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Review

Global financial cycles and exchange rate forecast: A factor analysis

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Abstract

This study applies portfolio balance theory in forecasting exchange rate. The study further argues for the need to account for the role of Global Financial Cycle (GFCy). As such, the first stage of the analysis is estimate a GFCy model and obtain the idiosyncratic shock. Next, we use the results in the first stage as a predictor for exchange rate. The study builds dataset for 20 advanced and emerging countries from 1990Q1-2017Q2. Among other things, there are three important results to note. First, our approach to forecast exchange rate is able to beat the benchmark random walk model. Second, the best prediction is made at short term forecasting horizons, i.e. 1 and 4 quarters forecast ahead. Third, the performance of the early sample size outweighs that of the late sample size.
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1. Introduction

Since Meese and Rogoff (1983a, b, hereinafter MR), the general conclusion in the literature posits that macro-based variables/models do not accurately predict out-of-sample exchange rate.[1] Among the reasons attributed as the cause of the puzzle is the ease to which macro variables or fundamentals are prone to measurement errors (Chinn & Meese, 1995; Engel et al., 2015; Groen, 2000, 2005; Mark & Sul, 2001; Meese & Rogoff, 1983b; Neely & Sarno, 2002).[2]

Studies have relied on the use of some statistical/econometric models to solve this problem. In what has become the norm, in the literature, is the use of factor model.[3] An emerging strand of the exchange rate predictive studies has shown that the use of latent factor modelling helps to improve the information content of the predictive model. Hence, factor models provide forecasts that outperform the traditional or naïve random walk (see Kavtaradze & Mokhtari, 2018, for survey on factor models of exchange rate prediction).

The out-of-sample forecast of exchange rate has been tested using various theoretical frameworks (see Taylor, 1995; Frankel & Rose, 1995; Sarno & Taylor, 2002 and Chinn, 2011 Rossi, 2013 for both theoretical and empirical surveys). What is, however, recent is the application of the Portfolio Balance Theory (PBT) of exchange rate. Studies that have used this theory have shown that their models were able to (weakly) outperform the traditional naïve random walk model (Cushman, 2007; Gourinchas & Rey, 2007, herein after GR;

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[1] It should be noted that the initial attempt to solve this puzzle was microeconomic inclined. Essentially, these studies laid more emphasis on private information. It is explained that investor order flows cause exchange rate changes through private information, which when released, could have significant effects on exchange rate (Evans & Lyons, 2002). More recently, studies have confirmed that with proper econometric tools and models, macroeconomic fundamentals could accurately forecast exchange rate (see Eichenbaum et al., 2017; Itskhoki & Mukhin, 2017).

[2] Other causes identified in the literature are: endogeneity and/or persistence and parameter instability.

[3] Factor model is a framework that entails the efficient use of data, due to its ability to extract only useful information or factors from a large pool of variables (Kavtaradze & Mokhtari, 2018).

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Alquist & Chinn, 2008; Della Corte et al., 2010). There are some reservations against these studies. The direct use of various measures of capital flows is still susceptible to measurement errors. It is common knowledge that Balance of Payment (BOP) is a very difficult concept to measure. In fact, there is provision for "errors and omissions" in the computation of BOP. This is just to ensure that BOP "balances". Another reservation is the inability of these studies to account for an important and recent phenomenon of capital flow-the Global Financial Cycle (GFCy). The inability to account for this feature, particularly when it exists, has the tendency to severely bias the results and thus lead to wrong policy implications. These reservations could be the reason for the poor performance of the portfolio balance theory, though it was still able to beat the random walk model.

Rey (2013) in her influential Jackson Hole paper argued that capital flows have high common components. The argument GFCy portends is that some factors, extracted from a large pool of variables, account for a considerable proportion of the variations in capital flows. These factors are grouped into two classes: global and country-specific factors. She further orates that GFCy are more related to retrenchments and surges in capital flows. Forbes and Warnock (2012) show that extreme capital flows episodes are associated with global factors. In another strand of the literature, GFCy has been identified to account for a large variation in capital flows (Sarno et al., 2016; and Barrot & Servens, 2018). The resultant summary of these studies shows that GFCy is an important driver of capital flows. As such, when linking capital flows to other macroeconomic variables (say for instance, exchange rate), GFCy should be accounted for.

In light of this reasoning, this study hypothesizes that GFCy should be used as proxy capital flows. The model formulation/specification of GFCy is comprised of three components: global, country-specific and idiosyncratic. Using any or all of these components to proxy capital flows and thus use as predictor for exchange rate has important implication. However, this study is of the view that the idiosyncratic component should be used. This is due to the intuition that global factors have no information about domestic price movements neither do domestic factors influence the foreign/global price movements. Another reason could be due to the conclusion of Cerutti, Claessens and Rose (2017) that GFCy explains little variation in capital flows, even when using an approach that is bias towards making it important. They further argue that GFCy rarely account for more than 25% of the variations of capital flows. Thus, a significant proportion is being explained by the idiosyncratic shock. In addition, this act could somewhat solve the "scapegoat" problem of Bacchetta and van Wincoop. In a recent and closely related paper, Baku (2018) extracted factors from exchange rate in line with Engel et al. (2015) and then estimates the cointegration test (using the factors and other variables). The residual from this test is used as a predictor for exchange rate.

Based on the foregoing, the objective of this study to model the out-of-sample forecast of exchange rate in a two-step approach. In the first step, we model the GFCy and obtain the idiosyncratic shock. In the second stage, we use the result in the first stage as a predictor for exchange rate.

We make four major contributions to the literature: first, GFCy has not been linked to exchange rate forecast. Second, studies on PBT are burgeoning and have some promising results on the accurate exchange rate prediction (Cushman, 2007; Gourinchas & Rey, 2007; Alquist & Chinn, 2008; and; Della Corte et al., 2010). However, it is too early to conclude that capital flows has predictive information content on exchange rate because of the limited number of these studies. This is in addition to the fact that some of these studies are conducted for a relative few countries (majorly the United States). Hence, the generalization of these results to other countries does not arise. This is due to the believe that capital flows are heterogeneous to a number of factors, recipients countries inclusive. Third, PBT studies have ignored the role of factor modelling. This stance can be justified on the notion that PBT studies are majorly time series based, while the implementation of factor model requires panel data structure. Fourth, most PBT based studies have limited their analysis to FDI.[4] Hence, their conclusion could not be replicated for other components of capital flows. Circumventing this problem, other common forms of capital flows are explored (portfolio investment, bank flows and other foreign capital flows).

