y}$) to a new data matrix (**X**) which is white, i.e., $\mathbf{X} = \mathbf{\Gamma}^{-1/2}\mathbf{\Psi}'\mathbf{Y}$, in which $\mathbf{\Psi}$ is the orthogonal matrix of the eigenvectors of $\mathrm{E}[\mathbf{YY}']$ and $\mathbf{\Gamma}$ is the diagonal matrix of eigenvalues. Whitening transforms the original mixing matrix ($\mathbf{A}_{o}$) to a new one ($\mathbf{A} = \mathbf{\Gamma}^{-1/2}\mathbf{\Psi}'\mathbf{A}_{o}$) that is orthogonal. Therefore, whitening reduces the number of parameters to be estimated.

3. We assume that **X** follows a linear noisy independent component model: $\mathbf{X} = \mathbf{AF} + \mathbf{v}$, where **F** is a $K \times T_0$ $(K \le N)$ matrix of latent stationary sources ($\widehat{\Delta f}_{j,t}s$), $\mathbf{A}$ is a $N \times K$ mixing matrix, and $\mathbf{v}$ consists of i.i.d. Gaussian noises. Apply the DSS algorithm to estimate the mixing matrix ($\hat{\mathbf{A}}$) and stationary sources ($\widehat{\Delta f}_{j,t}s$) from the pre-whitened data matrix **X**. The distance to normality is measured by skewness. The detailed estimation procedure is described in Särelä and Valpola (2005). The mixing matrix corresponding to **Y** is $\hat{\mathbf{A}}^{o} = (\mathbf{\Gamma}^{-1/2}\mathbf{\Psi}')^{-1}\hat{\mathbf{A}}$.

4. Order stationary sources ($\widehat{\Delta f}_{j,t}s$) based on the algorithm provided by Wu et al. (2006), which applies the mean squared errors criterion. This is done because the variance may not be the quantity of interest for strongly non-Gaussian processes. Given the selected number of sources, we cumulate stationary sources to obtain level sources ($\hat{f}_{j,t} = \sum_{\tau=2}^{t} \widehat{\Delta f}_{j,\tau}$), and then construct the IC-based fundamental exchange rates ($\hat{E}_{i,t}^{I}$s) by multiplying the estimated level sources with the mixing coefficient estimates in $\hat{\mathbf{A}}^{o}$.

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Footnotes:

1 Engel (2013) provides an interesting survey on the determination of nominal exchange rates since 1995.

2 One can only estimate the independent component model of Gaussian data up to an orthogonal transformation, and the mixing matrix is not identifiable if there are more than two Gaussian independent components (Hyvärinen et al., 2001).

3 The DSS algorithm can be justified as an expectation-maximization (EM) algorithm that proceeds by alternating between the E-step and the M-step. In the E-step, the posterior distribution of sources is computed based on the known data and the current estimates of mixing vectors using Bayes' theorem. In the M-step, the posterior distribution of the sources is used to compute new maximum likelihood estimates of mixing vectors and sources. The detailed discussion of the algorithm is given in Särelä and Valpola (2005) and the code of the DSS (2005) is available from Professor Valpola's webpage.

4 $e_{i,t}^{n} = [e_{i,t} - \mu_{e,i}]/\sigma_{e,i}$, where $\mu_{e,i}$ and $\sigma_{e,i}$ are the mean and standard deviation of $e_{i,t}$.

5 We apply normalized exchange rates to estimate $\hat{E}_{i,t}^{I}$; hence, it matches with $e_{i,t}^{n}$ instead of $e_{i,t}$.

6 The estimated source number is also three if IC_{p1} or IC_{p3} is applied. The accuracy of IC_{p} is good, relative to other criterions, even though the cross-sectional size is small (Bai and Ng, 2002).

7 For noisy ICA models, the algorithm using only second-order moments of the data in the pre-whitening step is able to consistently estimate the mixing matrix if the number of common sources is less than the Ledermann bound: LB=(2N+1-$\sqrt{8\text{N}+1}$)/2 (Bonhomme and Robin, 2009). Our empirical analysis in section 3 is based on the number of sources up to three that is less than the Ledermann bound which is 11.65 for the period before the launch of the euro and 5.23 for the period after the Bretton Woods system ended.

