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Determinants of Foreign Currency Savings: Evidence from Google Search Data

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Abstract

This empirical study investigates the economic and psychological factors influencing the households' saving preferences to savings currency focusing on the European Union (EU) countries outside the euro area with their own currencies. This paper focuses on basic macroeconomic shocks given by International Fisher Effect, capital account and remittances while a special attention is put on perception and sentiments of economic agents. The main contribution of the paper is based on the sentiment indicators received from Google search data. To estimate the model we applied Bayesian Model Averaging because we have not appropriate economic theory to select Google search keywords. The main findings of this empirical study suggest that foreign currency savings are not affected by earning motives but only by the risks related to depreciation of international remittances and perception of selected risks, e.g. political risks and economic activity.

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Keywords: Bayesian Model Averaging, International Fisher Effect, perception, sentiment, Google Trends, savings behaviour

1. Introduction

Traditionally households' saving behaviour was investigated focusing on fundamental socio-economic and demographic determinants. And only recently economists Fidrmuc et al. (2013), Crespo Cuaresma et al. (2014) have begun to study the households' saving behaviour from behavioural economics perspective. As more and more daily

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activities take place online, data on internet behaviour is becoming a key information source explaining individuals' behaviour. The increasing role of internet in individuals' daily life shows the statistical data provided by Eurostat and WebCertain Group – a leading multilingual digital marketing agency. In 2015 more than 80 per cent of all individuals in EU used internet in the last 12 months and 67 per cent of all individuals used internet daily. The Webcertain Global Search & Social Report 2015 shows that in most of the EU countries internet penetration accounts for 80–90 per cent. The statistical data provided by Eurostat demonstrates that internet activities of individuals focus mainly on sending/receiving e-mails (in 2015 69 per cent of all individuals in EU used internet for this purpose), reading online news sites/newspapers/news magazines (54 per cent), and participating in social or professional networks (52 percent). Since 2007 the usage of internet for these activities has doubled in EU suggesting about a crucial role of internet in individuals' daily life. According to the Webcertain Global Search & Social Report 2015, in almost all EU countries internet users rely heavily on Google as a mean for looking up information and navigating around the web. Indeed, Google continues to account for more than 90 per cent searches carried out on the web in EU over the past year and despite having a marginal decline in market share over the past year Google continues its complete domination of the category. According to the Webcertain Global Search & Social Report 2015, the dominance of Google looks very unlikely to abate in the near future. For this reason this empirical study will apply a novel manner to investigate individuals' saving behaviour using weekly internet search volume time series drawn from the Google Trends database. The objective of this study is to identify the economic and psychological factors influencing the households' saving preferences to savings currency testing the usefulness of Google Trends data for explanation of households' saving behaviour.

2. Literature review

Traditionally, most of scientists focus on determinants of private and public saving rate and try to explain private saving behaviour during different stages of life cycle. Only a few empirical studies investigated the determinants of households' savings in domestic or foreign currency. Arifovic (2001) explored economic agents' decisions about the currency of their savings and investment portfolio. According to Arifovic (2001), the currency of the country with larger deficit becomes valueless and a flight away from the currency of this country is observed. Sharma et al. (2005) investigated the importance of the U.S. dollar to six Asian economies as a substitute or complement to domestic monetary assets. They found that the U.S. dollar and the domestic currency are Morishima substitutes and the demand for the U.S. dollar relative to the domestic currency appears to respond to the exchange rate depreciation than the domestic interest rate. Bresser-Pereira et al. (2014) investigated the relations between domestic savings, foreign savings, and the real exchange rate and in Brazil. The results of an econometric analysis of the Brazilian case study indicate a long-run relationship between the real exchange rate and domestic savings and confirm the presence of substitution of foreign for domestic savings. Bresser-Pereira et al. (2014) state that a positive and statistically significant effect of relative devaluation of the real exchange rate on domestic savings is observed.

