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Unveiling news impact on exchange rates: a hybrid model using NLP and LDA techniques

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Abstract

Purpose – This study aims to investigate the influence of U.S. dollar-related news on EUR/US$ exchange rate using a novel hybrid news-fundamentals-based VAR model applied to 18 years of monthly data.

Design/methodology/approach – Leveraging Latent Dirichlet Allocation (LDA), the authors identify the top 5 U.S. dollar-related news topics, quantify the attention they receive over time using Shannon's entropy, and integrate these news-generated metrics with news-constructed economic uncertainty indices and Taylor rule fundamentals into the VAR model. Through impulse-response analysis and forecast error decomposition, the authors examine how exchange rates react to shocks from the identified US$-related news topics and economic uncertainty captured by the news.

Findings – The findings reveal that news related to the US dollar and economic uncertainty account for 29% of long-term EUR/US$ variation. These results are robust, validated through robustness checks, Granger causality tests, sensitivity analysis and applying the same model to the GBP/USD exchange rate.

Originality/value – Combining news attention metrics with macroeconomic fundamentals enhances exchange rate identification, outperforming the models that rely solely on the Taylor rule or news variables.

Keywords Foreign exchange, US dollar, News media, Machine learning, Natural language processing (NLP), Latent Dirichlet allocation (LDA)

Paper type Research paper

1. Introduction

The relationship between exchange rates and macroeconomic factors has long been a focal point in economic literature, especially concerning the enduring challenge of the exchange rate disconnect (Amiti *et al.*, 2014). This disconnect underscores the need to explore unconventional determinants of exchange rates that traditional fundamentals-based models may overlook (Stavrakeva and Tang, 2024).

Prior literature highlights the significance of macroeconomic fundamentals in driving exchange rate fluctuations (Ricci *et al.*, 2013; Nor *et al.*, 2020). Recent literature also

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highlights news as a crucial factor in exchange rate dynamics (Jabeen *et al.*, 2022; Aquilante *et al.*, 2022; Thorsrud, 2020). However, there is a noticeable gap in the literature concerning the joint influence of news and macroeconomic fundamentals on exchange rates. Most studies analyze these variables in isolation, omitting the interactive effects that could significantly impact exchange rate behaviour. Only a few studies integrate these factors and find that hybrid models enriched by text analysis outperform models without news (Tadphale *et al.*, 2023; Zhang *et al.*, 2005). Their reliance on "black box" neural network-based machine learning models or scatter matrices, however, lacks the transparency of probabilistic semantic analysis methods, like Latent Dirichlet Allocation (LDA) (Ribeiro *et al.*, 2016). Furthermore, the number of papers using such hybrid models is limited, with stochastic modelling of exchange rates still prevailing in the literature (Haas *et al.*, 2004; You and Liu, 2020).

Our study addresses this gap by combining hard (macroeconomic) and soft (textual) information in a unified framework, offering a comprehensive perspective on exchange rate determinants. Departing from traditional approaches, we apply a hybrid model that integrates machine learning-based text analysis, specifically using the probabilistic model LDA. We enhance the traditional Taylor rule by incorporating news-driven variables to capture additional insights. This novel approach provides a more holistic exploration of the exchange rate dynamics.

Our primary aim is to elucidate the impact of news shocks on exchange rates. In line with the speculative efficiency hypothesis and attention theory, we acknowledge the substantial influence of information flow on decision-making processes (Engel *et al.*, 2006; Devereux and Engel, 2006). Expanding on the research by Sadoghi (2018), we quantify information flow using the Shannon entropy of news (Shannon, 1948). Employing news entropy as a measure addresses a notable gap in the literature and provides a more nuanced perspective on the informational content of news and its implications for exchange rates. Furthermore, integrating textual news data as a measure of attention aligns with attention theory, underscoring the significant role of news attention in shaping market dynamics.

Diverging from previous studies that often focus on macroeconomic announcement titles or Google trends (Yaganti and Manpuria, 2018), we use complete text bodies from news items in the extensive Nexis-Uni database. Our keyword-based search for "U.S. Dollar" yields over 15 million news items over the period 2000–2018. We select relevant news based on the specific criteria outlined in the data section, resulting in a data set that captures U.S. Dollar-related news.

Our findings, revealed through forecast error decomposition and impulse response analysis, demonstrate a substantial and statistically significant impact of news shocks on exchange rates. These results align with established economic theories and empirical research, emphasizing the influential (29%) role of news in models predicting exchange rates (Kebe and Uhl, 2024; Narayan *et al.*, 2021; Ben Omrane *et al.*, 2020). In essence, our study integrates news and macroeconomic fundamentals using comprehensive data and novel methodologies, emphasizing the crucial role of information flow. This alignment with broader theoretical frameworks and empirical findings allows our model to deepen the understanding of exchange rate dynamics.