8 Exchange rates reveal a significant common break at 1985 in the Early sample and two significant common breaks at 1985 and 2002 in the Long sample. If data are characterized by structural changes, the rolling scheme has the advantage of using only those data relevant to the present data generating process in estimation. However, if the amount of data is not large, reducing the sample in estimation to reduce heterogeneity increases the variance of the parameter estimates, causing the mean square forecast error to increase (Clark and McCracken, 2004). This could be the reason why it is more common to construct forecasts with a recursive scheme in the macroeconomic literature (Mark, 1995; Kilian and Taylor, 2003; Engle et al., 2007, 2012; Stock and Watson, 2003).

9 Though no article has formally discussed whether the CW test works satisfactorily in a panel setting, we do believe that the CW test should work fine if the number of observations is much larger than the number of countries in the panel. We thank Professor Kenneth West's comment.

10 The data on money supply deserve some description. Due to the lack of consistent

data among countries, different definitions of money are used. Money supply is basically defined as M1 if it is available. Otherwise, for a given country, the definition of money that has the longest run of available data will be used. There are eight countries with M1, two with M2, one with M3, five with currency in circulation, one with quasi money, and one with money plus quasi money. The sample period for the monetary-based and Taylor-rule-based fundamentals end at 2009Q2 and 2011Q1, respectively, due to data availability.

11The forecast results for the period beginning in 1999 (Late) are examined in the robustness section.

12 We assume cointegration between sources and exchange rates; hence, $\hat{E}^I_{i,t} - e^n_{i,t}$ in (2) is stationary. The superiority of the IC method in out-of-sample contests could be spurious if $\hat{E}^I_{i,t} - e^n_{i,t}$ is highly persistent (Rossi, 2005). We apply Pesaran's (2007) CIPS statistic to test the unit-root hypothesis of $\hat{E}^I_{i,t} - e^n_{i,t}$ where $\hat{E}^I_{i,t}$ is constructed with the number of sources being determined by IC_{p2}. The model with an intercept is applied and the lag order of the model is set to 4. The *CIPS* statistic rejects the unit-root hypothesis of $\hat{E}^I_{i,t} - e^n_{i,t}$ for the Early sample, but fails to reject the hypothesis for the Long sample. The reason could be due to the small panel size for the Long sample (N=9) that reduces the power of the test. Given the rejection of the unit-root hypothesis for the Early sample, we therefore assume that $\hat{E}^I_{i,t} - e^n_{i,t}$ is stationary.

13 The criterion of *CPV* is to determine the number of factors by calculating the sum of the first m eigenvalues to exceed 50% of the total variance.

14 Data are pre-whitened before estimating the mixing matrix and independent sources in ICA. The pre-whiten step is similar to PCA and catches the information up to the second moment.

15 We appreciate a reviewer's comment on this point.

16 Empirical results in this section are available from the authors upon request.

17 The critical values of the Max *t*-statistic (adj.) are simulated based on 1,000 bootstraps for constructing the sample correlation matrix between the adjusted difference in MSPEs across models and the random walk and on 10,000 Monte-Carlo simulations for obtaining critical values of the test statistic. The data generating processes (DGP) include N random walk processes for log nominal exchange rates and 3N equations for deviations from macroeconomic fundamentals, assumed to follow an AR(p) process. The lag order of the AR(p) process is determined by the BIC rule with 4 being the maximum lag setting. The DGP includes 68 (17×4) equations for the Early sample and 36 (9×4) equations for the Long sample. The long-horizon predictive equation is estimated using the method provided by Mark and Sul (2001).

18 Our simulation results (available from the authors upon request) indicate that the superiority of the IC method to the PC method in out-of-sample forecasts is stronger under the recursive scheme when structural changes appear in the data

19 Simulation results are not affected if $f^{*I}_{j,t}$ is replaced by $\hat{f}^I_{j,t}$ in each replication, or if $\sigma_i^2 \sim$ i.i.d.U(0.5, 1.5) in (4), or if a rolling scheme is applied.