The rest of this paper is structure as follows: section two reviews the literature on the subject matter. Section three dwells on methodology and data. Results are presented in section four. Section five concludes the study.

2. Succinct empirical review

The literature on Exchange Rate Disconnect Puzzle is huge and there have been enormous attempts to document literature survey on the subject matter.[5] In an attempt to avoid duplication of effort, this section aims to review articles that had relied on factor model in the forecast of exchange rate. Existing studies on factor modelling could be grouped into two classes. The first class argues that factors should be extracted from exchange rate. The second group hypothesize that factors are better extracted from finance-related series.

2.1. First classification (factors extracted from exchange rate)

The prominent paper that uses factor model to predict exchange rate is Engel et al. (2015).[6] Arising from the difficulty

[4] A set of the literature concludes that the exact effect of the macroeconomic variables (exchange rate inclusive) is heterogeneous to the components of capital flows (FDI, portfolio invest, bank flows) (see Guichard, 2017; Koepke, 2015).

[5] Examples include Frankel and Rose (1995); Rogoff (1996); Chinn (2011); Melvin et al. (2011); and more recently, Rossi (2013).

[6] This study is aware of other prior studies that had predicted out-of-sample exchange rate. Among the list include Groen (2006); Aggarwal and Simmons (2008); and Cayen et al. (2010). These studies have extracted factors from a smaller number of bilateral exchange rates. Hence, it is assumed that such factors would have less information as compared to those obtained by Engel et al.

in measuring fundamentals, it was further hypothesized that exchange rate itself has information that cannot be easily extracted from observable fundamentals. Thus, the best variable which factors could be extracted from is exchange rate.[7] The difference between the factors and exchange rate are used as predictor for exchange rate.[8] Their results show lower room mean squared prediction error (RMSE) for these proposed models as compared to the traditional and benchmark random walk model. The approach of Engel et al. (2015) has become norm in the literature. Succeeding studies have followed this approach with little innovations. For instance, Greenway-McGrevy et al. (2018) extracted two factors contain in three currency-pairs: yen, swiss franc and the euro benchmarked against the US dollar. The authors were able to show that their models significantly outperform both the random walk and the bi-lateral PPP model. Other similar studies include Engel et al. (2009), Felício and Junior (2014), Kavtaradze (2016).

It should be emphasized here that what the innovations succeeding papers have put forward is more empirically/methodologically driven. These innovations can be justified on the ground that there are diverse ways of factor modelling.[9] Despite these diverse approaches, the basic cannon of the results of Engel et al. have not been refuted. While validating Engel et al.'s results, succeeding studies have shown that their results improve on the former.

The first rejoinder to Engel et al. is Wu and Wang (2012). Rather than use PCA, Wu and Wang relied on the independent component factors (ICF). The basic limitation of PCA is that it can only exploit information up to the second moments. However, ICF has the ability to exploit information on higher moments because it treats exchange rate as a signal. This signal is decomposed into independent sources rather than orthogonal factors. The key import of their results is that ICF based model defeats the random walk model irrespective of the sample periods and forecast horizons. Solat and Tsang (2017) made case for the use of generalized principal components (GPC). PCA exploits information in a contemporaneous nature across variables, while GPC exploits information across time variation for each variable as well as across variables. The authors use similar data as Engel et al. Results based on GPC was found to have superior performance as compared with those based on PCA.

Berge and Mark (2015) hypothesize that the approach of Engel et al. (2015) suffers from omitted variable bias. Thus, there is the need to account for a "third country" or "spillover" effect from the rest of the world. The proposed effect is factor extracted from a Taylor type or monetary model (inflation, output gap and interest rates). In the model build up, there are 3 countries. Country A is more interested in the domestic affairs, while Countries B and C have similar exchange rate management. It was alternatively suggested that country B follows Country C in the implementation of the monetary policies, while Country A's focus is tilted to domestic matters. Thus, differences in monetary policies would cause interest rate in policy in countries A and B to respond differently to shocks from C, which generates fluctuations in the exchange rate between A and B. Results show that the third country effect: (i) is an important determinant of bilateral exchange rate and (ii) boost the explanatory power of the model.

The general conclusion in this strand of the literature is that the various proposed models beat the random walk model of exchange rate prediction.

2.2. Second classification (factors extracted from variables aside exchange rate)

Aside constructing factors from exchange rate, some studies have proposed alternative approaches. In this realm of scientific enquiry is a strand of the literature that had relied on asset pricing models to predict exchange rate. For instance, Lustig et al. (2011) propose the construction of currency-based risk factors. The first factor is coined "dollar factor", which is computed average of excess returns between the domestic and other foreign currencies. The second factor is termed "carry risk factor", which is constructed as the average differential between high interest and low interest rate currencies. Menkhoff et al. (2012) added a third factor, innovations in the global foreign exchange volatility defines as the average of daily absolute return of currencies.

An emerging strand of the literature is inclined towards behavioural finance. Hence, there is the need to explore the important role of heterogeneous expectations of agents (see Morales-Arias & Moura, 2013). Ahmed et al. (2016) propose a new set of predictors for exchange rate: unconditional and conditional expectations of currency-based risk factors. Another group of studies have advocated for the use of combination of factors extracted from both conventional macro and financial variables (see Wright, 2008; and Della-Corte et al., 2010).

There is a common trend in this strand of the literature. These models perform well in the in-sample predictability of exchange rate. However, the out-of-sample forecast is not very impressive. These models hardly beat the benchmark (random walk with and without draft). These results still hold after augmenting the factors with conventional exchange rate theory models.

More recently, Kim and Park (2018) orate that extracting factors from few selected macroeconomic variables is prone to selection bias. Rather, Kim and Park use factors extracted

[7] A common practise in the literature is to nomenclate the extracted factors. This is usually done by examining the factors with a set of exchange rate. For instance, the first factor has shown to have high correlation with USD. Thus, this factor is tagged the "dollar" or "global" factor (see Engel et al., 2015; Greenway-McGrevy et al., 2018; Ponomareva et al., 2018). However, there seems to be disagreement in the nomenclature of the second factor. Some studies tag it euro-factor (eg. Engel et al., 2015; Greenway-McGrevy et al., 2018), others name it "Japan" factor (see Ponomareva et al., 2018), while Engel et al., 2015 tagged it mark factor.