Scientific literature provides substantial empirical evidence confirming the usefulness of internet search data in forecasting economic indicators. The usefulness of internet search data for economic indicators forecasting was demonstrated in Choi and Varian (2009a, 2009b, 2012). Choi and Varian (2009a, 2009b, 2012) showed how Google Trends data can improve short-term forecasts of economic indicators (e.g. travel destinations, home sales, retail sales, or car sales) and that unemployment, private consumption and house prices can be forecasted using internet search indices. Schmidt and Vosen (2009) showed that Google Trends can outperformed forecasting results of the two most common indicators of private consumption in the U.S. Pescyova (2011) used the unemployment data in Slovakia and showed that internet search data improved predictions substantially. McLaren and Shanbhogue (2011) also showed that unemployment forecasts in the UK can also be improved using internet search data. They also confirmed that prediction of house prices using internet search data can outperform some existing indicators. These empirical findings were also confirmed by Beracha and Wintoki (2013). D'Amuri and Marcucci (2012) proposed to use an index of internet job-search intensity as the best leading indicator to forecast the US unemployment rate. Fondeur and Karamé (2013) employed Google data in order to forecast French youth unemployment rate. Bangwayo-Skeete and Skeete (2015) introduced the indicator constructed from Google Trends' search query time series data and tested the forecasting performance of the indicator for tourism demand forecasts. The empirical results suggests that Google Trends information offers significant benefits to forecasters (particularly in tourism). Business practitioners and policy makers can improve significantly the forecasting capability of Google search data for their planning purposes. Vicente et al. (2015) explored the usefulness of Google Trends data in forecasting of unemployment. The presented empirical evidence confirmed the usefulness of internet search-related data for the forecasting of economic variables (unemployment).

Some empirical studies confirm the usefulness of internet search data in explaining individuals' behaviour. Da et al. (2011) derived a measure of investor attention using Google search data. The empirical results indicate that Google search data is able to capture investors' attention more efficiently comparing to existing measures of attention. Vlastakis and Markellos (2012) studied information supply and demand at the company and market level using data for the largest stocks traded on NASDAQ and NYSE. They used time series data from the Google Trends database in order to assess the information demand. The empirical results confirmed usefulness of Google Trends data as a proxy of information demand. Saxa (2014) examined the usefulness of Google Trends data for forecasting mortgage lending in the Czech Republic. The empirical results confirmed that internet search data improved mortgage lending predictions significantly. Irresberger et al. (2015) estimated different measures of market-level and individual crisis sentiment using Google Trends' search volume data on crisis-related queries. The empirical results of this study suggest that stock prices of international banks were significantly driven by investors' irrational system-wide crisis sentiment irrespective of macroeconomic fundamentals. Yang et al. (2015) analysed the trends of the searchers' preferences for travel products and possible prediction of their future travel behaviour using the search data of two different search engines: Google and Baidu. The study verified that both types of search engine data helped to significantly decrease forecasting errors of visitor numbers for a popular tourist destination in China.

In summary, the aforementioned empirical studies confirmed usefulness of internet search data as a novel manner in forecasting economic indicators and explaining individuals' behaviour.

3. Data and Methodology

Our empirical analysis employs quarterly observations for the period 2004Q1 to 2014Q4 on macroeconomic shocks (nominal effective exchange rate, nominal GDP, money market interest rate differential (national vs. eurozone and vs. USA), inflation differential (national vs. eurozone and vs. USA, measured by deflator), current account balance, index of personal remittances), behavioural factors (Google Trends searches for selected 42 keywords) and perception indicators (present and future savings, financial situation, future employment, future economic situation, future financial situation) which are expected to affect the allocation of household deposits between the national and other foreign currencies. The selection of macroeconomic determinants is based on the economic intuition that the appreciation of the national currency against a basket of selected currencies as well as economic growth of country could motivate households to increase the share of savings in national currency, and vice versa. Economic theory suggests that a higher money market interest rate differential could motivate households to prefer saving in national currency rather than in foreign currencies, whereas a higher inflation differential could have an opposite effect and motivate households to save in foreign currencies. While the CEECs are the most dependent economies on international remittances in the EU (e.g. the highest dependency rates on international remittances measured by the share of inflows in personal remittances in percentage of the respective country's GDP were observed in Latvia (5.7% of GDP) and Lithuania (4.4% of GDP) in 2014), economic theory suggests to include the current account balance and index of personal remittances as macroeconomic determinants that could explain households savings preferences to save in national or foreign currencies. The joint harmonised EU consumer survey provides the information about households' capacities to save some money in view of the general economic situation as well as about changes of the financial situation of households' over the last 12 months. This survey also provides the information about households' capacities to save some money over next 12 months, unemployment expectations, the general economic situation in the country, and financial situation over next 12 months. The opinion of households about the present and future financial and economic situation, unemployment expectations, capacities to save some money in present as well as in future could explain psychological aspects of households' savings behaviour and saving decisions regarding saving currency. While in almost all EU countries internet users rely heavily on Google as a mean for searching for information and navigating around the web, this empirical study will apply a novel manner to investigate psychological aspects of individuals' saving behaviour using weekly internet search volume time series drawn from the Google Trends database (Google Trends searches for selected 42 keywords).