Table 1. Summary statistics of log nominal exchange rate changes

	Mean	Median	Max	Min	Std	Skew	Kurt	JB
				The Long sample (153 observations)				
AUT	0.002	-0.003	0.185	-0.166	0.054	0.547*	4.205*	16.90*
CAN	0.000	0.000	0.144	-0.084	0.031	0.128	6.038*	59.25*
DEN	-0.001	0.003	0.135	-0.147	0.058	0.050	2.627	0.95
JAP	-0.008	-0.002	0.150	-0.170	0.059	-0.409*	2.951	4.29
KOR	0.006	0.000	0.617	-0.203	0.067	5.080*	48.791*	14025*
NOR	-0.001	-0.001	0.191	-0.168	0.054	0.475*	4.391*	18.1*
SWD	0.002	-0.003	0.286	-0.147	0.059	0.843*	5.846*	69.75*
SWZ	-0.009	-0.002	0.169	-0.186	0.065	-0.205	2.992	1.07
UK	0.003	0.001	0.211	-0.144	0.053	0.456*	4.477*	19.21*
				The Early sample (103 observations)				
AUT	0.008	0.000	0.160	-0.089	0.047	0.735*	3.742	11.63*
AUS	-0.005	-0.005	0.136	-0.140	0.061	0.097	2.603	0.84
BEL	-0.001	0.003	0.169	-0.140	0.063	0.248	2.804	1.22
CAN	0.004	0.003	0.051	-0.056	0.021	-0.013	3.287	0.36
DEN	0.000	0.006	0.135	-0.147	0.059	0.087	2.679	0.57
FIN	0.003	0.003	0.149	-0.112	0.050	0.232	2.944	0.94
FRN	0.002	0.000	0.145	-0.136	0.059	0.103	2.737	0.48
GER	-0.005	-0.002	0.139	-0.157	0.063	0.057	2.791	0.24
JAP	-0.008	0.001	0.150	-0.170	0.062	-0.356	2.826	2.31
ITA	0.010	0.002	0.206	-0.126	0.058	0.596*	3.742	8.47*
KOR	0.011	0.000	0.617	-0.203	0.073	5.647*	49.552*	9847*
NET	-0.004	0.000	0.135	-0.151	0.062	0.151	2.640	0.95
NOR	0.002	0.006	0.191	-0.098	0.051	0.635*	4.054*	11.69*
SPN	0.009	0.005	0.196	-0.112	0.056	0.471*	3.370	4.40
SWD	0.006	-0.003	0.286	-0.096	0.057	1.281*	7.367*	110.02*
SWZ	-0.008	-0.003	0.169	-0.186	0.069	-0.177	2.961	0.55
UK	0.004	-0.001	0.165	-0.138	0.054	0.259	3.148	1.25

Notes: AUT, AUS, BEL, CAN, DEN, FIN, FRN, GER, JAP, ITA, KOR, NET,NOR, SPN, SWD, SWZ and UK indicate Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Japan, Italy, Korea, Netherland, Norway, Spain, Sweden, Switzerland and the United Kingdom, respectively. 'Std' and 'Kur' indicate the standard deviation and Kurtosis, respectively. 'JB' is the Jarque-Bera normality test. The asterisk (*) indicates significance at the 5 percent level. Early and Long refer to the periods 1973-1998 and 1973-2011, respectively.