[8] The extracted factors are further augmented with other models such as Taylor Rule, Monetary model and Purchasing Power Parity (PPP).

[9] The commonly used approach is the principal component analysis (PCA). Other approaches that have been argued to be superior to CPA include factor modelling.

from 121 monthly US macro-variable to predict bilateral exchange rate for 26 currencies[10]. Results show that the factors are able to predict both in- and out-of-sample forecast. The predictive power of the individual factors differs across horizons. For instance, the "US Stock" factor thrives in short-horizon while other factors have improved performance for long-horizon. Furthermore, the predictive model was augmented with factors extracted from the Korean time series. It is shown that the later model is able to substantially predict a significant proportion of the USD- KRW movements.

3. Methodology and data

3.1. Methodology

Contrary to economic intuition, exchange rate's movement seems not be accurately explained by other macroeconomic variables (MR). This is just as its impact on other macro variable seems limited (Kim & Park, 2018). The standard exchange rate predictive model is presented below:

$$s_{it} = \beta_{0i} + \beta_1 X'_{it} + \varepsilon_{it} \tag{1}$$

where s_{it} is the bilateral exchange rate between country i and the US dollars (USD). Exchange rate is defined as the number of the local currency units to 1 USD. X′ is a vector of macroeconomic variables.[11] One of the problems with this approach is the restrictiveness of the model. The conclusion in the literature is that the dynamics of exchange rate model is dependent upon the variables selected, sample size, forecast horizons, methodology and scope of the study. Also, Cheung and Chinn (2001) concluded that forex participants are decreasingly laying importance on the connection between macro variables and exchange rate.

Engel et al. (2015) changed the direction of the research, as they argue that the dispersions of the exchange rate from its central tendencies are good predictors of exchange rate. Hence, factors extracted from exchange have some predictive information content on exchange rate itself. This has become the standard norm in the literature (see Kavtaradze & Mokhtari, 2018 for literature survey on factor models of exchange rate). A typical standard factor predictive model of exchange rate is specified below:

$$s_{it} = \propto F_{it} + \beta Z_{it} + v_{it} \tag{2}$$

where F is the factor(s) extracted from a set of exchange rate. In a one factor model, $F_{it} = \delta_i f_{1t}$ where δ_i is the factor loading for currency i and f_{1t} is the factor. The idiosyncratic shock, v_{it}, is expected to be uncorrelated with the factor. Z′ is a vector of some macro variables.

Drawing inspiration from the portfolio balance theory of exchange rate, we opine that global finance cycle (GFCy) could accurately predict the exchange rate better than the benchmark model (random walk). GFCy measures the comovement in capital flows. In the operationalization of the GFCy, two factors are specified: the global and country-specific factors. This is attributable to the fact that the literature on capital flows have concluded that those factors are the broad determinants of capital flows (see Calvo et al., 1993, pp. 108−151 and 1996).

Taking a cue from Barrot and Servens (2018), we specify a two-level GFCy model below:

$$CF_{it} = (\theta_i)' G_t + (\pi_i)' C_{it} + \varepsilon_{it} \quad i = 1, \ldots, N; and\ t = 1, \ldots T \tag{3}$$

CF_{it} is the measure of capital flows (% of GDP) for country i over period t; G_t is the set of r_G unobserved common global or world factor, while C_{it} is a set of r_m unobserved country-specific factors. As such, θ_i and π_i are the factor loadings respectively. ε_{it} is the error term.

Both G_t and C_{it} are extracted from a number of relevant variables. In line with existing studies, the variables used for global factors are: (i) global risk, measured by VIX index; (ii) global short-term interest rate, proxied by 3-months treasury bills; (iii) global economic growth, proxied by the G7's growth rate, (iv) global money supply proxied by US M2 growth rate and (v) commodity (oil) price. On the flipside, the variables that capture country-specific factors are: (i) financial openness, measured by the Chin-Ito index; (ii) trade openness and (iii) financial depth, measured as the credit to the private sector (Fratzscher, 2012; Forbes & Warnock, 2012; Ahmed & Zlate, 2014; Hanan, 2017; and; Avdjiev et al., 2017). Appendix provides a clearer description of the manuscript. It has been argued that the effect of macroeconomic variables on capital flows is heterogeneous. To examine whether this finding is also applicable to exchange rate prediction, the study proposes to use four measures of capital flows: FDI, PI, BNK and OI.[12]

As argued Baku (2018) confirm that the error term from a factor model is best used to predict exchange rate. Thus, the error term in equation (3) is used as the predictor of exchange rate. Thus, the exchange rate predictive model based on the dynamics of GFCy is written below:

$$S_{it} = \propto + \beta CAP_{it} + \varepsilon_{it} \tag{4}$$

CAP is the error component of the equation of equation (3) above. In essence, the error term generated in equation is used as the predictor of exchange rate.

A common practise in the factor-based exchange rate forecast studies is to complement the factors with other exchange rate theories or models (for example, see Engel et al., 2015; Felicio & Junior, 2014; Mc-Grevy et al., 2018; Wu &

[10] The four factors extracted are US stock market, interest rate spreads, government-issued bond yields, and employment variables.

[11] The variables to be considered in dependent upon the underlying theory of the model. See Rossi (2013) for a detailed explanation on exchange rate theories. It.

[12] In this first stage analysis, we only used the first factors extracted from both global and country-specific components. This is due to the fact that these first factors account for over 70% of the variance in the components. Ponomareva et al. (2018) also limited their analysis to the first factors.

Wang, 2012 among others). This study is constrained from performing such exercise. This is due to the approach in which the factors are extracted. While the previous studies extract factors from exchange rate itself, we extracted factors from a list of variables (as specified in equation (1)). As such, augmenting the factors with other models could lead to multicollinearity. This is especially so when such variables had already been used in the build-up to factor extraction.[13] Based on the foregoing, the factor series will be the only predictor to be used.

