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Fundamentals and Exchange Rate Prediction Revisited

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 U.S. 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 codes: F31, F47

Keywords: independent components, principal components, random walk, exchange rates, out-of-sample prediction.

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

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helps the IC-based model to predict exchange rates. Using the panel data of the U.S. plus 17 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, Mark, and West, 2015). 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 U.S. 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 (Rapach and Wohar 2004, Mark and Sul 2001, 2011, Groen, 2005, Engel, Mark, and West 2007). Mark and Sul (2001) show 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 and West 2005, Groen 2006, Engel, Mark, and West, 2015). 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, Mark, and West (2015) 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 PC 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, Mark,

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

and West (2015) 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 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, Ma, and Wohar 2013). It seems reasonable to assume that these components are independent of each other. Moreover, the nonnormality of exchange rate changes has received substantial support in the literature (Domowitz and Hakkio 1985, Boothe and Glassman 1987, 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, Mark, and West (2015) 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 that 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, construct the sources-based fundamental exchange rates, and describe the strategy of out-of-sample prediction in Section 1. In Section 2, we describe the data, discuss the estimates of mixing coefficients and independent sources, and elucidate out-of-sample prediction results. Section 3 examines the robustness of our results. Section 4 proposes a simulation analysis to explain why IC-based models are better than PC-based models in out-of-sample prediction. Finally, Section 5 concludes. The Appendix describes the construction of the IC-based fundamental exchange rates.

1. THE EMPIRICAL MODEL AND ITS ESTIMATION

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

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

$$i = 1, \dots, N, t = 1, \dots, T, \quad (1)$$

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, Karhunen, and Oja 2001).

where $e_{i,t}$ indicates the log nominal exchange rate; $f_{j,t}$ is the j th source at time t and $\delta_{i,j}$ is the i th country's mixing coefficient on the j th 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, that is, $u_{i,t} \sim \text{i.i.d. } N(0, \sigma_{u_i}^2)$. 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, $e_{i,t}$, $i = 1, \dots, N$, $t = 1, \dots, T$.

Assuming cointegration between $e_{i,t}$ and the $f_{j,t}$'s, Engel, Mark, and West (2015) 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, Stefan, and Pedersen (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 (Hyvärinen, Karhunen, and Oja 2001, Särelä and Vigario 2003). The denoising 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 ($\hat{f}_{j,t} = \sum_{s=2}^t \widehat{\Delta f}_{j,s}$) 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 ($e_{i,t}^n$) and then calculate its changes.⁴ After estimating mixing coefficients and level sources, we construct the IC-based fundamental exchange rate ($\hat{E}_{i,t}^I$) accordingly (see the Appendix for details). The deviation of the exchange rate from its IC-based fundamental rate is measured by $\hat{E}_{i,t}^I - e_{i,t}^n$.⁵

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

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 $e_{i,t}$.

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 U.S. 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 PCs 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 TR model (Molodtsova and Papell 2009), and the PPP model (Kilian and Taylor 2003, Engel, Mark, and West 2007) are helpful to forecast exchange rates. The long-horizon predictive equation for a fundamental augmented source-based model is:

$$\begin{aligned} e_{i,t} - e_{i,t-h} &= \beta_{k,h}^d (\hat{E}_{i,t-h}^d - e_{i,t-h}^n) + \gamma_{k,h}^d (z_{i,k,t-h} - e_{i,t-h}) + v_{i,k,h,t}^d \\ v_{i,k,h,t}^d &= c_{i,k,h}^d + u_{i,k,h,t}^d, \quad k = TR, M, PPP; h = 1, 4, 8, 12; i = 1, \dots, N; d = I, P, \end{aligned} \quad (2)$$

where h is the forecast horizon and is set to 1, 4, 8, and 12 quarters, $z_{i,k,t}$ is the k th model-based fundamental exchange rate for country i , and the regression error $v_{i,k,h,t}^d$ includes an individual-specific effect, $c_{i,k,h}^d$.