The empirical analysis focuses on the European Union (EU) countries outside the euro area with their own currencies: Bulgaria (BG), Czech Republic (CZ), Hungary (HU), Poland (PL), Romania (RO), Sweden (SE), the United Kingdom (UK), and three Baltic countries (Estonia (EE), Latvia (LV), and Lithuania (LT)) that have recently adopted the euro (Estonia in 2011, Latvia in 2014 and Lithuania in 2015). Croatia was not included in the data sample since this country joined the EU only on 1 July 2013 as well as Denmark due the statistical data availability.

For our analysis we draw the data from publicly available datasets of national central banks (household deposits, current account balance for BG, money market interest rate for CZ), Eurostat (nominal GDP, current account balance, money market interest rate, remittances), OECD Main Economic Indicators (money market interest rate for HU), IMF International Financial Statistics (money market interest rate for EE), Business and Consumer Surveys conducted by the European Commission (perception indicators) and Google Trends.

As we mentioned previously, possible determinants of savings behaviour are specific macroeconomic shocks, and a quite long list of keywords received from Google search which represent sentiment of economic agents. The empirical analysis is based on the pooled-regression where interest coverage ratio of country $i = 1, \dots, N$ is regressed on an intercept α and number of explanatory variables selected from a set of k variables in a matrix X of dimension $N \times K$. Assume that rank $(\iota_N : X) = K + 1$, where ι_N is an N-dimensional vector of ones, and define β as the full k-dimensional vector of regression coefficients:

$$y = \alpha\iota_N + X_r\beta_r + \varepsilon, \tag{1}$$

where we assume $r = 1, \dots, R$ models, denoted by M_r and X_r is a $N \times k_r$ matrix containing (or all) columns of X. The N-vector of errors, ε, is assumed to be $N(0_N, h^{-1}I_T)$. Thus, $R = 2^K$ because there are 2^K possible subsets of X and 2^K possible choices for X_r (Koop, 2003). We consider up to 65 regressors to be included in the model that means 2^{65} different models to deal with.

To solve the problem of evaluation we follow Markov chain Monte Carlo techniques (MC3) provided by De Luca and Magnus (2011). The results are based on taking 1 100 000 draws and discarding the first 100 000 draws models as burn-in replications.

In a Bayesian framework we receive posterior model probabilities $p(M_r|y)$, for $r = 1, \dots, R$, where each model depends upon a vector of parameters θ_r and is characterized by prior $p(\theta_r|M_r)$ likelihood $p(y|\theta_r, M_r)$ and posterior $p(\theta_r|y, M_r)$. Assume vector of parameters ϕ which is function of θ_r for each of $r = 1, \dots, R$. Then we should obtain results for every model under consideration and average them where the weights in the averaging are the posterior model probabilities:

$$p(\phi|y) = \sum_{r=1}^{R} p(\phi|y, M_r)p(M_r|y), \tag{2}$$

alternatively, if $g(\phi)$ is a function of ϕ, the rules of conditional expectation imply that

$$E[g(\phi)|y] = \sum_{r=1}^{R} E[(g(\phi)|y, M_r)]p(M_r|y), \tag{3}$$

where $E[g(\phi)|y, M_r]$ and $p(M_r|y)$ are calculated by posterior simulation (Koop, 2003). The likelihood function for each model is based on the Normal linear regression model in formula (1) with prior for β_r:

$$\beta_r|h \sim N\left(\underline{\beta_r}, h^{-1}\underline{V_r}\right). \tag{4}$$

To ensure that the noninformative prior for the intercept has the same implication for each model we followed approach applied by Fernandez et al. (2001), who recommended standardization of all explanatory variables by subtracting off their means. Thus, we use noninformative priors for α and h, and for the slope coefficient β_r:

$$\beta_r|h \sim N\left(0_{k_r}, h^{-1}[g_r, X'_r X_r]^{-1}\right) \tag{5}$$

and g-prior is given by different values of N (Fernandez et al., 2001):

$$g_r = \begin{cases} \frac{1}{K^2}, N \leq K^2 \\ \frac{1}{N}, N > K^2 \end{cases}. \tag{6}$$

At the second step, we differentiate between different shocks and extend the formula (1) by dummies interacted with all other regressors. Especially, we differentiate between (1) depreciation and appreciation shocks, and (2) volatility in exchange rate over and below the average.

