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Abstract
The exchange rate disconnect puzzle argues that macroeconomic fundamentals are not able to accurately predict exchange rate. Recent studies have shown that the puzzle could be upturned if: (i) the dataset is structured in a panel form; (ii) the model is based on the portfolio balance theory (PBT); (iii) factor models are employed and (iv) time-varying parameter (TVP) regression is used. This study combines these strands of the literature. Essentially, the study conjectures that Global Financial Cycle (GFCy), drawing inspiration from PBT, has some predictive information content on exchange rate. Using dataset for 25 countries, we produced some mixed results. On the whole, the GFCy is able to produce lower forecast error, as compared to the benchmark model. However, its effectiveness is dependent upon the regression type (TVP vs Panel Fixed Effect); forecast horizons (short vs long); the sample period (early vs. late) and measures of GFCy. The results are robust to a number of checks.

Keywords: Exchange rate, forecasting, Global financial cycle and Time-varying parameters.
JEL classification: C52, E52, F37, G17.

Introduction

Exchange rate disconnect puzzle hypothesizes the inability of macroeconomic fundamentals to accurately predict exchange rate. This stance comes from the works of Messe and Rogoff (1983), which concludes that the exchange rate exhibits a random walk. Succeeding studies, spanning over two decades, have found it difficult to upturn this conclusion. However, more recent studies have shown that the predictive prowess of macro variables on the exchange rate has improved significantly. Various theoretical models have been formulated to forecast exchange rate[1]. The performances of these models have produced mixed findings (see Chinn, 2011, and Rossi, 2013 for both theoretical and empirical surveys).

Unlike other theories of exchange rate, the Portfolio Balance Theory (PBT) has recorded relatively low patronage, both from the empirical and theoretical perspectives. On a bright side, there tends to be consensus as regards the impressive performance of this theory. The application of the theory is in two tranches: the international financial adjustment (as pioneered by Gourinchas and Rey (2007) and a general approach (see Cushman, 2007). In this study, we take a new twist in the application of the PBT. Essentially, the argument we put forth is that the Global Financial Cycle (GFCy) is a reliable predictor of exchange rate. The GFCy literature hypothesizes that there is high comovement in the capital flow models. This comovement explains a large chunk of variations in capital flow models. Succinctly, monetary fundamentals of the developed countries are the major determinants of capitals flows (Rey, 2013). Other studies have shown that the variables from the centre economies have high explanatory power in the various capital flow models (Sarno et al. 2016; and Barrot and Serven, 2018). Based on the foregoing, we hypothesize that GFCy, rather than the individual components of financial assets, as postulated by the theory, should be used as the predictor of exchange rate.

It has been widely acknowledged that one of the causes of the poor performance of the macro fundamentals in predicting exchange rate is due to parameter instability (Rossi and Sekhposyan, 2011). The ensuing instability is caused by the evolution and often times sudden changes in the dynamics of exchange rate, macroeconomic variables and policy actions (Byrne et al., 2016). Interestingly, Rossi (2013) proffer that researchers should exploit such instabilities in order to improve the performance of exchange rate predictive models. We add a new twist to the issue of instability. We opine that the source of instability is related to capital flow dynamics and by extension, the GFCy. Capital flow literature has shown that the dynamics of capital flows has changed overtime (Bluedorn et al., 2013; Pagliairi and Hanan, 2017). Of the various ways of accounting for instability, this study favours Time-Varying Parameters (TVP). Our preference for the latter is due to the peculiarity and nature of the model. Due to the fact that the dynamics of capital flows changes, it could imply that the predictive content of the variable is dependent upon statistically accounting for the time-varying feature.

The objective of the study is to examine the out-of-sample prediction of exchange rate using GFCy as the predictor in a TVP framework. Broadly, we proffer answers to the inquiry of whether GFCy could beat the benchmark models (random walk- with and without drift) in the prediction of exchange rate. This objective is pursued using TVP model. The estimated parameters is based on information in the likelihood using the Bayesian model.

[1] Among which include Taylor rule, Uncovered interest rate parity, monetary models (flexible and stick prices, forward-looking models), interest rate differential.

This present study makes three major contributions to the literature. First, it joins the list of relatively small, but growing, numbers of TVP based studies. As such, we hope to extend on the results of Della Corte et al. (2009), Abbate and Marcellino (2014), Byrne et al., (2016) and Haskamp (2017). Second, the application of the PBT is another novel contribution. As an extension, this is one of the first attempts to use GFCy as a predictor of exchange rate. Third, we used four variants of capital flows. This is based on the heterogeneous nature of the variants of capital flows on macro-financial series.

This present paper is similar to some earlier studies in terms of an aspect of our methodology (i.e. factor modelling). Relatedly, there are two branches of the literature. The first branch extract factors from exchange itself (Engel et al., 2015; Mc-Grevy et al., 2018; Ponomareva et al. 2018). The second branch of the literature have extracted factors from other variables asides exchange rate. For instance, Kim and Park (2018) extracted factors from over 120 US macro fundamentals, while Morales-Arias and Moura (2013) and Ahmed et al. (2016) considered expectation risk based factors

Foreshadowing the results, we show that GFCy is able to produce lower forecast error, as compared to the benchmark model. However, its effectiveness is dependent upon the regression type (TVP vs Panel Fixed Effect); forecast horizons (short vs long) and the sample period (early vs. late). The results are robust to a number of checks. Following this introduction, the rest of the study is structured as follows. An overview of the literature is presented in Section 2. The mechanics of TVP is presented in Section 3. Data and Methodology are discussed in Section 4. Empirical results are presented in Section 5. Section 6 concludes the paper, with suggestion for future research.

