Is Exchange Rate Moody? Forecasting Exchange Rate with Google Trends Data

Michał Chojnowski[*♣] and **Piotr Dybka**[†♣]

[♣]Warsaw School of Economics

Submitted: October 17, 2017 • Accepted: February 21, 2017

ABSTRACT: This paper proposes a novel method of exchange rate forecasting. We extend the present value model based on observable fundamentals by including three unobserved fundamentals: credit-market, financial-market, and price-market sentiments. We develop a method of sentiments extraction from Google Trends data on searched queries for different markets. Our method is based on evolutionary algorithms of variable selection and principal component analysis (PCA). Our results show that the extended vector autoregressive model (VAR) which includes markets' sentiment, shows better forecasting capabilities than the model based solely on fundamental variables or the random walk model (naïve forecast).

JEL classification: C53, F31, F37, G17

Keywords: exchange rate, forecasting, market sentiment, Google Trends, PCA, VAR

[*]Email: michal.chojnowski@doktorant.sgh.waw.pl
[†]Email: pdybka@gmail.com

Introduction and Research Motivation

Providing a reliable exchange rate forecast is a difficult problem, which can be addressed with different methods. For instance, Mark and Sul (2012) showed that using a panel data approach (when the heterogeneity of the sample is not large) can provide additional information that can further improve the forecasting capabilities of a model. Ince (2014) studied how purchasing power parity (PPP) and macroeconomic fundamentals stemming from Taylor rule could be used for forecasting exchange rates in 10 OECD[1] countries; PPP performs better in the longer term and can be improved by adopting the panel data approach. Garratt and Mise (2014) proposed not only to use the panel data approach, but also to combine several models into one, which can improve point forecasts of the exchange rate. On the other hand, Ca' Zorzi et al. (2016) took a different, simpler approach in which they introduced a model that focused on the mean-reverting behavior of exchange rates, which seems to perform better than the random walk.

In our analysis, we propose a different approach, closer to Morales-Arias and Moura (2013) who extended the set of explanatory variables to improve forecasts. In their model they considered not only macroeconomic fundamentals, but also data on returns and volatility of asset markets as well as cyclical (confidence) indicators that measure economic sentiments on the basis of surveys conducted among investors, consumers, business people, etc. In our approach, instead of using data from financial markets, we extend the model by capturing unobservable fundamentals related to market sentiment and including them as endogenous variables in the vector autoregressive (VAR) model framework. We measure the unobservable fundamentals (market sentiment) on the basis of Google Trends time series on specific queries searched with the Google engine. As a benchmark macroeconomic model, we take the present value model proposed by Ko and Ogaki (2015), who focused on changes in the USD exchange rate against several major currencies and explained them with macroeconomic fundamentals (i.e., income, prices, money, and interest rate).

The inclusion of unobserved fundamentals into economic models has recently become widely discussed in the economic literature. In our model, we represent unobserved fundamentals with measures of market sentiment (i.e., consumers' optimism and pessimism). These sentiments are examples of economic sunspots—factors that do not influence the payoff, but might change the players' behavior, leading to a different equilibrium. Angeletos (2008) elaborated how sunspots influence the equilibrium and how they are constructed; his results stimulated us to investigate the effect of market sentiments on the economy using applied econometric methods. We propose to detect sentiments by observing Internet search activity.

[1] Organisation for Economic Co-operation and Development

Predictive models that incorporate scattered information from the Internet are a still-developing area of forecasting and economic analysis. Askitas and Zimmermann (2009) initiated the use of Google Trends; they developed methodology related to such data that takes into account various issues such as the importance of Google Trends in short-term forecasting.

Choi and Varian (2012) elaborated further on this forecasting approach by introducing a simple model that also provides insights for this article. The authors stated that Google Trends data increase the accuracy of short-term forecasts and nowcasts by 20%. Moreover Choi and Varian (2012) provided an important contribution to the solution of variable selection and mixed frequency estimation problems. Furthermore, D'Amuri and Marcucci (2012) conducted a broad analysis of the models that might be used in forecasting; their work stands in favor of using Google Trends as a good source of indicator data for forecasting models.

McLaren and Shanbhogue (2011) argued in their work that Google Trends might be a cheaper way to evaluate consumer preferences, as it can avoid problems with non-response and inaccurate responses. However, they also warned that Internet search results might be gathered from non-representative samples.

Our contribution to the literature can be viewed from two angles. First, we introduce the concept of using market sentiment in the context of exchange rate forecasting. Although the use of market sentiment in predictive modeling is increasingly being discussed in the literature, it has so far not been used for exchange rate forecasting. It is worth noting that the foreign exchange market seems to be an environment where the effect of market sentiment should be observed easily, and, as currencies are constantly traded at large volumes all over the world using the Internet, the spread of information must be very quick. In this article, we have shown that capturing sentiments in three different markets can be successfully used to create more accurate forecasts in comparison with models based solely on macroeconomic fundamentals.

We make the additional contribution of the development of an algorithm that enables the aggregation of dozens of Google query time series into a single time series reflecting the changes in market sentiment in three different markets. The key advantage of our algorithm is that, instead of combining a discretionary selection of Google queries, it selects the queries that are most suitable for the quantification of the sentiments in different markets based on an evolutionary mechanism.