4. Results

Table 1 presents the results of Model 1 and Model 2. In the Model 1, there is a full list of variables which covers 308 observations in 8 countries because perception surveys are not at disposal only for the EU Members States. The Model 2 represents all macroeconomic shocks and Google Trends Keywords in the all 10 countries and covers 376 observations. The first column presents posterior probabilities which indicate the probability of including variable in the model. The both models confirmed that interest rate differentials have no impact on the savings behaviour. There are expected significant dummy variables represent the financial crisis after the year 2007 and the European debt crisis in the years 2010–2012. There are also probable significant perceived risks, e.g. policy risks represented by keyword “attack” or “war”, stock market risks represented by keywords “stock exchange”, “shares”, “market” and “bond”, and several keyword related to the economic activity. These economic activity perceptions are related to unemployment risks, investments or generally growth.

Table 1. Bayesian Model Averaging Results – Basic.

Explanatory Variables		Model 1 BMA Post.Prob.	Model 1 Post. Mean	Model 1 Post. St. Dev.	Model 2 BMA Post.Prob.	Model 2 Post. Mean	Model 2 Post. St. Dev.
Macroeconomic Shocks	NEER	1.0000	0.0028	0.0004	1.0000	0.0045	0.0005
	Interest Rate Diff EU	0.0232	0.0000	0.0003	0.0725	0.0194	0.0118
	Interest Rate Diff US	0.0241	0.0000	0.0003	0.0118	−0.0086	0.0117
	GDP (Index)	1.0000	−0.2891	0.0401	1.0000	−0.5882	0.0491
	Current Account (Index)	0.0198	0.0000	0.0007	0.0205	−0.0001	0.0009
	Inflation Diff EU	0.9635	0.0064	0.0038	0.9775	0.0245	0.0148
	Inflation Diff US	0.1621	−0.0010	0.0037	0.6710	−0.0180	0.0151
	Remittances (Index)	0.1116	−0.0012	0.0040	0.0978	0.0013	0.0044
Perception Survey	Present Savings	0.0866	−0.0001	0.0002			
	Future Savings	0.9999	−0.0023	0.0003			
	Financial Situation	0.0367	0.0000	0.0003			
	Future Unemployment	0.0246	0.0000	0.0001			
	Future Econ Situation	0.9248	−0.0015	0.0006			
	Future Fin Situation	0.9477	0.0024	0.0008			
Google Trends	"crisis"	0.0665	0.0000	0.0001	0.0183	0.0000	0.0000
	Currency Name (Short)	0.7003	−0.0010	0.0007	0.4645	0.0007	0.0008
	Currency Name (Full)	0.3308	−0.0003	0.0005	0.0973	−0.0001	0.0003