2 Brief Literature Review

Empirical analyses of this study is based on the adoption of portfolio PBT of exchange rate determination. Diverging from the other contemporary studies, we used GFCy as the predictor and subject the same to TVP model. As such, this study is in the heart of two influential strands of the literature: PBT and TVP.

2.1 Portfolio Balance Theory

The main cannon of this theory is that exchange rate is determined by the interaction of demand and supply of assets in the financial market. In the model build-up, there are three classes of assets: domestic money (M), domestic bonds (B) and foreign bonds (F) (see, Branson et al., 1977; Bisignano and Hoover, 1982; Sarantis, 1987). The Wealth (W) equation of the PBT model is therefore defined as thus:

$$W = M + B + F \tag{1}$$

Interest rate differential, between domestic and foreign markets, are the main determinants of demand for these assets. The demand is homogenous of degree 1 in relation to nominal wealth and is mathematically expressed as:

$$M = m(i, i^* + \Delta s^e)W, \qquad m_i < 0, m_{i^*+\Delta s^e} < 0 \tag{2}$$

$$B = b(i, i^* + \Delta s^e)W, \qquad b_i > 0, b_{i^*+\Delta s^e} < 0 \tag{3}$$

$$F = f(i, i^* + \Delta s^e)W, \qquad f_i < 0, f_{i^*+\Delta s^e} > 0 \tag{4}$$

Taking the first derivatives of equations (2)-(4) shows that when there is an increase in the rate of an asset, this triggers increase in its demand. Since these assets are perfect substitutes (i.e. $b_i > f_i$ and $f_{i^*+\Delta s^e} > b_{i^*+\Delta s^e}$), increase in domestic wealth will lead to increase in the demand domestic assets (bonds) in comparison to foreign assets.

The empirical studies that had applied the PBT are quite few, an attributable cause could be linked to data unavailability for non-monetary assets. However, the existing studies on PBT have expanded the frontier of knowledge. These studies can be categorized into two: international adjustment-based studies and "others". Gourinchas and Rey (2007) made the seminal contribution in the international financial adjustment process. The authors show that the two identified channels of the adjustment process: trade and valuation, are potential predictors of exchange rate. Empirical validation of this claim confirms the hypothesis, as both channels were able to predict US's real-effective exchange rate. Alquist ad Chinn (2008) use myriad theories of exchange rate, PBT inclusive. Among other things, it was shown that export and foreign assets are able to predict bilateral exchange rate, thus validating the results of GR. Similarly, Della-Corte et al. (2010) towed the approach of Gourinchas and Rey's measure of financial adjustment. Using bilateral exchange rate between the US dollars and four other major currencies (CAD, GBP, JPN and GER), the authors were able to confirm the results of Gourinchas and Rey. Lane and Shambaugh (2010) explored the valuation channel of exchange rate determination, via currency composition of financial assets and liabilities. Other studies that have explored the balance sheet effect of exchange rate (Benetrix et al., 2015; Maggiori et al., 2018).

The "Other" type based studies include Cushion (2007) who applied the PBT on the US-Canadian exchange rate and found that the model is able to beat the benchmark model, in some out-of-sample forecast horizon. He acknowledged that the results are not quite satisfactory, but are consistent with theoretical underpinnings and are better than fundamental based model. Breedon and Vitale (2010) examined the relationship between order flow model of exchange rate and assets in the portfolio balance model. They show that, to a large extent, PBT explains the intervention of exchange rate. Furthermore, it is pointed out that the transmission mechanism of order flow to exchange rate is via the portfolio balance.

The TVP is one of the popular approaches to accounting for non-linearity and the main cannon of the model is that the relationship between exchange rate and macroeconomic fundamentals do evolve overtime. This evolution is a form of instability, which has been identified to be an important cause of the exchange rate disconnect puzzle. It is opined that the performance of exchange rate predictive models would improve if models could account for evolution in the estimated parameters. An overview of the literature have shown that the TVP models are able to beat the random walk models (Hall et al., 2008; Engel et al., 2008; Molodtsova and Papell, 2009; Della Corte et al., 2009; Abbate and Marcellino, 2014; Haskamp, 2017). TVP has been modelled in different variants: the traditional Bayesian model (Byrne et al., 2016), Bayesian-VAR (Della Corte et al., 2009), dynamic Bayesian-VAR (Abbate and Marcellino, 2014). Similarly, TVP has been tested using various theories (see Yuksel et al., 2013 for literature survey).

3. The Mechanics of Time-Varying Parameters Regression

It is common knowledge that forecasting exchange rate requires specifying a model where the change in exchange rate is a function of the deviation from its implied value. This implies that in the short-run, exchange rate deviates from its implied fundamentals (Mark, 1995). Mathematically, this is expressed below:

$$\Delta s_{t+h} = \alpha_t + \beta_t Z_t + \varepsilon_{t+h}, \qquad \varepsilon_{t+h} \sim N(0, R) \tag{5}$$

$$Z_t = \Omega_t - s_t \tag{6}$$

It will be observed from equation 5 that subscript *t* is attached to the parameters (i.e. α and β), thus making them change overtime. We follow Stock and Watson (1996) and Rossi (2006) on the coefficient's law of motion. In line with Byrne et al. (2016), we assume that the model follows a Random Walk Time-Varying Parameter process and is specified as:

$$\beta_t = \beta_{t-1} + \upsilon_t \tag{7}$$

Where υ_t is the error term and is expected not to correlate with the ε_{t+h} (as in equation 1). The state-space model is the combination of equations 5 and 7, where the former is the measurement equation and the latter is the transition equation.

