Exchange Rate Forecast Enhancement Using Sentiments from Google Trends

Hussain Yaganti* and Yash Manpuria**

Does incorporation of sentiments from credit, financial and price markets add to the forecasting abilities of the models using fundamental factors in exchange rate forecasting? The present study attempts to answer this question by introducing a different method of exchange rate forecasting by considering sentiments from Google Trends along with macroeconomic fundamentals. It attempts to increase the predictive powers of foreign exchange forecasting models based on macroeconomic observable fundamental factors by incorporating the sentiments from the above-mentioned three markets. This work is based on Principal Component Analysis (PCA) and Vector Autoregression (VAR). The study has extracted sentiments by preserving 90% cumulative variance in principle components from each of these three markets. Further, it estimated VARs with and without sentiments. It is observed that the estimates of VAR model with sentiments provide better results as compared to fundamental VAR model. Finally, this study concludes that sentiments can enhance predictive content of foreign exchange rate along with macroeconomic variables.

Introduction

Prediction of the prices of financial securities has always been an area of interest for both academia and the industry because it brings with it the ability to generate gains and hedge against losses. One such market which has been the cynosure among the investment community is the foreign exchange market because of the large volumes of transactions and high net worth institutions like banks and hedge funds involved that constantly seek to gain a competitive advantage in terms their ability to forecast prices. There have been multiple attempts to model the forex market in the past ranging from pure fundamental frameworks to computationally intensive neural network prediction systems over the years. As a part of hedging, Yaganti and Kamaiah (2015) magnify the importance of exchange rate forecasting.

Mark and Sul (2012) find that in the 1990s and early 2000s forecasts of exchange rates found using time series regression models have given poor results, while pooled regression models based on panel data, after adjusting for fixed effects, have performed superior in comparison to when the heterogeneity in the data is not very large. Ince (2014), for a period between 1973 and 2009, tries to evaluate out of sample exchange rate forecasting using the PPP concept and Taylor's rule for a set of nine OECD countries for both the short and long

* Assistant Professor, Department of Economics and Finance, BITS PILANI, Hyderabad Campus, Hyderabad 500078, Telangana, India. E-mail: hussain@hyderabad.bits-pilani.ac.in

** Postgraduate Student (Economics), BITS PILANI, Hyderabad Campus, Hyderabad 500078, Telangana, India. E-mail: f20140791@hyderabad.bits-pilani.ac.in

time frames and found that the Taylor fundamentals are not improved upon by panel specifications for one quarter time frame, while the PPP model for 16 quarters is improved by panel specifications. Garratt and Mise (2014) proposed using multiple models to forecast the exchange rates while using panel data to improve the point estimate of the rates thus bringing in the concept of model averaging. Ca' Zorzi *et al.* (2016) extend the PPP debate. They show that the half-life PPP model outperforms the forecasting of both real and nominal exchange rate for both the long and short horizon using the mean reverting approach. Chen and Lazer prefer regression over complex classification models due to speed, importance of magnitude and accuracy. In this study too a regression-based model has been used.

Morales and Moura (2013) show that exchange rate forecasts generated from a wide range of information sets improve forecasting precision and lead to better market timing than most single predictors. The predictors used include macroeconomic fundamentals, market return/volatility and cyclical and confidence intervals collected from surveys filled by varied market participants. The present study takes inspiration and extends the VAR model via similar sentiment additions to the models as endogenous variables generated through Google Trend data. The study takes Ko and Ogaki (2015) as the benchmark model as it uses only fundamentals to forecast the rates and hence enables the present study to predict on the predictive abilities of sentiments for the Indian forex markets when the present results are compared to the benchmarks.

Predictive model based on sentiments is an upcoming research area in the field of behavioral finance. Bollen (2010) indicated that the accuracy of DJIA predictions can be significantly improved by the inclusion of specific public mood dimensions but not others and achieves 87% accuracy in prediction using sentiments using opinion finder and GPOMS. It derives from Nofsinger (2005) who said that financial decisions are significantly driven by emotions and mood. De Bondt (1993) found a positive and statistically significant relationship between S&P500 returns and future changes in sentiments of individual investors. Mittal and Goel (2012) used GPOMS and found some sentiments to be Granger causative for financial market movements, thus reconfirming Bollen's claim. Meir and Fisher (2000) provided an interesting contrarian perspective by saying that "studies of sentiment of investors teach us about the biases in market forecasts and opportunity to earn extra returns by exploiting those biases."