	"exchange rate"	0.0294	0.0000	0.0000	0.0252	0.0000	0.0001
	"debt"	0.0279	0.0000	0.0000	0.0193	0.0000	0.0000
	"indebtedness"	0.0290	0.0000	0.0000	0.0237	0.0000	0.0000
	"money"	0.1097	0.0001	0.0002	0.1338	0.0001	0.0003
	"salary"	0.0273	0.0000	0.0001	0.0268	0.0000	0.0001
	"credit"	0.1319	−0.0001	0.0002	0.2910	0.0002	0.0004
	"saving"	0.0454	0.0000	0.0001	1.0000	−0.0011	0.0002
	"loan"	0.0225	0.0000	0.0000	0.0234	0.0000	0.0000
	"mortgage"	0.9527	0.0007	0.0003	0.1668	0.0001	0.0002
	"bank"	0.0206	0.0000	0.0001	1.0000	−0.0018	0.0003
	"GDP"	0.6033	0.0004	0.0004	1.0000	0.0015	0.0002
	"growth"	0.0802	0.0000	0.0001	0.9994	−0.0012	0.0003
	"economy"	0.0846	0.0000	0.0001	0.0254	0.0000	0.0001
	"employment"	0.2520	−0.0001	0.0002	0.7839	−0.0007	0.0004
	"unemployment"	0.0223	0.0000	0.0000	0.0557	0.0000	0.0001
	"job"	1.0000	−0.0028	0.0003	0.0500	0.0000	0.0001
	"investment"	0.3435	0.0002	0.0002	0.7916	0.0007	0.0004
	"stability"	0.0195	0.0000	0.0000	0.0301	0.0000	0.0001
	"recession"	0.0186	0.0000	0.0000	0.0423	0.0000	0.0001
	"credit card"	0.0186	0.0000	0.0000	0.9105	0.0009	0.0004
	"attack"	0.5400	−0.0005	0.0005	0.9942	−0.0014	0.0003
	"war"	0.9984	−0.0012	0.0003	0.9735	−0.0012	0.0004
	"corruption"	0.0234	0.0000	0.0000	0.0709	0.0000	0.0002
	"political"	0.3824	0.0003	0.0005	0.2330	0.0002	0.0004
	"election"	0.0180	0.0000	0.0001	0.0677	−0.0001	0.0002
	"freedom"	0.0218	0.0000	0.0000	0.0236	0.0000	0.0000
	"government"	0.0192	0.0000	0.0000	0.0303	0.0000	0.0001
	"president"	0.0291	0.0000	0.0001	0.0260	0.0000	0.0001
	"parliament"	0.0168	0.0000	0.0000	0.0282	0.0000	0.0001
	"senate"	0.0932	−0.0001	0.0002	0.0179	0.0000	0.0001
	"premier"	0.0209	0.0000	0.0000	0.9885	−0.0010	0.0003
	"court"	0.0193	0.0000	0.0000	0.1833	−0.0001	0.0003
	"shares"	0.0245	0.0000	0.0000	0.9996	0.0014	0.0002
	"bond"	0.2977	0.0002	0.0003	1.0000	0.0022	0.0003
	"market"	0.0201	0.0000	0.0000	0.9899	0.0014	0.0004
	"stock exchange"	0.0979	0.0000	0.0001	0.8131	−0.0006	0.0004
	"risk"	0.0299	0.0000	0.0001	0.0272	0.0000	0.0001
	"volatility"	0.0326	0.0000	0.0000	0.0208	0.0000	0.0000
	"loss"	0.0188	0.0000	0.0000	0.0212	0.0000	0.0000
Time Dummies	y2006	0.0161	0.0000	0.0014	0.0295	0.0002	0.0042
	y2007	0.0214	0.0001	0.0016	0.9022	0.0549	0.0234
	y2008	0.0185	0.0000	0.0014	0.8817	0.0724	0.0408

y2009	0.0192	0.0001	0.0016	0.0723	−0.0022	0.0102
y2010	0.0503	0.0007	0.0038	0.9101	0.0489	0.0209
y2011	0.0213	0.0002	0.0017	0.4849	0.0221	0.0273
y2012	0.0316	−0.0004	0.0027	0.2645	−0.0102	0.0199
y2013	0.0302	0.0004	0.0029	0.1379	0.0030	0.0134
y2014	0.2414	−0.0098	0.0192	0.1666	−0.0086	0.0226
Mean number of regressors in models			15.4152			25.5249
Prob of top 10 models out of total No of models			0.0823			0.1171
No of observations			308			376

Second, we expect nonlinearities in the exchange rate effects on savings behaviour. Therefore we interacted dummies with the all regressors. Model 3 presents results where variable denoted as (a) represents depreciation and variable denoted as (b) represents appreciation shock. Thus, we can differentiate between both the depreciation and appreciation shocks. Our results show significant probability of remittances only in the case of depreciation shock. Thus, economic agents increase their foreign savings with increasing remittances only to protect their earnings from devaluation. Similar results we found in the case of keywords “risk” or “political”.

Table 2. Bayesian Model Averaging Results – Dummy variables interaction.