There are two approaches to estimating state-space models: Bayesian method and Kalman filter maximum likelihood approach (Kim and Nelson, 1999). The latter is susceptible to accumulation error as a result of evaluation from a very large number of likelihood functions, which could bias the estimated parameters. Another related problem is the identification of the objective priors of the Kalman filter. Conversely, the Bayesian method is able to effectively deal with these identified shortcomings. Hence, this study adopts the Bayesian method to estimate the time-varying parameters. Also, we follow the Carter and Kohn (1994) algorithm and the Gibbs sampler to simulate draws from the parameters' posterior distribution. There are three procedures to follow in estimating the model: (i) stimulate priors for unknown parameters; (ii) highlight the conditional distributions for the priors; and (iii) draw samples from the prior distributions[2].

4 Methodology and Data

4.1 Methodology

To recall, the broad objective of this study is to determine the extent to which GFCy could predict exchange rate. In essence, GFCy is regarded as the predictor of exchange rate. The first stage of the analysis is to construct GFCy, as it is not a readily available variable. There is no

[2] Byrne et al. (2016) provide detailed explanations on the priors elicitations and the steps of the algorithm.

consensus as regards the measurements of GFCy (Cerutti et al., 2017). However, there tend to be unison as regards the approach to measuring it, as most studies have favoured using factor modelling (see Cerutti et al., 2017; Barrot and Servens, 2018; Scheubel et al., 2019). Cerutti et al. (2017) extracted factors from measurement of capital flows, while Barrot and Servens factor loadings are based on macroeconomic and financial variables. Scheubel at al. (2019) considered two variants of GFCy: price- and quantity- based. In a simple approach, Rey (2013) captures GFCy using investors' risk appetite, i.e. the VIX index. It is important to assert that these measures of GFCy have varying effects on the dynamics of capital flows. This study seeks to examine the extent to which these various measures of GFCy affects exchange rate prediction.

4.1.1 Constructing GFCy (Approach 1)

This approach is based on the work of Barrot and Servens (2018) who specified a capital flow model and captures the regressors into two groups: global and country-specific. This categorization is to reflect the dichotomization of the determinants of capital flows in line with the seminal papers of Calvo et al. (1996).

Analytically, the factor model is specified below:

$$CF_{it} = (\alpha_i)'G_t + (\beta_i)'C_{it} + \varepsilon_{it} \qquad (8)$$

Where CF denotes measures of gross capital inflows for country *i* at period *t*. We consider four measures of capital flows: Foreign Direct Investment (FDI), Portfolio Investment (PI), bank flows (Bank) and Other Investments (OI). G_t and C_{it} are the unobserved global common and country-specific factors, respectively. α_i and β_i are their respective factor loadings. The variables associated to the global factors are: (i) global uncertainty, measured by economic policy uncertainty, by Baker et al. (2016)[3]; (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-Brent) price. The country specific factors are (i) financial openness, measured by the Chin-Ito index; (ii) trade openness (sum of the log import and export scaled to log of GDP); (iii) financial depth, measured as the credit to the private sector (% of GDP) and (iv) log of consumer price index.

An overview of equation 8 shows that there are three major factors: global, country-specific and idiosyncratic factors. This tends lead to an inquiry "which of these factors should be used as the predictor?" In line with Baku (2018), we used the idiosyncratic factor.

4.1.2 Constructing GFCy (Approach 2)

Cerutti et al. (2017) relied on both dynamic and static factor model to extract factor, based on the largest eigenvalue, from the various measures of capital flows. For the dynamic factor models, up to two lags of capital flows were used. In an interesting twist, the authors also extracted factors from different groups of countries. This is to allow for the possibility that

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[3] Barrot and Servens (2018) used global risk, proxied by the VIX index. Our decision to use global uncertainty, in place of risk, is due to the fact that the risk is later used as a measure of GFCy.

factors relevant for the advanced countries might not be the same as those of emerging countries. Thus, the three groups captured in the study are advanced, emerging and a mixture of advanced and emerging countries.

4.1.3 Constructing GFCy (Approach 3)

Rey (2013) and Bruno and Shin (2015) had simply used VIX index[4]. As such, their measure of GFCy does not require construction.

The second stage of our analysis requires specifying the exchange rate predictive model, where GFCy is used as the predictor, as shown below:

$$S_{it} = \propto_t + \beta_t GFCy_{it} + \varepsilon_{it} \quad (9)$$

Where S is the bilateral exchange rate between country i and the United States Dollars (USD). S is defined as the number of units of local currency that is equivalent to 1 USD. A section of the literature has shown that accounting for the role of macroeconomic fundamentals does improve the performance of the predictive model (Salisu et al., 2019). Also, it has become a norm to expand the bivariate model to capture other variables relevant for exchange rate determination (see Wu and Wang, 2012; Engel et al. 2015; Mc-Grevy et al. 2018). The expanded model is specified below:

$$S_{it} = \propto + \beta GFCy_{it} + \gamma Z'_{it}\ \varepsilon_{it} \quad (10)$$

Where Z' is a vector of explanatory variables, which includes inflation, money supply, output and trade openness.[5]

4.2 Forecast Implementation and Evaluation

Our data is divided into two components: in-sample and out-of-sample. The in-sample component is updated recursively to estimate the parameters in equation 9 or 10, as the case might be. In line with the extant literature, our forecasting horizon captures both the short-run horizon (i.e. H = 1 and 4 quarters ahead) and long-run horizon (i.e. H = 8 and 12 quarters ahead). The adopted benchmark model is the random walk without drift.

The forecast performance is based on the Root Mean Squared Error (RMSE). In the model set-up, there are two models: Model 1 (restricted or the random walk model) and Model 2 (unrestricted or the GFCy model). Theil-U statistics is computed as the model 2/model 1. The resulting statistic that is less than unity implies that model 2 has a higher predictive power, hence, the GFCy model is able to accurately predict exchange rate.