Table 2. Mixing coefficient estimates

	The Early sample						The Long Sample					
	PCA			ICA			PCA			ICA		
	$\hat{\delta}^P_{i,1}$	$\hat{\delta}^P_{i,2}$	$\hat{\delta}^P_{i,3}$	$\hat{\delta}^I_{i,1}$	$\hat{\delta}^I_{i,2}$	$\hat{\delta}^I_{i,3}$	$\hat{\delta}^P_{i,1}$	$\hat{\delta}^P_{i,2}$	$\hat{\delta}^P_{i,3}$	$\hat{\delta}^I_{i,1}$	$\hat{\delta}^I_{i,2}$	$\hat{\delta}^I_{i,3}$
AUT	0.292	-0.129	0.121	0.032	0.003	0.047	0.401	-0.051	-0.274	0.034	0.065	0.039
CAN	0.286	-0.096	-0.539	0.045	-0.022	-0.050	0.346	0.149	-0.711	0.109	-0.033	0.016
DEN	0.202	0.298	0.003	0.253	0.087	0.054	0.211	0.537	0.154	0.194	0.206	0.112
JAP	-0.193	0.303	-0.217	0.095	0.035	0.000	-0.274	0.474	-0.047	0.072	-0.005	0.113
KOR	0.291	-0.068	-0.516	0.013	-0.004	-0.032	0.367	-0.205	0.066	0.015	0.002	0.023
NOR	0.300	0.114	0.141	0.234	0.077	0.180	0.376	0.267	0.002	0.191	0.184	0.091
SWD	0.316	0.025	0.063	0.127	0.136	0.060	0.411	0.023	0.148	0.117	0.110	0.059
SWZ	-0.151	0.341	-0.005	0.161	0.102	0.031	-0.185	0.567	-0.098	0.143	0.093	0.061
UK	0.286	0.076	0.504	0.212	0.073	0.051	0.347	0.162	0.597	0.043	0.143	0.222
AUS	-0.080	0.384	-0.100	0.225	0.080	0.050	---	---	---	---	---	---
BEL	0.130	0.360	0.093	0.246	0.096	0.058	---	---	---	---	---	---
FIN	0.280	0.131	-0.180	0.184	0.157	0.077	---	---	---	---	---	---
FRN	0.256	0.226	0.184	0.233	0.093	0.060	---	---	---	---	---	---
GER	-0.067	0.388	-0.093	0.236	0.084	0.050	---	---	---	---	---	---
ITA	0.318	-0.020	0.001	0.125	0.073	0.025	---	---	---	---	---	---
NET	-0.031	0.396	-0.095	0.249	0.089	0.041	---	---	---	---	---	---
SPN	0.320	0.016	-0.020	0.121	0.019	0.023	---	---	---	---	---	---

Note: $e^n_{i,t} = \hat{\delta}^P_{i,1}\hat{f}^P_{1,t} + \hat{\delta}^P_{i,2}\hat{f}^P_{2,t} + \hat{\delta}^P_{i,3}\hat{f}^P_{3,t}$, $\Delta e^n_{i,t} = \hat{\delta}^I_{i,1}\widehat{\Delta f}^I_{1,t} + \hat{\delta}^I_{i,2}\widehat{\Delta f}^I_{2,t} + \hat{\delta}^I_{i,3}\widehat{\Delta f}^I_{3,t}$. PCA and ICA indicate principal and independent component analysis, respectively. $\widehat{\Delta f}^I_{j,t}$ denotes the jth stationary independent source and $\hat{f}^P_{j,t}$ is the jth level principal component. Others are the same as those in Table 1.

Table 3. Out-of-sample prediction of the PC- and IC-based models

$$\text{PC:}\quad e_{i,t+h} - e_{i,t} = c^{P}_{i,h} + \beta^{P}_{h}(\hat{E}^{P}_{i,t} - e^{n}_{it}) + u^{P}_{1,t+h},$$

$$\text{IC:}\quad e_{i,t+h} - e_{i,t} = c^{I}_{i,h} + \beta^{I}_{h}(\hat{E}^{I}_{i,t} - e^{n}_{it}) + u^{I}_{1,t+h},$$