Askifas and Zimmerman (2009) showed the use of Internet data related to keyword query searches to get fast information to predict economic behavior to find results relating to unemployment in Germany and successfully established the possible use of Google Trends in short-term forecasting. Choi and Varian (2011) showed the prediction of short-term economic variables like sales and consumer confidence using search engine data and found that AR models that include Google Trend variables outperform non-trend AR models by up to 20% accuracy. They showed that Google Trend query index is often correlated to various variables in economic studies and is useful for short-term prediction. D'Amuri and Marcucci (2012) analyzed a whole spectrum of models that can be tried in forecasting problems and the results obtained suggested using Google Trends as a reliable source of data for predictive modeling. Nick and Shanbhoge (2011) summarized how web search data can be used for economic now-casting by central banks.

Using the learnings from the literature, this study uses sentiments in forecasting the exchange rate and builds a model to quantify the sentiments from three different markets, namely, price, financial and credit markets obtained via Google Trends and use it to build the predictive framework.

The rest of the study is structured as follows: it presents the theoretical foundations of macroeconomic model, followed by description of the data and estimation methods used in the study. Subsequently, it discusses the results, and finally, the conclusion is offered.

Theoretical Model

Macroeconomic Variables Affecting Exchange Rate

Using the Engel and West (2005) and Ko and Ogaki (2015) present value model of exchange rate, the money output relation is given as:

$$m_t = p_t + \varphi y_t - \lambda i_i + \upsilon_t$$
$$m_t^* = p_t^* + \varphi y_t^* - \lambda i_i^* + \upsilon_t$$

where

m is the log of money supply;

p is the log of price level;

y is the log of income;

i is the annual interest rate for that period; and

υ represents the factors other than those mentioned above which affect the money supply.

If the first equation is for India and the second is for USA, the issuer of dollars, in our ₹/$ empirical study. Here ϕ is the income elasticity of money demand and $\lambda > 0$ is the interest rate semi-elasticity of money demand. ϕ and λ are assumed to be identical for both the nations in the study.

Using the purchasing price parity concept, the nominal exchange rate is:

$$s_t = p_t - p_t^* + q_t$$

where q denotes the unobservable factors affecting the nominal exchange rate not captured by the difference in prices.

Using uncovered interest rate parity we get,

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

where the expectation is rational at time, $t + 1$ and ρ represents unobserved factors like rumors, political news among others.

Inclusion of Market Sentiments

The unobservable factors are variables which are difficult to obtain because they are not observed directly, including market and customer sentiments, political situations and the aftermaths of natural phenomena. Our model is macroeconomic in nature and hence we compute aggregated unobserved signals. If positive sentiments are equal to negative sentiments, the sentiments are counterbalanced and the observed fundamentals model is sufficient, but this is only a special case and we should accommodate sentiments in general to improve model accuracy.

We already include observable macroeconomic variables in our models and hence we do not include them as part of sentiment signal to avoid multicollinearity. The signal that the investors receive is taken to be linearly dependent on a combination of components from Principal Component Analysis (PCA), which represents the indirect capture of unobservable factors.

Equations of our pure fundamental model can be decomposed to accommodate two types of shocks, namely, shocks related to sentiments that are specific to the price, credit and financial markets, and shocks affecting the observable sentiments. So the decomposition is as follows:

$$\begin{aligned}
\upsilon_t &= \overline{\upsilon}_t + \widetilde{\upsilon}_t \\
q_t &= \overline{q}_t + \widetilde{q}_t \\
\rho_t &= \overline{\rho}_t + \widetilde{\rho}_t
\end{aligned}$$

where the first factors with a $(\overline{\ })$ on top are related to the sentiments in the price, credit and financial markets and obtained via Google queries index and the second factors are unobserved factors in the fundamental equations.