Equation (2) degenerates to a source-based model if $\gamma_{k,h}^d = 0$, to a fundamental-based model if $\beta_{k,h}^d = 0$, to the random walk with drift if $\gamma_{k,h}^d = \beta_{k,h}^d = 0$, and to the driftless random walk if $c_{i,k,h}^d = \beta_{k,h}^d = \gamma_{k,h}^d = 0$. Engel, Mark, and West (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 $\hat{E}_{i,t}^I$ is better than $\hat{E}_{i,t}^P$ in measuring the i th country's latent fundamental exchange rate, equation (2) should produce stronger evidence of defeating

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 criteria, 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 prewhitening step is able to consistently estimate the mixing matrix if the number of common sources is less than the Ledermann bound: $LB = (2N + 1 - \sqrt{8N + 1})/2$ (Bonhomme and Robin 2009). Our empirical analysis in Section 2 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.

the random walk than when $\hat{E}_{i,t}^I - e_{i,t}^n$ in equation (2) is replaced with $\hat{E}_{i,t}^P - e_{i,t}^n$. The information on nonstandard fundamentals is helpful for predicting exchange rates if the model based on equation (2) with $\gamma_{k,h}^d = 0$ 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, Mark, and West (2015), the TR-based fundamental exchange rate is:

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

where $y_{i,t}^{\text{gap}}$ 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 .

1.1 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:

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

where T_0 is the last period of time in the in-sample period. The recursive scheme with the initial estimation window being 14 years is applied in out-of-sample contests (Engel, Mark, and West, 2015).⁸ The number of out-of-sample forecasts decreases with the forecast horizon, h . The source number in each recursive sample is determined

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 are 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, Stock and Watson 2003, Engle, Mark, and West 2007, 2015).

by IC_{p2} . After conducting out-of-sample forecasts, we add the recent observations to the in-sample data and then reestimate the output gaps, the number of sources, mixing coefficients, and latent sources; recalculate source-based fundamental exchange rates; and reconstruct 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 reconstructed 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, Mark, and West, 2015). 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 .

2. EMPIRICAL INVESTIGATIONS

2.1 Data Description

Quarterly data for end-of-period nominal exchange rates (foreign currency per U.S. 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 17 other OECD countries are considered. The 17 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 (1973Q1–2011Q2, Long) and the period before the appearance of the

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 8 countries with M1, 2 with M2, 1 with M3, 5 with currency in circulation, 1 with quasi-money, and 1 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.

TABLE 1
SUMMARY STATISTICS OF LOG NOMINAL EXCHANGE RATE CHANGES

	Mean	Median	Max	Min	Std	Skew	Kurt	JB
Panel A. 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*
Panel B. 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, Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom, respectively. “Std” and “Kurt” indicate the standard deviation and Kurtosis, respectively. “JB” is the Jarque–Bera normality test. The asterisk (*) indicates significance at the 5% level. Early and Long refer to the periods 1973–98 and 1973–2011, respectively.

euro (1973Q1–1998Q4, Early).¹¹ Data are available in the Early sample for all 17 countries, but are available for only 9 countries in the Long sample.

2.2 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 6 out of 9 (6 out of 17) countries in the Long (Early) sample. The kurtosis is significantly greater than 3.0 for 6 out of 9 (3 out of 17) countries in the Long (Early) sample. The Jarque–Bera normality test rejects the normality hypothesis for 6 out of 9 (5 out of 17) countries in the Long (Early)

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

TABLE 2
MIXING COEFFICIENT ESTIMATES

	The Early sample						The Long sample					
	PCA			ICA			PCA			ICA		
	$\hat{\delta}_{i,1}^P$	$\hat{\delta}_{i,2}^P$	$\hat{\delta}_{i,3}^P$	$\hat{\delta}_{i,1}^I$	$\hat{\delta}_{i,2}^I$	$\hat{\delta}_{i,3}^I$	$\hat{\delta}_{i,1}^P$	$\hat{\delta}_{i,2}^P$	$\hat{\delta}_{i,3}^P$	$\hat{\delta}_{i,1}^I$	$\hat{\delta}_{i,2}^I$	$\hat{\delta}_{i,3}^I$
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	—	—	—	—	—	—

NOTES: $e_{i,t}^n = \hat{\delta}_{i,1}^P \hat{f}_{1,t}^P + \hat{\delta}_{i,2}^P \hat{f}_{2,t}^P + \hat{\delta}_{i,3}^P \hat{f}_{3,t}^P$, $\Delta e_{i,t}^n = \hat{\delta}_{i,1}^I \Delta \hat{f}_{1,t}^I + \hat{\delta}_{i,2}^I \Delta \hat{f}_{2,t}^I + \hat{\delta}_{i,3}^I \Delta \hat{f}_{3,t}^I$. PCA and ICA indicate principal and independent component analysis, respectively. $\Delta \hat{f}_{j,t}^I$ denotes the j th stationary independent source and $\hat{f}_{j,t}^P$ is the j th level principal component. Others are the same as those in Table 1.