[4] VIX is perceived to measure the level of risk averseness of investors. It is calculated as the volatility of the Chicago Board Options Exchange. A popular measure of the stock market's expectation of volatility based on S&P 500 index.

[5] For the first measure of GFCy, we do not include control variables, as some of the variables were already used in the factor modelling. Thus, GFCy is the sole predictor of exchange rate using this method. As a robustness check, we include variables such as capital control.

The two measures of forecast evaluation adopted are the Clark and West (2007, hereafter, CW) and the Diebold and Mariano (1995) and West (1996) [DMW] tests. These tests examine the significance of the forecasting model. There is no consensus as regards which of the test is superior to the other. For instance, DMW has been found to undersize the forecast errors for two nested models (CW). On the flipside, Rogoff and Stavrakeva (2008) proved that CW test does not always report the minimum forecast errors, hence suggested that bootstrapping p-value based tests (i.e. DMW) is superior.
The CW test shows that sample difference between the forecast errors of two nested model is biased in favour of the random walk model.

The procedure for estimating CW is as follows:

$$\hat{f}_{t+k} = \left(GFCy_{t+k} - \hat{G}FCY_{1t,t+k}\right)^2 - \left[\left(GFCy_{t+k} - \hat{G}FCY_{1t,t+k}\right)^2 - \left(\hat{G}FCy_{1t,t+k} - \hat{G}FCy_{2t,t+k}\right)^2\right] \quad (11)$$

Where k is the forecast period; $\left(GFCy_{t+k} - \hat{G}FCY_{1t,t+k}\right)^2$is the squared error for the restricted model (i.e model 1), $\left(GFCy_{t+k} - \hat{G}FCY_{1t,t+k}\right)^2$ is the squared error for the unrestricted model (i.e. model 2), while $\left(\hat{G}FCy_{1t,t+k} - \hat{G}FCy_{2t,t+k}\right)^2$ is the adjusted squared error due to the introduction of C-W to correct for the noise associated with larger model's forecast. Thus, the sample average $\hat{f}_{t+k}$ is expressed as: $RMSE_1 - (RMSE_2 - adj.)$. Each term is computed as:

$$RMSE_1 = P^{-1}\left(GFCy_{t+k} - \hat{G}FCY_{1t,t+k}\right)^2;$$

$$RMSE_2 = P^{-1}\sum\left(GFCy_{t+k} - \hat{G}FCY_{1t,t+k}\right)^2; \text{ and}$$

$$\text{Adj.} = P^{-1}\sum\left(\hat{G}FCy_{1t,t+k} - \hat{G}FCy_{2t,t+k}\right)^2$$

Where P is the number of predictions used in computing the averages. In order to examine the equality of the forecasting performance between model 1 and 2, the $\hat{f}_{t+k}$ is regressed on a constant and the resulting t-statistic for a zero coefficient is used to draw inference.

4.3 Data

Empirical analysis is based on 25 advanced and emerging countries for the period 1990Q1 – 2014Q4.[6] The selected countries are those regarded to have floating exchange regime and record substantial amount of capital inflows. Exchange rate is measured in terms of the end-of-quarters values. Data on VIX, 3-month treasury bills, US money supply are sourced from FRED St Louis databank, while capital flows data are from Cerutti et al., (2017). EPU data is collected from Baker et al., (2016), while other data specified in the model are sourced from the International Financial Statistics (IFS). Taking a cue from Engel et al. (2015), our dataset

[6] These countries are Australia, Brazil, Canada, Chile, Costa Rica, Finland, France, Germany, Hungary, Iceland, Israel, Italy, Japan, Korea, Mexico, Netherlands, New Zealand, Norway, Portugal, Romania, South Africa, Spain, Sweden, Switzerland and Turkey.

is divided into two samples. The first sample, which we coined "early sample" range between 1990Q1 – 2007Q1., while the late sample is between 2007Q1-2014Q4[7].

5. Empirical Results

The starting point of our analysis is extract the factors. As indicated in section 3 above, two measures of GFCy warrant construction. Figure 1 depicts the results of using Barrot and Servens (2018) approach, while Figure 2 shows that of Cerutti et al. (2017).

The empirical results are presented in Tables 1 and 2. An overview of the Tables shows the three forecast evaluations for each estimated model: Theil U statistics, CW and DMW. The U-Statistics is the Theil U-statistics, which measures the forecast horizons. The reported statistics is the median of the U-statistics for the countries in the sample. The U-Statistics is defined as the ratio between RMSE of the GFCy model (i.e. unrestricted model) to RMSE of the benchmark or random walk model (i.e. restricted model). The lower this statistic, the better the forecasting performance of the model. The CW test evaluates the statistical significance of the two nested models (i.e. the restricted and unrestricted).

Table 1 presents the results of the early sample. There are three main points to deduce from the table. First, the performance of the PFE model outweighs that of the TVP model (with the exception of the FDI model). This stance is based on the fact that the PFE has lower reported median U-statistics, as compared to the TVP model. A section of the literature had reported improved performance of the PFE regressions, in contrasts to the random walk model (see Engel et al., 2008; Cerra and Saxena, 2010; and Ince, 2014; Engel et al., 2015). Second, the predictability performance of the TVP model is more enhanced at the short term forecast horizons (i.e. at H = 1 and H = 4). However, the accuracy of the PFE model cuts across both the short- and long- term horizons. Third, FDI model is the least accurate model (for both the TVP and PFE regressions). While FDI is merely able to correctly predict, at most, 13 countries, other models accurately predicted up to 20 countries.