So, the modified fundamental equations with error term decomposition will now be as follows:

$$\begin{aligned}
m_t &= p_t + \varphi y_t - \lambda i_t + \overline{\upsilon}_t + \widetilde{\upsilon}_t \\
s_t &= p_t - p_t^* + \overline{q}_t + \widetilde{q}_t \\
E_t s_{t+1} - s_t &= i_t - i_t^* + \overline{\rho}_t + \widetilde{\rho}_t
\end{aligned}$$

Hence a part of residual variation in the forex market can be explained by the changes in investors belied concerning the changes in financial markets, i.e., sentiments.

Data and Methodology

The query list for the Google Trends data is taken from Chojnowski and Dybka (2017) and adapted for the Indian financial markets for all the three markets for the period January 2013 to April 2017 on a monthly basis using only India as our search zone. The weekly series so obtained is converted to a monthly series by preserving the values for the first week of each month to better match our CPI data which is available for the 1st of each month. The data for the fundamental variables have been taken from investing.com, data.gov.in (Open Government Data Platform India) and the Federal Reserve Bank of St. Louis (FRED). The IIP values are used as a proxy for income and annualized money market yields are taken for interest rate for the two nations.

Principal Component Analysis

The Google Trend scores for each query are scaled between 0 and 100 and are linear in nature. So, a query with an index score of 100 on a day was queried double as compared to a day with score 50. Using 15 queries for each market, we get a time series for the period mentioned for each query, and hence obtain a panel of query versus month for three markets each. These time series undergo PCA decomposition, and we preserve 90% of the variance as our threshold and obtain seven components in the price and financial markets and eight in the credit market. The principal components so obtained capture the variation of sentiments in the observed markets. The standard deviation, proportion of variance and the cumulative variance for each of the 15 components in all the PCAs are shown in Tables 1, 2 and 3.

Table 1: Price Market Principal Components

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
SD	1.942361	1.925174	1.445502	1.142005	0.98221	0.897146	0.871297
Proportion of Variance	0.25152	0.24709	0.1393	0.08694	0.06432	0.05366	0.05061
Cumulative Proportion	0.25152	0.4986	0.6379	0.72485	0.78916	0.84282	**0.89343**

Table 2: Credit Market Principal Components

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
SD	2.258068	1.745148	1.172712	1.057306	0.963148	0.859516	0.82364	0.68745
Proportion of Variance	0.33992	0.20304	0.09168	0.07453	0.06184	0.04925	0.04523	0.03151
Cumulative Proportion	0.33992	0.54296	0.63464	0.70917	0.77101	0.82027	0.86549	**0.897**

Table 3: Financial Market Principal Components							
	PC1	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**
SD	2.352874	1.796761	1.301155	1.072351	0.935228	0.89182	0.708877
Proportion of Variance	0.36907	0.21522	0.11287	0.07666	0.05831	0.05302	0.0335
Cumulative Proportion	0.36907	0.58429	0.69716	0.77382	0.83213	0.88515	**0.91865**

The two elasticities in our pure fundamental equations are estimated by regressing the log of money supply versus the log on income and the coefficient is captured as the income elasticity of money demand as 1.302, which is greater than 1, the reasoning behind which is explained in Pattanaik and Subhadra (2011). Similarly, log of money supply is regressed versus the interest rate to find the interest rate semi-elasticity of money demand, which comes to be negative as expected. Using the elasticities and the monthly series for the macroeconomic variables, the residuals for the three markets are calculated using the Ko and Ogaki equations as shown above.

We then regress our three residuals to be decomposed, with the principal components (giving a cumulative variance proportion of 90% of the original Google Trends matrix) of the corresponding market. We preserve only the independent variables which are significant at 1% and re-run the regressions for each of the three markets to obtain the fitted values and obtain adjusted R^2 of 0.71 for the price market, 0.40 for the financial markets and 0.44 for the credit market respectively. These R^2 values indicate that a part of variation in the unexplained part of the fundamental equations can be explained by the sentiment unobserved fundamentals. The results for the regression are given in Tables 4 to 9.