The article is structured as follows. In Section 1 we outline the theoretical foundations of our model. Section 2 focuses on the estimation strategy, as well as the aggregation of Google Trends data. We present our results in Section 3 and conclude the article in Section 4. The Appendix provides information that can be used to replicate the analysis.

1 Theoretical Foundations

1.1 Fundamental Variables Affecting Exchange Rate

Following the present-value model of exchange rates as in Engel and West (2005) and Ko and Ogaki (2015), the money-output relationship is given as:

$$m_t = p_t + \varphi y_t - \lambda i_t + \upsilon_t \tag{1}$$

$$m_t^* = p_t^* + \varphi y_t^* - \lambda i_t^* + \upsilon_t \tag{2}$$

where the variable m_t represents the money supply, p_t is the logarithm of the price level, y_t is the log of income, and i_t is the interest rate at period t. The υ_t denotes unobservable factors affecting money supply that are not related to income, prices, or interest rate. The asterisk (equation 2) denotes that these are the same variables in a second (foreign) country. The parameter $0 < \varphi < 1$ is the income elasticity of money demand and $\lambda > 0$ is the interest rate semi-elasticity of money demand. These parameters are identical for the money demand in both the foreign and the home country.

With PPP, the nominal exchange rate is expressed as:

$$s_t = p_t - p_t^* + q_t \tag{3}$$

Here, q_t denotes unobservable elements influencing the nominal exchange rate that are not related to the prices. Furthermore, the market equilibrium is given by the uncovered interest rate parity (UIRP):

$$E_t s_{t+1} = s_t + i_t - i_t^* + \rho_t \tag{4}$$

where $E_t s_{t+1}$ is the rational expectation of the exchange rate at time $t + 1$, and ρ_t are the other components changing the expectations (e.g., risk premium, personal beliefs, rumors, political events, etc.).

1.2 Incorporation of Market Sentiment

The unobservable fundamentals are variables which are cumbersome to attain because they are not observed directly, including market and customer sentiments, the aftermath of natural phenomena, and political situations. This description fits the definition of private sunspots: signals which are distorted by individuals. Such signals can be described as:

$$\psi_{i,t} = g_t + \varepsilon_{i,t} \tag{5}$$

where $\psi_{i,t}$ is a private sunspot of individual i at time period t, g_t is an observable signal at time period t, and $\varepsilon_{i,t}$ is the residual representing specific characteristics of the individual that affect the response to the signal.

As our model is nested in macroeconomic data, we are interested in aggregated signals. On one hand, if the aggregated signals are equal to 0, then pessimistic individuals counterbalance optimistic ones and, in such a situation, a model based solely on macroeconomic fundamentals should suffice. On the other hand, if any distortion related to sentiments has happened, the extended model should be able to explain possible discrepancies.

In our model, the observable signal might be a macroeconomic indicator; however, these are already included as endogenous variables. Therefore, to avoid collinearity, observable fundamentals are excluded as part of the signal. However, unobservable fundamentals contain information which might influence consumer behavior, such as confidence, rumors, and expectations. In this article, the signal that investors receive is assumed to be linearly dependent on a combination of components from a principal components analysis (PCA), which represents the indirect capture of unobservable fundamentals. We provide a detailed explanation of our approach to the PCA in Section 2.1.

For the purposes of this analysis, equations (1), (3), and (4) are extended to account for two types of shock: namely, shocks affecting the observable fundamentals (income, prices, interest rate, and money supply) and shocks related to sentiments that are specific to the given type of market. This means that υ_t, q_t, and ρ_t from equations (1), (3), and (4) are decomposed into two factors:

$$\upsilon_t = \bar{\upsilon}_t + \tilde{\upsilon}_t \tag{6}$$

$$q_t = \bar{q}_t + \tilde{q}_t \tag{7}$$

$$\rho_t = \bar{\rho}_t + \tilde{\rho}_t \tag{8}$$

The first factor, denoted with a bar ($\bar{\ }$), is related to the sentiments in specific markets and is estimated on the basis of Google query data, whereas a tilde ($\tilde{\ }$) denotes the remaining unobservable factor (it can be calculated as the difference between the error term from the original equation and the estimated value of the first factor). Therefore, the money relationship is described as follows:

$$m_t = p_t + \varphi y_t - \lambda i_t + \bar{\upsilon}_t + \tilde{\upsilon}_t \tag{9}$$

The $\bar{\upsilon}_t$ represents the sentiment in the money market that is related to the credit market situation. In this analysis we focus on the changes in the nominal exchange rate that are given as:

$$s_t = p_t - p_t^* + \bar{q}_t + \tilde{q}_t \tag{10}$$

where $\bar{q}_t$ represents shocks that are associated with consumers' beliefs regarding the changes in prices. The interest rate parity is then as follows:

$$E_t s_{t+1} - s_t = i_t - i_t^* + \bar{\rho}_t + \tilde{\rho}_t \tag{11}$$

Here, the existence of $\bar{\rho}_t$ suggests that the economy operates under information that also includes some noise and it incorporates an agent's belief concerning changes in the financial markets.

