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EXCHANGE RATE MOVEMENTS AND FUNDAMENTALS: IMPACT OF OIL PRICES AND CHINA'S GROWTH

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Exchange Rate Movements and Fundamentals: Impact of Oil Prices and China's Growth[*]

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Abstract

This paper identifies five factors that can capture 95% of the variance across 39 US dollar exchange rates based on the principal component method. A time-varying parameter factor-augmented vector autoregressive (TVP-FAVAR) model is used to analyze the determinants of movements in these exchange rates, revealing that impact of global oil prices and China's growth has increased significantly since 2008. In particular, shocks to these two fundamentals drive the movements of both commodity and non-commodity currencies recently. The impact of monetary policy shocks on the currency pairs is comparatively small.

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1 Introduction

This paper demonstrates that the fluctuations of US dollar-based exchange rates can be captured by a low dimension of principal components. We analyze the evolution of exchange rate dynamics and show the movements in exchange rates can be largely explained by shocks to two fundamentals – global oil prices and China's growth. This finding holds for both commodity and non-commodity currency pairs, extending the results in the previous literature. The explanatory power of economic fundamentals has increased significantly since the 2007-2008 financial crisis because of the rapid rise in uncertainty. We also find that global oil prices are most important during the financial crisis, whereas China's growth contributes to half of the variance in the past five years.

From a global perspective, Chen and Rogoff (2003) and Chen, Rogoff and Rossi (2010) indicate that commodity prices are of importance for commodity currencies. When global investors infer economic conditions from commodity price information, the exchange rate movements of non-commodity currencies will also be severely influenced by price changes. China, as the world's biggest importer of commodities, can affect commodity prices to a large extent from its strong trade linkages, see Frankel (2006).[1] Yin and Han (2016) show that macroeconomic factors of China have significant impact on commodity markets. To this end, we are interested in whether the rise of China affects global exchange rate dynamics, especially after the financial crisis. The changing exchange rate dynamics are captured by a novel methodology – the time-varying parameter factor-augmented vector autoregressive (TVP-FAVAR) model. It follows from the evidence of Chen, Rogoff and Rossi (2010) that there are potential structural breaks in the exchange rate structure as observed empirically. Moreover, this approach is helpful in modeling potential stochastic trends that can induce the unit root behavior of exchange rates indicated in Engel and West (2005). By allowing for time-varying parameters, the approach provides informative implications about economic fundamentals and economic regimes.

Our analysis is related to the present-value model proposed in the seminal paper of Engel and West (2005). When market participants price fundamentals into the exchange rate through its anticipated impact on future exchange rate values, the nominal exchange rate tends to be sensitive to shocks to current global market conditions. Therefore, the uncertainty in fundamentals may drive global exchange rates to comove even before a real effect materializes. If China's growth, for example, is an important economic indicator monitored by investors, the shocks to this indicator can potentially cause global fluctuations in exchange rates.

In order to estimate the true dynamics, our approach embodies rich information implied in exchange rates that is orthogonal to fundamentals. Building upon the factor structure in Engel, Mark and West (2015), we employ the principal component method to identify five global latent factors that capture most of the variance of 39 currencies from 1995 to 2015. In a TVP-FAVAR we jointly model the dynamics

[1] See also Hummels (2011) for a discussion about China's growing role in world trade.

of fundamentals and exchange rate latent factors, which reveals the time-varying patterns of global exchange rate drivers. We examine to what extent the global oil prices and China's growth contribute to the movements of exchange rates over time. The uncertainty in oil prices and China's growth has increased rapidly since the financial crisis, and the exchange rate fluctuations across countries are essentially captured by the shocks to these two fundamentals in the past ten years. The surprisingly high explanatory power of these shocks has structural interpretations. The effects of global oil prices are consistent with the purchasing power parity (PPP) model, and we find that the exchange rates tend to adjust more quickly to the oil prices in the latest period. Moreover, we find that influence of China's growth increases sharply in 2008 and dominates other factors, which is new to the literature. In addition to the trade channel, unexpected changes in China's growth potentially affect global investors' demand for currency assets, causing quick responses and comovement of related currency pairs.

The remainder of the paper is structured as follows. Section 2 describes our model and the estimation. Section 3 describes the data and reports the results. Specifically, Section 3.2 discusses the economic content of the global latent factors. Sections 3.3 and 3.4 analyze the time-varying patterns of the fundamentals of global exchange rates. In Section 4 we conduct robustness checks. Section 5 concludes.

2 Methodology

As suggested by Bernanke, Boivin and Eliasz (2005), incorporating information not reflected in standard macro fundamentals is important to properly identify the underlying transmission mechanism. Therefore, we aim to consider a system with rich information, which potentially provides a more comprehensive and coherent picture of exchange rate dynamics. In the following, we describe a two-step procedure to properly exact different layers of information, particularly from the cross section of exchange rates.

Extraction of cross-sectional information In the first step, we identify a set of linear latent factors from the below equation:

$$s_{t,i} = \alpha_i' I_t + \epsilon_t^i, \tag{2.1}$$

where I_t collects the common factors across countries, α are factor loadings that are mapped from γ^G, ψ and the VAR parameters, and $\epsilon_t^i = \beta_i' I_{t,i}$ denotes the country-specific variation. The above representation is consistent with the factor structure specified in Engel, Mark and West (2015).[2] We can identify the common factors I_t using the principal component method proposed by Stock and Watson

[2] We can establish a linear relationship between the log nominal exchange rate and a set of latent global factors from a present-value model, see Appendix C for details.

(2002).

The identified factors I_t include the information of both observable fundamentals and unobservable variables. As we would like to focus only on the explanatory power of a specific set of observable fundamentals f_t, in the second step we construct a factor-augmented vector autoregressive model that incorporates both f_t and I_t.

The factor-augmented time-series dynamics We proceed to the second step with a reduced-form equation that describes the exchange rate movements driven by fundamentals f_t and latent factors (principal components) I_t:

$$s_{t,i}^{G} = \alpha_i^{*\prime} \begin{bmatrix} f_t \\ I_t \end{bmatrix}. \tag{2.2}$$

With Equation (2.2), we can evaluate to what extent structural shocks to f_t can explain movements in exchange rates. We achieve this goal by estimating the joint dynamics with fundamentals in a factor-augmented vector autoregressive model (FAVAR, see Bernanke, Boivin and Eliasz (2005)), as they suggest a rich information set is helpful in revealing the true dynamics. For now we assume the variables in the system are stationary, but we will discuss the nonstationary case and motivate a novel method in the next section. Accordingly, the joint dynamics of (f_t, I_t) are given by

$$\begin{bmatrix} f_t \\ I_t \end{bmatrix} = c + \Phi(L) \begin{bmatrix} f_{t-1} \\ I_{t-1} \end{bmatrix} + v_t, \tag{2.3}$$

where c is vector of constants, $\Phi(L)$ is a conformable lag polynomial of finite order d, and the error term v_t is mean zero with covariance matrix Q.

2.1 TVP-FAVAR

As indicated by Chen, Rogoff and Rossi (2010), it is important to allow for the time variability in exchange rate dynamics. More importantly, Engel and West (2005) suggest at least some of the nominal exchange rates have unit roots, so the nonstationary behavior of exchange rate determinants may not be well captured in a constant-parameter FAVAR model. These findings are echoed by Baillie and Bollerslev (1989), who present strong evidence that stochastic trends are a source of the unit root behavior of exchange rates. Therefore, we extend Equation (2.3) to a time-varying parameter (TVP) FAVAR model, in which stochastic intercepts are explicitly specified:

$$\begin{bmatrix} f_t \\ \\ I_t \end{bmatrix} = c_t + \Phi_t(L) \begin{bmatrix} f_{t-1} \\ \\ I_{t-1} \end{bmatrix} + v_t, \tag{2.4}$$

where c_t are the stochastic intercepts, which are useful in capturing potential unit root behavior of exchange rate determinants. This novel model has a state space representation and can be estimated by the Kalman filter.[3] For better description of the state space structure, we rewrite the p-lag TVP-FAVAR in the following compact form

$$Z_t = X_t \beta_t + v_t, \tag{2.5}$$

where $Z_t = [f_t, I_t]'$, f_t is a $m \times 1$ vector of fundamentals, I_t is a $q \times 1$ vector of latent factors, $X_t = I_n \otimes \left[Z'_{t-1}, ..., Z'_{t-p}\right]$ for $n = m + q$, $\beta_t = \left[c_t, vec\left(B_{1t}\right)', \cdots, vec\left(B_{pt}\right)'\right]'$ is a vector summarizing all VAR coefficients and $v_t \sim N\left(0, \Sigma_t\right)$ with Σ_t an $n \times n$ covariance matrix.[4] This regression-type equation is completed by describing the law of motion of the time-varying parameters β_t and Σ_t. For β_t we follow the standard practice in the literature from Primiceri (2005) and consider random walk evolution for the VAR coefficients,

$$\beta_{t+1} = \beta_t + \mu_t, \tag{2.6}$$

based upon a prior β_0 discussed below, and $\mu_t \sim N\left(0, Q_t\right)$. Following Koop and Korobilis (2013) we set $Q_t = \left(\Lambda^{-1} - 1\right) cov\left(\beta_{t-1} | \mathcal{D}_{t-1}\right)$ where $\mathcal{D}_{t-1}$ denotes all the available data at time $t-1$ and scalar $\Lambda \in (0, 1]$ is a "forgetting factor" discounting older observations.

The covariance matrix Σ_t evolves according to a Wishart matrix discount process (Prado and West (2010)) of the form:

$$\Sigma_t \sim iW\left(S_t, n_t\right), \tag{2.7}$$

$$n_t = \delta n_{t-1} + 1, \tag{2.8}$$

$$S_t = \delta S_{t-1} + f\left(v_t' v_t\right), \tag{2.9}$$

where n_t and S_t are the degrees of freedom and scale matrix, respectively, of the inverse Wishart distribution, δ is a "decay factor" discounting older observations, and $f\left(v_t' v_t\right)$ is a specific function of the squared residuals of our model.

[3] Chang, Miller and Park (2009) show that stochastic trends in a state space model can be plausibly estimated using the Kalman filter.

[4] In this paper we use one lag, i.e. $p = 1$, following Engel, Mark and West (2015). As the factor system is persistent and has the Markov property, our findings are robust to other lag selections.

The VAR system allows for the interdependence of endogenous variables. The time-varying nature of our method allows us to compute different variance decomposition and impulse response functions at different points in time. We therefore can analyze the evolution of exchange rate dynamics by identifying structural shocks of fundamentals. We employ the standard Cholesky identification scheme to identify orthogonal structural shocks. Our baseline specification of VAR consists of six fundamentals (global oil prices, China's industrial production (IP), China's import, the US effective federal fund rate, and short rates of the euro area and Japan) and five exchange rate factors collected in I_t, and we orthogonalize shocks recursively in that order. This ordering allows us to pin down exactly how much variance of exchange rates is driven by shocks to fundamentals f_t without double counting the same information incorporated in I_t.