Table 4: Price Market Residual Regression with Seven Sentiment PCs				
Term	**Estimate**	**Std. Error**	**Statistic**	***p*-Value**
C	63.04462	0.283293	222.5419	8.70E-69
*PC*1	1.617416	0.147273	10.98244	3.43E-14
*PC*2	–0.39052	0.148588	–2.62822	0.011774
*PC*3	0.498733	0.197895	2.520195	0.015431
*PC*4	0.332092	0.250487	1.325786	0.191753
*PC*5	0.18128	0.291238	0.622445	0.536862
*PC*6	–0.46498	0.318852	–1.45829	0.151862
*PC*7	0.225158	0.328312	0.685804	0.496434
Residual Standard Error: 2.043 on 44 degrees of freedom				
Multiple R^2: 0.7591			Adjusted R^2: 0.7207	
F-Statistic: 19.8 on 7 and 44 df			*p*-value: 1.084E-11	

Table 5: Price Market Final Regression

Term	Estimate	Std. Error	Statistic	*p*-Value
C	63.04462	0.285475	220.8414	7.64E-74
*PC*1	1.617416	0.148407	10.89852	1.41E-14
*PC*2	–0.39052	0.149732	–2.60814	0.012098
*PC*3	0.498733	0.199419	2.500937	0.015853

Residual Standard Error: 2.059 on 48 degrees of freedom
Multiple R^2: 0.7331 Adjusted R^2: 0.7164
F-statistic: 43.94 on 3 and 48 df p-value: 8.275E-14

Table 6: Financial Market Residual Regression with Seven Sentiment PCs

Term	Estimate	Std. Error	Statistic	*p*-Value
C	–6.91319	0.229425	–30.1326	5.17E-31
*PC*1	0.436379	0.09846	4.432044	6.13E-05
*PC*2	–0.17389	0.128934	–1.34867	0.184345
*PC*3	0.077923	0.178045	0.43766	0.663774
*PC*4	–0.47298	0.216034	–2.1894	0.033916
*PC*5	–0.6167	0.247708	–2.48961	0.01664
*PC*6	0.026338	0.259765	0.101393	0.919699
*PC*7	–0.82423	0.326804	–2.5221	0.015359

Residual Standard Error: 1.654 on 44 degrees of freedom
Multiple R^2: 0.47 Adjusted R^2: 0.3857
F-statistic: 5.574 on 7 and 44 df p-value: 0.0001217

Table 7: Financial Market Final Regression

Term	Estimate	Std. Error	Statistic	*p*-Value
C	–6.91319	0.227023	–30.4515	1.36E-32
*PC*1	0.436379	0.097429	4.47895	4.78E-05
*PC*4	–0.47298	0.213771	–2.21257	0.031822
*PC*5	–0.6167	0.245114	–2.51596	0.015345
*PC*7	–0.82423	0.323382	–2.54879	0.014135

Residual Standard Error: 1.637 on 47 degrees of freedom
Multiple R^2: 0.4456 Adjusted R^2: 0.3985
F-statistic: 9.446 on 4 and 47 df p-value: 1.093E-05

Table 8: Credit Market Residual Regression with Eight Sentiment PCs				
Term	Estimate	Std. Error	Statistic	*p*-Value
C	10.91355	0.038668	282.2399	6.62E–72
*PC*1	0.059133	0.017291	3.4198	0.001384
*PC*2	0.098183	0.022373	4.388395	7.28E–05
*PC*3	0.080895	0.033295	2.429678	0.019362
*PC*4	–0.0764	0.036929	–2.06892	0.044599
*PC*5	0.036293	0.040539	0.89527	0.375627
*PC*6	–0.02778	0.045427	–0.61158	0.544037
*PC*7	0.022893	0.047405	0.482914	0.631607
*PC*8	0.013936	0.056797	0.245363	0.807343
Residual Standard Error: 0.2788 on 43 degrees of freedom Multiple R^2: 0.4977 Adjusted R^2: 0.4042 *F*-statistic: 5.326 on 8 and 43 df *p*-value: 0.0001136				