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 ICs and PCs constructed from both samples, and they appear to follow a unit-root process. Except for the second IC in the Early sample, ICs are more volatile than PCs, especially in the Long sample. The mixing coefficients of ICs and PCs ($\hat{\delta}_{i,j}^I$, $\hat{\delta}_{i,j}^P$, $i = 1, \dots, N$, $j = 1, 2, 3$) 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 first source, $\hat{\delta}_{i,1}^I$'s, are larger than those of the second source, $\hat{\delta}_{i,2}^I$'s, for 16 out of 17 countries in the Early sample and for 6 out of 9 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, Mark, and West, 2015). Furthermore, the mixing coefficient estimates differ across countries, indicating that currencies are not treated equally in estimating latent

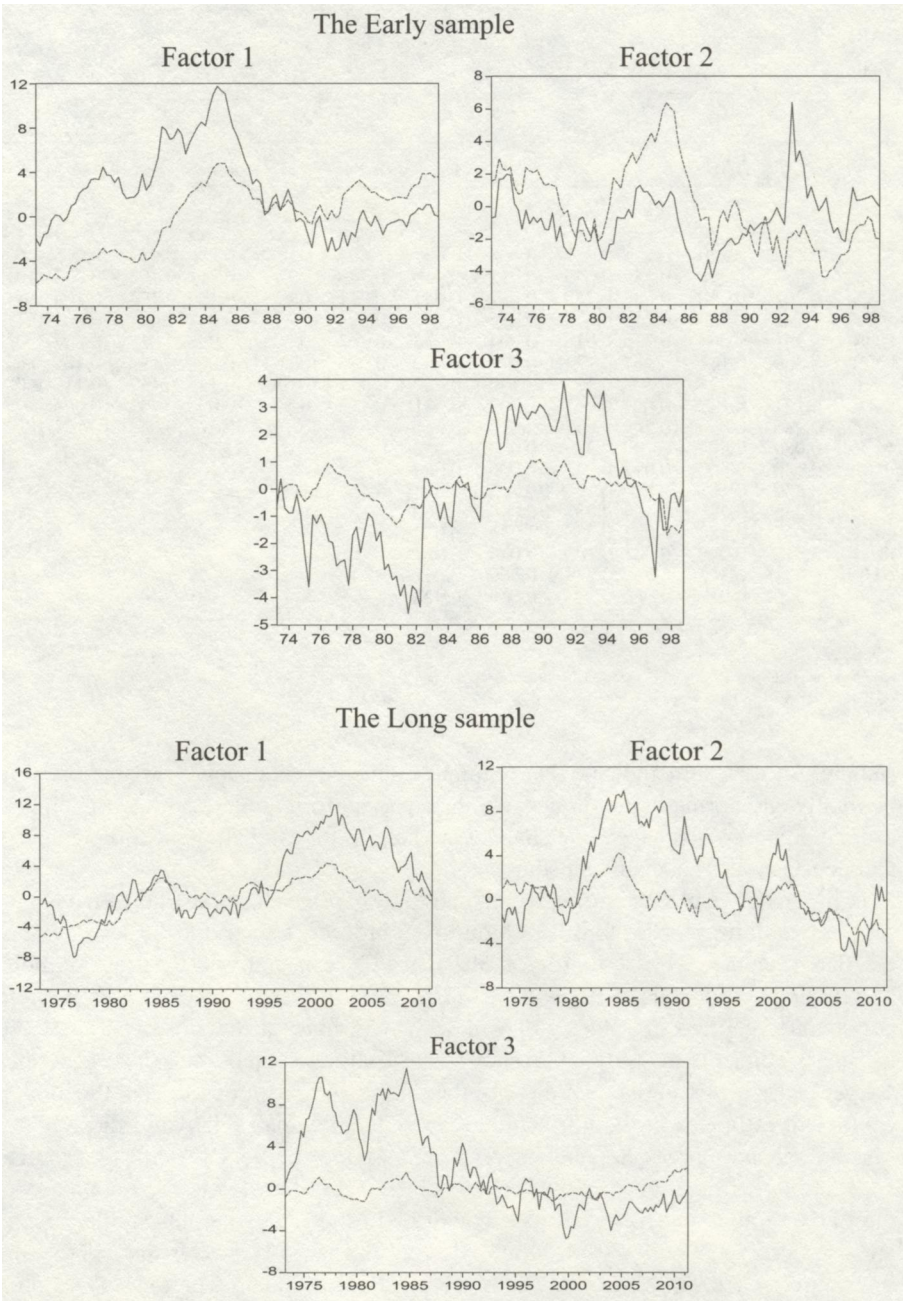


FIG. 1. The Plot of Independent Components (Solid Line) and Principal Components (Broken Line) over the Early and Long Samples.

sources. Fourth, the absolute values of the mixing coefficient estimates from ICA are generally smaller than those from PCA ($\hat{\delta}_{i,j}^I < \hat{\delta}_{i,j}^P$) 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 $\hat{E}_{i,t}^I - e_{i,t}^n$ contains more helpful information than $\hat{E}_{i,t}^P - e_{i,t}^n$ in predicting exchange rates, which will be examined in the next section.

2.3 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 horizons (the first number in each row under columns 3–6), the number of countries having the TU -statistic less than 1.0 for different forecast horizons (the second number in 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

