Forecasting Tehran's Free-Market USD Exchange Rate Using Google Trends and Time Series Models

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Abstract

Forecasting exchange rates, particularly in volatile markets, is crucial for economic planning and decision-making. Recent studies have shown that Internet search data (Google Trends) can capture public interest and sentiment, improving nowcasting of economic indicators (Askitas & Zimmermann, 2009; Choi & Varian, 2009). This paper develops a forecasting framework for Iran's free-market US dollar rate by combining daily exchange-rate data with Google Trends indices for relevant search terms. We review the literature on Google Trends in economic forecasting, describe our ARIMA-based modeling approach, and demonstrate how search data are incorporated. Our model achieves low forecast errors (in-sample MAPE under a few percent) on recent data. The results suggest that Google search volumes provide timely signals that enhance currency forecasts, complementing traditional econometric techniques (Bulut, 2018; Ito, Masuda, Naito, & Takeda, 2021). We discuss implications for data-driven finance and outline directions for future research.

1 Introduction

Forecasting exchange rates is a long-standing challenge in economics. Traditional models rely on macroeconomic fundamentals (inflation, interest rates, trade balances), but these often become available with lags and may miss rapid market shifts. In contrast, big data sources like online search activity can provide real-time sentiment indicators. For example, Askitas and Zimmermann (2009) find strong correlations between Google search keywords and unemployment in Germany, and Choi and Varian (2009) show that adding Google Trends terms to autoregressive (AR) models can improve predictions by up to 18%.

2 Literature Review

A growing literature explores Google Trends (GT) as a forecasting tool. GT provides a Search Volume Index (SVI), a normalized 0–100 score for keyword query frequency over time. Askitas and Zimmermann (2009) coin the term "Google Econometrics," demonstrating that keyword search volumes strongly correlate with official economic series (e.g. unemployment). Similarly, Choi and Varian (2009) show that including GT variables in AR models improves forecasts of retail sales and housing starts by up to 18%.

Research specifically on exchange rates has leveraged this idea. Bulut (2018) apply GT data to forecast OECD currency rates, finding that search-query-based predictions outperform traditional structural models in forecasting currency movement direction. Ito et al. (2021) construct a GT-based sentiment index for USD/JPY and show that adding this index significantly lowers mean-squared forecast errors. However, Schaer, Kourentzes, and Fildes (2019) caution that online data do not automatically enhance every forecast, finding in some demand-forecasting cases that simple univariate methods outperformed models augmented with search or social-media inputs.

3 Data and Methodology

We assemble a two-year daily time series of Iran's free-market USD/Rial exchange rate using data from TGJU. We obtain Google Trends data for a set of English-transliterated search terms (e.g. "kharid dollar," "torom," "tahrim"). Each GT series is a normalized SVI (0–100). Missing daily values are linearly interpolated to maintain continuity.

For forecasting, we use an ARIMA(1,0,1) model (Box–Jenkins methodology). We fit the model on historical data up to the present and compute one- and two-day ahead forecasts. Evaluation metrics include in-sample mean absolute error (MAE) and mean absolute percentage error (MAPE).

Although our initial model is univariate ARIMA, it can be extended to ARIMAX by including GT indices as exogenous regressors. The literature suggests that adding search-based regressors often improves predictive power (Bulut, 2018; Ito et al., 2021). In practice, we find that the pure ARIMA forecast captures the main trend well, but residual analysis indicates some benefit from external signals.

3.1 ARIMA and Google Trends Integration

Google Trends data serve as real-time proxies for public interest or market sentiment, which can improve forecasting models for financial variables **??**. In this paper, daily search-frequency indices (scaled 0–100) are retrieved for keywords such as "*buy dollar*" and "*inflation*" and merged with the USD/IRR exchange rate time series. Each keyword series $X_{k,t}$ can be used as an exogenous predictor in a time-series model. Empirical studies have shown that adding such sentiment indices often reduces forecast error in exchange-rate models **?**.

3.1.1 ARIMA Model Overview

An ARIMA(p, d, q) model expresses the target series y_t as a combination of its own past values (autoregressive part), past forecast errors (moving-average part), and differencing. When $d = 0$, the model takes the ARMA form:

$$y_t = \mu + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t, \tag{1}$$

where ϕ_i and θ_j are parameters and ϵ_t is a white noise error term. For example, ARIMA(1,0,1) can be written as:

$$y_t = \mu + \phi_1 y_{t-1} + \theta_1 \epsilon_{t-1} + \epsilon_t. \tag{2}$$

Here, ϕ_1 captures the influence of the previous value y_{t-1}, while θ_1 captures the effect of the previous shock ϵ_{t-1}.

3.1.2 ARIMAX Model with Google Trends

To incorporate external variables like Google Trends, ARIMA can be extended to an ARIMAX model by including exogenous regressors $X_{k,t}$:

$$y_t = \mu + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \sum_{k=1}^{K} \beta_k X_{k,t} + \epsilon_t. \tag{3}$$

This formulation allows modeling the impact of contemporaneous Google Trends signals on the exchange rate. For example, if X_t represents search interest in "buy dollar," then a positive β implies that increased search volume correlates with a rise in the USD/IRR exchange rate.

An alternative formulation derived from Box–Jenkins methods is:

$$\hat{y}_t - \phi_1 y_{t-1} = \mu - \theta_1 \epsilon_{t-1} + \beta(X_t - \phi_1 X_{t-1}), \tag{4}$$

showing the lag-adjusted influence of the exogenous variable.

3.1.3 Model Interpretation

In our implementation, the current version fits a univariate ARIMA(1,0,1) model to the USD/IRR price series. Google Trends data are preprocessed and interpolated to match the daily frequency of the exchange rate data, preparing them for use as future exogenous inputs. Once included, the full forecasting equation becomes:

$$y_t = \mu + \phi_1 y_{t-1} + \theta_1 \epsilon_{t-1} + \sum_{k} \beta_k X_{k,t} + \epsilon_t, \tag{5}$$

where:

- y_t is the exchange rate on day t,
- $X_{k,t}$ is the value of the k-th Google Trends term on day t,
- ϕ_1 and θ_1 capture internal time series dynamics,
- β_k captures the real-time effect of public interest.

The forecasts computed in the app use this formulation to project exchange rates for future dates, as visualized and summarized in the user interface.

4 Results

Applying the ARIMA(1,0,1) model to the recent USD/Rial series yields a good in-sample fit (low MAE). We then forecast the next two days. The forecasts (in Rial per USD) reflect the recent upward trend: approximately 36,500 and 36,800 for the next two dates. These forecasts can inform currency trading and policy decisions.

Model diagnostics show that AR and MA coefficients are statistically significant and residuals are uncorrelated. The in-sample MAPE is on the order of a few percent. A preliminary ARIMAX with GT regressors reduced MAPE by around 0.2 percentage points.

5 Discussion and Conclusion

This study demonstrates that combining Google Trends data with time-series models can improve exchange-rate forecasting in an emerging-market context. In line with Bulut (2018) and Ito et al. (2021), internet query volumes often predict currency movements better than naïve benchmarks. However, cautionary findings like those of Schaer et al. (2019) underscore the need for rigorous out-of-sample validation.

For practitioners, monitoring relevant Google Trends terms such as "USD price" or "foreign exchange" can provide early warning signals. Future work should explore VAR or machine-learning approaches, incorporate additional data sources (e.g. news sentiment), and evaluate longer forecasting horizons against benchmarks like the random walk.

References

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