2 Estimation Strategy

Our research focuses on a single country—Poland—and its relation to the Euro area—between January 2004 and May 2016. The monthly data on the exchange rate (EURPLN) and observable fundamentals are taken from Eurostat, except the money supply data, which is taken from the National Bank of Poland.

2.1 Measuring Market Sentiments with Google Trends Data

Google Trends present an index of search activity for a given query. The index is normalized so that it takes 100 as a maximum value, whereas 0 represents an insignificantly low number of searches for a term or phrase. The normalization is linear therefore an index value of 50 represents number of searches half as large as for an index value of 100. Such representation of the data does not influence the model. The geographical scope was restricted to Polish data only; therefore, we have not considered queries searched outside Poland.

Markets sentiment is calculated from the Google Trends data. First, time series were collected on specific queries (the query terms can be found in the appendices). Because the number of examined queries exceeds the number of observations, we propose the following algorithm to constrain the number of time series that could be later included into the model:[2]

1. First, a benchmark value for market sentiment in each market is calculated using model estimation for each market described in equations (1), (3), and (4). Then, the error term is saved and used as a benchmark value for the sentiment calculation. The value for each market is calculated separately.

2. The researcher creates a sample set, which consists of chosen Google Trends queries. In this algorithm, a sample set defines all the available external information. There is no

[2] Our algorithm can be viewed as an evolutionary algorithm, as with each iteration one can observe the evolution of the optimal information set.

restriction on the size of the sample set; however, if several queries exceed the benchmark's number of observations, then it is impossible to compute principal components. Therefore, subset selection is necessary.

3. To select the best performing subset out of a sample set, the evolutionary algorithm was proposed.[3] In each iteration, the parents replicate eight children; hence, in total, a generation consists of 10 inclusion vectors. In the selection algorithm, the inclusion vector consists of binary values (where TRUE describes inclusion and FALSE describes exclusion). It is assumed that 4 children are clones of their parents, whereas 4 children swap statuses between parents. Then a random mutation with a given prior probability occurs for each of the children, which switches the inclusion status of queries (from TRUE to FALSE and vice versa). The set of queries for which status is TRUE is labeled as an information set (ω), which is further used as a basis for PCA.

4. Using the PCA method, the selected Google queries included in information set ω are transformed into new time series, called components. Then the benchmark is explained in a separate linear model with components obtained in the PCA:

   $$\upsilon_t = \beta_1 c_t^1 + \beta_2 c_t^2 + \cdots + \beta_{10} c_t^{10} + \tilde{\upsilon}_t$$

   Here, c_t^i describes the i^{th} component (components are sorted from highest to lowest in terms of the explained part of variation of the analyzed variables) from the PCA.[4] The worst-performing components are removed using stepwise regression until all the remaining variables in the model are statistically significant at a 5% level or there is only one component left. We treat the fitted values of the above regression as approximate value of the economic sentiment on a given market.

   The R^2 of the final regression is treated as the maximization statistic. We would like to point out that in every iteration of this step we are comparing different components, which means that the crucial issue is not the number of components used, but their ability to explain the error term from the equations (1), (3), and (4).

5. The best information set ($\omega : \omega \subset \Omega$) describing market sentiment is found using the Monte Carlo algorithm. Steps 1 and 2 are reiterated. If the R^2 statistic corresponding

[3] Evolutionary algorithms are based on the concept that there are at least two objects called parents, which possess given characteristics (genes). Then, other objects are created by copying given characteristics from given parents. Those newly created vectors are called children. Moreover, children are subject to mutation, which is the switching of the value after they have adopted it. The set of parents and children is called a generation. Out of a given generation the best performing objects are taken as parents for the new generation to create. The cycle is continuous.

[4] Only the top 10 components from the PCA are taken into consideration, i.e., only the most valuable components in terms of explained variance.

to the newly found information set ω is greater than the value obtained in the previous iteration, it becomes a new baseline value.

6. The previous steps are repeated until the results become stable, i.e., the information set ω and the R^2 statistics obtained on its basis do not change in the next 100 iterations. Then, the estimated value of sentiment ($\bar{\upsilon}_t$, $\bar{q}_t$, and $\bar{\rho}_t$) is saved.

The above-mentioned algorithm creates a snapshot of disturbances in the examined economy and explains them by mapping time series that illustrate consumer behavior. This means that the algorithm finds a best-fitted signal of consumer behavior that can be used later in a more complex model.

Our information set for the credit market consists of queries related to the largest Polish banks, financial institutions (Bureau of Credit Information), and goods usually purchased with credit (real estate, cars). Price sentiment is identified based on queries that include names of big retail chains, popular goods, and energy providers. For financial market sentiment, we use the names of Polish stock indices and exchange rates of Polish zloty against main currencies. In the analysis, both levels and first differences of the Google Trends indices were used. Nevertheless, they are subject to the PCA algorithm's rescaling. The library of Google queries used in the analysis is presented in Table 8.