12. We assume cointegration between sources and exchange rates; hence, $\hat{E}_{i,t}^I - e_{i,t}^n$ in (2) is stationary. The superiority of the IC method in out-of-sample contests could be spurious if $\hat{E}_{i,t}^I - e_{i,t}^n$ is highly persistent (Rossi 2005). We apply Pesaran's (2007) *CIPS* statistic to test the unit-root hypothesis of $\hat{E}_{i,t}^I - e_{i,t}^n$, where $\hat{E}_{i,t}^I$ 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 $\hat{E}_{i,t}^I - e_{i,t}^n$ 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 $\hat{E}_{i,t}^I - e_{i,t}^n$ is stationary.

TABLE 3
OUT-OF-SAMPLE PREDICTION OF THE PC- AND IC-BASED MODELS

$$PC: e_{i,t+h} - e_{i,t} = c_{i,h}^P + \beta_h^P(\hat{E}_{i,t}^P - e_{it}^n) + u_{i,t+h}^P$$
$$IC: e_{i,t+h} - e_{i,t} = c_{i,h}^I + \beta_h^I(\hat{E}_{i,t}^I - e_{it}^n) + u_{i,t+h}^I$$
$$i = 1, \dots, N; h = 1, \dots, H,$$

Median TU , # $TU < 1$ or ($CW < -1.282$)								
Sample/ N	Model	$h = 1$	4	8	12	\overline{TU}	$\overline{CW1}$	$\overline{CW2}$
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 $\hat{E}_{i,t}^I$ and $\hat{E}_{i,t}^P$ 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: $e_{i,t+1} - e_{i,t} = u_{i,t+1}$. There are three numbers in each row under columns 3–6. The first number is the median of the TU -statistic, and it appears in bold if it is less than 1.0. TU -statistic 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 1.0. The second number is the number of currencies having the TU -statistic (across N) less than 1.0, and the third number, in a parenthesis, denotes the number of currencies for which the CW -statistic rejects the hypothesis of equal forecast accuracy at the 10% level. The CW -statistic examines if the two models have the same mean square prediction errors, and the hypothesis of equal accuracy is rejected if it is less than -1.282 . TU and CW indicate the TU - and CW -statistic, respectively. \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 1973–98 and 1973–2011, respectively.

$\overline{CW2}$ 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, Mark, and West, 2015).

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

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.