3.2. Forecast implementation and evaluation

The out-of-sample for this study is based on both short-run and long-run horizons. In line with the extant literature, we use a direct method to forecast exchange rate h-quarters ahead change in exchange rate of h = 1, 4, 8 and 12 quarters (see Wu & Wang, 2012; Engel et al., 2015, Byrne et al., 2016 among others). The commonly used benchmark model is the random walk without drift.[14] The forecasting procedure uses rolling window approach.[15]

The three measures of forecast evaluation used in this study are: Clark and West (2007, hereafter CW test); Campbell and Thompson (2008, hereafter CT test) and Theil's U- Statistics. The Theil's U statistics is computed as the ratio of the Root Mean Squared Error (RMSE) of model 2 (unrestricted) relative to the RMSE of model 1 (restricted). In the context of this study, restricted model is the traditional naïve model (i.e. random walk model), while the unrestricted model is the residual factor-augmented model. A Theil's U-statistics less than 1 implies that the unrestricted model outperforms the restricted model and vice-versa.

The CT test is considered to be out-of-sample R^2 (OOS_ R) statistics, which is computed as OOS_R = 1- Theil's U-statistics $\{(\widehat{RMSE}_2/\widehat{RMSE}_1)\}$, where $\widehat{RMSE}_2$ *and* $\widehat{RMSE}_1$ are the Root Mean Square Error for models 2 and 1, respectively. A positive CT value suggests that model 2 outperforms model 1 and vice-versa. The shortcoming of C-T is its inability to show its level of statistical significance.[16] However, Clark and West (2007) herein after CW provide test to examine the statistical significance of C-T.[17] The null hypothesis of the test is that he benchmark (smaller) model describes the DGP equally well as the alternative (big) model. The null hypothesis is rejected if the t-statistics is larger than +1.286 (for a one sided 0.10 test) or +1.645 (for a one-sided 0.05 test).

Exchange rate has been found to be a volatile series. Among the criticisms of OLS is its inability to accurately estimate models in which the series are not stationary. However, Rossi (2005) concludes that models with unit root tend to falsify and overate the performance of exchange rate forecast as compared to models that allows for autoregressive in parameters. Auto Regressive Distributed Lag (ARDL) or bound testing has been identified to salvage this problem. In the operationalization of ARDL, it accounts for the level of stationarity of the series in the model prior to estimation. Due to this advantage, analysis is conducted using ARDL.

3.3. Data

The focus of this study is based on both developed and emerging countries. The developed (OECD)[18] countries are: Australia (AUD), Canada (CAD), Finland (FIN), France (FRA), Germany (GER), Italy (ITA), Japan (JPN), Korea (KOR), The Netherlands (NLD), New Zealand (NZL), Norway (NOR), Portugal (PRT), Spain (ESP), Sweden (SWE), and Switzerland (CHE). The emerging countries included are Brazil (BRA), Chile (CHL), Hungary (HUN), Mexico (MEX), and South Africa (ZAR).

In terms of time frame, the period 1990Q1-2017Q2 is considered. The earlier part of the post Bretton Woods system was impeded by data unavailability, hence the need to use 1990 as this study's start period. The out-of-sample analysis is based on multiple sample size (50% and 75% of the total sample size). Thus, for the 50% sample size, the first quarter of forecast starts from 2004Q4. In a similar vein, the forecast for the 75% sample size starts from 2009Q1. The 75% sample size coincidentally falls during the global financial crisis. The 50% and 75% sample sizes are coined the early and late sample, respectively. Since the first out-of-sample forecast is in 2003, the need to the need to dichotomize the sample size into pre-euro era and post-euro era, because of the formation of economic and monetary union does not arise.[19]

In line with the requirement of factor models, the scope of the analysis will be in panel data structure. The dataset is

[13] For instance, the PPP model dwells on the price differential between foreign and home country. Coincidentally, the price level of the home country had already been used to extract domestic. Similar logic applies to Taylor rule, monetary model, (Un)conventional Interest Rate Parity UIRP/CIRP, productivity differential models.

[14] An alternative approach is the random walk model with drift. Rossi (2013) concludes that the choice between the models (drift and driftless) does not have significant effect on the results of exchange rate forecast.

[15] While rolling window approach helps parameters to adopt easily to structural changes, it becomes less effective with smaller sample size. We overcome this problem by setting the window size to be at least half of the total sample. Studies such as MR, Clark and West (2006), Molodtsova and Papell (2012), among others, used the rolling window.

[16] Due to the inter-linkage between Theil's U-statistics and CT test and for ease to understand the results tabulation, we refrain from presenting the CT test results in the main text. In situations where the U-statistics is less than 1, mathematically, it is expected that the CT test would be positive and vice-versa. The CT results can be made available upon request.

[17] Until recently, the commonly used test is the Diebold and Mariano (1995). However, the test is only suitable for non-nested models, while C-W is renowned to work better in nested models.

[18] Organization for Economic Co-operation and Development.

[19] A fundamental point to note is that the factor model is estimated using the full sample. This naturally limits the analysis to "in-sample". However, it should be noted that the predictive model divides the sample size into two: in- and out-of-sample sizes. The model we specified does not make forecast beyond the available dataset. Hence, the resulting estimate is regarded as "out-of-sample" analysis within in-sample data. For the ease of expression, we prefer to refer to these analyses as "out-of-sample", similar to what is obtainable in related studies (Salisu & Ndako, 2018; Westerlund & Narayan, 2016). We thank the reviewer for point this out to our attention.

Table 1
Factor loadings.

	Global	Country-Specific
VIX	0.7581	
3-MTH	0.6895	
GROWTH	−0.5874	
M2	0.4129	
OIL	0.2105	
KAO		0.5268
TRADE		0.9658
FIN		0.4476
INF		−0.1204
ECO		0.3260

Source: Author's computation.
Note: VIX is the VIX index, 3-MTH is 3-months treasury bills, M2 is the growth rate of US money supply, GROWTH is the G7's average economic growth rate and OIL is the commodity price index. For the country-specific factors, KAO represents the current account openness, TRADE represents trade openness, FIN and INF are measures of financial depth and inflation, respectively. ECO is the economic growth rate of the countries.

collected based on two criteria: (i) the countries have floating or managed floating, without a predetermined path, exchange rate regime[20]; (ii) the countries are financially connected to the rest of the world i.e. there is little or no incidence of capital control.