2.2 VAR Model Based on Fundamentals

For the main part of our analysis – forecasting the exchange rate – we use VAR models as described in Section 1. Additionally, structural VAR (SVAR) models were built and used to analyze the forecast error variance decomposition. The SVAR model based on fundamentals has the following representation:

$$\mathbf{Y}_t = \mathbf{c} + \Sigma_{i=1}^{p} \mathbf{A}_i \mathbf{Y}_{i,t-i} + \mathbf{A}_0^{-1} \mathbf{B}_0 \mathbf{u}_t \tag{12}$$

where $\mathbf{Y}_t$ is the vector of endogenous variables:

$$\mathbf{Y}_t = \begin{bmatrix} y_t \\ m_t \\ p_t \\ i_t \\ s_t \end{bmatrix} \tag{13}$$

and y_t is the industrial production, m_t is the money supply, p_t represents the prices, i_t is the interest rate (measured as the 3-month money market interest rate), and s_t is the nominal exchange rate itself. The $\mathbf{B_0}$ is assumed to be an identity matrix and $\mathbf{A_0}^{-1}$ is a lower triangular matrix of the following form:

$$\begin{bmatrix} \varepsilon_t^y \\ \varepsilon_t^m \\ \varepsilon_t^p \\ \varepsilon_t^i \\ \varepsilon_t^s \end{bmatrix} = \begin{bmatrix} a_{1,1} & 0 & 0 & 0 & 0 \\ a_{2,1} & a_{2,2} & 0 & 0 & 0 \\ a_{3,1} & a_{3,2} & a_{3,3} & 0 & 0 \\ a_{4,1} & a_{4,2} & a_{4,3} & a_{4,4} & 0 \\ a_{5,1} & a_{5,2} & a_{5,3} & a_{5,4} & a_{5,5} \end{bmatrix} \begin{bmatrix} u_t^y \\ u_t^m \\ u_t^p \\ u_t^i \\ u_t^s \end{bmatrix} \tag{14}$$

The y_t is brought to the front based on the assumption that there is no contemporaneous reaction of the real sector (output) to the shocks in the monetary sector. The second equation indicates that the instantaneous reaction of the money supply takes place only in the case of shocks to the real economy. Moreover, prices respond to contemporary shocks in both real output and money supply. The fourth equation in (11) can be viewed as the monetary policy response to changes in the real economy and the monetary sector (resembling a standard Taylor rule). The last equation describes the exchange rate that reacts instantly to the changes in all the previously described variables.

2.3 Extended Model Including Market Sentiments

In the proposed extension of the Ko and Ogaki (2015) model, the exchange rate is dependent on observable fundamentals and the unobservable part (eq. 6–8). In this Section, the focus is put on the unobservable part.

The final model can be represented in the following form:

$$\mathbf{Y}_t = \begin{bmatrix} y_t \\ m_t \\ p_t \\ i_t \\ \bar{\upsilon}_t \\ \bar{q}_t \\ \bar{\rho}_t \\ s_t \end{bmatrix} \tag{15}$$

Where $\bar{\upsilon}_t$ is the sentiment in the money (credit) market, $\bar{q}_t$ represents consumers' beliefs concerning inflation, $\bar{\rho}_t$ denotes sentiment on the financial markets, and s_t is the exchange rate of local currency (PLN refers to the Polish zloty) against the Euro.

Identifying restrictions are defined as follows:

$$\begin{bmatrix} \varepsilon_t^y \\ \varepsilon_t^m \\ \varepsilon_t^p \\ \varepsilon_t^i \\ \varepsilon_t^{\bar{v}} \\ \varepsilon_t^{\bar{q}} \\ \varepsilon_t^{\bar{\rho}} \\ \varepsilon_t^s \end{bmatrix} = \begin{bmatrix} a_{1,1} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{2,1} & a_{2,2} & 0 & 0 & a_{2,5} & 0 & 0 & 0 \\ a_{3,1} & a_{3,2} & a_{3,3} & 0 & 0 & 0 & a_{3,7} & 0 \\ a_{4,1} & a_{4,2} & a_{4,3} & a_{4,4} & 0 & a_{4,5} & 0 & 0 \\ a_{5,1} & 0 & 0 & a_{5,4} & a_{5,5} & a_{5,6} & a_{5,7} & 0 \\ a_{6,1} & 0 & a_{6,3} & 0 & 0 & a_{6,6} & 0 & 0 \\ a_{7,1} & 0 & a_{7,3} & a_{7,4} & a_{7,5} & a_{7,6} & a_{7,7} & 0 \\ a_{8,1} & a_{8,2} & a_{8,3} & a_{8,4} & a_{8,5} & a_{8,6} & a_{8,7} & a_{8,8} \end{bmatrix} \begin{bmatrix} u_t^y \\ u_t^m \\ u_t^p \\ u_t^i \\ u_t^{\bar{v}} \\ u_t^{\bar{q}} \\ u_t^{\bar{\rho}} \\ u_t^s \end{bmatrix} \tag{16}$$

The identification strategy is based on the theoretical assumptions described in Section 1. By ordering the industrial production in front, we assume no immediate reaction of the real sector to changes in the monetary sector and market sentiments. In our model, the money supply reacts instantaneously to changes in output and credit market sentiment, whereas the prices are affected by output, money supply, and financial markets. The fourth equation can be viewed as the monetary policy reaction function that accounts for changes in the real sector, money supply, prices, and price sentiment. We assume that sentiments' reactions to each other are correlated. In addition, we assume that all sentiments are affected by changes in the output. Furthermore, credit sentiment is shaped by interest rates, price sentiment depends on prices, and financial markets react to changes in prices and interest rates. Finally, we assume all the above variables will cause an immediate reaction to the exchange rate.