$$i=1,\ldots,N;\ h=1,\ldots,H,$$

Sample/ N	Model	Median TU #TU<1 or (CW<-1.282)				$\overline{TU}$	$\overline{CW1}$	$\overline{CW2}$
		h=1	4	8	12			
		Criterion: CPV						
Early/N=17	PC	1.015 4(2)	1.017 6(1)	1.036 5(2)	1.158 4(2)	0.28	0.10	0.12
	IC	**0.999** 11(0)	**0.991** 13(5)	**0.950** 13(8)	**0.965** 10(7)	**0.69**	0.29	0.44
Long /N=9	PC	1.022 2(0)	1.094 1(0)	1.192 2(0)	1.309 1(0)	0.17	0.00	0.00
	IC	1.000 4(0)	**0.986** 7(3)	**0.956** 7(5)	**0.946** 9(5)	**0.75**	0.36	**0.56**
		Criterion: BIC_3						
Early/N=17	PC	1.007 4(1)	1.047 3(3)	1.078 4(5)	1.146 6(3)	0.25	0.18	0.24
	IC	**0.999** 10(1)	**0.994** 13(3)	**0.956** 14(8)	**0.964** 10(7)	**0.69**	0.28	0.44
Long /N=9	PC	1.013 4(1)	1.054 3(1)	1.089 3(1)	1.126 1(2)	0.31	0.14	0.17
	IC	1.000 4(2)	**0.991** 8(4)	**0.955** 7(6)	**0.941** 9(5)	**0.78**	0.47,	**0.61**
		Criterion: IC_{p2}						
Early/N=17	PC	1.009 4(1)	1.042 5(1)	1.070 6(3)	1.141 3(1)	0.26	0.09	0.12
	IC	1.000 7(0)	**0.999** 9(0)	**0.976** 14(8)	**0.976** 10(8)	**0.59**	0.24	0.47
Long /N=9	PC	1.015 3(0)	1.051 2(1)	1.059 2(1)	1.103 1(1)	0.22	0.08	0.11
	IC	1.001 3(2)	1.002 3(2)	**0.974** 7(5)	**0.951** 9(3)	**0.61**	0.33	0.44

Notes: $e_{i,t}$ is the log nominal exchange rate, and $\hat{E}^{I}_{i,t}$ and $\hat{E}^{P}_{i,t}$ are IC- and PC-based fundamental exchange rates constructed with the source number being determined by the criterion of *CPV* (Jackson, 1993), BIC_3 and IC_{p2} (Bai and Ng, 2002), respectively. PC and IC indicate a PC-based and an IC-based model, respectively. The benchmark is the driftless random walk: $e_{i,t+1} - e_{i,t} = u_{i,t+1}$. The numbers in the first line of each row under columns 3-6 are the medians of the *TU*-statistics, and they appear in bold if they are less than 1.0. *TU* is the ratio of the root mean square errors from a model relative to that from the driftless random walk. The model is superior to the driftless random walk if the *TU*-statistic is less than one. The *CW*-statistic examines if the two models have the same mean square prediction errors, and the hypothesis of equal accuracy is rejected if the *CW*-statistic is less than -1.282. There are two numbers in the second line of each row for each column under columns 3-6. The first number is the number of counties having the *TU*-statistic (across *N*) less than 1.0, and the second number, in parentheses, denotes the number of currencies for which the *CW*-statistic rejects the hypothesis of equal forecast accuracy at the 10% level. $\overline{TU}$ is the percentage of the *TU*-statistics less than 1.0 over all horizons. $\overline{CW1}$ and $\overline{CW2}$ denote the rejection percentages of the *CW*-statistic over all horizons and over the medium and long horizons, respectively. These percentages are boldfaced if they are greater than or equal to 0.5. Early and Long refer to the periods 1973-1998 and 1973-2011, respectively.

Table 4. Out-of-sample prediction of fundamental augmented PC- and IC-based models

$$\text{PC+k: } e_{i,t+h} - e_{i,t} = c^P_{i,k,h} + \beta^P_{k,h}(\hat{E}^P_{i,t} - e^n_{i,t}) + \gamma^P_{k,h}(z_{i,k,t} - e_{i,t}) + u^P_{i,k,t+h}$$

$$\text{IC+k: } e_{i,t+h} - e_{i,t} = c^I_{i,k,h} + \beta^I_{k,h}(\hat{E}^I_{i,t} - e^n_{i,t}) + \gamma^I_{k,h}(z_{i,k,t} - e_{i,t}) + u^I_{i,k,t+h},$$