The identified structural shocks of these macro fundamentals allow us to analyze at each point in time the relative importance of these macroeconomic sources in driving the exchange rate movements. The variance decomposition of these structural shocks is given by

$$Var(s^G_{t,i}) = \alpha'_{i,f} Var(f_t)\alpha_{i,f} + \alpha'_{i,I} Var(I_t)\alpha_{i,I}, \tag{2.10}$$

where $\alpha_{i,f}$ and $\alpha_{i,I}$ are obtained by regressing exchange rates on (f_t, I_t) according to Equation (2.2).

In summary, we specify a FAVAR with drifting coefficients, which allows for model structural instability and regime changes in the joint dynamics of the exchange rate factors and the fundamentals. We also allow for stochastic volatility, so an unconditional fat tail distribution in the data is taken into consideration. Here we extend the methodology of Koop and Korobilis (2013) and conduct an efficient estimation scheme to provide accurate results while largely speeding up the estimation of our large TVP-FAVAR (11 variables). This method is computationally convenient as no Markov Chain Monte Carlo (MCMC) is needed. We use what is known as a "forgetting factor" or "decay factor" to discount the previous information when updating the parameter estimates; detailed information of our empirical methodology can be found in Appendix B.

3 Data and Results

3.1 Data Description

Our exchange rate data and global oil prices are from the Bloomberg Database, which includes 37 currencies in the following countries or regions: Argentina, Australia, Brazil, Canada, Switzerland, Chile, China, Colombia, Czech Republic, Denmark, Egypt, Eurozone, the UK, Ghana, Hong Kong, Hungary, Indonesia, India, Iceland, Japan, Kenya, South Korea, Mexico, Malaysia, Norway, New Zealand, Peru, Philippines, Poland, Russia, Sweden, Singapore, Thailand, Turkey, Taiwan, Central Africa and South

Africa. In addition, we include gold and IMF Special Drawing Rights (SDR). For all currencies we use the US dollar as the base currency. The data of China's industrial production and import is from the CEIC Database, and we use the annual growth rates of these two variables. The US effective federal fund rate (shadow rate) is from the Federal Reserve Bank of Atlanta, which is computed based on the method proposed by Wu and Xia (2016). The shadow short rates (SSR) of the euro area and Japan are from the Reserve Bank of New Zealand.[5] The full sample is monthly data from 1995:01 to 2015:12, and we use the data before 2001:01 as the training sample to form the prior distributions.[6]

3.2 Principal Components

In this section we show that a low dimension of principal components can capture the exchange rate fluctuations in levels. Using the principal component method, the first five global currency factors account for around 95% of the global currency variance.[7] These principal components extracted by a statistical method have economic content.

As shown in Figure 1, the first principal component (PC1) strongly correlates with the currencies of most developed countries and is mostly correlated with the Special Drawing Right (SDR) value of the U.S. dollar. In general, these countries have relatively sophisticated financial markets and flexible exchange rate regimes. The second factor, in contrast, is highly correlated with emerging market currencies, such as the Turkish Lira, Russian Ruble, Indonesian Rupiah and Indian Rupee. The third factor, in particular, is heavily correlated with the British Pound with a correlation coefficient of 0.89. The last two factors do not have particularly high correlation with any currencies, but they are generally quite important in driving Asian currencies, such as the Japanese Yen, South Korean Won and Hong Kong Dollar. The results of all currencies are reported in Table 1.[8]

Our results parallel and extend the findings in Engel, Mark and West (2015) and Greenaway-McGrevy et al. (2015). Engel, Mark and West (2015) construct global factors from a cross section of exchange rates and show that using factors combined with macro fundamentals can significantly improve forecasting performance. The identification of Greenaway-McGrevy et al. (2015) also motivates multilateral models for bilateral exchange rates. We confirm the previous findings and show that these global factors potentially correspond to financial market sophistication and regional effects; the former controls the efficiency of capital flows and the latter can be linked to trade. The economic appeal of these exchange rate factors is intuitive, as capital and trade flows are basic elements of the balance of international payments. In the following sections, we jointly model exchange rates with fundamentals related

[5] The data is produced from the research of Leo Krippner, and the details can be found on the website http://www.rbnz.govt.nz/research-and-publications/research-programme/additional-research.

[6] Appendix A sets out charts of our fundamental variables.

[7] We weight the currency pairs according to the foreign exchange turnover data of April 2016, which is from the Triennial Central Bank Survey conducted by the Bank for International Settlements (BIS). We thank Andrew Rose for this suggestion.

[8] In the following sections, we may use currency acronyms reported in this table for convenience.

to commodity prices and reveal the time-varying dynamics of the system.

3.3 Variance Decomposition of Shocks to Fundamentals

As discussed in the methodology section, our TVP-FAVAR jointly models the dynamics of two groups of variables f_t and I_t, and our identification scheme can directly evaluate the influence of f_t on exchange rates. In specific, there are six fundamentals: global oil prices, China's industrial production (IP), China's import, US EFFR, Euro-area SSR and Japan SSR. The decomposition of these structural shocks is described in Equation (2.10).

Figure 2 shows the variance decomposition of our model, which displays time-varying patterns of exchange rate fluctuations across BRICS or G7 countries. The rest of the variance is accounted by the shocks to I_t in Equation (2.3).[9] The patterns of different countries share a common trend. The importance of our fundamentals in driving exchange rate movements has significantly increased since 2005, despite a drop in 2007 for most of the countries. The Chinese Yuan, however, has a stable upward trend after its 2005 exchange rate reform, but in 2015 there is a slight decline. We can interpret the increase in the share of fundamentals for China as an effort to introduce a floating exchange rate regime, as it reflects the market expectations about the current economy. For almost all countries in the past ten years, the fundamentals account for on average $70-80\%$ of the exchange rate variance. A special case is the currency of Japan: For the Japanese Yen, the portion accounted by these fundamentals is quite volatile in past three years.

Among all fundamentals, global oil prices and China's IP are underlined in terms of their strong time variability in the variance decomposition. Tables 2 and 3 report the contribution of shocks to variance of exchange rates, averaged over different periods. It is clear that the global oil price is the dominant source before 2010, while China's growth takes over the top position for almost all countries after 2010. Monetary policy shocks are comparatively small in the past five years. However, this does not mean policy rates are not important in driving exchange rates, as the variation in policy rates is potentially due to the reactions to changes in global oil prices or China's growth.[10]

Figures 3 and 4 show the 120-month-ahead forecast error variance decomposition of six respective fundamentals over time. For the BRICS countries, the variance shares driven by global oil prices peak twice during the whole sample period (in 2006 and 2008, respectively). For the G7 currencies, there tends to be only one peak, which is in the global financial crisis.

In 2008, global oil price shocks can account for a surprisingly high share (around 80%) of the variance of exchange rate movements; this finding holds for both commodity and non-commodity currencies,

[9] These orthogonal shocks can be difficult to interpret, as they encompass non-market forces such as the exchange rate peg or capital controls.

[10] The generalized forecast error variance decomposition proposed by Koop, Pesaran and Potter (1996) can validate this argument.

extending the results in Chen and Rogoff (2003). If investors infer the global demand for all industrial commodities from global oil prices, all currencies can be severely influenced by the oil price shocks.[11]

The relative importance of China's growth, measured by growth rates of industrial production, has increased significantly since 2008. The cutting point for most countries is around 2010, when the importance of China's growth exceeds global oil prices and becomes the most important driving force. In the past five years, China's growth accounts for $40-60\%$ of the exchange rate variance across different currencies. Note that the influence is not necessarily through the trade channel, as the currencies of two major trading partners of China, Brazil and Japan, do not have a strong and stable response to the growth shocks when compared with others.

The orthogonal shocks to China's import or the US monetary policy do not have strong impact on the exchange rate movements. That said, the monetary policy shocks are nonnegligible before 2006, primarily for advanced economies. The importance of China's import shocks peaks after China joined WTO, accounting for $10-20\%$ of the variance across countries.

3.4 An Interpretation of Impulse Responses

The economic rationale for the above results is by all means desirable. To interpret the results, in Figure 5 we firstly set out the time-varying uncertainty in the fundamentals estimated from our TVP-FAVAR model. We find that the volatility of global oil prices and China's industrial production has risen significantly since the global financial crisis, while the monetary policy shocks to the US, the euro area and Japan are relatively stable in our sample period. The impact of joining WTO on China's import is very high, as the volatility has increased by four times since joining.

Figures 6 and 7 plot the impulse responses of log exchange rates to one standard deviation shocks (to fundamentals) for selected currencies, which helps understand how these shocks drive the exchange rate fluctuations. In the following we display the impact of oil prices, China's industrial production and China's import during four periods: 2001:11 (before China joined the WTO), 2007:06 (after China's 2005 exchange rate reform), 2008:10 (during the global financial crisis) and 2015:12 (China's economic slowdown), and discuss the underlying economic mechanism.

In the previous section, we find the global oil prices start to spark after 2005, which is again confirmed by Figures 6 and 7. The responses to oil price shocks are strong and quite stable across countries from 2007 to 2008, but are weak in 2001. The strong time variability is consistent with Chen, Rogoff and Rossi (2010), who reveal strong evidence in favor of a time-varying relationship between exchange rates and commodity prices. During the 2007-2008 period, the exchange rates respond negatively to oil

[11] A complement to the classical trade channel implied by the PPP theory is a channel about investor expectations, which means global (nominal) exchange rates can react quickly to nominal oil prices through the adjustment in market expectations about the global economic condition. This argument parallels the finding of Kilian (2009) that real oil prices are driven primarily by global commodity demand shocks from 2005 to 2008.

price shocks, peaking in the medium term (around 24 months). This mechanism can be explained by the standard purchasing power parity model, in which commodity price shocks can be considered as terms of trade fluctuations, through a channel similar to the Balassa-Samuelson effect (Balassa (1964) and Samuelson (1964)).[12] The exchange rate behavior at the end of our sample period (2015:12) changes substantially, except for the Japanese Yen. For most of the countries the exchange rate reacts swiftly to oil price shocks in 2015.[13]

Regarding the shocks to China's growth, the impact on nominal exchange rates improves remarkably after the financial crisis. The impulse responses do not vary much across currencies. Moreover, the impulse responses of each currency are quite similar in terms of the magnitude and the pattern for 2008:10 and 2015:12, except that, for the latter period, the shocks are more persistent. There is a common pattern of overshooting in two years for all countries. These effects do not violate the PPP theory, but we suspect that the trade channel through which China's growth affects the exchange rates only plays a limited role. On the one hand, when comparing the impulse responses in 2007:06 to that in 2008:10, it is difficult to explain why the impact on exchange rates increases so much in only one year. In particular, the importance of China's growth increased rapidly before a sharp decrease in China's import in 2008, which means the changes in exchange rates probably originated from the changes in investors' expectations. On the other hand, the influence of China's growth is fast and stable for different currencies, even though China may not be the major trade partner of all these countries. Moreover, the impact of China's import is small when compared with China's growth, which is in sharp contrast to the argument that the trade channel is the major channel.