The exchange rates are end-of the quarter values of the national (home) currency relative to the U.S dollars (foreign). As such, an increase in the exchange rate is regarded as depreciation of the national currency. Following International Monetary Fund (IMF) classification, the four types of capital flows analysed in this study include Foreign Direct Investment (FDI), Portfolio Investment (PI), Bank Flows (BNK) and Other Investment (OI). These flows are expressed as a ratio of GDP.

The main data sources are the International Financial Statistics, Federal Reserve Economic Data (FRED) and Haver analytics. Capital flow data is mostly collected from Cerutti et al. (2017), which is complemented with data from Balance of Payments and International Investment Position of the IMF.

4. Empirical results

In line with the extant literature, this study presents the factor loadings in Table 1. It is expected that the factors should be uncorrelated. We present the result of the correlation in Table 2.

Fig. 1 shows the estimate of the factors. It should be recalled that there are four models to be estimated, as such, four factors are expected to be generated.

An overview of the factors suggests that the series might be susceptible to unit root problem. This is in addition to the fact that exchange rate has been confirmed to be a difference stationary series. Thus, the need to conduct unit root, for both

[20] This is because little or no information could be extracted from a pegged exchange rate system.

Table 2
Correlation between global and country-specific factors.

	Global	Country-Specific
Global	1.000	
Country-Specific	0.002	1.000

Source: Author's computation.

exchange rate and the factors arises. Table 3 presents the Augmented Dickey-Fuller unit root test results. A snapshot of Panel A of the table shows that exchange rate is first-difference stationary for most of the currencies. The only exception is Romanian Leu that is stationary at level. Panel B shows results of the factors. It can also be deduced that the series are stationary at first difference.

Tables 4 and 5 present the forecasting results. The starting point of the analysis is based on the usage of 50% (early) sample size. The statistics presented in the table represent the median of all currencies forecasted.[21] To read Table 4, consider model FDI. The value 0.7416 implies that the median value of the U-statistics is 0.7416. Being explicit, this statistic show that about 15 countries have U-statistics less than one and the remaining countries have U-statistics less than one.[22] The Theil's U- statistics (below the median U-statistics), for horizon 1 (first quarter forecast) means that the FDI model outperforms the random walk model for 15 out of the 20 currencies considered. The corresponding figure to the CW shows the number of times the null hypothesis was rejected for t-statistics of RMSE at 5%. The impressive performance of the CW test is similar to Mc-Grevy et al. (2018). Hence, the results obtained are statistically significant.

Bank flows and other investments flows are found to significantly improve the exchange rate forecast at both short and long forecast horizons (i.e. 1-12 quarter). The same argument could have been extended to FDI and portfolio flows if not for their inability to forecast exchange rate at long horizons (i.e. at 8 and 12 quarters). A plausible justification to the seemingly relative poor performance of the FDI model could be attributed to its low level of volatility. Historical data and empirical evidences have confirmed the stability of FDI among other various measures of capital flows (Broner et al., 2013 among others). Hence, it is empirically valid for series that are relatively less volatile to have lower predictive prowess as compared to the series with high volatility. Another important point to note is that stance that the value of U-statistics increases as the forecast horizon increases. Hence, it implies that predictability models loose their performance at long horizon forecast. This is theoretically valid. Studies have shown that best prediction is obtained at the short-medium forecast range (Engel et al., 2015). Essentially, the results

[21] The results for the individual currency can be made available on request.
[22] Caution must be exercised when interpreting the median U-statistics. An implicit assumption in the usage of the median U-statistics is that there is tendency for approximation. Hence, U-statistics that are tightly clustered around 1 are seen to be less than 1 and those that are widely dispersed from 1 are considered to be greater than 1. See Engel et al. (2015) for more details.