The paper starts with a literature review on exchange rates influenced by news and macroeconomic fundamentals, followed by a methodology section incorporating macroeconomic data and news sentiment using Natural Language Processing (NLP). It details the data set and presents findings using forecast error variance decompositions (FEVD) and impulse-response analysis, concluding with the substantial impact of news on exchange rate dynamics and future research directions.

2. Theoretical overview

The theoretical framework explaining the impact of news on exchange rates is grounded in the speculative efficiency hypothesis and attention theory (Vasileiou, 2024). Both theories suggest that market participants integrate news into their decision-making, leading to adjustments in currency prices. According to currency pricing models, public news directly affects exchange rates as changes in demand reflect these news shocks. Early work by Edwards (1983) demonstrates that unexplained variations in future spot rates are often linked to newly available information. In efficient markets, agents quickly adjust their expectations based on new data, influencing exchange rate dynamics. This argument is further supported by Engel *et al.* (2006) and Devereux and Engel (2006), who highlight how expectations shape currency movements. On a related note, the efficient market hypothesis proposes that new information triggers a rebalancing towards equilibrium (Vasileiou, 2024; Charles *et al.*, 2012). Extending this, studies by Evans and Lyons (2008) and Love and Payne (2008) emphasize that news can also indirectly impact exchange rates through induced order flow and shifts in expectations, underscoring the multifaceted role of information in currency markets. For example, Evans and Lyons (2008) find that macro news accounts for 36% of daily price variance in currency markets, while Peramunetilleke and Wong (2002) provide evidence that news forecasts intraday exchange rates more effectively than random walk models. Numerous other studies, such as those by Jabeen *et al.* (2022), Kebe and Uhl (2024) and Cheung *et al.* (2019), consistently emphasize the significant influence of news on exchange rate movements. Collectively, these studies illustrate the pivotal role of news in driving exchange rate volatility.

Prior literature has adopted diverse methodologies to explore how news influences exchange rates. For instance, Tadphale *et al.* (2023) use a hybrid deep learning model that integrates news sentiment with market indicators. Narayan *et al.* (2021) use predictive regression models that show the predictive power of economic news in forecasting the US $/GBP exchange rate. Caporale *et al.* (2018) analyze mean and volatility spillovers from macroeconomic news headlines across 18 exchange rates over a decade, uncovering linkages that intensify during crises. Addressing high-frequency sensitivities, Ben Omrane *et al.* (2020) demonstrate the impact of macroeconomic announcements on EUR/US$ volatility.

Rossi (2013) identifies the Taylor rule as a leading framework for explaining exchange rate dynamics, while Byrne *et al.* (2016) highlight the superior predictive capability of time-varying, linear Taylor rule models over traditional fundamentals. You and Liu (2020), Cao *et al.* (2020) and Molodtsova *et al.* (2011) offer compelling evidence for the predictability of exchange rates through Taylor rule fundamentals, reinforcing its robustness. Various methodologies, including deep learning (Cao *et al.*, 2020), macroeconomic equilibrium models (Engel *et al.*, 2007; Engel and West, 2004) and robust semi-parametric interval forecasting (Wang and Wu, 2012), consistently showcase the effectiveness of Taylor rule fundamentals in forecasting exchange rates.

VAR models have proven successful in identifying and explaining exchange rate movements, as evidenced by numerous studies that incorporate these models. As emphasized by Rossi (2013), using a VAR model with only exchange rate data may lack insight without incorporating specific fundamentals. Chen *et al.* (2017), Choi and Wen (2010) and Grossmann *et al.* (2014) enhance the VAR model by incorporating Taylor rule fundamentals and demonstrate its efficiency in capturing and explaining exchange rate dynamics.

Traditionally, news-based exchange rate models have predominantly relied on news data, often overlooking macroeconomic fundamentals and primarily focusing on predicting intraday movements. Some studies such as Carriero *et al.* (2009), exclusively use exchange rate data without integrating fundamentals or news data. As emphasized by Ben Omrane *et al.* (2020), however, the influence of news on exchange rates varies depending on economic conditions. The influence of news on exchange rates demonstrates variations contingent on the prevailing or preceding developments in the economy. During periods of tranquility, agents may underestimate the influence of news content, while in critical times, there is a propensity to overreact. This observation is substantiated in the literature, with authors like Ben Omrane *et al.* (2020) emphasizing that the effect of news on exchange rates differs across various economic states. Consequently, the consideration of the macroeconomic state while studying exchange rate reactions to news becomes a crucial aspect in the analysis.