$$i=1,\dots, N;\ h=1,\dots,H;\ k=TR, M, PPP.$$

Model	Median TU #TU<1 or (CW<-1.282)				$\overline{TU}$	$\overline{CW1}$	$\overline{CW2}$
	h=1	4	8	12			
			Early/N=17				
PC+TR	1.008	1.042	1.066	1.134	0.25	0.09	0.09
	3(2)	5(1)	6(3)	3(0)			
IC+TR	**0.999**	**0.998**	**0.971**	**0.975**	**0.66**	0.28	0.47
	12(3)	9(0)	14(8)	10(8)			
PC+M	1.007	1.032	1.055	1.058	0.32	0.18	0.21
	5(2)	5(3)	6(5)	6(2)			
IC+M	**0.996**	**0.985**	**0.934**	**0.945**	**0.76**	0.37	**0.50**
	11(2)	14(6)	15(9)	12(8)			
PC+PPP	1.008	1.005	**0.953**	**0.981**	**0.51**	0.43	**0.56**
	8(2)	8(8)	10(11)	9(8)			
IC+PPP	**0.995**	**0.953**	**0.882**	**0.898**	**0.63**	**0.51**	**0.53**
	11(6)	12(11)	11(9)	9(9)			
			Long/N=9				
PC+TR	1.014	1.059	1.061	1.095	0.22	0.08	0.11
	3(0)	2(1)	2(1)	1(1)			
IC+TR	1.001	1.001	**0.974**	**0.947**	**0.64**	0.31	**0.50**
	3(1)	4(1)	7(5)	9(4)			
PC+M	1.011	1.032	1.113	1.150	0.19	0.08	0.11
	1(0)	1(1)	3(1)	2(1)			
IC+M	1.004	1.014	1.047	1.025	0.31	0.31	0.28
	3(3)	3(3)	3(3)	2(2)			
PC+PPP	1.003	**0.991**	**0.962**	**0.969**	**0.55**	**0.53**	**0.78**
	4(1)	5(4)	5(8)	6(6)			
IC+PPP	**0.991**	**0.980**	**0.934**	**0.916**	**0.69**	**0.69**	**0.83**
	6(5)	6(5)	7(8)	6(7)			

Notes: $z_{i,TR,t}$, $z_{i,M,t}$ and $z_{i,PPP,t}$ are fundamental exchange rates measured by the Taylor-rule (TR), monetary (M) and purchasing power parity (PPP) fundamentals, respectively. PC+k and IC+k indicate that forecasts are constructed based on the kth fundamental augmented PC-based and the kth fundamental augmented IC-based models, respectively. The number of sources is determined by IC_{p2}. Others are the same as those in Table 3.

Table 5. Out-of-sample forecasts with the five currencies rejecting normality and the twelve currencies failing to reject normality in the Early sample

$$\text{PC:}\ \ e_{i,t+h} - e_{i,t} = c^{P}_{i,h} + \beta^{P}_{h}(\hat{E}^{P}_{i,t} - e^{n}_{i,t}) + u^{P}_{i,t+h}\,,$$
$$\text{IC:}\ \ e_{i,t+h} - e_{i,t} = c^{I}_{i,h} + \beta^{I}_{h}(\hat{E}^{I}_{i,t} - e^{n}_{i,t}) + u^{I}_{i,t+h}\,,$$
$$\text{PC+k :}\ \ e_{i,t+h} - e_{i,t} = c^{P}_{i,k,h} + \beta^{P}_{k,h}(\hat{E}^{P}_{i,t} - e^{n}_{i,t}) + \gamma^{P}_{k,h}(z_{i,k,t} - e_{i,t}) + u^{P}_{i,k,t+h}\,,$$
$$\text{IC+k:}\ \ e_{i,t+h} - e_{i,t} = c^{I}_{i,k,h} + \beta^{I}_{k,h}(\hat{E}^{I}_{i,t} - e^{n}_{i,t}) + \gamma^{I}_{k,h}(z_{i,k,t} - e_{i,t}) + u^{I}_{i,k,t+h}\,.$$
$$i=1,\ldots,N;\ h=1,\ldots,H;\ k=TR, M, PPP.$$