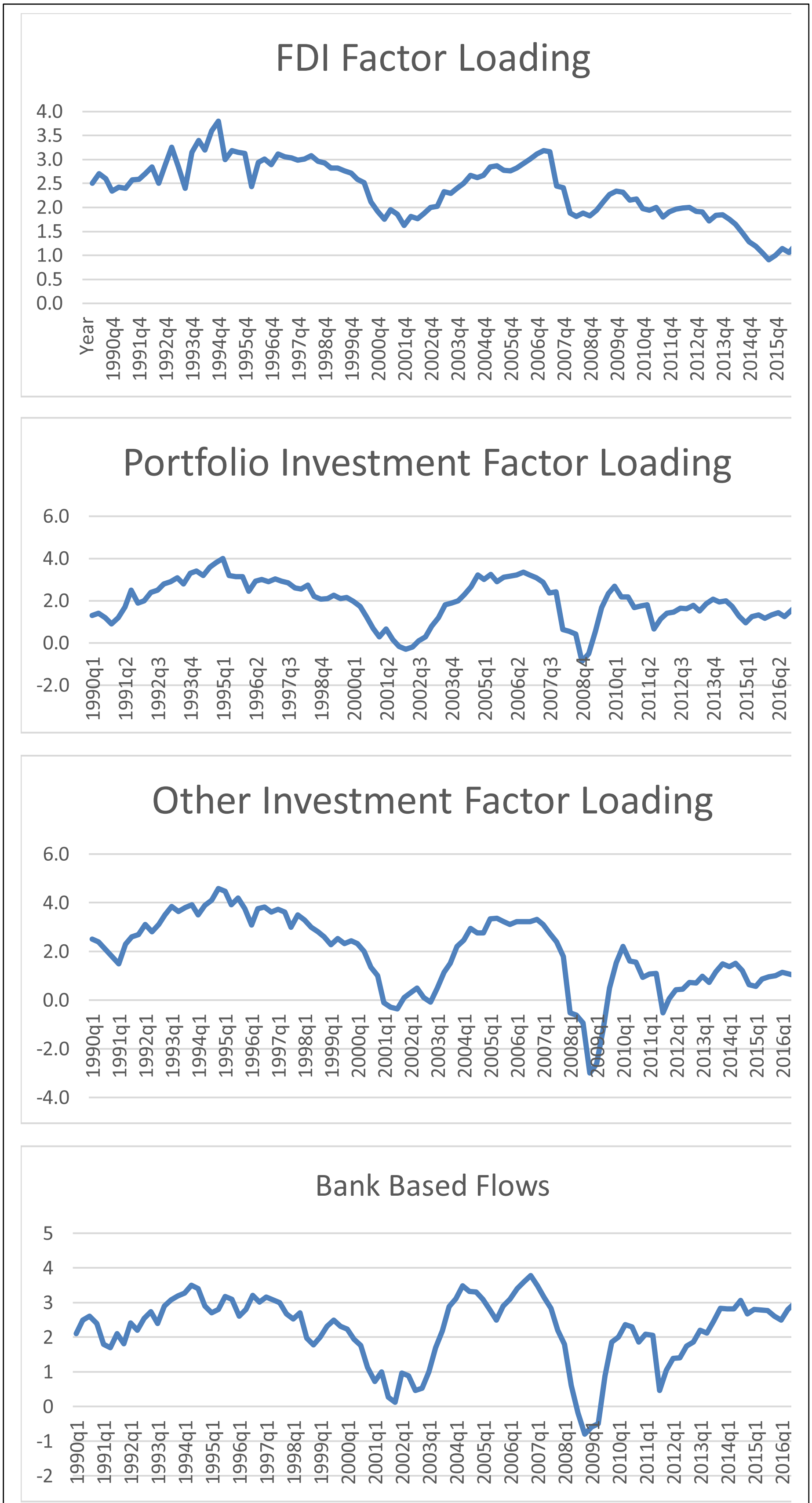

Fig. 1. Trend of factors.

Table 3
Unit root.

Country	Panel A	Panel B			
	Exc. Rate	FDI	Portfolio	Other Inv.	Bank Flow
Australia	I (1)	I (1)	I (1)	I (1)	I (1)
Brazil	I (1)	I (1)	I (1)	I (1)	I (1)
Canada	I (1)	I (1)	I (1)	I (1)	I (1)
Chile	I (1)	I (1)	I (1)	I (1)	I (1)
Costa Rica	I (1)	I (1)	I (1)	I (1)	I (1)
Finland	I (1)	I (1)	I (1)	I (1)	I (1)
France	I (1)	I (1)	I (1)	I (1)	I (1)
Germany	I (1)	I (1)	I (1)	I (1)	I (1)
Hungary	I (1)	I (1)	I (1)	I (1)	I (1)
Iceland	I (1)	I (1)	I (1)	I (1)	I (1)
Israel	I (1)	I (1)	I (1)	I (1)	I (1)
Italy	I (1)	I (1)	I (1)	I (1)	I (1)
Japan	I (1)	I (1)	I (1)	I (1)	I (1)
Korea	I (1)	I (1)	I (1)	I (1)	I (1)
Mexico	I (1)	I (1)	I (1)	I (1)	I (1)
Netherlands	I (1)	I (1)	I (1)	I (1)	I (1)
New Zealand	I (1)	I (1)	I (1)	I (1)	I (1)
Norway	I (1)	I (1)	I (1)	I (1)	I (1)
Portugal	I (1)	I (1)	I (1)	I (1)	I (1)
Romania	I (1)	I (0)	I (1)	I (0)	I (0)
South Africa	I (1)	I (1)	I (1)	I (1)	I (1)
Spain	I (1)	I (1)	I (1)	I (1)	I (1)
Sweden	I (1)	I (1)	I (1)	I (1)	I (1)
Switzerland	I (1)	I (1)	I (1)	I (1)	I (1)
Turkey	I (1)	I (1)	I (1)	I (1)	I (1)

Source: Author's computation.

Table 5
ARDL-based forecast results (late sample).

Model	Test	Horizon h (Quarters)			
		1	4	8	12
FDI	Median U-Stat	0.9854	1.0179	1.2154	1.4583
	U < 1	12	12	11	9
	CW	16	15	13	16
PI	Median U-Stat	1.1548	1.2652	1.3211	1.3916
	U < 1	14	14	12	10
	CW	16	16	17	15
OI	Median U-Stat	0.8468	0.8678	0.9613	1.0055
	U < 1	16	15	15	13
	CW	18	18	19	17
BNK	Median U-Stat	0.8543	0.8816	0.9018	0.9768
	U < 1	13	13	10	9
	CW	15	15	16	17

Source: Author's computation.
Notes: U-Stat is the Thiel U-Statistics. Median U-Statistics is the median of the U-statistics for the 25 currencies under investigation. The U-Statistics is defined as the ratio between RMSE of the unrestricted model to RMSE of the restricted model i.e (RMSE of Model/RMSE of the random walk). U < 1 implies that the magnitude of RMSE of the model is lower than that of the random walk. The corresponding number to U < 1 shows that number of currencies that hold the hypothesis U < 1. The CW presents results of the Clark and West (2007) test. The null hypothesis of the test is that U = 1 against the alternative test U < 1. The corresponding number shows the number of currencies that rejects the null hypothesis using (t > 1.68) at 5% level.
Note for the Model: FDI= Foreign Direct Investment; PI is Portfolio Investment, OI is other investments and BNK is Bank flows.

Table 4
ARDL-based forecast results (early sample).

Model	Test	Horizon h (Quarters)			
		1	4	8	12
FDI	Median U-Stat	0.7416	0.8569	1.0021	1.0157
	U < 1	15	14	14	12
	CW	17	17	16	15
PI	Median U-Stat	0.8145	0.8654	1.1012	1.1154
	U < 1	17	16	15	15
	CW	18	18	16	16
OI	Median U-Stat	0.6015	0.6147	0.6684	0.7017
	U < 1	18	17	17	16
	CW	18	18	18	18
BNK	Median U-Stat	0.7026	0.7216	0.7549	0.7782
	U < 1	17	17	16	15
	CW	18	18	17	16

Source: Author's computation.
Notes: U-Stat is the Thiel U-Statistics. Median U-Statistics is the median of the U-statistics for the 25 currencies under investigation. The U-Statistics is defined as the ratio between RMSE of the unrestricted model to RMSE of the restricted model i.e (RMSE of Model/RMSE of the random walk). U < 1 implies that the magnitude of RMSE of the model is lower than that of the random walk. The corresponding number to U < 1 shows that number of currencies that hold the hypothesis U < 1. The CW presents results of the Clark and West (2007) test. The null hypothesis of the test is that U = 1 against the alternative test U < 1. The corresponding number shows the number of currencies that rejects the null hypothesis using (t > 1.68) at 5% level.
Note for the Model: FDI= Foreign Direct Investment; PI is Portfolio Investment, OI is other investments and BNK is Bank flows.