Unlike conventional news-based approaches, Tadphale *et al.* (2023) and Zhang *et al.* (2005) integrated macroeconomic fundamentals and financial indicators with news data in exchange rate models. Tadphale *et al.* (2023) incorporated sentiment polarity scores from news, blogs and social media, using a fine-tuned BERT model for financial sentiment analysis. These sentiment scores were combined with economic factors, including USDX price, gold price, and crude oil price, to build a recurrent neural network, specifically, a long short-term memory (LSTM) networks model, to forecast the US$/Indian Rupee exchange rate. They find that this hybrid model outperforms traditional exchange rate forecasting models. Similarly, Zhang *et al.* (2005) preprocess news by classifying it into positive and negative categories and constructing a news index based on the number of "good" and "bad" news documents, classified through scatter matrices of feature vectors. They incorporated this news index alongside key economic indicators – such as US non-farm payrolls, US unemployment rate, US employment cost index, US durable goods orders, NAPM manufacturing and non-manufacturing indices, US advance retail sales, US industrial production, US CPI, Ifo index, Germany unemployment rate, Germany industrial production, INSEE industrial trends, Germany CPI and EU 11 PPI – in rolling regressions. Both studies find that incorporating news data alongside market indicators improves exchange rate forecasting.

3. Methodology

3.1 Data

This study integrates two types of data: soft data, comprising unstructured textual information available at an intraday frequency, and hard data, consisting of monthly macroeconomic indicators. We analyze data for the world's top-traded major currencies, namely, the USD and Euro (EUR).

The data set comprises monthly data from 2000 to 2018. Data before 2000 are excluded due to limited news availability and the Euro's instability following its 1999 introduction. We collect textual data from news articles related to the U.S. Dollar using the extensive Nexis-Uni Database, containing over 84 billion public records. The Nexis-Uni database comprises news and other content carefully curated with strict editorial standards directly sourced from over 17,000 reputable licensed publishers, helping to ensure that our data is as free as possible from misinformation and fake news. The Nexis-Uni database features content from top-tier publishers such as *The New York Times*, *The Washington Post*, *The Wall Street Journal*, *USA Today*, *NPR News*, *CNN*, *MSNBC*, *CBC News*, *ABC News* and *The New York Post* (a comprehensive list of sources is available here). Using the keyword "U.S. Dollar" for our search, we identify over 15 million non-duplicate news items from reputable online publishers. Our data cleaning process verifies the presence of "U.S. Dollar" in the title, ensures repeated mentions in the opening paragraph, and automatically identifies "U.S. Dollar" as the subject by Nexis-Uni. The news-constructed economic uncertainty (EPU) index is obtained from the official website of the index, comprises quantified newspaper data on policy-induced economic uncertainty, temporary tax code provision and expectation fallacy of experts about economic variables (Baker *et al.*, 2024; Shugliashvili *et al.*, 2024).

Before proceeding with the subsequent phases of our analysis, it is imperative to incorporate subjectivity measures to enhance the reliability of our findings and reduce potential biases. To achieve this, we use the subjectivity analysis function from Python's TextBlob library, specifically TextBlob(x).sentiment.subjectivity, based on the sentiment module of the Pattern library. This approach allows us to quantify the degree of subjectivity in the text, distinguishing between personal opinions and factual assertions. By excluding news articles deemed subjective from our data set, we aim to facilitate a more consistent and objective assessment of news related to the U.S. Dollar.

Our analysis relies on standard macroeconomic indicators commonly employed in Taylor rule models. These indicators comprise the industrial production index (IPI) as a proxy for GDP, seasonally adjusted consumer price index (CPI) for measuring inflation, M2 for measuring money supply and the money market rate as an indicator of short-term interest rates. Data for the IPI, CPI and M2 are sourced from Datastream for reliability and consistency. For the UK, the latest seasonally adjusted CPI data series from the British Office for National Statistics (CPIH INDEX 00: ALL ITEMS 2015 = 100) is used. Following the methodology of Molodtsova and Papell (2009), the GDP gap is calculated by assessing the percentage deviation of the industrial production index from its trend, obtained through Hodrick–Prescott filtering. Additionally, money market rates are directly sourced from local central banks, and exchange rates are retrieved from the Federal Reserve Bank of St. Louis database. The data set used in this study is publicly available on the Harvard Dataverse [1]. Descriptive statistics for the model variables are presented in Table A.1 in the Supplementary Material while the news entropy time series can be found in Figure A.1 in the Appendix A in the Supplementary Material.