Results of the statistical checks pose some interesting findings. Essentially, it is shown that the statistical significance is dependent upon the test/measure. The bootstrap critical values generally show less significance, across the various estimated models. For instance, the TVP regressions produce U-statistics less than unity for more than half of the currencies, we find maximally 7 currencies with statistical significance. Also, the number of statistical significance decreases as the forecasting horizon increases. However, the CW test produces improved results. Also, the CW is significant, for at least, the number of currencies whose U-statistics is less than unity. These findings partly illustrate the results of Byrne et al. (2016) who showed that statistical significance is better illustrated using the CW test.

[7] 50 percent of the data is used for in-sample, while the balance is meant for out-of-sample forecast.

Figure 1: Trend of Factor Loadings Using Approach 1

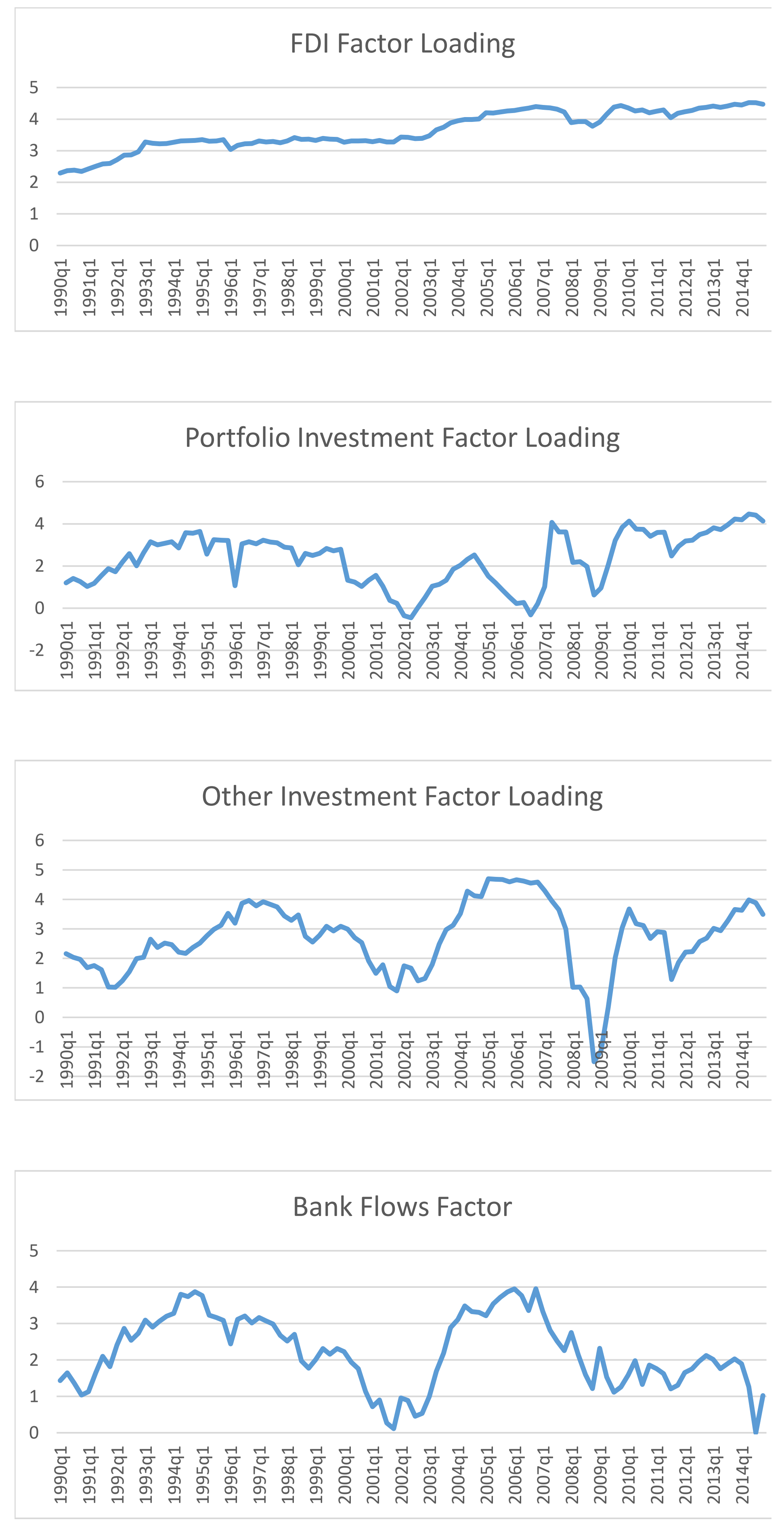

Figure 2: Trend of Factor Loadings Using Approach 2

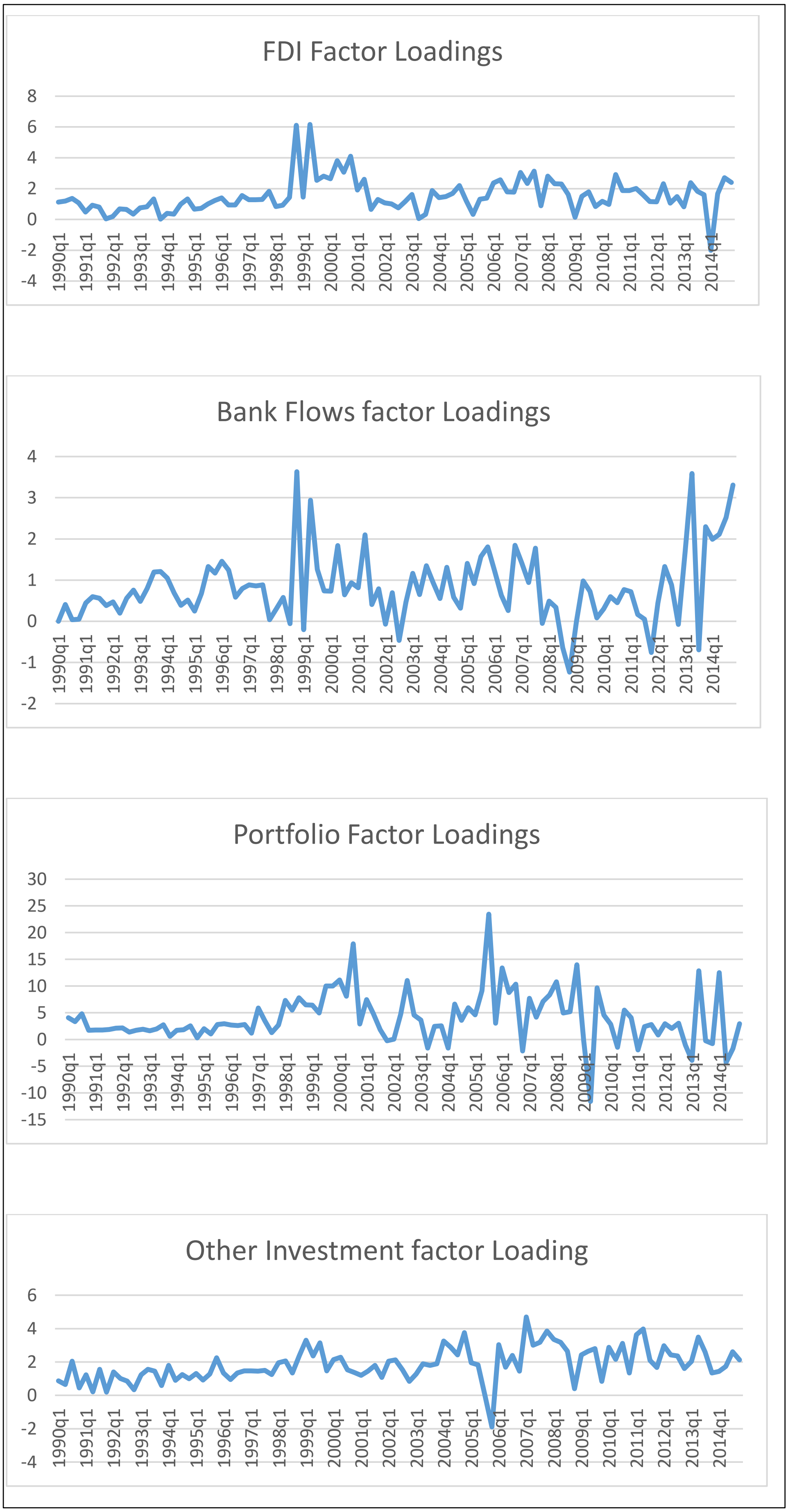

Table 1: Early Sample Results

		Time-Varying Regression				Panel Fixed Effect			
Model	Statistics	H=1	H=4	H=8	H=12	H=1	H=4	H=8	H=12
FDI	U-Stat	0.8542	0.8788	0.9354	1.0152	1.1249	1.1776	1.2574	1.4066
	U<1	11	12	12	13	5	2	1	2
	CW	13	13	18	14	9	9	15	17
	DMW	5	5	3	1	2	2	3	1
PI	U-Stat	0.9854	9.9981	1.0246	1.1466	0.8783	0.8491	0.8561	0.8466
	U<1	18	18	17	16	14	14	14	16
	CW	19	20	22	18	13	14	13	15
	DMW	6	6	4	3	3	2	2	1
OI	U-Stat	0.9658	0.9813	1.0689	1.210	0.8469	0.8511	0.7859	0.7721
	U<1	20	21	19	18	15	15	15	15
	CW	18	17	18	18	23	21	20	24
	DMW	7	8	5	2	4	4	2	0
BANK	U-Stat	1.1596	1.0136	0.9756	0.9613	0.8418	0.8515	0.7805	0.7736
	U<1	17	16	17	17	15	15	15	15
	CW	18	18	19	16	23	21	20	24
	DMW	6	4	2	1	5	5	4	4

Source: Author's Computation

Note: U-Stat, CW and DMW are the Theil U-Statistics, Clark and West test, and Diebold, Mariano and West test, respectively. U<1 implies the number of countries whose forecast error of the restricted model is less than that of unrestricted model.