Table 9: Credit Market Final Regression				
Term	Estimate	Std. Error	Statistic	*p*-Value
C	10.91355	0.037612	290.1609	4.06E-78
*PC*1	0.059133	0.016819	3.515776	0.000983
*PC*2	0.098183	0.021763	4.511554	4.29E-05
*PC*3	0.080895	0.032386	2.497866	0.016052
*PC*4	–0.0764	0.035921	–2.12699	0.038699
Residual Standard Error: 0.2712 on 47 degrees of freedom Multiple R^2: 0.4805 Adjusted R^2: 0.3985 *F*-statistic: 10.87 on 4 and 47 df *p*-value: 2.542E-06				

VAR Model with and Without Sentiments

There is an issue of whether the variables in our VAR need to be stationary. Sims (1980) recommended against differencing when the variables contain a unit root. They argued that the goal of VAR analysis is to determine the relationship among variables, and the other argument against differencing being that it 'throws away' information concerning the co-movements in the data and thus data need not be detrended. So, we have estimated our model VAR in level form even though the fundamental variables are non-stationary.

For the main part of our analysis, we use two unrestricted VAR models, one with pure macroeconomic fundamental variables, and the other, with the addition of sentiments to compare the two models and test the ability of sentiments to enhance forecast of exchange rates.

The VAR model without sentiments is defined as follows:

$$Y_t = \begin{bmatrix} y_t \\ m_t \\ p_t \\ i_t \\ s_t \end{bmatrix}$$

where Y is the vector of endogenous variables and other symbols have their usual meaning.

We extend this model to include unobservable fundamental and extend the Ko and Ogaki model using the VAR framework as follows:

$$Y_t = \begin{bmatrix} y_t \\ m_t \\ p_t \\ i_t \\ \overline{\upsilon}_t \\ \overline{q}_t \\ \overline{\rho}_t \\ s_t \end{bmatrix}$$

where the three new variables included represent the fitted values obtained from the regressions run for the price, credit and financial markets.

Results and Discussion

Next, we attempt a diagnostic test of our models. We first attempt to find the optimal number of lags in our VAR model using the maximum of Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz information Criterion (SC), and Hannan-Quinn (HQ) information criterion. Out of the five tests undertaken, four tests suggest an optimal lag of two, while one suggests a lag of one and so we go with two lags for our VAR model. The results of the lag criterion test for both the VAR models without and with sentiments are shown in Tables 10 and 11 respectively. The stability of the model is tested using the Eigenvalues of the companion matrix. The model turns out to be stable as all the points lie within the unit circle for both the VARs without and with sentiments as shown in Figures 1 and 2 respectively.

Table 10: VAR Without Sentiments – Lag Order Selection Criteria						
Endogenous Variables: *LIIIP, LM1, LICPI, I, E*						
Exogenous Variables: C						
Sample: 2013M01-2017M04						
Included Observations: 50						
Lag	**Log*L***	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	198.6677	NA	2.97e–10	–7.74671	–7.5555	–7.6739
1	373.1330	307.0591	7.57e–13	–13.7253	–12.57811*	–13.2885
2	**413.4297**	**62.86275***	**4.24e–13***	**–14.337***	**–12.234**	**–13.536***

Note: * indicates lag order selected by the criterion; and LR: Sequential modified LR test statistic (each test at 5% level).

Table 11: VAR With Sentiments – Lag Order Selection Criteria						
Endogenous Variables: *LIIIP, LM1, LICPI, I, CR, P, F, E*						
Exogenous Variables: C						
Sample: 2013M01-2017M04						
Included Observations: 50						
Lag	**Log*L***	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	99.16941	NA	3.60e–12	–3.64678	–3.34085	–3.53028
1	314.6929	353.4585	8.67e–15	–9.70772	–6.954403*	–8.65924
2	**419.2675**	**138.0385***	**2.08e–15***	**–11.330***	**–6.13**	**–9.3502***

Note: * indicates lag order selected by the criterion; LR: sequential modified LR test statistic (each test at 5% level).