Table 6
ARDL-based forecast results (early sample MSE).

Model	Test	Horizon h (Quarters)			
		1	4	8	12
FDI	Median U-Stat	0.8458	0.8751	0.9852	1.0015
	U < 1	16	16	14	11
	CW	18	17	15	15
PI	Median U-Stat	0.9158	0.9355	0.9896	1.0586
	U < 1	15	14	14	13
	CW	18	18	15	14
OI	Median U-Stat	0.7558	0.7896	0.8168	0.8305
	U < 1	18	17	15	15
	CW	19	18	17	18
BNK	Median U-Stat	0.7268	0.7388	0.7508	0.7899
	U < 1	17	17	16	15
	CW	18	17	17	16

Source: Author's computation.
Notes: U-Stat is the Thiel U-Statistics. Median U-Statistics is the median of the U-statistics for the 25 currencies under investigation. The U-Statistics is defined as the ratio between RMSE of the unrestricted model to RMSE of the restricted model i.e (RMSE of Model/RMSE of the random walk). U < 1 implies that the magnitude of RMSE of the model is lower than that of the random walk. The corresponding number to U < 1 shows that number of currencies that hold the hypothesis U < 1. The CW presents results of the Clark and West (2007) test. The null hypothesis of the test is that U = 1 against the alternative test U < 1. The corresponding number shows the number of currencies that rejects the null hypothesis using (t > 1.68) at 5% level.
Note for the Model: FDI= Foreign Direct Investment; PI is Portfolio Investment, OI is other investments and BNK is Bank flows.

Table 7
ARDL-based forecast results (late sample MAE).

Model	Test	Horizon h (Quarters)			
		1	4	8	12
FDI	Median U-Stat	1.001	1.1254	1.3352	1.5084
	U < 1	11	11	10	9
	CW	17	16	16	17
PI	Median U-Stat	0.9875	1.0146	1.2658	1.4876
	U < 1	12	12	11	10
	CW	15	16	17	16
OI	Median U-Stat	0.7986	0.8157	0.8354	0.9562
	U < 1	17	16	16	14
	CW	17	17	18	16
BNK	Median U-Stat	0.6582	0.6781	0.7098	0.7284
	U < 1	12	12	11	10
	CW	15	15	16	17

Source: Author's computation.
Notes: U-Stat is the Thiel U-Statistics. Median U-Statistics is the median of the U-statistics for the 25 currencies under investigation. The U-Statistics is defined as the ratio between RMSE of the unrestricted model to RMSE of the restricted model i.e (RMSE of Model/RMSE of the random walk). U < 1 implies that the magnitude of RMSE of the model is lower than that of the random walk. The corresponding number to U < 1 shows that number of currencies that hold the hypothesis U < 1. The CW presents results of the Clark and West (2007) test. The null hypothesis of the test is that U = 1 against the alternative test U < 1. The corresponding number shows the number of currencies that rejects the null hypothesis using (t > 1.68) at 5% level.
Note for the Model: FDI= Foreign Direct Investment; PI is Portfolio Investment, OI is other investments and BNK is Bank flows.

Table 8
ARDL-based forecast results (early sample MSE and GBP).

Model	Test	Horizon h (Quarters)			
		1	4	8	12
FDI	Median U-Stat	0.9186	0.9582	0.9756	1.058
	U < 1	17	16	15	12
	CW	18	17	16	17
PI	Median U-Stat	0.9466	1.0665	1.1588	1.4632
	U < 1	14	14	13	11
	CW	17	18	16	17
OI	Median U-Stat	0.6846	0.7159	0.7766	0.8146
	U < 1	17	16	16	14
	CW	18	17	17	16
BNK	Median U-Stat	0.7125	0.7752	0.7899	0.8012
	U < 1	17	16	15	13
	CW	18	16	16	16

Source: Author's computation.
Notes: U-Stat is the Thiel U-Statistics. Median U-Statistics is the median of the U-statistics for the 25 currencies under investigation. The U-Statistics is defined as the ratio between RMSE of the unrestricted model to RMSE of the restricted model i.e (RMSE of Model/RMSE of the random walk). U < 1 implies that the magnitude of RMSE of the model is lower than that of the random walk. The corresponding number to U < 1 shows that number of currencies that hold the hypothesis U < 1. The CW presents results of the Clark and West (2007) test. The null hypothesis of the test is that U = 1 against the alternative test U < 1. The corresponding number shows the number of currencies that rejects the null hypothesis using (t > 1.68) at 5% level.
Note for the Model: FDI= Foreign Direct Investment; PI is Portfolio Investment, OI is other investments and BNK is Bank flows.

obtained thus far do not align with the conclusion of Meese and Rogoff (1983b).

Results of the late sample is presented in Table 5. In comparison to the results presented earlier, there are two major distinctions. First, FDI and PI's lost their predictability performance. More worrisome is the fact that PI does not predict exchange rate at any horizon. However, more than half of the sample size have still have their U-statistics less than unity. Second, there is generally higher value of the U-statistics across capital flows types and horizon. This implies that the early sample data provided the best prediction. A prominent justification to this scenario is the influence of the global financial crisis. Recall that the first quarter of the late sample is 2009Q1. The post financial crisis has witnessed drastic decline in the level of global capital flow (Hanan, 2017; Tunc & Tissot, 2017). It could be seen that the capital flows bubble actually happen sometime around the crisis-period. This is just as some macroeconomic indicators are struggling to attain the level they were prior to the crisis (Chen et al., 2019).

The successful performance of our models is similar to those obtained from previous studies. It has thus become a norm that forecasting exchange rate with the use of factor model helps beat the random walk model. For instance, Wu and Wang (2012) use independent component factor to extract factors and conclude that both the factors and factor augmented models beat random walk model of exchange rate determination. Engel et al. (2015), used deviation from factors constructed from exchange rate as a predictor. They further complimented these factors with other models just as the

Table 9
ARDL-based forecast results (late sample MAE and GBP).