TABLE 4
OUT-OF-SAMPLE PREDICTION OF FUNDAMENTAL AUGMENTED PC- AND IC-BASED MODELS

$$PC + k: e_{i,t+h} - e_{i,t} = c_{i,k,h}^p + \beta_{k,h}^p(\hat{E}_{i,t}^p - e_{i,t}^n) + \gamma_{k,h}^p(z_{i,k,t} - e_{i,t}) + u_{i,k,t+h}^p$$
$$IC + k: e_{i,t+h} - e_{i,t} = c_{i,k,h}^l + \beta_{k,h}^l(\hat{E}_{i,t}^l - e_{i,t}^n) + \gamma_{k,h}^l(z_{i,k,t} - e_{i,t}) + u_{i,k,t+h}^l,$$
$$i = 1, \dots, N; h = 1, \dots, H; k = TR, M, PPP$$

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

NOTE: $z_{i,TR,t}$, $z_{i,M,t}$, 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 k th fundamental augmented PC-based and the k th fundamental augmented IC-based models, respectively. The number of sources is determined by IC_{p2} . Others are the same as those in Table 3.

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, Mark, and West, 2015).

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 nonnormality in data, we first exclude the five currencies rejecting normality form the Early panel: AUT, ITA, KOR, NOR, and SWD. If the nonnormality of exchange rate changes is crucial for the IC method, then removing the above five currencies should 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

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

TABLE 5
OUT-OF-SAMPLE FORECASTS WITH THE 5 CURRENCIES REJECTING NORMALITY AND THE 12 CURRENCIES FAILING TO REJECT NORMALITY IN THE EARLY, SAMPLE

$$\begin{aligned} \text{PC: } e_{i,t+h} - e_{i,t} &= c_{i,h}^P + \beta_h^P(\hat{E}_{i,t}^P - e_{i,t}^n) + u_{i,t+h}^P \\ \text{IC: } e_{i,t+h} - e_{i,t} &= c_{i,h}^I + \beta_h^I(\hat{E}_{i,t}^I - e_{i,t}^n) + u_{i,t+h}^I \\ \text{PC} + k: e_{i,t+h} - e_{i,t} &= c_{i,k,h}^P + \beta_{k,h}^P(\hat{E}_{i,t}^P - e_{i,t}^n) + \gamma_{k,h}^P(z_{i,k,t} - e_{i,t}) + u_{i,k,t+h}^P \\ \text{IC} + k: e_{i,t+h} - e_{i,t} &= c_{i,k,h}^I + \beta_{k,h}^I(\hat{E}_{i,t}^I - e_{i,t}^n) + \gamma_{k,h}^I(z_{i,k,t} - e_{i,t}) + u_{i,k,t+h}^I, \\ & i = 1, \dots, N; h = 1, \dots, H; k = TR, M, PPP \end{aligned}$$

	Median TU , # $TU < 1$ or ($CW < -1.282$)						
Model	$h = 1$	4	8	12	\overline{TU}	$\overline{CW1}$	$\overline{CW2}$
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 12. Early2 indicates the panel including 5 countries: AUT, ITA, KOR, NOR, and SWD. Others are the same as those in Tables 3 and 4.

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 5 countries than for the other 12. 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

3. ROBUSTNESS¹⁶

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)

15. We appreciate a reviewer's comment on this point.
16. Empirical results in this section are available from the authors upon request.

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 14 years to both 16 and 12 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 U.S.-based exchange rates can be interpreted as the "U.S. sources." How important are the U.S. sources in the out-of-sample prediction of nominal exchange rates? This paper first reexamines 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 U.S. sources are important for the superiority of the IC method in the out-of-sample prediction of exchange rates. Finally, we reexamine the out-of-sample contests by using the rolling scheme with the rolling window being 10 years as suggested by Clark and McCracken (2004). Only the TR-augmented IC-based model defeats the random

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).

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 14 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 criteria 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 U.S. sources and the recursive scheme are applied.