The uncertainty in global oil prices and China's growth has increased sharply since the financial crisis, which helps explain the magnitude of exchange rate fluctuations caused by these shocks. However, how to explain the rapid response of exchange rates to the latest shocks? Under the home bias assumption,[14] a demand shift biased toward the domestic good raises the price of the home good relative to that of the foreign (terms of trade), thereby appreciating the exchange rate, and vice versa. An alternative, but potentially more plausible explanation, is to interpret these shocks as investors' demand shocks, which can influence the nominal exchange rates mainly by capital flows. As suggested by Pavlova and Rigobon (2007), an underlying source can produce cross-country spillovers or comovement in currency markets, when considering substitution effects among currency pairs. In particular, by accounting for time-varying parameters, our model presents empirical evidence that China's growth significantly affects nominal exchange rate movements across different countries in the past five years. The rapid response of exchange rates to this shock is more consistent with the movements in capital

[12] An increase in the world price of a country's commodity exports will exert upward pressure on its real exchange rate, through its effect on wages and the demand for non-traded goods. In the presence of nominal price rigidities, the nominal exchange rate, rather than prices, will need to appreciate to restore the efficient relative price facing a positive price shock.

[13] This observation seems more consistent with the changes in investor expectations about the global commodity demand, which we have discussed in the last section.

[14] The agent has preference bias towards the home good.

flows, for example, income effects or an investment channel. To the best of our knowledge, the finding is new to the literature.

4 Robustness

4.1 A Simplified Model with Core Fundamentals

The previous sections have indicated that global oil prices and China's growth are two core fundamentals that contribute to most of the variation in exchange rates. To verify this point, we consider a smaller TVP-FAVAR with only two core fundamentals and five common factors. Note that in the factor augmented system, we always use five factors in order to account for most of the variance of log exchange rates. Moreover, as suggested by Bernanke, Boivin and Eliasz (2005), using more factors is important to properly identify the underlying transmission mechanism.

Using the smaller TVP-FAVAR, we have quantitatively similar results. As shown in Figure 8, two core fundamentals account for large fractions of the variance of different currencies. Therefore, we are convinced that the shocks to these two fundamentals are indeed dominant sources in driving global exchange rates.[15] In fact, with five latent factors we are able to recover the dynamic system insensitive to the choice of variables, as relevant information implied in exchange rates is incorporated. The FAVAR literature has indicated that the factor augmentation is useful in mitigating omitted variable bias or the non-fundamentalness problem; this argument also applies in this context.

4.2 Generalized Forecast Error Variance Decomposition

One novel finding in this paper is that China's growth is very important for exchange rate movements in the past five years. One may suspect that this conclusion is sensitive to the ordering of variables as we use Cholesky decomposition to identify structural shocks. To ensure the robustness, we need to consider an identification method that is not sensitive to the ordering of variables.

Proposed by Koop, Pesaran and Potter (1996), the generalized variance decomposition is invariant to the ordering of the variables in the VAR.[16] The sums of forecast error variance contributions are not necessarily unity, so here we calculate the normalized weights, which add up to unity following Diebold and Yilmaz (2014). Table 9 shows the results from the generalized variance decomposition. This decomposition scheme actually strengthens the previous results, suggesting that a different ordering in the Cholesky decomposition is highly unlikely to alter our new finding. The contribution of China's growth is very distinctive, especially in the past five years. At each time point, the fractions are even more consistent across countries.

[15] More details about variance decomposition and impulse responses are available upon request.

[16] We encourage readers to consult the original papers for motivation and background.

4.3 Parameter Uncertainty

In this paper we conduct a Bayesian analysis allowing for parameter uncertainty. In specific, the coefficients of the VAR system are uncertain and follow a normal distribution. Therefore, we need to consider whether the contribution of China's growth is robust to the uncertainty in parameters.

We conduct the following robustness check. At each point in time, we generate 1000 draws from the estimated distribution. For each draw, we use the generalized variance decomposition to decompose the shock to China's growth. By doing so, we can easily calculate the median and the 90% credible interval for the average of the fraction explained by China's growth shock over a sample period. Table 4 shows the contribution of the shock to China's growth is highly consistent for all countries in each of the sample periods we consider. The 90% credible intervals are reasonably tight. Based on this evidence, our new finding is very robust: The contribution of China's growth shock to global exchange rates is statistically significant.

5 Conclusion

This paper explores the movements in US dollar-based nominal exchange rates across 39 regions and potential sources that drive the comovement. Building upon a factor structure, we identify five exchange rate common factors that capture 95% of the variance of global exchange rates. We further analyze the evolution of exchange rate dynamics using a TVP-FAVAR model, which shows that our fundamentals have become the main driver of exchange rate movements in the past ten years. Our results reveal that uncertainty in global oil prices and China's growth has increased substantially since the global financial crisis. Moreover, the increased uncertainty is of essence in understanding why global exchange rate fluctuations can be largely explained by fundamentals. We find that global oil prices are extremely important during the global financial crisis, while China's growth dominates during the past five years. In addition to the trade channel implied by the PPP theory, we link unexpected changes in China's growth to shocks to global investors' demand for exchange rate assets. In this paper we underline the impact of China on US exchange rates, but this does not mean other factors, for example, US industrial production and VIX, are unimportant. A more comprehensive analysis can be done by considering a richer set of variables, and we leave this direction for further research.

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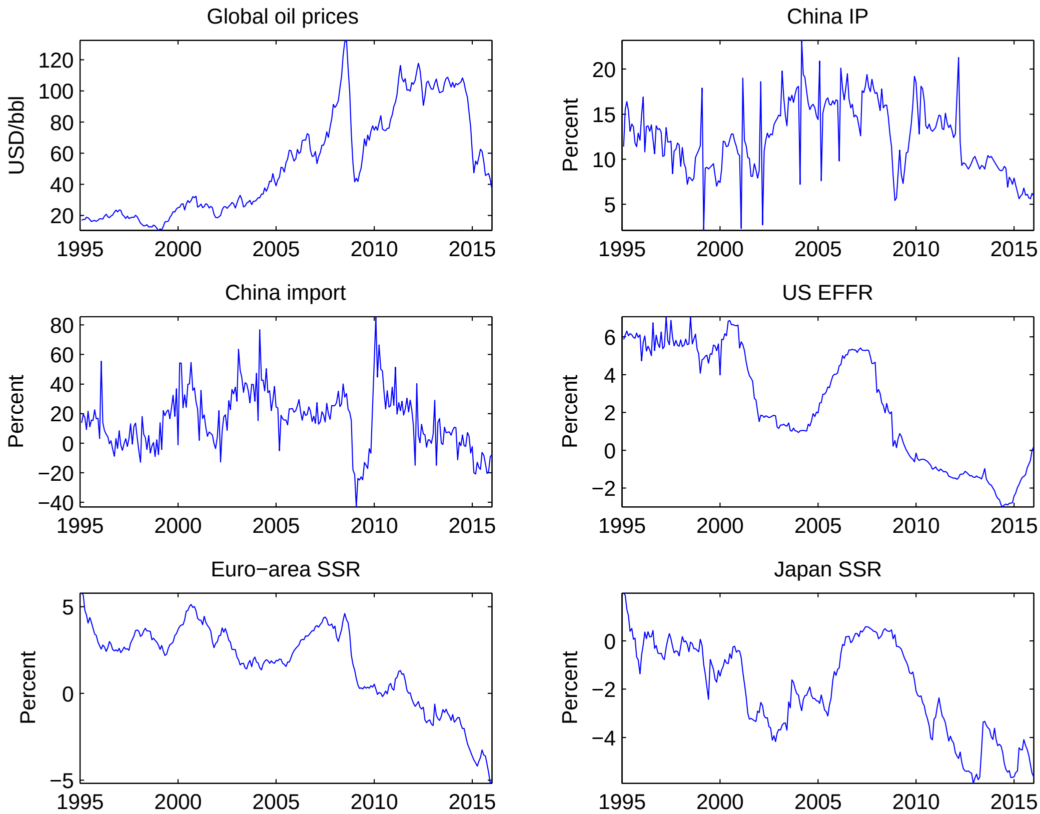
Appendix A Data Appendix

Figure A.1: Charts of fundamentals



Notes:
This figure displays the fundamental variables: global oil price, China's industrial production, China's import, US EFFR, Euro-area SSR and Japan SSR.

Appendix B Econometric Method

We conduct the Kalman filter estimation for the state space model with Eq. (2.5) and Eq. (2.6):

$$Z_t = X_t \beta_t + v_t,$$

$$\beta_{t+1} = \beta_t + \mu_t,$$

where Z_t is an $n \times 1$ vector of variables, $X_t = I_n \otimes \left[Z'_{t-1}, ..., Z'_{t-p}\right]'$, β_t are VAR coefficients, $v_t \sim N(0, \Sigma_t)$ with Σ_t an $n \times n$ covariance matrix, and $\mu_t \sim N(0, Q_t)$.

Given that all the data from time 1 to t denoted as D_t, the Bayesian solution to updating about the coefficients β_t takes the form

$$\begin{aligned} p(\beta_t | D_t) &\propto \mathbf{L}(\beta_t; Z_t) \, p(\beta_t | D_{t-1}), \\ p(\beta_t | D_{t-1}) &= \int_{\wp} p(\beta_t | D_{t-1}, \beta_{t-1}) \, p(\beta_{t-1} | D_{t-1}) \, d\beta_{t-1}, \end{aligned}$$

where $\wp$ is the support of β_{t-1}. The solution to this problem can be defined using a Bayesian generalization of the typical Kalman filter recursions. Given an initial condition $\beta_0 \sim N(m_0, \Phi_0)$ we can define (cf. West and Harrison (1997)):[17]

1. Posterior at time $t-1$

$$\beta_{t-1} | D_{t-1} \sim N(m_{t-1}, \Phi_{t-1}),$$

2. Prior at time t

$$\beta_t | D_{t-1} \sim N\left(m_{t|t-1}, \Phi_{t|t-1}\right),$$

where $m_{t|t-1} = m_{t-1}$ and $\Phi_{t|t-1} = \Phi_{t-1} + Q_t$.

3. Posterior at time t

$$\beta_t | D_t \sim N(m_t, \Phi_t), \tag{B.1}$$

where $m_t = m_{t|t-1} + \Phi_{t|t-1} X'_t (V_t^{-1})' \widetilde{v}_t$ and $\Phi_t = \Phi_{t|t-1} - \Phi_{t|t-1} X'_t (V_t^{-1})' X_t \Phi'_{t|t-1}$, with $\widetilde{v}_t = Z_t - X_t m_{t|t-1}$ the prediction error and $V_t = X_t \Phi_{t|t-1} X'_t + \Sigma_t$ its covariance matrix.