Figure 1: Stability Test for VAR Without Sentiments

Inverse Roots of AR Characteristic Polynomial

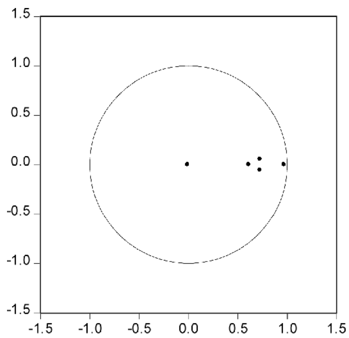
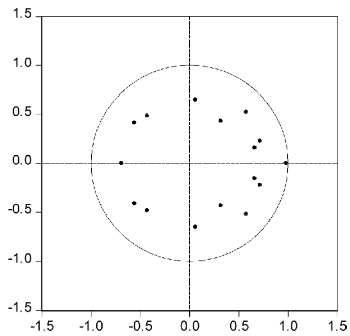


Figure 2: Stability Test for VAR with Sentiments

Inverse Roots of AR Characteristic Polynomial



We perform the variance decomposition test for both the VAR models to evaluate how shocks reverberate through a system, i.e., to assess the passthrough of external shocks to each variable. The variance decomposition test of the exchange rate (*E*) is carried out for both the VAR models without and with sentiments for periods 1 to 10 and the results are shown in Tables 12 and 13 respectively. The standard error of the exchange rate ranges from 1.27 to 2.03 for periods 1 to 10 for VAR without sentiments, while it ranges from just 0.013 to 0.019 for VAR model with sentiments showing a sharp decline in standard error with the inclusion of sentiments. The sentiments play a crucial role in forecasting variance. For the exchange rate, our adjusted R^2 increases to 0.933 from 0.90 and the sum squared of residuals falls from 43.27 to 26.39 with the addition of sentiments and some of the lagged sentiment variables turn out to be significant at 95% confidence interval as well, as shown in Table 14.

To check if the inclusion of sentiments improves the forecast accuracy, we undertake the forecast evaluation tests for both the VAR models with and without sentiments. We use the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Theil inequality coefficient to compare our two models. We observe the RMSE for exchange rate forecast is 0.93 for VAR without sentiments and 0.72 for VAR models with sentiments. The results of the two tests are presented in Table 15. Thus, it is observed that our model with sentiments performs better than the pure fundamental model in all four tests.

Table 12: Variance Decomposition of VAR Without Sentiments

Period	SE	*LIIIP*	*LM1*	*LICPI*	*I*	*E*
1	**1.271657**	11.36836	3.165047	2.166037	5.863451	77.43711
2	**1.604994**	15.29858	1.988447	2.598326	5.377053	74.73759
3	**1.757188**	15.46814	2.348126	3.013046	5.437906	73.73279
4	**1.843215**	14.99479	3.533282	3.392887	5.446497	72.63255
5	**1.899369**	14.42929	5.060375	3.740221	5.376143	71.39397
6	**1.939949**	13.92031	6.630086	4.061524	5.262701	70.12537
7	**1.971332**	13.49916	8.089056	4.362914	5.138116	68.91075
8	**1.996693**	13.15973	9.377430	4.648740	5.020716	67.79338
9	**2.017801**	12.88644	10.48624	4.921554	4.918148	66.78762
10	**2.035742**	12.66388	11.43004	5.182547	4.831853	65.89167

Note: Cholesky Ordering: *LIIIP LM1 LICPI I E*.

Table 13: Variance Decomposition of VAR with Sentiments									
Period	SE	*LIIIP*	*LM1*	*LICPI*	*I*	CR	*P*	*F*	E
1	**0.012951**	17.8042	0.08762	9.52748	12.9502	0.26585	0.03940	3.74342	55.5817
2	**0.015124**	23.2602	1.51162	11.2932	21.2256	0.14490	0.75240	9.11296	32.6990
3	**0.016287**	35.7104	2.26150	13.1622	13.9151	3.11759	0.52239	7.00719	24.3034
4	**0.017212**	36.1360	5.07139	15.0019	12.8896	2.53759	2.79746	5.36054	20.2052
5	**0.018003**	31.7782	10.6213	12.9121	10.3988	5.20814	8.34053	4.80310	15.9376
6	**0.018602**	26.5849	18.2750	11.0023	8.38223	6.64935	9.83953	5.96334	13.3032
7	**0.018831**	22.5895	22.8026	9.49400	7.19790	7.17774	12.1575	7.11296	11.4676
8	**0.019032**	20.2758	25.0449	8.56270	6.60469	7.88536	13.1372	8.03885	10.4503
9	**0.019241**	19.1940	25.5135	8.18749	6.25244	7.97580	14.0140	8.75656	10.1059
10	**0.019472**	18.6713	25.1624	8.00398	6.11526	7.98910	15.1247	9.05266	9.88049