3 Empirical results

In this Section, we begin with diagnostic testing of our model and then present the accuracy of the forecast based on the rolling-window approach. Each window consists of 60 observations (for the first window: February 2004 to January 2009) and it is shifted by one month each iteration.[5] For the total timespan, January 2004 to May 2016, we generated 76 windows, which provides a sufficient sample of forecasts to analyze. Due to practical reasons, the presented values in Section 3.1 contain results only for the first window.[6]

[5]We started from February 2004 because we lost the first observation due to taking first differences of the time series related to the Google queries.

[6]All 76 models were tested for stability and autocorrelation of the error term, and they all performed well.

3.1 Model Diagnostics

The key question for our analysis is the number of lags that should be included in the model. Because the number of variables equals 8, we chose the Schwartz Information criterion (SIC) that favors parsimonious specifications, to avoid building a VAR model that would be too large.

Table 1 shows that the SIC values indicate 1 to be the optimal number of lags; therefore, in a further diagnostic, VAR (1) is used by default. Furthermore, the stability of the model is tested using the eigenvalues of a companion matrix. If all the eigenvalues lie within the unit circle, the model is regarded as stable.

To analyze how unobserved sentiments influence the Euro exchange rate, the forecast error variance decomposition comparison was performed. Table 2 and Table 3 represent variance decomposition for the model without sentiments and the model incorporating sentiments, respectively. The sentiments play a crucial role in forecasting variance. In the model using Google queries, the fundamentals do not explain any variance in the exchange forecast. Keeping in mind that the data used in the model have monthly frequency, these results should not be surprising. If the change in the fundamentals was expected, then the change was gradually monetarized on the market. If the change was unexpected, then it might affect the market for weeks until a new equilibrium price is found. Therefore, no long-lasting shocks should be present in the model.

3.2 Forecasting Capabilities of the Models

To check whether the use of Google Trends data increases forecast accuracy, rolling window simulation of three models was performed: naïve forecast, VAR model without Google Trends, and VAR model with Google Trends. Four time horizons for the forecast were considered in the analysis: 1-, 3-, 6-, and 12-month out-of-sample. A root-mean-square error (RMSE) statistic was chosen as a measure of the quality of the forecast. Forecasts were computed within the period February 2010 to May 2016, which ensured enough observations for analysis for each of the time horizons. The testing period was chosen to reach 60 months (5 years) prior.

In Table 4, the RMSE is presented for the above-mentioned horizons. Forecasts based on the model incorporating Google Trends data performed better than the model without Google Trends data, and the discrepancy between those models increased with time horizon. What is more, both models performed better in comparison to naïve forecasts.

The Diebold and Mariano (1995) test was used to assess whether the forecasts from the model that includes unobserved market sentiment were in fact significantly different than the forecasts from the model based only on macroeconomic fundamentals. With a short-term horizon (i.e., 1 or 3 months), the accuracy of the forecasts did not differ between the models with and without market sentiment. On the other hand, with a horizon longer than 6 months, the p-value came close to the 0.05 threshold. In addition, another variant of the test was used to check if forecasts from the model without market sentiments are less accurate. The Diebold-Mariano test indicated that, in our case, the model lacking the market sentiment provided less accurate forecasts with the 6-month horizon.

3.3 Sensitivity Analysis

While working on a large set of time series, there is a risk of overfitting the model—matching the queries, which are too specific for a given sample. This means that, although the model will provide a very accurate fit to the data (e.g., high statistic), it will not be able to provide reliable forecasts. To control this hazard, we introduced a statistic to validate Google query matching: persistence. This measures the percentage of queries that retained their status compared to the previous period. If persistence is low, it means our information set does not provide solid data and the algorithm matches random queries. The higher the persistence, the better the quality of the information set. It is hard to give a threshold above which an information set is regarded as informative due to the limited literature on this topic.

In this analysis, we focused on minimum and average persistence. Figure 1 presents the analysis of the changes in the composition of queries in our baseline model (where no restriction was imposed). The minimal persistency out of three sentiments was equal to 41.3%. In general, the queries used in the price sentiment estimation were much more stable as, on average, 62.9% of queries were unchanged. In the case of the credit market sentiment, on average, 60.0% of queries were unchanged when moving to the next period estimation. The composition of queries related to financial markets was also quite stable as, on average, 59.7% of queries remained in the sample in the next period. Table 5 summarizes minimum and average persistence.

3.3.1 Restricting the Algorithm

To check the sensitivity of our results, we imposed additional restrictions in our rolling window simulation. In our baseline scenario, in each period of the rolling window simulation, potentially all the queries are subject to change. To test the stability of the results, we fixed part of the queries so that they were forced to remain in the PCA for the next period of the simulation. We investigated the scenario where 70% of queries used in the previous period had to remain in the model. The results of the simulation are presented in Table 6.

The inclusion of the restriction in our algorithm leads to a deterioration of the obtained results, which can be attributed to two factors. To begin with, this restriction can prevent the algorithm from entering a path to the best result. In some cases, the algorithm can reach a state that seems stable because finding a better solution is very difficult, as most paths leading to this solution require a set that will be violating the restriction.