Following the discussion above, we need to find estimates for Σ_t and Q_t in the formulas above. We define the time t prior for Σ_t to be

$$\Sigma_t | D_{t-1} \sim iW(S_{t-1}, \delta n_{t-1}), \tag{B.2}$$

while the posterior takes the form

$$\Sigma_t | D_t \sim iW(S_t, n_t),$$

where $n_t = \delta n_{t-1} + 1$ and $S_t = \delta S_{t-1} + n_t^{-1}\left(S_{t-1}^{0.5} V_{t-1}^{-0.5} \widetilde{v}_{t|t-1} \widetilde{v}'_{t|t-1} V_{t-1}^{-0.5} S_{t-1}^{0.5}\right)$. In this formulation, v_t is replaced with the one-step ahead prediction error $\widetilde{v}_{t|t-1} = Z_t - m_{t|t-1} X_t$. The estimate for Σ_t is approximately equivalent numerically to the Exponentially Weighted Moving Average (EWMA) filter

[17] For a parameter θ we use the notation $\theta_{t|s}$ to denote the value of parameter θ_t given data up to time s (i.e. D_s) for $s > t$ or $s < t$. For the special case where $s = t$, I use the notation $\theta_{t|t} = \theta_t$

$\hat{\Sigma}_t = \delta\hat{\Sigma}_{t-1} + (1-\delta)\, v_t v_t'$. The parameter δ is the decay factor, where for $0 < \delta < 1$. In fact, Koop and Korobilis (2013) apply such a scheme directly to the covariance matrix Σ_t, which results in a point estimate. In this case, by applying variance discounting methods to the scale matrix S_t, we are able to approximate the full posterior distribution of Σ_t.

Regarding Q_t, we use the forgetting factor approach in Koop and Korobilis (2013); see also West and Harrison (1997) for a similar discounting approach. In this case Q_t is set to be proportionate to the filtered covariance $\Phi_{t-1} = cov\,(\beta_{t-1}|D_{t-1})$ and takes the following form

$$Q_t = \left(\Lambda^{-1} - 1\right)\Phi_{t-1}, \tag{B.3}$$

for a given forgetting factor Λ.

The brief interpretation of forgetting factors is that they control how much "recent past" information will be used. With the exponential decay for the forgetting factors, if it takes a value of 0.99, the information 24 periods ago (two years for monthly data) receives around 80% as much weight as the information of last period. If the forgetting factor takes 0.95, then forecast performance 24 periods ago receives only about 30% as much weight. The similar implication holds for the decay factor. Following Koop and Korobilis (2013), δ and Λ are calibrated to values close to 1 to ensure stability, which are 0.94 and 0.99, respectively. δ is set to a smaller value while ensuring the stability of the system, as it can provide a higher cumulative sum of predictive log-likelihood.

Appendix C Structural Interpretation about the Factor Structure

Following and extending Engel and West (2005) and Chen, Rogoff and Rossi (2010), the present-value model for the log nominal exchange rate $s_{t,i}$ of country i at time t is given in the following form:

$$s_{t,i} = \gamma_i^G \sum_{j=0}^{\infty} \psi_i^j E_t(z_{t+j}^G | I_t) + \gamma_i \sum_{j=0}^{\infty} \phi_i^j E_t(z_{t+j,i} | I_{t,i}), \tag{C.1}$$

where γ, ψ and ϕ are parameters dictated by the specific structural model, E_t is the expectation operator given a specific information set I_t or $I_{t,i}$, and z_t^G and $z_{t,i}$ collect global and country-specific fundamentals, respectively. This model implies the cross section of exchange rates contains the information of global fundamentals, although we have not specified what would be the fundamentals at this stage.

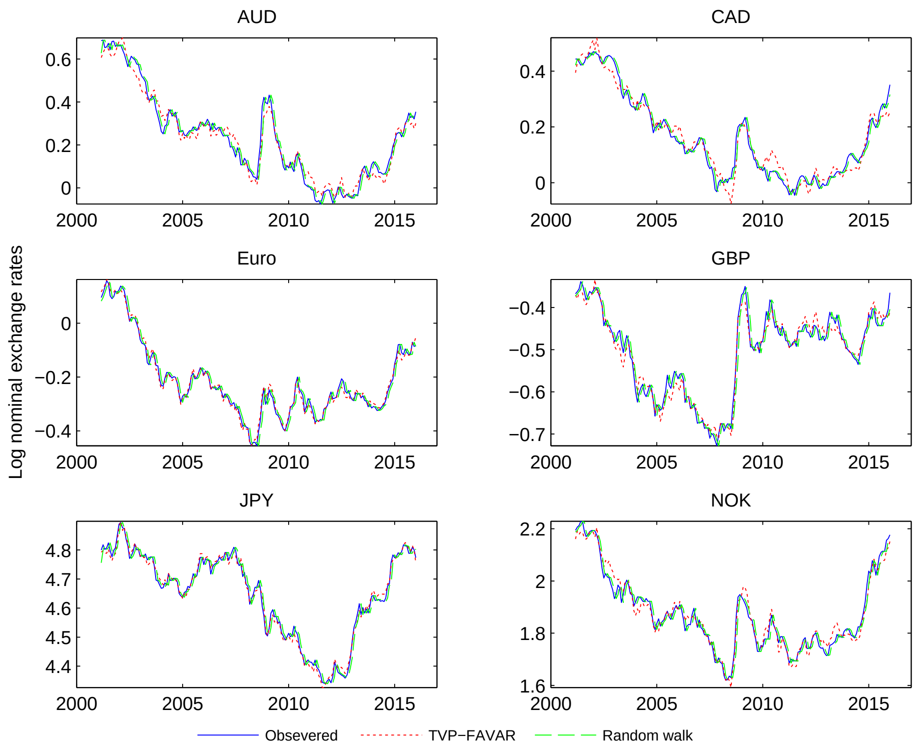
Following Engel and West (2006), a structural present-value model can be simplified, if we assume the underlying dynamics about the fundamentals are described by VAR forecasting equations. In particular, we can show the above present-value model is equivalent to a reduced-form representation in which log nominal exchange rates are linear in the global information set (factors). In this paper, our focus is not on the structural parameters and hence they will not be identified in our analysis.

Appendix D Additional Results

D.1 Comparison with the Random Walk Model

Our focus in this paper is to economically explain the movements of US dollar exchange rates, which cannot be done using a random walk model. That said, it is informative to compare the TVP-FAVAR to the random walk model, in order to evaluate how well our approach models and forecasts exchange rates. Figure D.1 shows the TVP-FAVAR and the random walk track the observed exchange rates well, but the TVP-FAVAR tends to predict higher variance of exchange rate innovations.[18] The random walk model, despite its lack of economic content, has better fits because of the high persistence of exchange rates. This observation is consistent with the empirical evidence in the previous literature that it is difficult to outperform the random walk, as least in the context of point forecasts. However, interest centers on more than just point forecasts when it comes to managing exchange rate risk, as suggested in Sarno and Valente (2005) and Rossi (2013). Economic agents may have loss functions that do not depend only on the realizations of future values of variables but also on the risk of these variables. In this case, agents are interested in forecasting not only the mean but also the variance, and the full predictive densities matter more than only point forecasts. Therefore, we go beyond point forecasts by evaluating the whole predictive density of a model specification.

Figure D.1: TVP-FAVAR vs. random walk



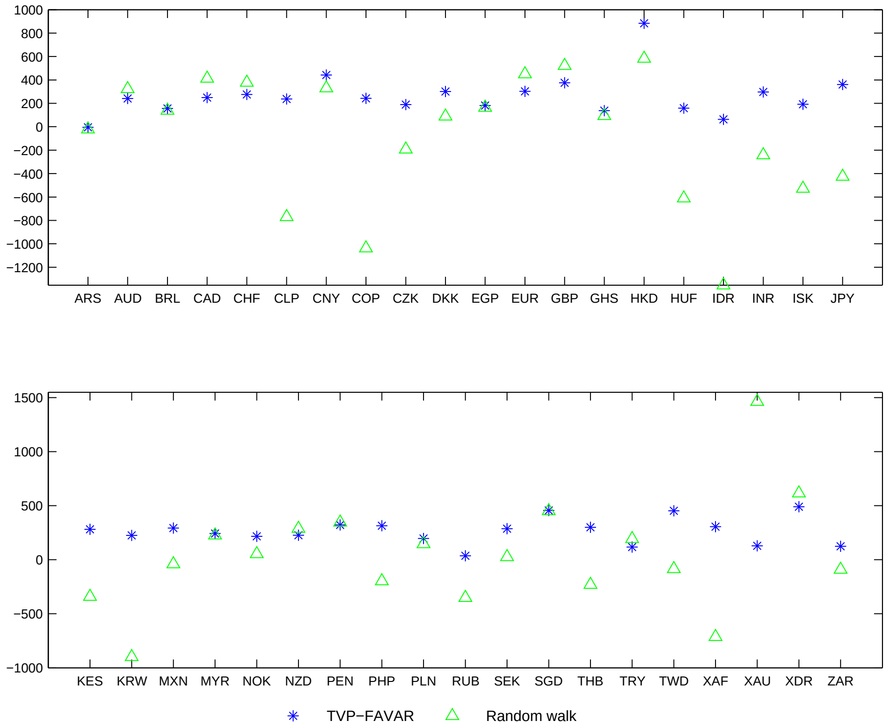
Notes:
This figure compares the fits of the TVP-FAVAR and the random walk model for six US dollar exchange rates. The estimates of the random walk model are one-month lagged values of the observed nominal exchange rates.

The evaluation of one-month ahead density forecasts is shown in Figure D.2. At each point in time, we use the conditional estimates of the TVP-FAVAR parameters assuming the future values are constant (unbiased forecasts), and the predictive likelihood function can be constructed using the estimated parameters.[19] In terms of the cumulative sum of predictive log-likelihood, the TVP-FAVAR outperforms

[18] We set out six currency pairs for the sake of brevity, but the results are similar for other currencies.
[19] Our implementation here is not a truly out-of-sample exercise because the cross-sectional parameters a_i^* are estimated

the random walk benchmark for two thirds of the currency pairs, and is similar to the random walk for the rest of the pairs (except for XAU). The TVP-FAVAR has stable forecast performance and positive cumulative sums in general. This suggests economic agents using the TVP-FAVAR are potentially better off in the risk-return tradeoff, as they correctly perceive the level of variation in exchange rates and are not likely to have extreme portfolio positions.[20]

Figure D.2: Cumulative sum of predictive log-likelihood



Notes:
This figure compares the one-month ahead density forecasts of the TVP-FAVAR and the random walk model for 39 US dollar exchange rates. The cumulative sum of predictive log-likelihood is calculated based on conditional forecasts, and the forecasting period is from 2000:12 to 2015:12. The conditional variance of the TVP-FAVAR is model-implied, and the conditional variance of the random walk is estimated recursively using exchange rate observations up to and including the time when forecasts are made.

using the full sample to avoid small-sample bias. But time-series parameters in the TVP-FAVAR system are conditional estimates.

[20] See Sarno and Valente (2005) for details about the economic utility evaluation.