	Explanatory Variables	Model 3 BMA Post. Prob.	Post. Mean	Post. St. Dev.	Model 4 BMA Post. Prob.	Post. Mean	Post. St. Dev.
Macroeconomic Shocks	Interest Rate Diff EU (a)	0.0113	0.0000	0.0003	0.1897	0.0016	0.0035
	Interest Rate Diff EU (b)	0.0612	0.0004	0.0017	0.0123	0.0000	0.0004
	Interest Rate Diff US (a)	0.0118	0.0000	0.0003	0.1312	0.0009	0.0027
	Interest Rate Diff US (b)	0.0479	0.0002	0.0013	0.0100	0.0000	0.0003
	GDP (Index) (a)	1.0000	−0.4687	0.0548	1.0000	−0.4766	0.0544
	GDP (Index) (b)	1.0000	−0.4658	0.0544	1.0000	−0.4749	0.0493
	Capital Acc (Index) (a)	0.1259	−0.0025	0.0074	0.0165	−0.0002	0.0023
	Current Acc (Index) (b)	0.0103	0.0000	0.0008	0.0148	−0.0001	0.0011
	Inflation Diff EU (a)	0.7386	0.0062	0.0037	0.5631	0.0031	0.0030
	Inflation Diff EU (b)	0.9742	0.0169	0.0119	0.8629	0.0076	0.0049
	Inflation Diff US (a)	0.2677	0.0022	0.0038	0.4441	0.0025	0.0031
	Inflation Diff US (b)	0.4415	−0.0092	0.0123	0.1824	0.0004	0.0048
	Remittances (Index) (a)	0.9845	0.0556	0.0146	0.0156	0.0001	0.0020
	Remittances (Index) (b)	0.0157	−0.0001	0.0015	0.0146	0.0001	0.0015
Google Trends Keywords	„crisis“ (a)	0.0596	0.0000	0.0002	0.0250	0.0000	0.0001
	„crisis“ (b)	0.0134	0.0000	0.0001	0.0286	0.0000	0.0001
	Currency Name (Short) (a)	0.0981	0.0001	0.0004	0.9603	0.0032	0.0010
	Currency Name (Short) (b)	0.5179	0.0011	0.0012	0.9692	0.0020	0.0006
	Currency Name (Full) (a)	0.9990	−0.0029	0.0006	0.9657	−0.0033	0.0010
	Currency Name (Full) (b)	0.4742	−0.0012	0.0013	0.9894	−0.0025	0.0006
	„exchange rate“ (a)	0.0299	0.0000	0.0001	0.0199	0.0000	0.0001
	„exchange rate“ (b)	0.1918	−0.0002	0.0004	0.0673	0.0000	0.0002

„debt“ (a)	0.0155	0.0000	0.0001	0.0230	0.0000	0.0001
„debt“ (b)	0.0181	0.0000	0.0001	0.0110	0.0000	0.0000
„indebtedness“ (a)	0.0218	0.0000	0.0001	0.0229	0.0000	0.0001
„indebtedness“ (b)	0.0224	0.0000	0.0001	0.0129	0.0000	0.0000
„money“ (a)	0.0222	0.0000	0.0001	0.0285	0.0000	0.0002
„money“ (b)	0.0094	0.0000	0.0000	0.0104	0.0000	0.0000
„salary“ (a)	0.0168	0.0000	0.0001	0.2283	0.0004	0.0007
„salary“ (b)	0.0131	0.0000	0.0001	0.0438	0.0000	0.0002
„credit“ (a)	0.0332	0.0000	0.0001	0.1281	0.0001	0.0004
„credit“ (b)	0.2067	0.0002	0.0004	0.1563	0.0001	0.0003
„saving“ (a)	0.0243	0.0000	0.0001	0.4790	−0.0005	0.0006
„saving“ (b)	0.7458	−0.0008	0.0005	0.0163	0.0000	0.0000
„loan“ (a)	0.0110	0.0000	0.0000	0.1134	0.0001	0.0003
„loan“ (b)	0.0131	0.0000	0.0001	0.0115	0.0000	0.0000
„mortgage“ (a)	0.0238	0.0000	0.0001	0.2215	0.0003	0.0005
„mortgage“ (b)	0.8990	0.0012	0.0005	0.1443	0.0001	0.0003
„bank“ (a)	0.0113	0.0000	0.0001	0.0341	0.0000	0.0002
„bank“ (b)	0.5196	−0.0007	0.0007	0.7947	−0.0012	0.0007
„GDP“ (a)	0.9640	0.0015	0.0005	0.0142	0.0000	0.0001
„GDP“ (b)	0.9810	0.0016	0.0004	1.0000	0.0023	0.0003
„growth“ (a)	0.0150	0.0000	0.0001	0.0270	0.0000	0.0001
„growth“ (b)	0.5553	−0.0006	0.0005	0.9740	−0.0011	0.0003
„economy“ (a)	0.0177	0.0000	0.0001	0.0162	0.0000	0.0001
„economy“ (b)	0.0338	0.0000	0.0001	0.0163	0.0000	0.0001
„employment“ (a)	0.0107	0.0000	0.0000	0.1022	−0.0001	0.0003
„employment“ (b)	0.0425	0.0000	0.0001	0.0115	0.0000	0.0000
„unemployment“ (a)	0.0451	0.0000	0.0002	0.0468	0.0000	0.0002
„unemployment“ (b)	0.0269	0.0000	0.0001	0.1006	0.0001	0.0003
„job“ (a)	0.0118	0.0000	0.0000	0.4690	−0.0007	0.0008
„job“ (b)	0.0281	0.0000	0.0001	0.0095	0.0000	0.0001
„investment“ (a)	0.0120	0.0000	0.0000	0.1057	−0.0001	0.0003
„investment“ (b)	0.0388	0.0000	0.0001	0.1523	0.0001	0.0003
„stability“ (a)	0.0155	0.0000	0.0001	0.0373	0.0000	0.0001
„stability“ (b)	0.0298	0.0000	0.0001	0.0192	0.0000	0.0001
„recession“ (a)	0.0570	0.0000	0.0002	0.1441	−0.0001	0.0004
„recession“ (b)	0.0128	0.0000	0.0001	0.0114	0.0000	0.0001
„credit card“ (a)	0.0105	0.0000	0.0000	0.0149	0.0000	0.0001
„credit card“ (b)	0.0191	0.0000	0.0001	0.0249	0.0000	0.0001
„attack“ (a)	0.0789	−0.0001	0.0004	0.7418	−0.0014	0.0010
„attack“ (b)	0.0225	0.0000	0.0001	0.0383	0.0000	0.0002
„war“ (a)	1.0000	−0.0027	0.0004	0.1606	−0.0003	0.0007
„war“ (b)	0.6161	−0.0011	0.0009	0.9794	−0.0019	0.0005