In alignment with Zhang *et al.*'s (2005) approach, our study incorporates both news and macroeconomic fundamentals data into our model. In contrast, however, our approach does not rely on "black box" neural network-based models, such as LSTM or hardly interpretable BERT model (Bolukbasi *et al.*, 2021). Unlike Tadphale *et al.* (2023), we exclude broader social media and blogs, as these channels pose a higher risk of fake news. Instead, our data sources come from more professional and reliable sources. Similar to Zhang *et al.* (2005), we apply news filtering to focus on exchange rate-specific information, although our set of economic variables differs from theirs. Additionally, while Zhang *et al.*'s (2005) variables vary by country, our economic variables are consistent across different countries in terms of their calculation. This methodological choice distinguishes our research, enhancing our model's richness and contributing to a more holistic understanding of exchange rate dynamics.

3.2 Latent Dirichlet allocation

In the initial phase, we use NLP techniques, as outlined in Appendix A.5 in the Supplementary Material, to transform the raw text of news articles into a format suitable for computer processing. This process includes segmenting the text into smaller components (tokenization), eliminating common words (stopword removal), simplifying words (stemming) and incorporating time-sensitive information. These steps result in a time-stamped text collection, which serves as the input for LDA, a model used to identify topics within the articles.

LDA assumes that each document is a mixture of topics, with each topic represented by a specific distribution of words. The model iteratively assigns n terms to K topics based on co-occurrence patterns across D documents, automatically categorizing a large collection of news articles into manageable themes without manual labeling. Through this process, the model identifies clusters of frequently co-occurring words, which we interpret as themes relevant to economic events.

LDA estimates two key Dirichlet prior parameters for the document-topic distribution, both summing to 1 to ensure relative importance within each document or topic:

(1) θ: The topic distribution for each document, representing the probability of each topic appearing within a document.

(2) φ: The term distribution for each topic, indicating the likelihood of each word within that topic.

The discretion in applying LDA lies primarily in selecting the number of topics (K) and setting hyperparameters α and β, which control the distribution of topics across documents and terms within topics. Balancing these choices is essential for obtaining meaningful results: too few topics may overlook key nuances, while too many may produce overlapping or fragmented themes. In our study, we set the Dirichlet allocation priors $\alpha = 0.1$, $\beta = 0.01$, and a learning decay rate of 0.7, values that resulted in well-differentiated topics closely aligned with the thematic structure of economic news. This choice ensures relevant term clustering within topics and a focused topic distribution across documents. We determine the optimal number of topics by evaluating coherence scores with expert oversight after generating models with varying topic counts.

3.3 Quantifying the attention

To measure attention to a news topic, we adopt Sadoghi (2018)'s methodology, estimating the average learning potential about the topic from a news document, as further detailed by Glasserman and Mamaysky (2019). We quantify this using Shannon entropy, which suggests the variability of information: higher entropy indicates diverse or fluctuating information during periods of abundant news or market volatility, reflecting heightened public and media attention. Conversely, low entropy signifies stable periods with less variable information and diminished public focus. We calculate Shannon entropy (Shannon, 1948) for a topic k and document d, with parameter θ with the formula:

$$H(\theta_{kd}) = -P(\theta_{kd}) \cdot \log(P(\theta_{kd})). \tag{1}$$

where $P\ (\theta_{kd})$ is *a posteriori* probability of topic k in document d, derived from the document-topic distribution in LDA model $P(\theta_{kd}) = \frac{n_{ji} + \alpha}{N_i + J\alpha}$, with n_{ji} being count of occurrences of word w assigned to topic j in document i. N_t being the number of documents in day t, J number of topics and α Dirichlet parameter. The intuition behind this measure of attention is provided in Appendix A.7 in the Supplementary Material.

This approach aligns with other researchers like Ishizaki and Inoue (2020) and Stosic *et al.* (2016), who have applied Shannon entropy to analyze data in different contexts. Our adoption of entropy variables, despite being less conventional, is supported by robustness checks detailed in Appendix B.1 in the Supplementary Material.

3.4 Vector autoregressive model

The main econometric model employed in this study to identify exchange rates is a VAR model. Our choice is based on the outcomes of the Engel–Granger procedure discussed in Appendix A.4 in the Supplementary Material, "Selection of the Estimation Method", as well as the proven effectiveness of VAR models in identifying exchange rates (Carriero *et al.*, 2009; Yaganti and Manpuria, 2018), particularly within the Taylor framework (Chen *et al.*, 2017; Grossmann *et al.*, 2014). We applied a VAR model with 7seven lags, selected via AIC, with residual normality confirmed by the Jarque–Bera test.