Table 1: Correlation between currencies and principal components

Currency		Correlation					$adjR^2$
		PC1	PC2	PC3	PC4	PC5	
Africa							
Central African Franc	XAF	0.94	0.13	0.25	0.00	-0.13	98.19%
S. African Rand	ZAR	-0.01	0.92	0.15	0.20	-0.01	90.94%
Kenyan Shilling	KES	-0.12	0.92	0.23	-0.02	-0.13	93.12%
Ghana Cedi	GHS	-0.39	0.90	0.07	0.10	-0.09	98.05%
Egyptian Pound	EGP	-0.52	0.78	-0.13	0.16	-0.14	93.65%
America							
Canadian Dollar	CAD	0.91	-0.25	0.06	0.06	0.02	90.16%
Peruvian New Sol	PEN	0.64	0.60	-0.39	-0.15	-0.08	94.28%
Chilean Peso	CLP	0.40	0.80	-0.16	-0.01	-0.12	84.34%
Colombian Peso	COP	0.20	0.90	-0.30	-0.10	-0.11	95.89%
Brazilian Real	BRL	0.16	0.89	-0.20	0.02	-0.22	90.97%
Mexican Peso	MXN	-0.40	0.87	0.05	0.09	0.10	93.82%
Argentine Peso	ARS	-0.56	0.75	0.00	0.24	-0.10	93.98%
Asia Pacific							
Australian Dollar	AUD	0.96	-0.04	-0.07	-0.04	0.06	92.41%
New Zealand Dollar	NZD	0.93	-0.02	0.05	-0.24	0.12	92.98%
Singapore Dollar	SGD	0.88	-0.01	-0.41	-0.20	0.05	97.51%
Japanese Yen	JPY	0.72	-0.03	-0.38	0.56	0.07	98.68%
Taiwan Dollar	TWD	0.50	0.63	-0.44	-0.10	0.29	93.34%
South Korean Won	KRW	0.39	0.64	0.10	-0.23	0.55	91.84%
Hong Kong Dollar	HKD	0.27	0.45	-0.41	-0.37	-0.39	72.60%
Chinese Renminbi	CNY	0.70	-0.54	-0.38	-0.18	-0.09	96.45%
Thai Baht	THB	0.68	0.52	-0.37	-0.18	0.17	93.50%
Malaysian Ringgit	MYR	0.53	0.68	-0.35	-0.06	0.25	93.01%
Philippines Peso	PHP	0.18	0.84	-0.40	-0.23	0.04	95.56%
Indonesian Rupiah	IDR	0.02	0.92	-0.16	-0.03	0.24	92.30%
Indian Rupee	INR	-0.12	0.90	0.26	0.25	0.01	94.52%
Europe							
Euro	EUR	0.94	0.13	0.25	0.00	-0.12	98.11%
Danish Krone	DKK	0.94	0.13	0.25	0.00	-0.12	97.98%
Czech Koruna	CZK	0.94	-0.24	0.13	0.02	-0.06	96.03%
Norwegian Krone	NOK	0.93	0.12	0.24	0.09	-0.01	93.41%
Swiss Franc	CHF	0.91	-0.28	-0.17	-0.15	-0.01	95.95%
Swedish Krona	SEK	0.91	0.23	0.20	-0.07	0.00	92.46%
Polish Zloty	PLN	0.78	0.47	0.19	-0.07	-0.05	86.08%
Hungarian Forint	HUF	0.53	0.75	0.26	0.04	-0.02	90.94%
British Pound	GBP	0.35	0.09	0.89	-0.07	0.08	93.09%
Iceland Krona	ISK	-0.32	0.64	0.63	0.02	0.16	94.10%
Russian Ruble	RUB	-0.05	0.95	-0.06	-0.09	-0.12	93.74%
Turkish Lira	TRY	-0.17	0.96	-0.13	-0.05	-0.06	97.80%
Others							
IMF SDR	XDR	0.97	0.02	0.19	0.13	-0.02	98.59%
Gold	XAU	0.84	-0.45	-0.24	-0.08	-0.01	97.61%

Notes: This table summarizes the correlation between each currency and five principal components (I_t) extracted using the principal component method. The last column reports the adjusted R^2 from the regression of each currency on the five principal components (PC1-5). This table reports 39 currencies (including the currency value of the SDR and the price of gold) and the US Dollar is used as the base currency. The sample period is 1995:01-2015:12.

Table 2: Contribution of shocks to variance of exchange rates (2001:01–2009:12)

		Oil Price	China IP	China Import	US EFFR	Euro-area SSR	Japan SSR
Argentine Peso	ARS	0.43	0.09	0.13	0.10	0.01	0.05
Australian Dollar	AUD	0.36	0.08	0.07	0.08	0.02	0.06
Brazilian Real	BRL	0.30	0.05	0.07	0.03	0.05	0.04
Canadian Dollar	CAD	0.43	0.11	0.08	0.08	0.02	0.06
Swiss Franc	CHF	0.38	0.09	0.08	0.08	0.02	0.06
Chilean Peso	CLP	0.34	0.05	0.10	0.05	0.04	0.04
Chinese Renminbi	CNY	0.35	0.12	0.08	0.06	0.02	0.07
Colombian Peso	COP	0.31	0.06	0.05	0.03	0.04	0.04
Czech Koruna	CZK	0.39	0.08	0.09	0.10	0.03	0.06
Danish Krone	DKK	0.37	0.07	0.07	0.09	0.01	0.07
Egyptian Pound	EGP	0.41	0.09	0.14	0.09	0.01	0.05
Euro	EUR	0.37	0.07	0.06	0.09	0.01	0.07
British Pound	GBP	0.36	0.08	0.06	0.08	0.02	0.06
Ghana Cedi	GHS	0.29	0.06	0.07	0.02	0.04	0.04
Hong Kong Dollar	HKD	0.24	0.04	0.06	0.03	0.07	0.07
Hungarian Forint	HUF	0.36	0.08	0.08	0.07	0.02	0.06
Indonesian Rupiah	IDR	0.34	0.07	0.07	0.06	0.02	0.07
Indian Rupee	INR	0.30	0.09	0.05	0.05	0.03	0.08
Iceland Krona	ISK	0.34	0.10	0.07	0.08	0.03	0.06
Japanese Yen	JPY	0.20	0.06	0.07	0.07	0.04	0.09
Kenyan Shilling	KES	0.31	0.06	0.06	0.03	0.04	0.05
South Korean Won	KRW	0.35	0.08	0.06	0.06	0.02	0.07
Mexican Peso	MXN	0.32	0.08	0.08	0.06	0.03	0.06
Malaysian Ringgit	MYR	0.34	0.07	0.08	0.06	0.02	0.07
Norwegian Krone	NOK	0.37	0.09	0.10	0.09	0.01	0.05
New Zealand Dollar	NZD	0.37	0.08	0.07	0.08	0.02	0.06
Peruvian New Sol	PEN	0.34	0.07	0.06	0.05	0.03	0.05
Philippines Peso	PHP	0.32	0.06	0.05	0.04	0.03	0.05
Polish Zloty	PLN	0.37	0.08	0.06	0.06	0.03	0.05
Russian Ruble (TOM)	RUB	0.31	0.06	0.06	0.03	0.04	0.05
Swedish Krona	SEK	0.36	0.08	0.06	0.08	0.02	0.06
Singapore Dollar	SGD	0.36	0.07	0.05	0.05	0.02	0.06
Thai Baht	THB	0.34	0.07	0.06	0.06	0.02	0.07
Turkish Lira	TRY	0.30	0.06	0.05	0.03	0.04	0.05
Taiwan Dollar	TWD	0.33	0.08	0.06	0.06	0.02	0.07
Central African Franc	XAF	0.37	0.07	0.06	0.09	0.01	0.07
Gold	XAU	0.39	0.10	0.07	0.08	0.03	0.06
IMF SDR	XDR	0.36	0.08	0.07	0.10	0.02	0.08
S. African Rand	ZAR	0.32	0.08	0.08	0.06	0.03	0.05

Notes: This table reports the fractions of the forecast error variance, at the 120-month horizon, explained by shocks to six fundamentals, respectively. For each country, the fractions are averaged over the sample period 2001:01-2009:12.

Table 3: Contribution of shocks to variance of exchange rates (2010:01–2015:12)

		Oil Price	China IP	China Import	US EFFR	Euro-area SSR	Japan SSR
Argentine Peso	ARS	0.21	0.50	0.04	0.01	0.02	0.02
Australian Dollar	AUD	0.27	0.44	0.03	0.01	0.02	0.02
Brazilian Real	BRL	0.27	0.26	0.02	0.01	0.02	0.02
Canadian Dollar	CAD	0.28	0.46	0.04	0.01	0.03	0.02
Swiss Franc	CHF	0.26	0.44	0.04	0.01	0.02	0.02
Chilean Peso	CLP	0.35	0.26	0.03	0.01	0.02	0.02
Chinese Renminbi	CNY	0.15	0.62	0.04	0.01	0.01	0.01
Colombian Peso	COP	0.33	0.27	0.03	0.01	0.01	0.02
Czech Koruna	CZK	0.24	0.47	0.04	0.01	0.03	0.02
Danish Krone	DKK	0.24	0.46	0.03	0.01	0.02	0.02
Egyptian Pound	EGP	0.20	0.52	0.04	0.01	0.02	0.02
Euro	EUR	0.24	0.46	0.03	0.01	0.02	0.02
British Pound	GBP	0.21	0.51	0.04	0.01	0.02	0.02
Ghana Cedi	GHS	0.17	0.47	0.05	0.01	0.01	0.01
Hong Kong Dollar	HKD	0.25	0.18	0.07	0.01	0.05	0.02
Hungarian Forint	HUF	0.24	0.47	0.03	0.01	0.02	0.02
Indonesian Rupiah	IDR	0.25	0.46	0.02	0.01	0.02	0.02
Indian Rupee	INR	0.21	0.52	0.02	0.01	0.03	0.02
Iceland Krona	ISK	0.19	0.56	0.04	0.01	0.02	0.01
Japanese Yen	JPY	0.22	0.34	0.06	0.01	0.05	0.04
Kenyan Shilling	KES	0.25	0.42	0.03	0.01	0.02	0.01
South Korean Won	KRW	0.24	0.48	0.03	0.01	0.02	0.01
Mexican Peso	MXN	0.24	0.46	0.03	0.01	0.02	0.01
Malaysian Ringgit	MYR	0.27	0.41	0.03	0.01	0.02	0.02
Norwegian Krone	NOK	0.26	0.46	0.03	0.01	0.03	0.02
New Zealand Dollar	NZD	0.25	0.46	0.03	0.01	0.02	0.02
Peruvian New Sol	PEN	0.30	0.36	0.03	0.01	0.02	0.02
Philippines Peso	PHP	0.29	0.33	0.02	0.01	0.02	0.02
Polish Zloty	PLN	0.27	0.44	0.03	0.01	0.03	0.02
Russian Ruble (TOM)	RUB	0.29	0.35	0.03	0.01	0.01	0.01
Swedish Krona	SEK	0.26	0.45	0.03	0.01	0.02	0.02
Singapore Dollar	SGD	0.30	0.37	0.03	0.01	0.02	0.02
Thai Baht	THB	0.27	0.41	0.03	0.01	0.02	0.02
Turkish Lira	TRY	0.26	0.37	0.03	0.01	0.01	0.02
Taiwan Dollar	TWD	0.27	0.41	0.03	0.01	0.02	0.02
Central African Franc	XAF	0.24	0.46	0.03	0.01	0.02	0.02
Gold	XAU	0.24	0.46	0.04	0.01	0.03	0.02
IMF SDR	XDR	0.24	0.47	0.04	0.01	0.03	0.03
S. African Rand	ZAR	0.22	0.49	0.03	0.01	0.02	0.02