Model	Median *TU* #*TU*<1 or (*CW*<-1.282)				$\overline{TU}$	$\overline{CW1}$	$\overline{CW2}$
	h=1	4	8	12			
Excluding the five currencies rejecting the normality in the Early sample							
Early1/*N*=12							
PC	1.013 0(0)	1.068 0(0)	1.084 1(1)	1.206 1(0)	0.04	0.02	0.04
IC	1.006 0(0)	1.009 1(0)	**0.995** 7(4)	1.026 5(3)	0.27	0.15	0.29
PC+TR	1.012 0(0)	1.067 0(0)	1.089 1(0)	1.229 1(0)	0.04	0.00	0.00
IC+TR	1.006 1(0)	1.011 1(0)	0.993 9(3)	1.024 4(3)	0.31	0.13	0.25
PC+M	1.012 1(0)	1.044 1(0)	1.069 3(1)	1.070 3(2)	0.17	0.06	0.13
IC+M	1.002 2(0)	**0.993** 7(0)	**0.973** 7(5)	1.009 6(4)	0.46	0.19	0.38
PC+PPP	1.010 3(2)	1.020 5(4)	1.004 6(6)	**0.997** 6(6)	0.42	0.38	**0.50**
IC+PPP	1.000 4(3)	**0.979** 8(6)	**0.971** 6(6)	1.010 6(4)	**0.50**	0.40	0.42
Including only the five currencies rejecting the normality in the Early sample							
Early2/*N*=5							
PC	1.011 1(0)	1.021 2(0)	**0.982** 3(2)	1.138 1(1)	0.35	0.15	0.30
IC	**0.995** 3(1)	**0.999** 3(0)	**0.981** 3(2)	**1.015** 2(1)	**0.55**	0.20	0.30
PC+TR	1.010 1(0)	1.017 1(0)	**0.993** 3(1)	1.110 1(1)	0.30	0.10	0.20
IC+TR	**0.994** 3(2)	**0.995** 3(1)	**0.999** 3(1)	**1.059** 1(2)	**0.50**	0.30	0.30
PC+M	**0.997** 3(0)	**0.989** 5(3)	**0.980** 4(4)	**0.991** 3(4)	**0.75**	**0.55**	**0.80**
IC+M	**0.983** 3(3)	**0.958** 4(4)	**0.929** 4(3)	**0.988** 3(3)	**0.70**	**0.65**	**0.60**
PC+PPP	1.008 1(1)	1.026 2(2)	1.005 2(3)	1.010 2(3)	0.35	0.45	**0.60**
IC+PPP	**0.985** 3(1)	**0.943** 3(3)	**0.839** 4(3)	**0.966** 3(3)	**0.65**	**0.50**	**0.60**

Notes: Early1 indicates the panel excluding AUT, ITA, KOR, NOR and SWD from the Early panel; hence, its panel size (*N*) is twelve. Early2 indicates the panel including five countries: AUT, ITA, KOR, NOR and SWD. Others are the same as those in Tables 3 and 4.

Table 6. The simulation results

$$\text{DGP:}\quad e^{*}_{i,t} = E^{*I}_{i,t} + \varepsilon_{i,t} \equiv \sum\nolimits_{j=1}^{K} \hat{\delta}_{ij} f^{*I}_{j,t} + \varepsilon^{*}_{i,t}\,,$$

$$\varepsilon^{*}_{i,t} \sim \text{i.i.d.}N(0,\sigma_i^2)\,,\quad \sigma_i^2 \sim \text{ i.i.d.}U(0.9,\,1.1),$$