Results of the late sample size are presented in Table 2 below. An overview of the table shows that the U statistics is predominantly less than 1 (for both PFE and TVP regressions). This implies that irrespective of the regression type, the GFCy model is able to beat the random walk model, for a large number of countries. Hence, GFCy is found to be a better predictor of exchange rate. A number of studies have shown that factor model based regressions tend to have higher prediction accuracy rate as compared to the benchmark model (e.g. Wu and Wang, 2012; Kavtaradze, 2016 and Mc-Grevy et al., 2018). The value addition this table offers to the extant literature is the comparison between TVP and PFE regressions. On the average, the TVP regressions produce related smaller forecast error as compared to the PFE statistics. Hence, TVP models are better predictor of exchange rates. These findings have been supported by previous studies (Della Corte et al., 2009; Abbate and Marcellino, 2014; Haskamp, 2017). Expectedly, the forecasting power reduces along forecasting horizons. Another point to note is that more countries have lower U statistics in the TVP model, as compared to the PFE model. This stance also holds when Tables 1 and 2 are contrasted against each other.

Table 3 presents the result using Cerutti's et al. (2017) approach. The predictability of the FDI model is rather low, as compared to other competing models. For instance, the U-statistics for FDI is predominantly in excess of one (for PFE model). Hence, the benchmark model produces more reliable forecast. This finding is somewhat intuitive, as FDI flows are long term based, while exchange rate is a high frequency series. As such, the predictive information on FDI is expected to be low. Contrarily, other types of capital flows have short-term dynamics. In comparison to Table 2, this measure of GFCy produces less impressive results, in terms of U-statistics, number of countries with U<1 and the two measures of the forecast evaluations.