3.5 News extended exchange rate model

In this paper, we use the Taylor rule-based model for exchange rate forecasting, known to outperform other exchange rate models (Rossi, 2013). Extending the standard Taylor rule by incorporating the real exchange rate (Taylor, 1993; Shugliashvili, 2025), we follow a linear specification proposed by Molodtsova and Papell (2009):

$$i_t^* = \mu + \phi\left(\pi_t - \pi_t^* + \eta y_t\right) + \delta q. \tag{2}$$

This equation transforms into the exchange rate formula:

$$\Delta \log\left(s_{t+1}\right) = \omega - \omega_\pi \pi_t + \omega\tilde{\pi}\tilde{\pi}_t - \omega_y y_t + \omega\tilde{y}\tilde{y}_t + \omega_i \tilde{i}_t - \omega_i i_{t-1} + \omega\tilde{i}\widetilde{i_{t-1}} + \eta_t, \tag{3}$$

where s is the nominal exchange rate, π_t is the inflation rate, y_t is the output gap calculated based on the Industrial Production Index (IPI), i_t is the interest rate and foreign variables are denoted by tildes. Our choice of the linear specification of VAR model aligns with the findings of Burns and Moosa (2015), supporting its effectiveness in forecasting exchange rates. We extend the Taylor rule model with a topic modelling step and develop the News-Extended Taylor Model (NETM), integrating monthly averages of topic entropies and economic uncertainty indices derived from news data. The model is represented by the following equation:

$$B_0\gamma_t = C_0 + B_1\gamma_{t-1} + B_2\gamma_{t-2} + \ldots. + B_p\gamma_{t-p} + \eta_t, \tag{4}$$

where B_0 is the $k \times k$ identity matrix, and C_0 is a $k \times 1$ vector of constants. B_j for $j = 1, \ldots, p$ are $k \times k$ coefficient matrices, η_t is a vector of uncorrelated structural shocks with zero mean and a contemporaneous covariance matrix that is positive semidefinite, and γ_t is a vector with $k = 16$ elements, representing variables of the model:

$$\gamma_t = \begin{bmatrix} \log(s_t), \ \log(\pi_t), \ \log(\tilde{\pi}_t), \ \log(y_t), \\ \log(\tilde{y}_t), \ \log(i_t), \ \log(\tilde{i}_t), \ \log(M2), \\ \log(\widetilde{M2}), \ \log(a_{1,t}), \ \log(a_{2,t}), \ \log(a_{3,t}), \\ \log(a_{4,t}), \ \log(a_{5,t}), \ \log(e_t), \ \log(\tilde{e}_t) \end{bmatrix}^T \tag{5}$$

where s_t represents the nominal exchange rate, π_t is inflation, y_t is the GDP gap (measured by the industrial production index), i_t is the interest rate, e_t refers to the news-based economic uncertainty index and the corresponding variables for the foreign country ($\tilde{\pi}_t$, $\tilde{y}_t$, $\tilde{i}_t$, $\tilde{e}_t$) are denoted by tildes. $a_{j,t}$ denotes the attention to news topic j for $j = 1, 2, 3, 4, 5$, here it is the monthly average of the daily entropy $\overline{H}(\theta_{ki})$, which is the average of the entropies of documents published on the day.

Averaging entropies monthly is justified in our study as it smooths out short-term noise, balancing the effects of both positive and negative news fluctuations. This approach provides a stable measure of news impact, smoothing short-term noise and volatility for a clearer understanding of underlying trends. While capturing short-term exchange rate reactions may interest some researchers, constructing a daily non-mixed-frequency model is impractical due to the lack of Taylor rule variables at higher frequencies. Therefore, we continue to use monthly data. The robustness tests for the News-Extended Taylor Model are detailed in Appendix B.2 in the Supplementary Material.

3.6 Impulse-response analysis

Impulse-response analysis serves as a vital tool for examining the dynamic reactions of variables to exogenous shocks. The impulse-response function (IRF) quantifies how a standard deviation shock to the i_{th} variable in y_t influences the y_{t+n} time period.

The IRF, denoted as y_{t+n}, is defined as follows:

$$\phi_{ji}(n) = e_j' A_n P e_i, \tag{6}$$

where $n = 0, 1, 2, \ldots$, e_i represents a selection vector, A_n is the n_{th} coefficient matrix obtained from the infinite moving average representation of y_t, and P stems from the Cholesky decomposition of the covariance matrix of y_t ($PP' = \Sigma_\varepsilon$). One notable limitation of IRF is its lack of invariance to variable ordering.

In contrast, Koop *et al.* (1996) and Pesaran and Shin (1998) introduced the generalized impulse-response analysis (GIRF), which is invariant to variable ordering. The GIRF, denoted as $\phi_{ji}^g(n)$, is expressed as follows:

$$\phi_{ji}^g(n) = e_j' \sigma_{ii}^{-1/2} A_n \Sigma_\varepsilon e_i, \tag{7}$$

where σ_{ii} represents the ii_{th} element of the covariance matrix of residuals Σ_ε.