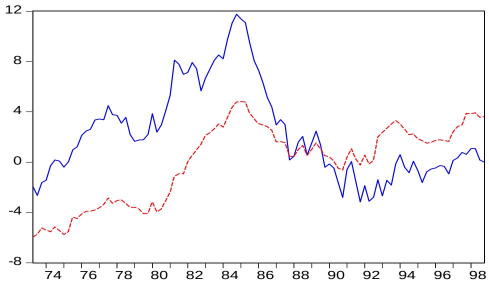
$$i=1,\dots,N,\ t=1,\dots,T,\ j=1,\dots,K,\ K=1,\,2,\,3,$$

	Early/N=17				Long/N=9			
$K \setminus h$	1	4	8	12	1	4	8	12
1	12.73	11.95	12.09	12.04	7.58	6.86	7.01	7.05
2	14.26	13.33	14.31	13.38	7.43	7.31	7.34	7.35
3	14.86	14.13	14.94	14.16	7.23	7.34	7.22	7.33

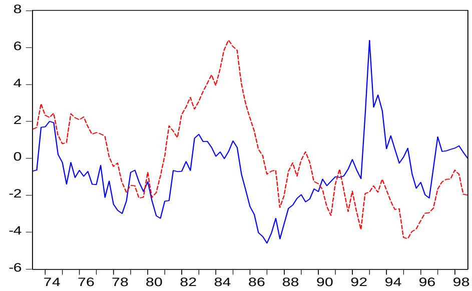
Note: $\hat{\delta}_{i,j}$ is the ith country's estimated mixing coefficient of the jth independent source and $f^{*I}_{j,t}$ is the jth independent source bootstrapped from the jth estimated independent source, $\hat{f}^{I}_{j,t}$. 'K' is the number of independent sources, and 'h' denotes the forecast horizon. The number of replications in simulation is 200, and the number in the table is the average number (across 200) of countries having TU < 1 under different forecast horizons. The TU statistic is defined as the ratio of the IC-based RMSE to the PC-based RMSE. The IC-based model is better than the PC-based model if the TU statistic is less than one.

The Early sample

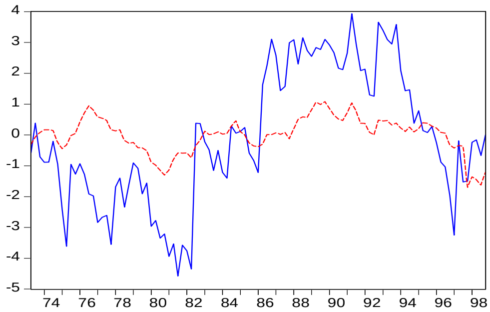
Factor 1



Factor 2

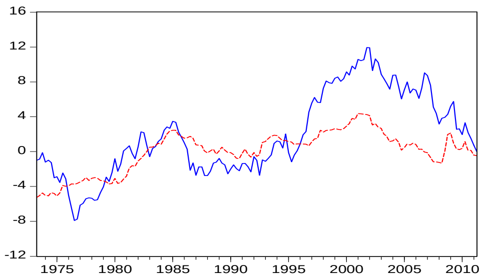


Factor 3

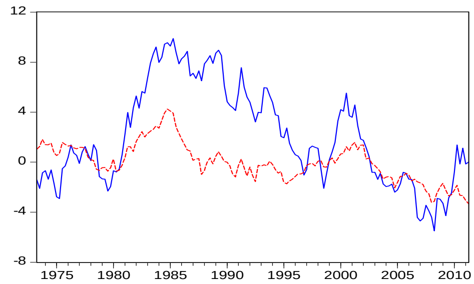


The Long sample

Factor 1



Factor 2



Factor 3

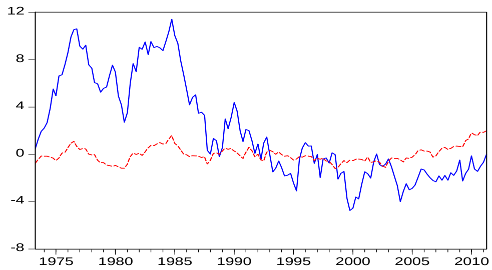


Figure 1: the plot of independent components (solid line) and principal components (broken line) over the Early and Long samples.