Note: Cholesky Ordering: *LIIIP LM1 LICPI I E*.

Table 14: Vector Autoregression Estimates			
Sample (Adjusted): 2013M03-2017M04			
Included Observations: 50 after adjustments			
Without Sentiments		With Sentiments	
Variable	E	Variable	E
LIIIP(–1)	–11.4474 (–1.09609)	*LIIIP*(–1)	–12.9172 (–1.26154)
LIIIP(–2)	–27.2722 (–2.78778)	*LIIIP*(–2)	–20.0645 (–1.92971)
LM1(–1)	–2.95837 (–0.365380	*LM1*(–1)	–4.03973 (–0.55359)
LM1(–2)	17.34433 (2.10414)	*LM1*(–2)	9.356450 (1.19746)
LICPI(–1)	43.91616 (0.73398)	*LICPI*(–1)	35.66044 (0.66781)
LICPI(–2)	–42.0266 (–0.73569)	*LICPI*(–2)	–29.6183 (–0.59937)
I(–1)	0.551817 (1.85567)	*I*(–1)	0.779353 (2.59899)

Table 14 (Cont.)

Without Sentiments		With Sentiments	
Variable	*E*	Variable	*E*
I(–2)	–1.12786 (–3.98487)	*I*(–2)	–0.85992 (–3.05389)
		CR(–1)	2.061108 (1.59294)
		CR(–2)	4.108621 (3.59217)
		P(–1)	0.354690 (2.34995)
		P(–2)	0.120140 (0.68196)
		F(–1)	0.535245 (2.99457)
		F(–2)	0.176601 (0.97582)
E(–1)	0.545007 (3.84780)	*E*(–1)	0.353519 (2.39667)
E(–2)	0.253879 (1.72800)	*E*(–2)	0.319740 (2.40533)
C	–99.0274 (–1.45964)	C	–86.6984 (–1.36751)
R^2	0.926749	R^2	0.955311
Adj. R^2	0.907966	Adj. R^2	0.933644
Sum Sq. Resids.	43.27153	Sum Sq. Resids.	26.39881
SE Equation	1.053341	SE Equation	0.894407
F-Statistic	49.34129	*F*-Statistic	44.09006
Log-Likelihood	–67.3337	Log-Likelihood	–54.9793
AIC	3.133349	AIC	2.879173
SC	3.553994	SC	3.529261
Mean Dependent	63.47948	Mean Dependent	63.47948
SD Dependent	3.472123	SD Dependent	3.472123
Log-Likelihood	413.4297	Log-Likelihood	419.2675
AIC	–14.3372	AIC	–11.3307
SC	–12.234	SC	–6.13

Note: *t*-Statistics in ( ). Multiple AIC and SC values in the table are explained as E-series values and total VAR values.

Table 15: Forecast Evaluation for Two VAR Models					
Sample: 2013M01-2017M04					
Included Observations: 52					
Variable	**Inc. Obs.**	**RMSE**	**MAE**	**MAPE**	**Theil**
E (Without Sentiments)	52	0.930285	0.768463	1.228219	0.007317
E (With Sentiments)	52	0.726620	0.559377	0.892674	0.005715