	„corruption“ (a)	0.0103	0.0000	0.0000	0.0341	0.0000	0.0002
	„corruption“ (b)	0.0258	0.0000	0.0001	0.0154	0.0000	0.0001
	„political“ (a)	0.9987	0.0025	0.0005	0.7113	0.0014	0.0010
	„political“ (b)	0.1074	0.0001	0.0004	0.2169	0.0003	0.0006
	„election“ (a)	0.0140	0.0000	0.0001	0.0161	0.0000	0.0001
	„election“ (b)	0.0535	−0.0001	0.0004	0.0232	0.0000	0.0002
	„freedom“ (a)	0.0109	0.0000	0.0000	0.0117	0.0000	0.0001
	„freedom“ (b)	0.0265	0.0000	0.0001	0.0177	0.0000	0.0001
	„government“ (a)	0.0103	0.0000	0.0000	0.0676	0.0001	0.0003
	„government“ (b)	0.1955	−0.0002	0.0005	0.0167	0.0000	0.0001
	„president“ (a)	0.0141	0.0000	0.0001	0.0226	0.0000	0.0003
	„president“ (b)	0.0196	0.0000	0.0001	0.0155	0.0000	0.0001
	„parliament“ (a)	0.0120	0.0000	0.0001	0.1480	0.0002	0.0005
	„parliament“ (b)	0.0340	0.0000	0.0001	0.1002	−0.0001	0.0003
	„senate“ (a)	0.0162	0.0000	0.0001	0.0137	0.0000	0.0001
	„senate“ (b)	0.0120	0.0000	0.0001	0.0092	0.0000	0.0001
	„premier“ (a)	0.2710	−0.0003	0.0005	0.1408	−0.0001	0.0004
	„premier“ (b)	0.9952	−0.0016	0.0004	0.9961	−0.0013	0.0003
	„court“ (a)	0.0135	0.0000	0.0001	0.1342	−0.0002	0.0005
	„court“ (b)	0.4477	−0.0006	0.0008	0.2900	−0.0003	0.0005
	„shares“ (a)	0.0179	0.0000	0.0001	0.0855	0.0001	0.0003
	„shares“ (b)	0.5657	0.0008	0.0007	0.0610	0.0000	0.0002
	„bond“ (a)	1.0000	0.0030	0.0004	0.9924	0.0025	0.0006
	„bond“ (b)	0.9991	0.0020	0.0004	1.0000	0.0025	0.0003
	„market“ (a)	0.0204	0.0000	0.0001	0.0872	0.0001	0.0003
	„market“ (b)	0.2297	0.0002	0.0005	0.8015	0.0011	0.0006
	„stock exchange“ (a)	0.1900	−0.0002	0.0004	0.0114	0.0000	0.0001
	„stock exchange“ (b)	0.1634	−0.0001	0.0003	0.0448	0.0000	0.0001
	„risk“ (a)	0.9950	−0.0017	0.0004	0.4064	−0.0005	0.0007
	„risk“ (b)	0.0802	−0.0001	0.0002	0.0646	0.0000	0.0002
	„volatility“ (a)	0.0132	0.0000	0.0001	0.0507	0.0000	0.0002
	„volatility“ (b)	0.0196	0.0000	0.0001	0.0211	0.0000	0.0001
	„loss“ (a)	0.0127	0.0000	0.0000	0.0264	0.0000	0.0001
	„loss“ (b)	0.0311	0.0000	0.0001	0.0166	0.0000	0.0001
Time Dummies	y2006	0.0139	0.0001	0.0026	0.0105	0.0000	0.0021
	y2007	0.8251	0.0435	0.0243	0.9689	0.0635	0.0185
	y2008	0.8995	0.0528	0.0235	0.9807	0.0699	0.0179
	y2009	0.0110	0.0000	0.0017	0.0123	−0.0001	0.0021
	y2010	0.0334	0.0007	0.0045	0.1189	0.0036	0.0108
	y2011	0.0114	0.0001	0.0016	0.0163	0.0002	0.0021
	y2012	0.0146	−0.0002	0.0025	0.0251	−0.0005	0.0035
	y2013	0.0096	0.0000	0.0016	0.0122	0.0001	0.0017