4. 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):

$$\begin{aligned}
 e_{i,t}^* &= E_{i,t}^{*I} + \varepsilon_{i,t} \equiv \sum_{j=1}^K \hat{\delta}_{ij} f_{j,t}^{*I} + \varepsilon_{i,t}^*, \quad i = 1, \dots, N, \\
 t &= 1, \dots, T, \quad j = 1, \dots, K, \quad K = 1, 2, 3 \\
 \varepsilon_{i,t}^* &\sim i.i.d.N(0, \sigma_i^2), \quad \sigma_i^2 \sim i.i.d.U(0.9, 1.1),
 \end{aligned} \tag{4}$$

where the $\hat{\delta}_{ij}$'s are estimated mixing coefficients reported in Table 2; $f_{j,t}^{*I}$ is the j th non-Gaussian independent source bootstrapped from the j th estimated source ($\hat{f}_{j,t}^I$) reported in Figure 1; $\varepsilon_{i,t}^*$ is an idiosyncratic error that is identically, independently, and 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 IC structure and that the i th 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 14 years. The IC-based model is better than the PC-based model if the TU -statistic is less than 1.0. Repeating the previous procedures 200 times, we report the average number of countries (across 200 replications) having the TU -statistic below 1.0 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

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.

TABLE 6
THE SIMULATION RESULTS

$$\begin{aligned} \text{DGP : } e_{i,t}^* &= E_{i,t}^{*I} + \varepsilon_{i,t} \equiv \sum_{j=1}^K \hat{\delta}_{ij} f_{j,t}^{*I} + \varepsilon_{i,t}^* \\ \varepsilon_{i,t}^* &\sim i.i.d.N(0, \sigma_i^2), \sigma_i^2 \sim i.i.d.U(0.9, 1.1), \\ i &= 1, \dots, N, t = 1, \dots, T, j = 1, \dots, K, K = 1, 2, 3 \end{aligned}$$

	Early/ $N = 17$				Long/ $N = 9$			
K/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

NOTES: $\hat{\delta}_{i,j}$ is the i th country's estimated mixing coefficient of the j th independent source and $f_{j,t}^{*I}$ is the j th independent source bootstrapped from the j th estimated independent source, $f_{j,t}^I$. 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.

Early (Long) sample.¹⁹ These results indicate that if nominal exchange rates are the mixture of non-Gaussian independent sources and the i th 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.

5. CONCLUSIONS

The major reason for Engel, Mark, and West (2015) 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 17 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 U.S. 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% of the variance of real depreciation rates for G-7 countries at the 5-year

19. Simulation results are not affected if $f_{j,t}^{*I}$ is replaced by $\hat{f}_{j,t}^I$ 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.

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, $[1, T_0]$.

- (i) Centering. Let \mathbf{Z}^0 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 \mathbf{Z} be the data matrix of $\Delta e_{i,t}^n (= e_{i,t}^n - e_{i,t-1}^n)$, $i = 1, \dots, N$, $t = 1, \dots, T_0 - 1$. Let \mathbf{Y} be the matrix that subtracts the mean vector of \mathbf{Z} from \mathbf{Z} , $\mathbf{Y} = \mathbf{Z} - \mathbf{E}(\mathbf{Z})$.
- (ii) Whitening. Transform the data matrix (\mathbf{Y}) to a new data matrix (\mathbf{X}), which is white, that is, $\mathbf{X} = \Gamma^{-1/2} \Psi' \mathbf{Y}$, in which Ψ is the orthogonal matrix of the eigenvectors of $E[\mathbf{Y}\mathbf{Y}']$ and Γ is the diagonal matrix of eigenvalues. Whitening transforms the original mixing matrix (\mathbf{A}_0) to a new one ($\mathbf{A} = \Gamma^{-1/2} \Psi' \mathbf{A}_0$) that is orthogonal. Therefore, whitening reduces the number of parameters to be estimated.
- (iii) We assume that \mathbf{X} follows a linear noisy independent component model: $\mathbf{X} = \mathbf{A}\mathbf{F} + \mathbf{v}$, where \mathbf{F} is a $K \times T_0$ ($K \leq N$) matrix of latent stationary sources ($\widehat{\Delta f}_{j,t}$'s), \mathbf{A} is an $N \times K$ 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 prewhitened data matrix \mathbf{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 \mathbf{Y} is $\hat{\mathbf{A}}^0 = (\Gamma^{-1/2} \Psi')^{-1} \hat{\mathbf{A}}$.
- (iv) 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 ($\hat{E}_{i,t}^f$'s) by multiplying the estimated level sources with the mixing coefficient estimates in $\hat{\mathbf{A}}^0$.

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