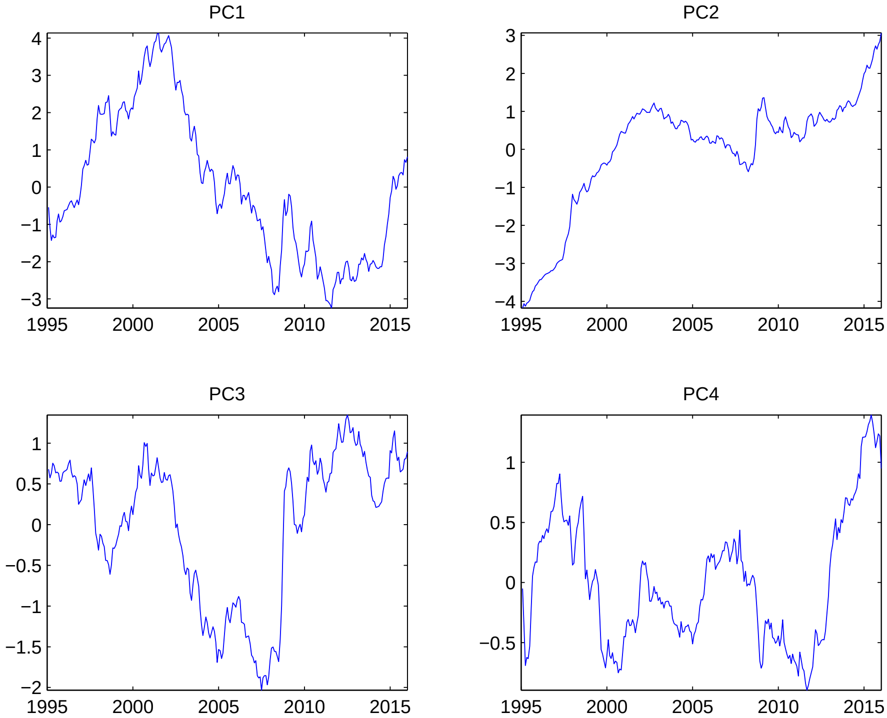
Notes: This table reports the fractions of the forecast error variance, at the 120-month horizon, explained by shocks to six fundamentals, respectively. For each country, the fractions are averaged over the sample period 2010:01-2015:12.

Table 4: Contribution of China's growth shock to variance of exchange rates

		2001 : 01 − −2009 : 12		2010 : 01 − −2015 : 12	
		Median	90% credible interval	Median	90% credible interval
Argentine Peso	ARS	0.187	[0.158,0.219]	0.721	[0.675,0.761]
Australian Dollar	AUD	0.187	[0.157,0.217]	0.721	[0.676,0.762]
Brazilian Real	BRL	0.187	[0.157,0.217]	0.718	[0.675,0.758]
Canadian Dollar	CAD	0.187	[0.158,0.217]	0.721	[0.675,0.763]
Swiss Franc	CHF	0.187	[0.157,0.217]	0.720	[0.676,0.762]
Chilean Peso	CLP	0.188	[0.157,0.217]	0.718	[0.674,0.760]
Chinese Renminbi	CNY	0.187	[0.159,0.217]	0.721	[0.676,0.763]
Colombian Peso	COP	0.188	[0.157,0.217]	0.718	[0.673,0.759]
Czech Koruna	CZK	0.186	[0.158,0.217]	0.722	[0.676,0.763]
Danish Krone	DKK	0.187	[0.157,0.216]	0.721	[0.678,0.761]
Egyptian Pound	EGP	0.187	[0.159,0.217]	0.721	[0.676,0.761]
Euro	EUR	0.187	[0.157,0.216]	0.721	[0.679,0.761]
British Pound	GBP	0.187	[0.159,0.219]	0.722	[0.678,0.761]
Ghana Cedi	GHS	0.188	[0.158,0.217]	0.719	[0.673,0.760]
Hong Kong Dollar	HKD	0.188	[0.157,0.216]	0.718	[0.674,0.759]
Hungarian Forint	HUF	0.187	[0.157,0.216]	0.722	[0.677,0.762]
Indonesian Rupiah	IDR	0.187	[0.157,0.218]	0.722	[0.677,0.759]
Indian Rupee	INR	0.188	[0.159,0.217]	0.722	[0.677,0.762]
Iceland Krona	ISK	0.187	[0.159,0.219]	0.723	[0.680,0.761]
Japanese Yen	JPY	0.187	[0.159,0.218]	0.719	[0.676,0.758]
Kenyan Shilling	KES	0.187	[0.158,0.217]	0.720	[0.673,0.761]
South Korean Won	KRW	0.187	[0.159,0.218]	0.722	[0.675,0.761]
Mexican Peso	MXN	0.187	[0.159,0.216]	0.720	[0.675,0.761]
Malaysian Ringgit	MYR	0.187	[0.158,0.217]	0.721	[0.676,0.760]
Norwegian Krone	NOK	0.187	[0.157,0.216]	0.722	[0.676,0.764]
New Zealand Dollar	NZD	0.187	[0.158,0.216]	0.722	[0.677,0.762]
Peruvian New Sol	PEN	0.187	[0.156,0.217]	0.720	[0.674,0.759]
Philippines Peso	PHP	0.187	[0.158,0.217]	0.718	[0.675,0.759]
Polish Zloty	PLN	0.187	[0.157,0.216]	0.721	[0.676,0.760]
Russian Ruble (TOM)	RUB	0.187	[0.157,0.217]	0.718	[0.675,0.760]
Swedish Krona	SEK	0.187	[0.157,0.216]	0.722	[0.677,0.762]
Singapore Dollar	SGD	0.187	[0.159,0.217]	0.720	[0.676,0.761]
Thai Baht	THB	0.187	[0.159,0.217]	0.721	[0.677,0.760]
Turkish Lira	TRY	0.188	[0.157,0.217]	0.719	[0.674,0.760]
Taiwan Dollar	TWD	0.187	[0.158,0.216]	0.721	[0.673,0.759]
Central African Franc	XAF	0.187	[0.158,0.216]	0.721	[0.678,0.761]
Gold	XAU	0.187	[0.158,0.217]	0.721	[0.674,0.761]
IMF SDR	XDR	0.187	[0.158,0.216]	0.722	[0.677,0.762]
S. African Rand	ZAR	0.188	[0.159,0.216]	0.721	[0.676,0.761]

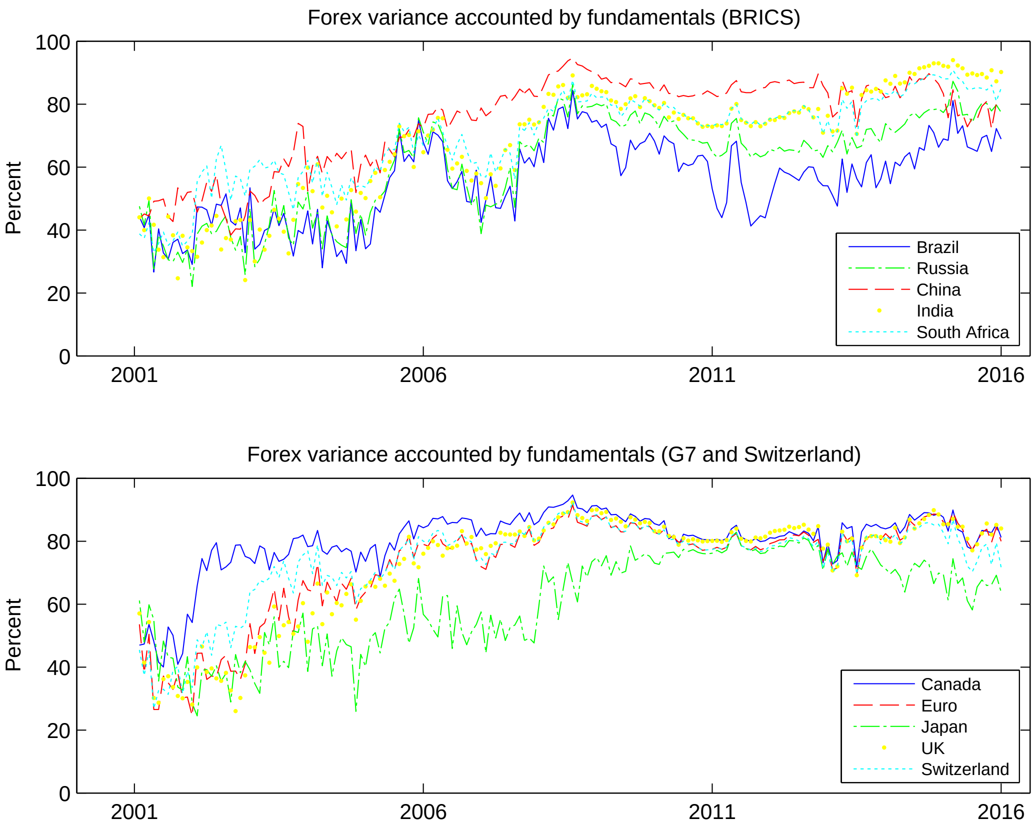
Notes: This table reports the fraction of the forecast error variance, at the 120-month horizon, explained by China's growth shock. The fractions are calculated based on the generalized variance decomposition method. For each country, the fractions are averaged over the specific sample period.