Furthermore, we are facing a trade-off between explaining the current state and the future states of the market. Market sentiments can be very volatile and difficult to measure, as the key queries for those markets can change very quickly. For instance, the current price sentiment might be driven by expectations related to changes in the oil prices, but after a few months they might be affected more by food prices. Consequently, we expect that the queries identified by our algorithm should be able to change with time.

4 Conclusions

The exchange rate can be viewed as the price of a currency on the financial market. As a result, it might be expected that it is shaped not only by macroeconomic fundamentals, but also by some other unobservable factors. To incorporate those unobserved fundamentals into econometric models we propose a new method that enables quantification of market sentiments. Our results indicate that inclusion of such market sentiments can improve the quality of models investigating exchange rates and the accuracy of provided forecasts. Because the baseline VAR model provided more accurate forecasts than the naïve forecast (random walk) and the inclusion of the market sentiments further increased the accuracy of the forecasts, we argue that our methodology can be used as a supplement to functioning forecasting models and, as such, it can improve their accuracy.

The model handles the issue of incorporating the sentiments, which describe the state of the economy and the level of optimism present in a market. However, one might think of short-term sentiments related to the speculation present in the media. It would require using additional sources other than Google Trends; however, we believe our model creates a solid foundation for such extensions.

Additionally, we estimated our model only for Poland, which is not sufficient to show that capturing unobservable fundamentals via Google Trends can be regarded as a general approach. More conclusions regarding the effectiveness of our methodology might be drawn if our results can be replicated in other countries, preferably in a panel data setting. We believe that the idea of using data on Internet activity is a promising field for further research in forecasting.

Acknowledgments

The authors are grateful to the anonymous referees and to participants of the Econometric Research in Finance Workshop 2016 held in Warsaw for valuable comments and suggestions.

References

Angeletos, G.-M. (2008). Idiosyncratic Sentiments and Coordination Failures. MIT Department of Economics Working Paper 08-12.

Askitas, N. and Zimmermann, K. (2009). Google Econometrics and Unemployment Forecasting. IZA Discussion Papers 4201, Institute for the Study of Labor (IZA).

Ca' Zorzi, M., Mućk, J., and Rubaszek, M. (2016). Real Exchange Rate Forecasting and PPP: This Time the Random Walk Loses. *Open Economies Review*, 27(3):585–609.

Choi, H. and Varian, H. (2012). Predicting the Present with Google Trends. *The Economic Record*, 88(s1):2–9.

D'Amuri, F. and Marcucci, J. (2012). The predictive power of Google searches in forecasting unemployment. Temi di discussione (Economic working papers) 891, Bank of Italy, Economic Research and International Relations Area.

Diebold, F. and Mariano, R. (1995). Comparing Predictive Accuracy. *Journal of Business and Economic Statistics*, 13(3):253–63.

Engel, C. and West, K. (2005). Exchange Rates and Fundamentals. *Journal of Political Economy*, 113(3):485–517.

Garratt, A. and Mise, E. (2014). Forecasting exchange rates using panel model and model averaging. *Economic Modelling*, 37(C):32–40.

Ince, O. (2014). Forecasting exchange rates out-of-sample with panel methods and real-time data. *Journal of International Money and Finance*, 43:1 – 18.

Ko, H.-H. and Ogaki, M. (2015). Granger causality from exchange rates to fundamentals: What does the bootstrap test show us? *International Review of Economics and Finance*, 38(C):198–206.