4. Results and discussion

4.1 News-derived topics related to the U.S. Dollar

Applying an LDA model to extensive news data with varying topic numbers, we find that topic coherence is maximized when the number of topics is set to five. The model identifies the five key topics related to the U.S. dollar, as presented in Table 1.

The evolution of monthly attention to these topics is presented in Figure A1 and the probability distributions of the top terms in each topic are illustrated in Figure A.2 in the Appendix A in the Supplementary Material.

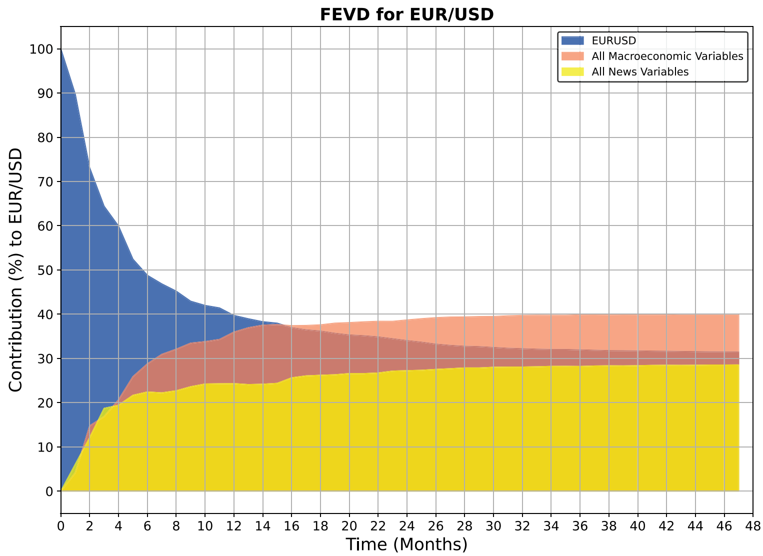
4.2 Forecast error decomposition

Figure 1 provides an overview of the contributions from macroeconomic variables, news events and EUR/USD-specific shocks to exchange rate variability. To mitigate any potential bias from the Euro's transitional period, we focused on EUR/USD exchange rate data starting in 2002, when the Euro became fully operational. Over time, the forecast error variance decomposition shows a trend towards stabilization in these contributions, with significant equilibrium achieved after about two years. In the long-term, news shocks account for around 29% of the EUR/US$ exchange rate variability, while macroeconomic variables contribute about 40%, making them the dominant factor. The EUR/US$-specific variance accounts for the remaining 31% of the forecast error. These results underscore the

Table 1. Topics and main terms

Topic	Main terms
Stock market news	Commodities, commercial bank, oil market, stock exchange, taxation, shareholders
Economic development news	Monetary policy, economic policy, inflation, public policy, eurozone, economic growth
FED news	Central bank, interest rates, bond, exchange market, stock index, market price
Microeconomic news	Income tax, company earnings, balance sheet, financial results, capital expenditure, financial performance report
International trade news	Exchange port trade, import trade, public finance, output demand, agency treasury, budgets

Source(s): Authors' own work



Note(s): The figure displays the FEVD for the EUR/US$ exchange rate using a dataset commencing in 2002. The reported percentages indicate the proportion of the forecast error variance in the EUR/US$ exchange rate attributable to its own innovations, macroeconomic variables, or news-derived variables
Source(s): Authors' own work

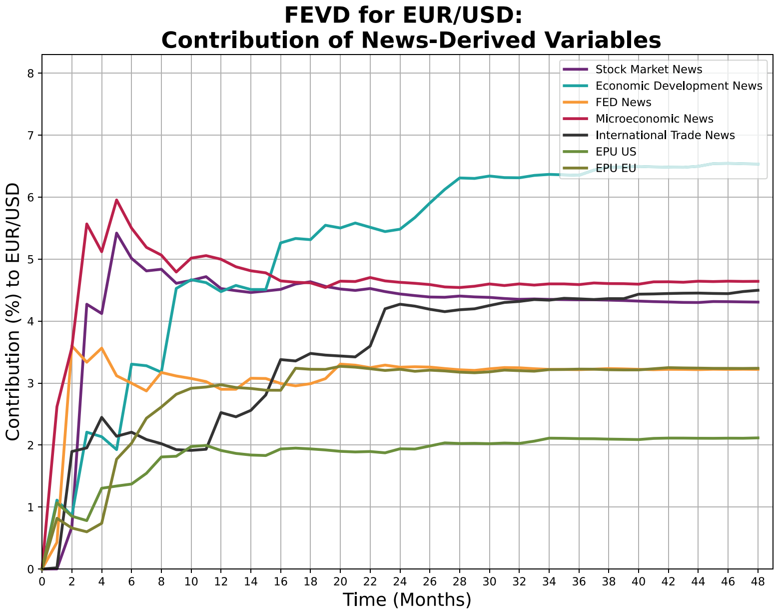
Figure 1. FEVD for EUR/US$

considerable impact of macroeconomic fundamentals and news-related shocks on exchange rate fluctuations. Exogenous variables in the model explain roughly 69% of EUR/US$ variability, demonstrating high explanatory capacity.