Figure 1: Principal components of currency pairs



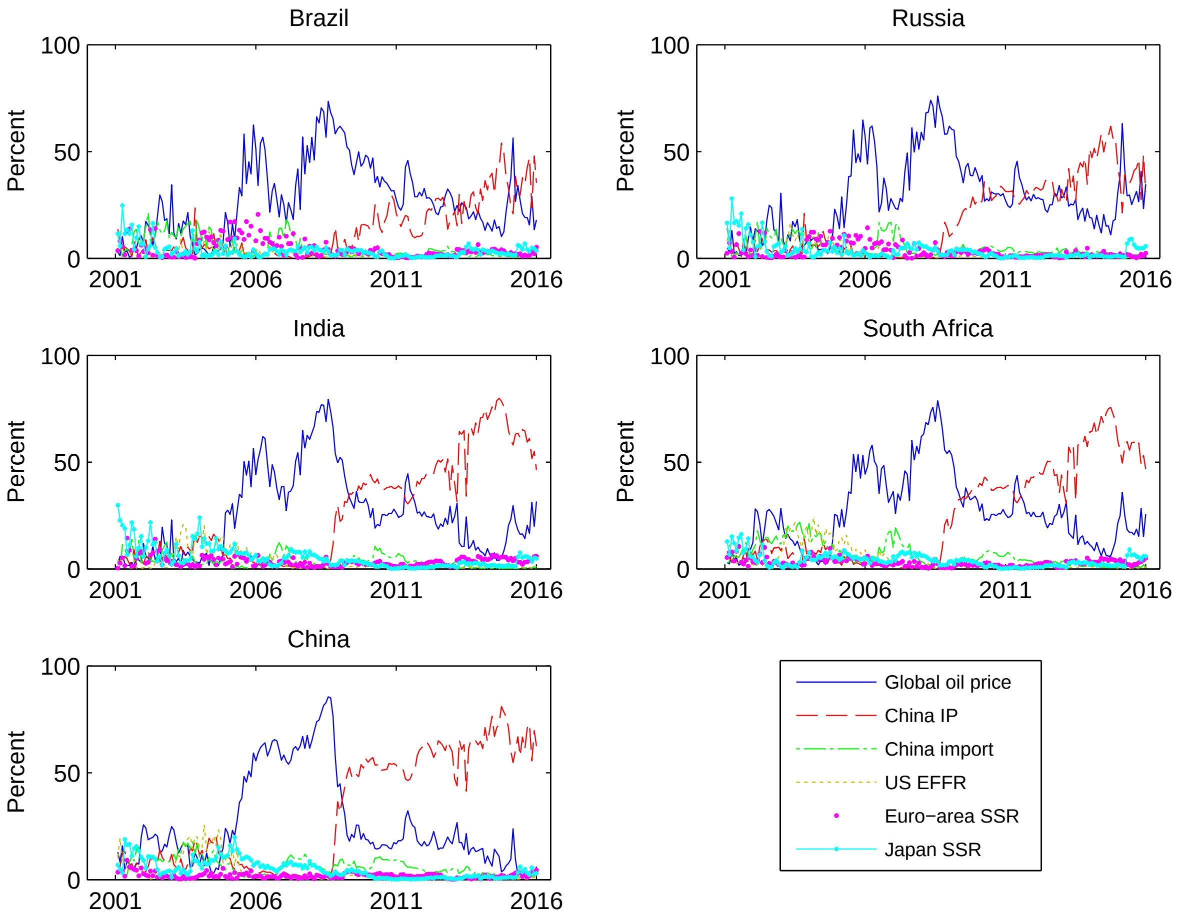
Notes:
This figure plots the first five principal components (I_t) of our currency pairs, as well as their most correlated pairs. The log nominal exchange rates are standardized for better illustration.

Figure 2: Foreign exchange variance accounted by fundamentals



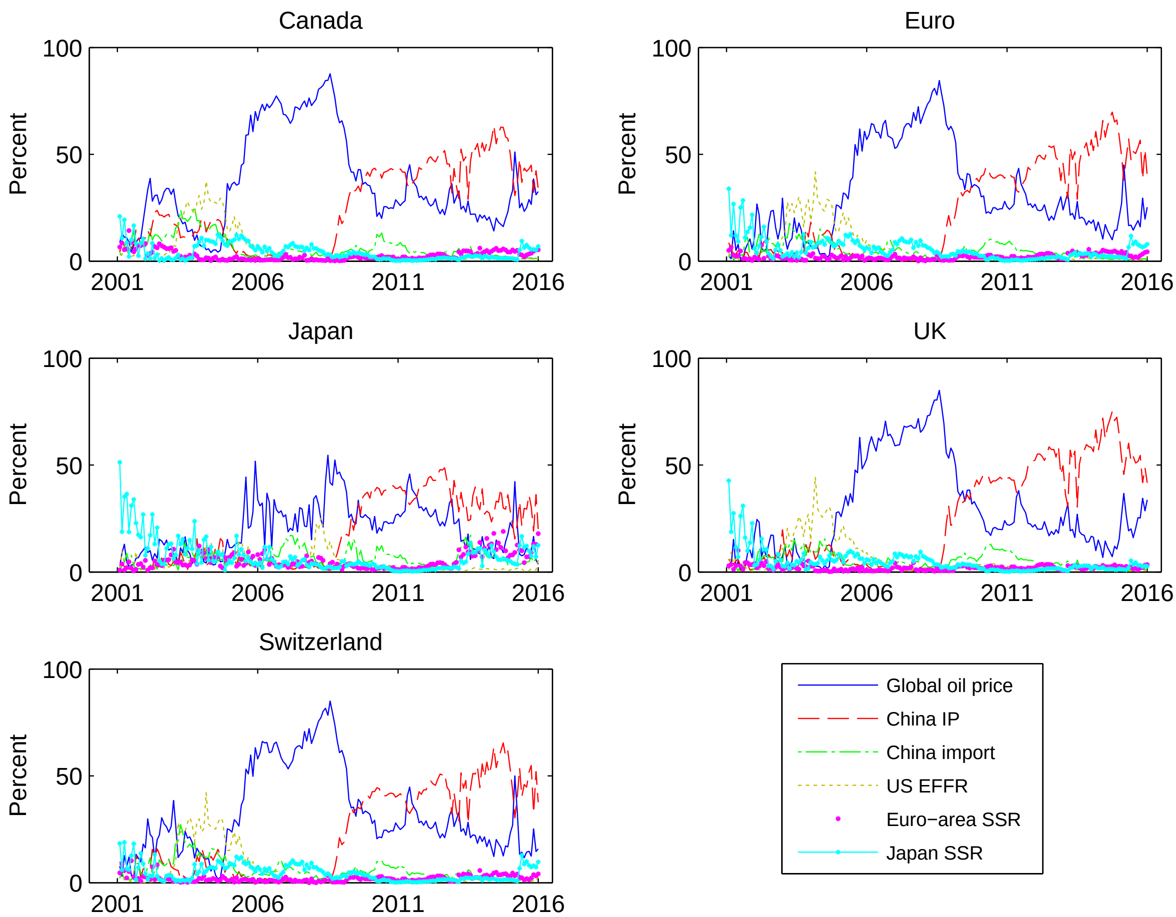
Notes:
This figure plots for each country the total fraction of 120-month-ahead forecast error variance of the foreign exchange (Forex) accounted by six fundamentals f_t we use in the TVP-FAVAR, i.e., the global oil price, China's industrial production, China's import, the US effective federal fund rate, and shadow short rates of the euro area and Japan. The upper chart displays the fractions of BRICS countries, and the lower chart displays the fractions of G7 countries and Switzerland. The decomposition is described in Equation (2.10).

Figure 3: Time-varying variance decomposition (BRICS)



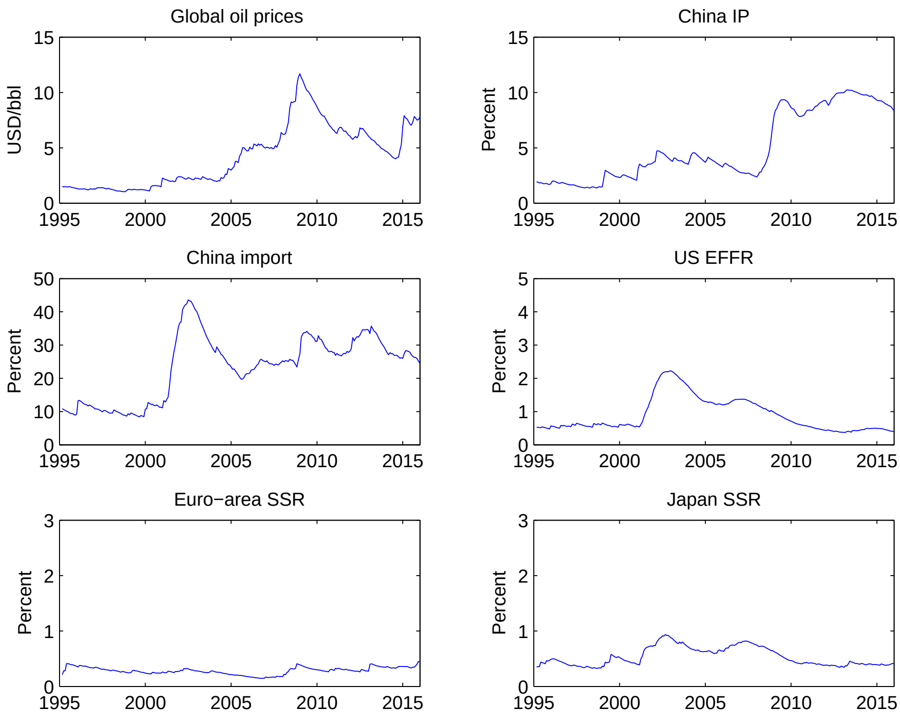
Notes:
This figure decomposes the 120-month-ahead forecast error variance of the foreign exchange accounted by fundamentals into six respective parts: the global oil price, China's industrial production, China's import, the US effective federal fund rate, and shadow short rates of the euro area and Japan. The countries reported are Brazil, Russia, India, China and South Africa (BRICS).

Figure 4: Time-varying variance decomposition (G7 and Switzerland)