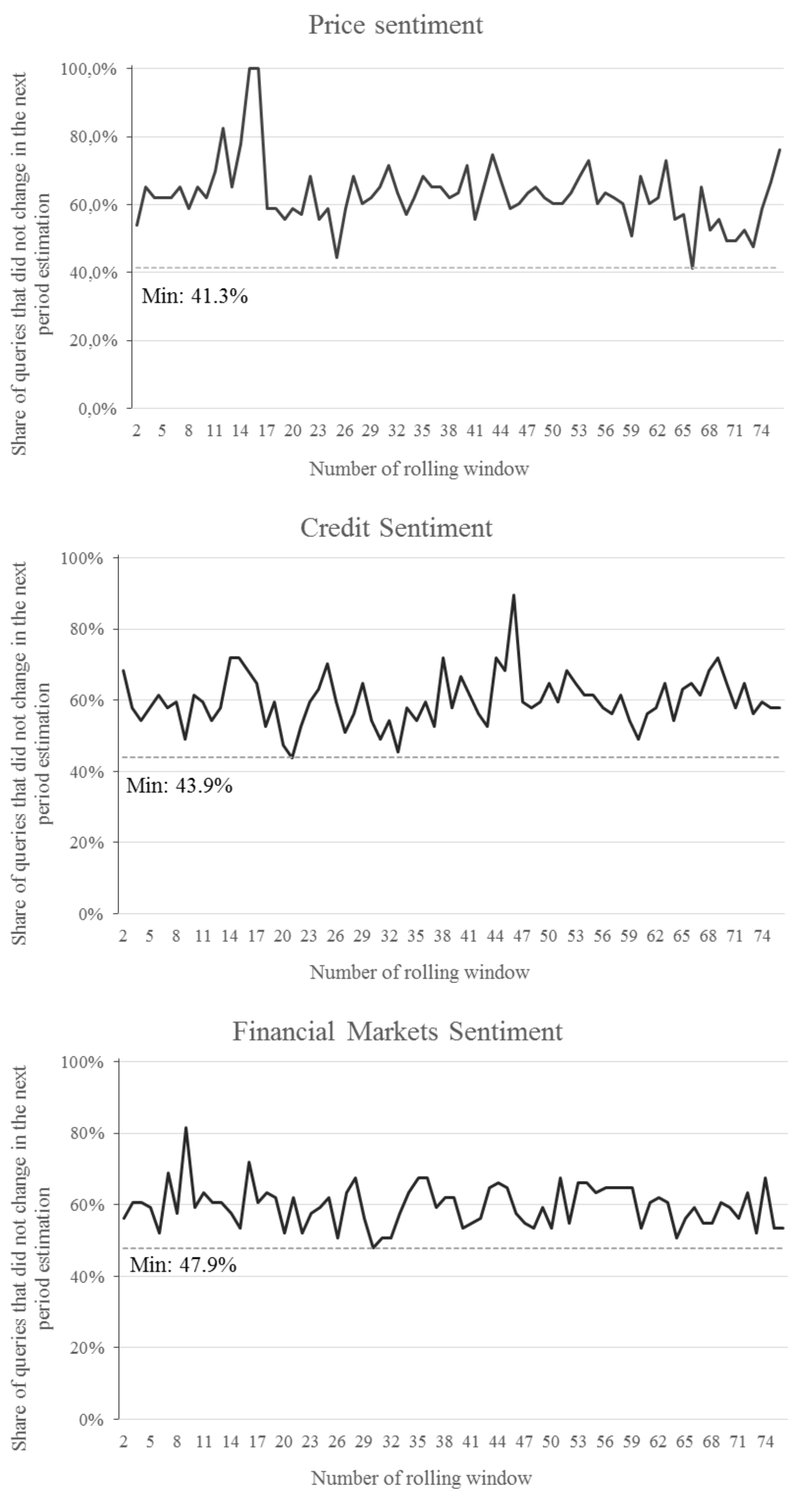
Mark, N. and Sul, D. (2012). When Are Pooled Panel-Data Regression Forecasts of Exchange Rates More Accurate than the Time-Series Regression Forecasts? In J. James, I. W. M.

and Sarno, L., editors, *Handbook of Exchange Rates*, chapter When are pooled panel-data regression forecasts of exchange rates more accurate than the time-series regression forecasts?, pages 265–281. Wiley-Blackwell.

McLaren, N. and Shanbhogue, R. (2011). Using internet search data as economic indicators. *Bank of England Quarterly Bulletin*, 51(2):134–140.

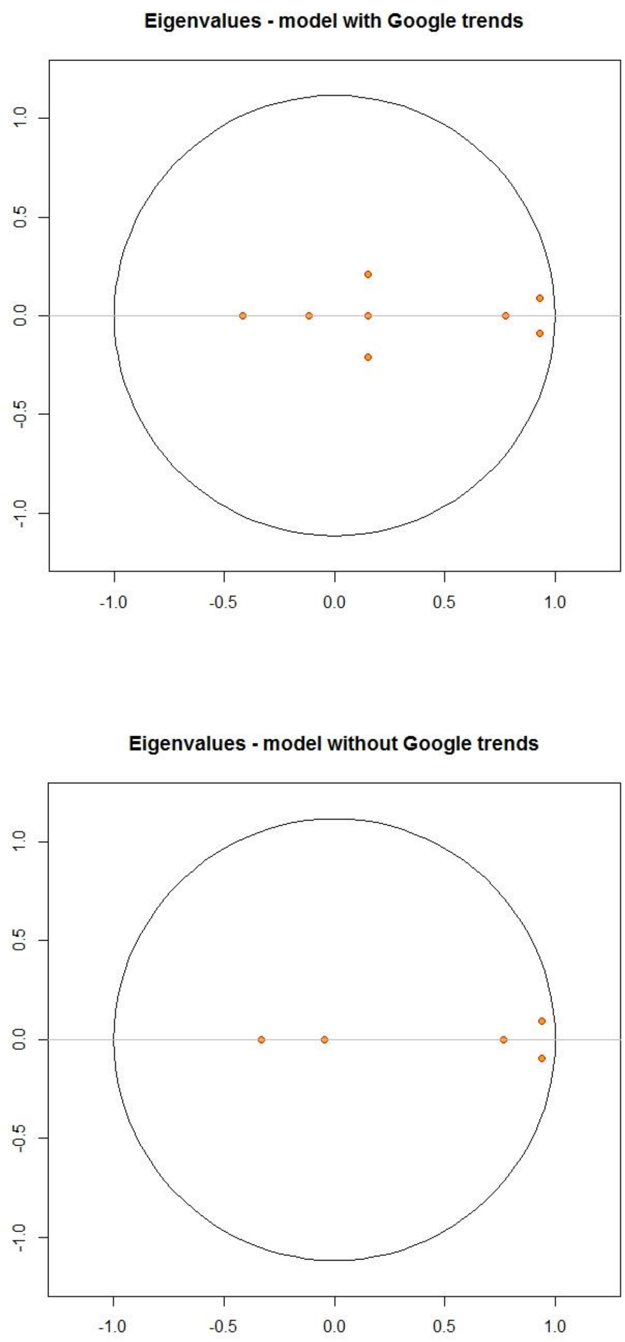
Morales-Arias, L. and Moura, G. (2013). Adaptive forecasting of exchange rates with panel data. *International Journal of Forecasting*, 29(3):493–509.