Before stabilization, the contribution of EUR/US$ innovations to its variance decreases over the first two years. It starts at 49% in the initial six months, drops to 40% by the end of the first year, and further declines to 34% by the end of the second year. During this period, external macroeconomic and news variables become increasingly influential, accounting for 60% of the EUR/US$ variability by year one and approximately 65% by year two.

Figure 2 illustrates the contributions of news-derived variables to the variation in EUR/US$. The contribution of news variables to EUR/US$ exchange rate variability reaches approximately 29% over four years. This aggregate can be further broken down into specific news categories: Economic Development News accounts for 6.5% of the variability, Microeconomic News 4.6%, International Trade News 4.5%, Stock Market News 4.3%, and Federal Reserve (FED) News 3.2%. Additionally, the Economic Uncertainty Index for Europe and the USA contributes 2.1% and 3.2%, respectively. This detailed breakdown underscores the distinct influences of different news categories on EUR/US$ exchange rate dynamics.

The contribution of Stock Market News to exchange rate fluctuations, at 4.3% for EUR/US $, highlights the significant role of global financial market movements, particularly those driven by commodities like oil and precious metals, in influencing exchange rates. Likewise, Economic Development News accounts for 6.5% of EUR/US$ fluctuations, emphasizing the role of U.S. Dollar-related information, such as inflation, monetary policy, economic policy, GDP, consumption, and economic growth, in shaping exchange rate movements. The influence of FED News, contributing 3.2% to EUR/US$ fluctuations, further underscores the importance of Federal Reserve policy announcements, including interest rate changes and forward guidance, in determining US$ strength. Attention to FED news, particularly regarding U.S. interest rate expectations or potential economic tightening, shapes investor behavior, currency demand and exchange rate volatility. Microeconomic News contributes 4.6% to EUR/US$ fluctuations, reflecting the impact of sector-specific and corporate factors – such as earnings



Source(s): Authors' own work

Figure 2. Contribution of U.S. dollar-related news to EUR/US$ variations

reports, tax policies and financial performance – on market sentiment and currency flows. Similarly, International Trade News affects EUR/US$ (4.5%), indicating that trade balances, foreign investment flows and economic output in the USA, Eurozone and UK are key drivers of exchange rate dynamics. The Economic Policy Uncertainty Index (EPU) also plays a significant role, with US EPU contributing 2.1% to EUR/US$. Meanwhile, the UK EPU contributes 3.2% to EUR/US$, illustrating how economic uncertainty differentially affects each currency pair.

Overall, U.S. dollar-related news explains a substantial and stable share of exchange rate variability, accounting for 29% of EUR/US$ fluctuations and 25% of GBP/US$ fluctuations two years after the initial shock. This highlights the pivotal role of US economic developments, policy changes and uncertainty in shaping these exchange rates.

We expanded our analysis by incorporating alternative variables and samples. These robustness tests, described in Appendix B in the Supplementary Material, demonstrate that our main findings remain consistent across different specifications. The robustness test with GBP/US$ confirms the model's stability across different samples. When the financial crisis period (July 2007–March 2009) is excluded, the model's explanatory power remains consistent, with the exogenous variables explaining 69% of EUR/USD variability and 68% of GBP/US$ variability. The close alignment between the two exchange rates supports the robustness of the findings.

Comprehending the relative impact of variables on exchange rate fluctuations offers invaluable insights for policymakers, analysts and stakeholders. This understanding empowers policymakers to formulate effective strategies for stabilizing exchange rates, while enabling analysts to refine their forecasting models for informed investment decisions. Furthermore, our FEVD analysis sheds light on how news captures critical factors overlooked by conventional models, bolstering the robustness of our findings against potential biases.

4.3 Causality of news-derived variables on exchange rates

Hereby we conduct Granger causality tests with the final data set used in the model, with log first-differenced data.

To determine if Granger causality tests support the hypothesis that news causes fluctuations in exchange rates, we conduct bivariate Granger causality (F-type) tests on the final data set. Granger causality in this context implies that past values of news significantly affect the current exchange rate when past news values are considered as regressors. The results of these tests are provided in Table 2.