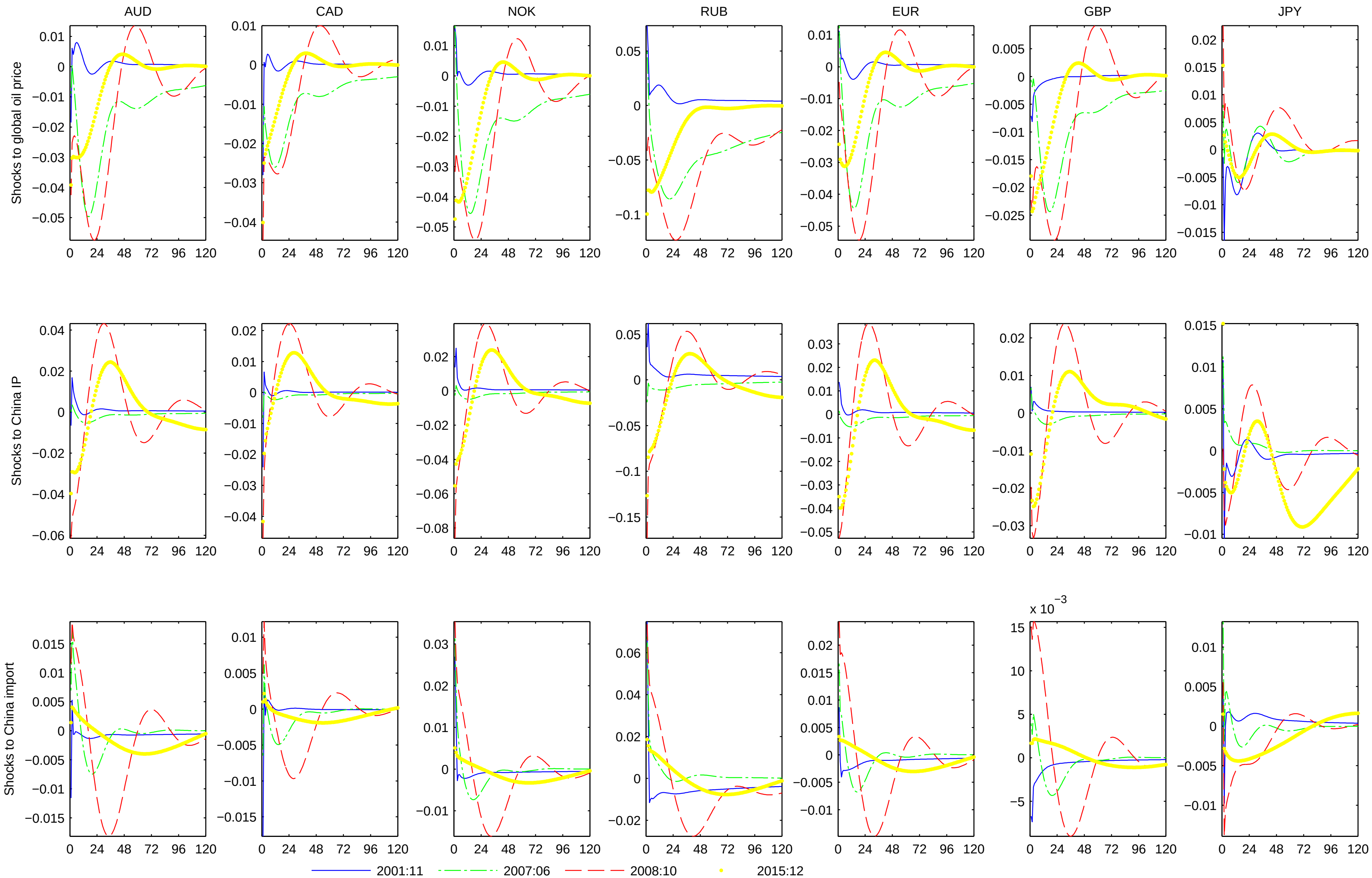
Notes:
This figure decomposes the 120-month-ahead forecast error variance of the foreign exchange accounted by fundamentals into six respective parts: the global oil price, China's industrial production, China's import, the US effective federal fund rate, and shadow short rates of the euro area and Japan. The regions reported are Canada, the euro area, Japan, Switzerland and the UK.

Figure 5: Stochastic volatility of fundamentals



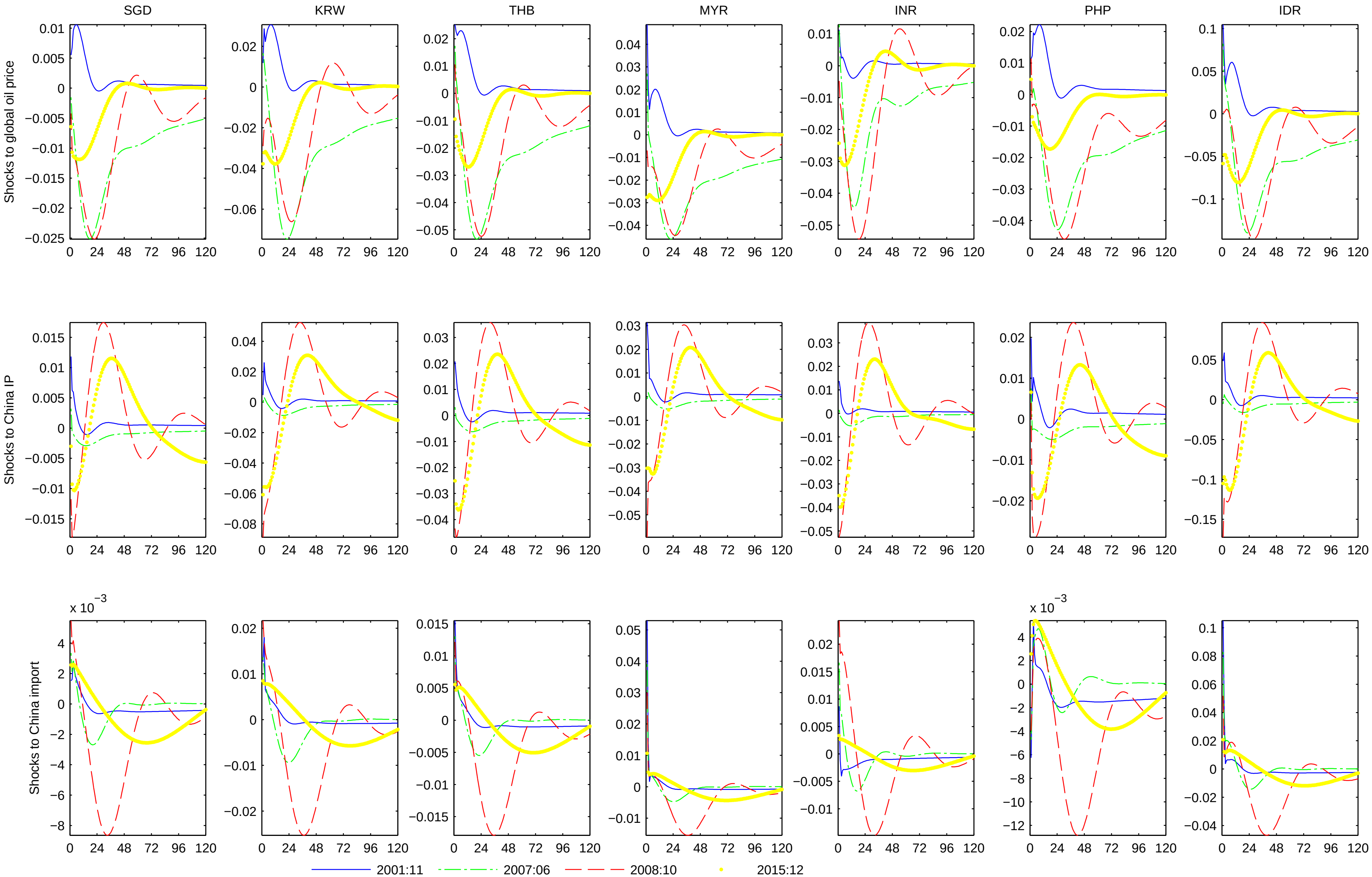
Notes:
This figure displays the (model-implied) time-varying standard deviations of the global oil price, China's industrial production, China's import, US EFFR, Euro-area SSR and Japan SSR.

Figure 6: Time-varying impulse response of log exchange rates



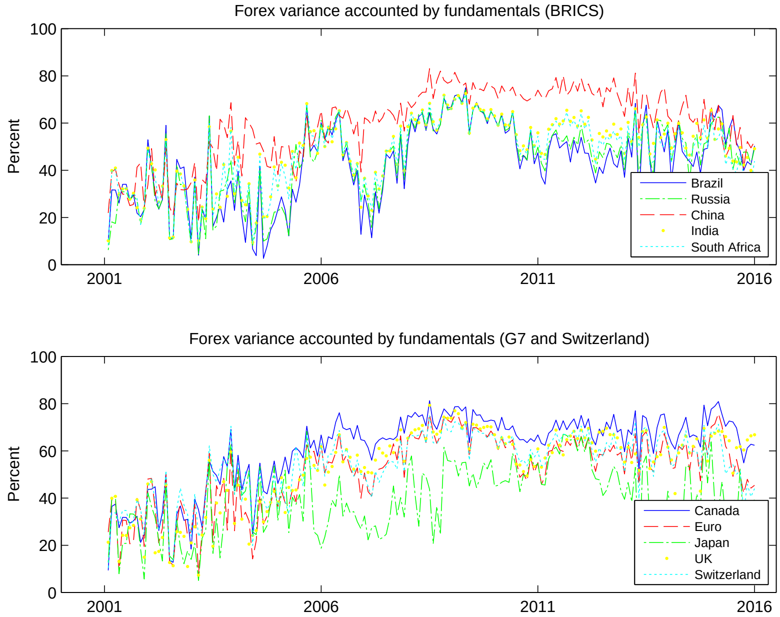
Notes:
This figure plots the impulse responses of the log exchange rates of different countries to one standard deviation shocks to respective fundamentals at different periods. The periods shown include: 2001:11 (before China joined the WTO), 2007:06 (after China's 2005 exchange rate reform), 2008:10 (during the financial crisis) and 2015:12 (China's economic slowdown).

Figure 7: Time-varying impulse response of log exchange rates (continued)



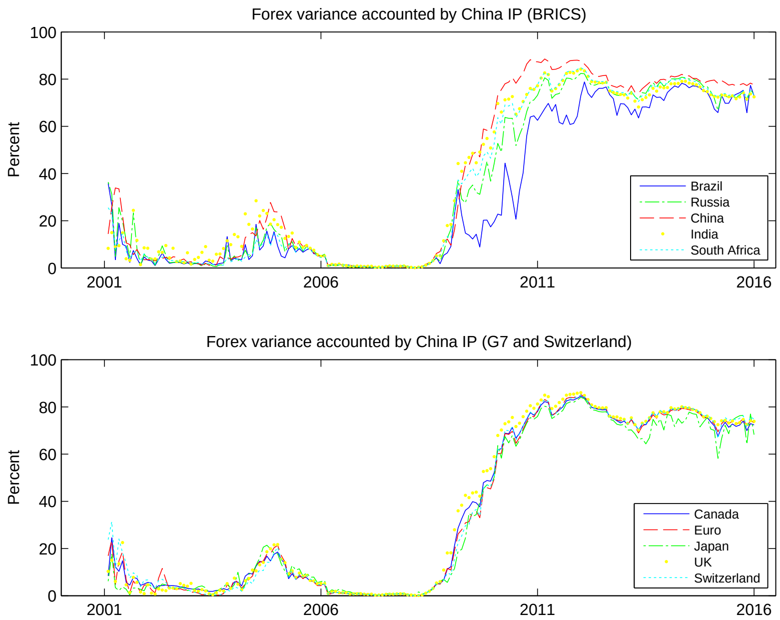
Notes:
This figure plots the impulse responses of the log exchange rates of different countries to one standard deviation shocks to respective fundamentals at different periods. The periods shown include: 2001:11 (before China joined the WTO), 2007:06 (after China's 2005 exchange rate reform), 2008:10 (during the financial crisis) and 2015:12 (China's economic slowdown).

Figure 8: Foreign exchange variance accounted by two core fundamentals



Notes:
This figure plots for each country the total fraction of 120-month-ahead forecast error variance of the foreign exchange (Forex) accounted by two core fundamentals, i.e., the global oil price and China's industrial production. The upper chart displays the fractions of BRICS countries, and the lower chart displays the fractions of G7 countries and Switzerland.

Figure 9: Foreign exchange variance accounted by China's growth



Notes:
This figure plots for each country the fraction of 120-month-ahead generalized forecast error variance of the foreign exchange (Forex) accounted by China's industrial production. The upper chart displays the fractions of BRICS countries, and the lower chart displays the fractions of G7 countries and Switzerland.