Table 2: Late Sample Results

		Time-Varying Regression				Panel Fixed Effect			
Model	Statistics	H=1	H=4	H=8	H=12	H=1	H=4	H=8	H=12
FDI	U-Stat	0.8651	0.8788	0.9011	0.9325	1.2934	1.1299	1.1278	1.1214
	U<1	16	16	15	12	6	7	8	7
	CW	10	13	13	12	21	21	22	22
	DMW	6	7	6	6	0	0	1	1
PI	U-Stat	0.7695	0.7751	0.7216	0.7015	0.8151	0.8689	0.8874	0.8637
	U<1	14	16	16	15	12	11	12	12
	CW	20	20	22	21	21	21	21	21
	DMW	11	13	11	11	1	1	2	1
OI	U-Stat	1.0123	0.9668	0.9463	0.9103	0.9088	0.9351	0.9509	0.9745
	U<1	17	17	16	17	11	11	11	10
	CW	21	22	21	19	23	20	19	19
	DMW	18	17	18	16	0	0	1	0
BANK	U-Stat	0.8016	0.8215	0.8139	0.8301	0.9076	0.9332	0.9487	0.9721
	U<1	15	16	15	17	11	11	11	10
	CW	20	22	21	21	23	22	20	20
	DMW	17	16	17	18	2	1	0	1

See notes in Table 1

Table 3: Factors from Capital Flow measures of GFCy

		Time-Varying Regression				Panel Fixed Effect			
Model	Statistics	H=1	H=4	H=8	H=12	H=1	H=4	H=8	H=12
FDI	U-Stat	1.0252	1.0361	0.9984	1.0276	1.2351	1.3210	1.0256	1.1206
	U<1	4	4	3	4	6	7	6	6
	CW	9	9	8	7	10	12	11	12
	DMW	6	6	5	4	3	2	0	1
PI	U-Stat	0.8765	0.8985	0.9016	0.9357	2.1125	2.2103	2.2879	2.4015
	U<1	3	3	0	0	5	6	5	5
	CW	9	10	11	9	8	8	6	7
	DMW	2	1	1	1	3	1	2	2
OI	U-Stat	0.9998	0.9785	0.9885	1.0138	0.9663	0.9751	0.9965	1.0686
	U<1	6	6	5	5	6	4	5	5
	CW	10	9	9	7	8	6	5	3
	DMW	3	5	5	2	3	2	2	0
BANK	U-Stat	0.8967	0.9016	0.9153	0.9356	0.9803	0.9963	1.0283	1.1342
	U<1	7	7	7	6	4	4	2	3
	CW	6	6	6	4	8	8	7	6
	DMW	3	1	0	0	2	2	1	0

See notes in Table 1

Table 4 presents the results of using VIX as the predictor. A striking finding emanating from the table reveals that VIX is unable to predict currencies at the early sample. This result is consistent across the forecasting horizons and the regression types (i.e. PFE and TVP). A plausible justification to this might be linked to the timing of the sample (i.e. pre-global finance crisis). Prior to this crisis, there was relative stability in the trend of VIX. Hypothetically, when

VIX is less volatile, it tends to disconnect from exchange rate. This is because less volatility would lead to less trading activities, as foreign investors are not motivated to change the composition of their portfolios. The late sample shows some promising results. Essentially, it is found that VIX is able to predict exchange rate in the TVP regressions and over short time period (i.e H= 1 and H=4). These results are quite intuitive. The attendant effect of the crisis has shown the ease of contagion. Hence, risk averse investors will redesign their asset portfolio to markets that are less volatile. This act of asset transfer will impact on exchange rate (i.e. the valuation channel). It is also important to note that the results of factor model induced measure of GFCy (i.e. Tables 1 and 2) are, on the average better than those reported in Table 4. In essence, the accurate prediction of exchange rate is sensitive the measures of GFCy

Table 4: VIX as a measure of GFCy

		Time-Varying Regression				Panel Fixed Effect			
Late	Statistics	H=1	H=4	H=8	H=12	H=1	H=4	H=8	H=12
Early	U-Stat	1.2643	1.3475	1.4441	1.5243	1.3551	1.4287	1.5699	1.3478
	U<1	4	4	5	4	8	7	7	8
	CW	11	13	15	15	18	16	16	17
	DMW	2	2	0	1	0	0	1	1
Late	U-Stat	0.7851	0.7965	1.0032	0.9879	0.9668	0.9768	1.0005	1.1325
	U<1	10	12	11	13	9	6	4	5
	CW	15	17	14	14	18	16	16	15
	DMW	4	4	3	1	0	0	1	1

See notes in Table 1

We conducted a number of robustness checks: (i) regressions based on rolling windows; (ii) forecast evaluation based on mean squared error; (iii) change in currency base from US Dollars to British Pounds Sterling; (iv) change of benchmark model to random walk with drift; and (v) inclusion of control variable (capital control)[8] to the first measure of GFCy. The choice of these checks is based on the contention in literature. For instance, a section of the literature has identified the weakness of rolling window forecasting procedure to breakdown when the sample size is small (see Molodtsova and Papell, 2012). Also, Engel et al. (2015) argued that it is worth checking for the sensitivities of the estimated results to changes in the currency numeri. Similarly (Salisu et al., 2019) concluded that the inclusion of control variables tends to improve the performance of forecasting models of financial series.