Figure 1: Changes in the composition of the queries used in the estimation of market sentiments



Source: Authors' calculations.

Figure 2: Model stability – eigenvalues of companion matrix



Source: Authors' calculations.

Table 1: Optimal number of lags

	1 lag	**2 lags**	**3 lags**	**4 lags**	**5 lags**
Schwartz information criterion	**-20.756**	-19.173	-17.068	-15.783	-15.827

Source: Authors' calculations

Table 2: Forecast error variance decomposition without market sentiments

Horizon/Variable	**Industry**	**M1**	**HICP**	**Interest rate**	**Euro rate**
1	0	0.149	0.300	0.186	0.365
2	0	0.149	0.300	0.188	0.363
...	...	...	...	...	...
48	0	0.159	0.320	0.193	0.327

Source: Authors' calculations

Table 3: Forecast error variance decomposition with market sentiments

Horizon /Variable	**Industry**	**M1**	**HICP**	**Interest rate**	**Credit Shock Google**	**Financial Shock Google**	**Price Shock Google**	**Euro rate**
1	0	0.003	0.005	0.003	0.001	0.005	0.001	0.983
2	0	0.005	0.004	0.004	0.002	0.007	0.002	0.975
...	...	...	...	...				...
48	0	0.020	0.099	0.022	0.004	0.065	0.007	0.783

Source: Authors' calculations

Table 4: Accuracy of given models

	1M	3M	6M	12M
Including market sentiments (RMSE)	0.094	0.134	0.162	0.204
Excluding market sentiments (RMSE)	0.095	0.143	0.177	0.223
naïve forecast (RSME)	0.090	0.190	0.309	0.405
Diebold-Mariano test* *(p-value)* Alternative hypothesis: The models with and without market sentiments provide different levels of accuracy	0.6154	0.417	0.053	0.007
Diebold-Mariano test* *(p-value)* Alternative hypothesis: The model without market sentiments provides lesser accuracy than the model with market sentiments	0.692	0.208	0.026	0.004

Source: Authors' calculations. *In the DM test, we compared the forecast's errors obtained from the VAR models with and without market sentiments.

Table 5: Persistence of sentiments

	Credit Shock Google	Financial Shock Google	Price Shock Google
Minimum persistence	43.9%	47.9%	41.3%
Average persistence	60.0%	59.7%	62.9%

Source: Authors' calculations.

Table 6: Accuracy of given models

	1M	**3M**	**6M**	**12M**
Baseline scenario-unrestricted	0.094 (0.692)	0.134 (0.208)	0.162 (0.026)	0.204 (0.004)
Restriction-a minimum of 70% of queries must remain in the next period	0.102 (0.842)	0.159 (0.831)	0.178 (0.511)	0.213 (0.220)

Source: Authors' calculations. Contained in parentheses is the p-value of the Diebold-Mariano test with alternative hypothesis: Model without market sentiments provides lesser accuracy.

Table 7: Data summary

Variable	**Source**	**Description**
EUR rate	Eurostat	Monthly averages of national currencies exchange rate
M1	Collected from countries' central banks databases	Monetary aggregate M1. Logarithmic monthly rate of change
Industrial production	Eurostat	Logarithmic monthly rate of change of industrial production (seasonally and working days adjusted)
Interest rate	Eurostat	3-month money market interest rate
Prices	Eurostat	HICP inflation rate
Sentiments	Own/Google	Market sentiments calculated out of PCA from Google Trends

Source: Authors' elaboration

Table 8: Google queries included in the analysis

Credit market sentiment	Price sentiment	Financial market sentiment
kredyt	skup	giełda
hipoteczny	biedronka	GPW
pko	żabka	notowania
gotówkowy	lidl	akcje
mieszkaniowy	tesco	obligacje
ING	netto	inwestor
millenium	lewiatan	wig
getin	allegro	wig20
mbank	eBay	bankier
bzwbk	rtv	puls biznesu
skok	agd	parkiet
lokata	media markt	eur pln
chwilówka	saturn	eur to pln
chwilówki	alkohole	eur in pln
BIK	monopolowy	pln euro
pożyczka	alkomat	fundusze
pożyczki	papierosy	money pl
mieszkania	rachunki	aegon
ceny mieszkania	upc	open finance
deweloper	netia	expander
developer	pgnig	zrównoważony
robyg	gaz	stabilnego wzrostu
marvipol	prąd	indeksy
millenium	lewiatan	inwestor
ronson	pge	kurs walut
dom development	energa	kurs nbp
polnord	rwe	oprocentowanie
otomoto	enea	wibor
samochody	lodówka	stopy procentowe
raty	pralka	stopy nbp
	zmywarka	rpp
	telefony	hossa
	tytoń	bessa
		eBay
		allegro
		import
		export

Source: Authors' elaboration