Conclusion

Exchange rate is the price of one currency with respect to some other currency. It is determined not only by fundamental macroeconomic variables but also by sentiments in the credit, price and financial markets. We incorporate the sentiments by adding unobservable fundamental variables into our VAR model and show that it outperforms the fundamental VAR model. Our results enable us to conclude that there is some predictive power enhancement by including investor and public sentiment in fundamental forex predictive models and hence this leads to gain comparative advantage in speculative profit making or hedging losses as compared to naïve random walk model or even pure observable fundamental model of foreign exchange prediction. The tests have been performed specific to India for ₹/$ and can be extended to other currencies. The model can be extended to test for currencies of monetary unions in future works.❖

References

1. Askitas N and Zimmermann K (2009), "Google Econometrics and Unemployment Forecasting", IZA Discussion Papers 4201, Institute for the Study of Labor (IZA).
2. Bollen, Mao and Jun Zeng (2010) "Twitter Mood Predicts the Stock Markets", *Journal of Computational Science*, Vol. 2, No. 1, p. 18.
3. Ca' Zorzi M, Múck J and Rubaszek M (2016), "Real Exchange Rate Forecasting and PPP: This Time the Random Walk Loses", *Open Economies Review*, Vol. 27, No. 3, pp. 585-609.
4. Choi H and Varian H (2012), "Predicting the Present with Google Trends", *The Economic Record*, Vol. 88, No. 1, pp. 2-9.
5. Chojnowski M and Dybka P (2017), "Is Exchange Rate Moody? Forecasting Exchange Rate with Google Trends Data", *Econometric Research in Finance*, Vol. 2, No. 1, pp. 1-21.
6. D'Amuri F and Marcucci J (2012), "The Predictive Power of Google Searches in Forecasting Unemployment", *Temi di discussione* (Economic Working Papers) 891, Economic Research and International Relations Area, Bank of Italy.
7. De Bondt (1993), "Betting on Trends: Intuitive Forecasts of Financial Risk and Return", *International Journal of Forecasting*, Vol. 9, No. 3, pp. 355-371.

8. Engel C and West K (2005), "Exchange Rates and Fundamentals", *Journal of Political Economy*, Vol. 113, No. 3, pp. 485-517.

9. Garratt A and Mise E (2014), "Forecasting Exchange Rates Using Panel Model and Model Averaging", *Economic Modelling*, Vol. 37 (C), pp. 32-40.

10. Ince O (2014), "Forecasting Exchange Rates Out-of-Sample with Panel Methods and Real-Time Data", *Journal of International Money and Finance*, Vol. 43, pp. 1-18.

11. 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*, Vol. 38 (C), pp. 198-206.

12. 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 L Sarno (Eds.), *Handbook of Exchange Rates*, pp. 265-281, Wiley-Blackwell.

13. Meir Statman and Fisher K L (2000), "Investor Sentiment and Stock Returns", *Financial Analysis Journal*, Vol. 56, No. 2, pp. 16-23.

14. Mittal and Goel (2012), "Stock Prediction Using Twitter Sentiment Analysis", CS229 2011, Standford University, available at http://cs229.stanfordedu/proj2011/GoelMittalStockMarketPredictionUsingTwitterSentimentAnalysis.pdf.

15. Morales-Arias and Moura (2013), "Adaptive Forecasting of Exchange Rates with Panel Data", *International Journal of Forecasting*, Vol. 29, No. 3, pp. 493-509.

16. Nick McLaren and Rachana Shanbhoge (2011), " Using Internet Search Data as Economic Indicators", *Bank of England Quarterly Bulletin*, June, available at URL http://www.bankofengland.co.uk/publications/quarterlybulletin/qb110206.pdf

17. Nofsinger (2005), "Social Mood and Financial Economics", *Journal of Behavioral Finance*, Vol. 6, No. 3.

18. Pattanaik and Subhadra S (2011), "The Velocity Crowding-out Impact: Why High Money Growth is not Always Inflationary", RBI Working Paper Series No. 6, RBI WPS (DEPR) 06/2011.

19. Sims (1980), "Macroeconomics and Reality", *Econometrica*, Vol. 48, No. 1, pp. 1-48.

20. Yaganti C H and Kamaiah B (2015) "Exchange Traded Currency Futures Markets and Risk Management in India", *Journal of International Economics*, Vol. 6, No. 2.

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