Model	Test	Horizon h (Quarters)			
		1	4	8	12
FDI	Median U-Stat	0.9987	1.0286	1.255	1.487
	U < 1	11	10	9	9
	CW	16	16	15	16
PI	Median U-Stat	1.4842	1.6988	1.7562	1.8161
	U < 1	11	10	9	8
	CW	15	16	17	16
OI	Median U-Stat	0.8895	0.9166	0.9541	1.0026
	U < 1	14	13	13	11
	CW	17	16	17	17
BNK	Median U-Stat	0.7895	0.8169	0.8546	0.8873
	U < 1	15	14	14	12
	CW	17	16	17	16

Source: Author's computation.
Notes: U-Stat is the Thiel U-Statistics. Median U-Statistics is the median of the U-statistics for the 25 currencies under investigation. The U-Statistics is defined as the ratio between RMSE of the unrestricted model to RMSE of the restricted model i.e (RMSE of Model/RMSE of the random walk). U < 1 implies that the magnitude of RMSE of the model is lower than that of the random walk. The corresponding number to U < 1 shows that number of currencies that hold the hypothesis U < 1. The CW presents results of the Clark and West (2007) test. The null hypothesis of the test is that U = 1 against the alternative test U < 1. The corresponding number shows the number of currencies that rejects the null hypothesis using (t > 1.68) at 5% level.
Note for the Model: FDI= Foreign Direct Investment; PI is Portfolio Investment, OI is other investments and BNK is Bank flows.

Taylor rule, PPP and monetary. They show that factor-based exchange rate model has satisfactory performance between 8 and 12 quarters. Similarly, Felicio and Junior (2014) (2012) concluded that factor model is able to beat the random walk model in medium to long-term forecast horizon. Kavtaradze (2016), using Georgian dataset, confirms the impressive performance of the of the factor model in the short run. In a related vein, Mc-Grevy et al. (2018) show that both the "dollar" and "euro" factors dominate the random walk bilateral exchange rate predictive models.

Based on the foregoing, it may be deduced that the exchange rate disconnect puzzle could be upturned with the application of the factor modelling. Our results lend support to the conclusion of Rossi et al. (2013) that the accurate exchange rate prediction does depend on the models used, sample period, the choice predictor, forecast horizon and forecast evaluation method.

4.1. Consistency tests

We conducted a number of robustness checks. First, we changed the forecasting measures and thus used Minimum Absolute Error (MAE) and Mean Square Error (MSE). Second, we also considered using the Great British Pounds as the benchmark currency. Evidently, our earlier results are robust to these changes. These results are presented in Tables 6−9.

5. Summary and conclusion

The study re-examines the exchange rate disconnect puzzle by lending support to that stance that among the causes of the puzzle is poor measurement of fundamentals that are used to predict exchange rate. Engel et al. (2015) show that exchange rate has inherent information that is difficult to extract from macroeconomic fundamentals. Thus, there is the need to circumvent the problem of accurately measuring the fundamentals. In what has become the norm in the literature, information is extracted from exchange rate which is used to predict exchange rate. Hence, studies have commonly resorted to the use of factor model.

Several theories have been used to forecast exchange rate. However, the portfolio balance theory is recently gaining attention. Despite the relative satisfactory performance of this theory, it has been observed that the important role of Global Financial Cycle has not been accounted for. Accounting for this feature is similar to solving the "scapegoat" effect. Thus, this study hypothesizes that Global financial cycle should be used as: (i) proxy for capital flows and (ii) predictor for exchange rate. The objective of the study is to forecast exchange rate. This objective is achieved in a two-step approach. In the first step, we extract factors and construct the global financial cycle based on four types of capital flows. The second stage dwells on using results from the first stage as predictors for exchange rate.

The study builds a dataset of 20 developed and emerging countries for the period 1990Q1-2017Q2. The Empirical evidences suggest that our approach to forecast exchange rate is able to beat the benchmark random walk model. The performance of all the models is quite impressive. For instance, the PI, OI and BANK models are able to, on the average, accurately predict 14, 17 and 17 bilateral exchange rates against the USD, respectively. Also, our results show that the performance of our model is more short term inclined. However, the performance of the late sample size is quite lower (in terms of Theil U statistics) for all the models. Accounting for statistical properties of the series in the model significantly improves the predictive prowess of the models. It is safe to conclude that the exchange rate premium puzzle is caused for poor measurement of the fundamentals. Once this problem is accounted for, the puzzle fizzles out, at worst or disappears, at best.

Appendix. Data Description and Source

Variable	Description/Definition	Measure	Source
Exchange Rate	Bilateral exchange rate between a country and the United States (U.S). Exchange rate is defined as the number of units of local currency per one American Dollar (USD).	Log	International Financial Statistics (IFS)
FDI	Foreign Direct Investment Inflow "… cross-border investments associated with a resident in one economy having control or a significant degree of influence on the management of an enterprise that is resident in another economy"	% of GDP	IMF International Investment Position Statistics

(*continued on next page*)

(*continued*)

Variable	Description/Definition	Measure	Source
Portfolio Investment	"… cross-border transactions and positions involving debt or equity securities, other than those included in direct investment or reserve asset".	% of GDP	IMF International Investment Position Statistics
Bank Flows	Category of cross-border investments classified in government-related flows and private flows, which are recorded within the banking industry	% of GDP	IMF International Investment Position Statistics
Other Flows	"a residual category that includes positions and transactions other than those included in direct investment, portfolio investment, financial derivatives and employee stock options, and reserve assets"	% of GDP	IMF International Investment Position Statistics
VIX Index	VIX measures market expectation of near term volatility conveyed by stock index option prices. It is used to measure investors' risk averseness.	It is an index	FRED St. Louis
3 Months T-Bill	Interest rate at which Treasury bills with a 3-month maturity are sold on the secondary market.	%	FRED St. Lousi
G7 Economic Growth	Average of economic growth rate of the G7 countries	%	IFS
Money Supply	Growth rate of the US M2 money supply	%	IFS
Commodity Price	Log of the quarter average of oil price (West Texas Intermediate)	%	IFS
trade openness;	Sum of the log import and export scaled to log of GDP	%	IFS
Financial Development	Credit to the private sector scaled to GDP	%	IFS

Note: Definition of the types of capital flows are extracted from the sixth edition of the IMF International Investment Position Manual (BPM6).
Source: Author's computation.

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