Results of these checks are presented in Table 5. Summarizing the Table, our results are robust to the first four checks. Although, there might be some minor differences in the number of currencies with less than one Theil-U statistics. This does not in any way alter the main position of our results. Results of check 5 negatively affect the predictive prowess of the GFCy model. These results support theoretical underpinnings, as countries with capital control measures tend to record limited capital flows (Straetman et al., 2013). Hence, capital flows will have decreased predictive information content for countries with capital control policies.

[8] Capital control is measured using dummy provided in the Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER)

Table 5: Robustness Checks: Does the restricted model outperforms the unrestricted model?

		Early Sample				Late Sample			
		H=1	H=4	H=8	H=12	H=1	H=4	H=8	H=12
Check 1	FDI	Yes(16)	Yes(15)	Yes(13)	Yes(12)	Yes(19)	Yes(17)	Yes(15)	Yes(14)
	PI	Yes(17)	Yes(17)	Yes(14)	Yes(13)	Yes(18)	Yes(16)	Yes(12)	Yes(10)
	OI	Yes(18)	Yes(16)	Yes(15)	Yes(15)	Yes(20)	Yes(19)	Yes(18)	Yes(16)
	BANK	Yes(15)	Yes(14)	Yes(14)	Yes(12)	Yes(17)	Yes(17)	Yes(16)	Yes(14)
Check 2	FDI	Yes(12)	Yes(11)	Yes(10)	Yes(9)	Yes(17)	Yes(15)	Yes(14)	Yes(16)
	PI	Yes(19)	Yes(17)	Yes(17)	Yes(15)	Yes(13)	Yes(13)	Yes(11)	Yes(12)
	OI	Yes(17)	Yes(16)	Yes(14)	Yes(12)	Yes(16)	Yes(15)	Yes(14)	Yes(13)
	BANK	Yes(19)	Yes(17)	Yes(14)	Yes(12)	Yes(19)	Yes(18)	Yes(17)	Yes(16)
Check 3	FDI	Yes(14)	Yes(14)	Yes(13)	Yes(11)	Yes(18)	Yes(17)	Yes(16)	Yes(14)
	PI	Yes(17)	Yes(15)	Yes(14)	Yes(13)	Yes(13)	Yes(11)	Yes(10)	Yes(10)
	OI	Yes(19)	Yes(20)	Yes(20)	Yes(19)	Yes(18)	Yes(16)	Yes(15)	Yes(15)
	BANK	Yes(17)	Yes(16)	Yes(14)	Yes(15)	Yes(17)	Yes(17)	Yes(16)	Yes(14)
Check 4	FDI	Yes(12)	Yes(13)	Yes(10)	Yes(12)	Yes(17)	Yes(15)	Yes(14)	Yes(16)
	PI	Yes(19)	Yes(17)	Yes(17)	Yes(15)	Yes(11)	Yes(11)	Yes(13)	Yes(12)
	OI	Yes(21)	Yes(20)	Yes(19)	Yes(18)	Yes(16)	Yes(15)	Yes(15)	Yes(14)
	BANK	Yes(19)	Yes(17)	Yes(15)	Yes(12)	Yes(19)	Yes(18)	Yes(17)	Yes(17)
Check 5	FDI	Yes(3)	No	No	No	Yes(5)	Yes(3)	No	No
	PI	Yes(2)	No	No	No	Yes(4)	Yes(2)	No	No
	OI	No	No	No	No	No	No	No	No
	BANK	Yes(1)	No	No	No	Yes(2)	No	No	No

6. Conclusion

This study ventures into the exchange rate disconnect premium puzzle, which argues that macroeconomic fundamentals are unable to accurately predict exchange rate. This argument was first postulated by Meese and Rogoff (1983). However, and more recently, four groups of study have shown that the puzzle could be upturn with the application of: (i) portfolio balance theory (PBT) of exchange rate (Lane and Shambaugh, 2010; Rey, 2013; Benetrix et al., 2015; Maggiori et al., 2018); (ii) factor modelling (Engel et al., 2015; Mc-Grevy et al., 2018); (iii) panel data structure (Cerra and Saxena, 2010; Ince, 2014) and time-varying parameter regression (Abbate and Marcellino, 2014Byrne, 2016; Haskamp, 2017). Importantly, the portfolio balance PBT is viewed from the prism of the global financial cycle (GFCy). This present study innovatively combines these strands of the literature.

The objective of the study is to examine the extent to which GFCy with Time-Varying Parameter (TVP) models could predict currencies of 25 selected OECD countries. Analyses are based on two sample sizes and four forecast horizons. The TVP results are also contrasted with Panel Fixed Effect (PFE). On the whole, these models yield mixed results. In the early sample, PFE tends to have lower forecast error as compared to TVP. The accuracy of the TVP model is short-termed (i.e when H =1 and 4). However, the exact opposite plays out in the late sample size. We also experimented whether these results are sensitive to the measures of the GFCy. Thus, two additional measures are employed (VIX and capital flows factor). Results from the VIX model provide better forecast performance (in terms of forecast error) in the late sample size. All these results are robust to a number of checks.

There are two policy implications attributable to these results. First, investors and policymakers should take cognisance of portfolio balance theory in the forecast of exchange rate. Simply put, reliable exchange rate forecasts could be made using capital flows as the predictor. As such, capital flows could be used as a policy tool that can be tweaked to influence exchange rate. Second, the performance of the model is short-termed. Hence, investors should be mindful of the fact that reliable forecast should not exceed 4-quarters forecast ahead. Analyses in this study is limited to 25 countries, with the sample sized skewed to developed/advanced countries. A section of the literature has argued that emerging and developing countries are currently shaping the dynamics of global capital flows (IMF, 2013; Eichengreen et al., 2017). Based on this, an obvious direction for future studies is to replicate this analysis for more emerging and developing countries.

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