y2014	0.0196	−0.0004	0.0041	0.0157	−0.0002	0.0033
Mean Number of Regressors in Models			25.8108			26.0113
Prob of top 10 models out of total No of models			0.0305			0.0083
No of observations			376			376

Finally, model 4 confirmed stability of the previous estimations. Regressors denoted as (a) represents dummies related to the exchange rate volatility over the average. Analogically, regressors denoted as (b) presents shocks related to the exchange rate volatility below the average.

Table 3 shows posterior model probabilities calculated by MLM function and MC3 algorithm. It is clear that there are really small differences between these results. It confirms the existence of the convergence of the MC3 algorithm and the correctness of the results in the Table 1 and Table 2.

Table 3. Posterior Model Probabilities for Top 10 Models.

	(1)		(2)		(3)		(4)	
	$p(M_r\|y)$ Analytical	$p(M_r\|y)$ MC^3 estimate	$p(M_r\|y)$ Analytical	$p(M_r\|y)$ MC^3 estimate	$p(M_r\|y)$ Analytical	$p(M_r\|y)$ MC^3 estimate	$p(M_r\|y)$ Analytical	$p(M_r\|y)$ MC^3 estimate
1	0.2911	0.2904	0.5047	0.4929	0.2530	0.2666	0.1396	0.1756
2	0.1460	0.1668	0.1101	0.1010	0.1239	0.1111	0.1164	0.0491
3	0.0838	0.0786	0.0768	0.0769	0.1088	0.1422	0.1116	0.1032
4	0.0836	0.0888	0.0520	0.0488	0.1038	0.1038	0.1055	0.1131
5	0.0822	0.0783	0.0519	0.0539	0.0934	0.1012	0.1010	0.0983
6	0.0757	0.0747	0.0499	0.0628	0.0842	0.0733	0.0960	0.0938
7	0.0653	0.0573	0.0483	0.0609	0.0789	0.076	0.0905	0.1529
8	0.0621	0.064	0.0363	0.0354	0.0551	0.0445	0.0878	0.0514
9	0.0556	0.0547	0.0352	0.0349	0.0530	0.057	0.0805	0.1123
10	0.0545	0.0465	0.0349	0.0325	0.0459	0.0242	0.0710	0.0503

5. Discussion and Conclusions

We employed Bayesian Model Averaging to estimate probabilities of regressors to be included in the model. We show that foreign currency savings are not affected by earning motives but only by the risks related to depreciation of remittances and perception of selected risks, e.g. political risks and economic activity. Economic activity risk perceptions are related especially to the unemployment or investments.

Thus, our results are not in accordance with the mainstream economic theory specified by International Fisher Effect. Our conclusions have several significant policy-making implications and indicate that interest rate changes (especially interest rate differential increasing) are not efficient to increase short-term capital inflows into the countries. We therefore recommend focusing on risk elimination, especially exchange rate volatility related to the risk of savings devaluation. Summarily, we conclude that savings behaviour is primarily affected by risk perceptions, compared to higher interest income.

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