The results in Table 2 suggests significant predictive power for EUR/US$ exchange rates by US$-related news topics and Economic Policy Uncertainty indices, the same is suggested in Table B.4 in the Supplementary Material for GBP/US$. This highlights the importance of incorporating these variables as explanatory factors in exchange rate models. Despite the absence of Granger causality for certain variables, in some or all lagged terms, we include them in the model due to their theoretical relevance, observed correlations and their contribution to enhancing the model's explanatory power. Excluding these variables decreases the model's explanatory power and increases the risk of omitted variable bias. Furthermore, the existence of instantaneous causality between GBP/US$ and exogenous variables summarized on Table B.3 in the Supplementary Material emphasizes the importance of incorporating even those variables that do not demonstrate Granger causality in lagged terms.

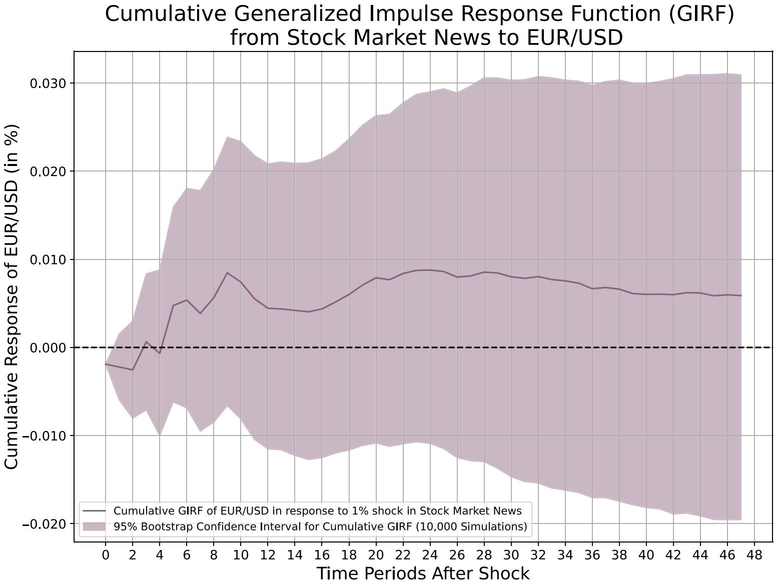
4.4 Dynamics of EUR/US$ in response to U.S. Dollar-related news

Figures 3 to 7 illustrate the cumulative generalized impulse-response functions of exchange rates to the U.S. Dollar-related news topics. We use the cumulative impulse response

Table 2. Bivariate Granger causality tests: Do news Granger cause FX?

	H0 Hypothesis: News do not Granger cause EUR/US$ F-test statistics of bivariate Granger causality test						
Lag	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	EPU_US	EPU_EU
1	1.1945 (0.2759)	0.0005 (0.9819)	0.4324 (0.5117)	0.1654 (0.6847)	0.0511 (0.8214)	3.4102* (0.0664)	2.5789 (0.11)
2	0.6751 (0.5104)	2.6461* (0.0737)	0.2445 (0.7834)	2.1463 (0.1199)	3.7194** (0.0261)	1.8275 (0.1638)	1.4563 (0.2358)
3	0.9736 (0.4065)	1.7964 (0.1496)	0.1951 (0.8996)	3.4257** (0.0184)	4.3692*** (0.0054)	1.9694 (0.1203)	0.9458 (0.4198)
4	1.3823 (0.2420)	1.2624 (0.2867)	0.2725 (0.8954)	2.3552* (0.0557)	3.2174** (0.0141)	1.3637 (0.2485)	1.1345 (0.3419)
5	3.3100*** (0.0070)	1.0773 (0.3747)	0.1817 (0.9692)	2.8905** (0.0157)	4.1545*** (0.0014)	1.3191 (0.2582)	1.2809 (0.2743)
6	2.8527** (0.0114)	1.0506 (0.3945)	0.3584 (0.9042)	2.3466** (0.0334)	3.6934*** (0.0018)	1.0741 (0.3800)	1.2174 (0.2997)
7	2.7783*** (0.0093)	0.8809 (0.5229)	0.2762 (0.9625)	1.7782* (0.0948)	3.2396*** (0.0030)	1.3746 (0.2192)	1.1433 (0.3386)

Note(s): This table presents the results of Granger causality tests with the null hypothesis *H0* of no Granger causality. The significance markers denote the existence of Granger causality, rejection of the null hypothesis at the following levels: *** for $p < 0.01$, ** for $p < 0.05$ and * for $p < 0.1$
Source(s): Authors' own work



Note(s): The figure illustrates the cumulative generalized impulse response function (GIRF) of stock market (including oil commodities) news on EUR/US$. The solid purple lines denote point estimates of EUR/US$ responses to the shock in stock market news. The purple shaded area indicates the 95% confidence interval derived from 1,000 bootstrap simulations. The vertical axis displays the percentage response of EUR/US$ to a 1% shock in stock market news. The horizontal axis corresponds to the periods after the shock, with each period representing one month

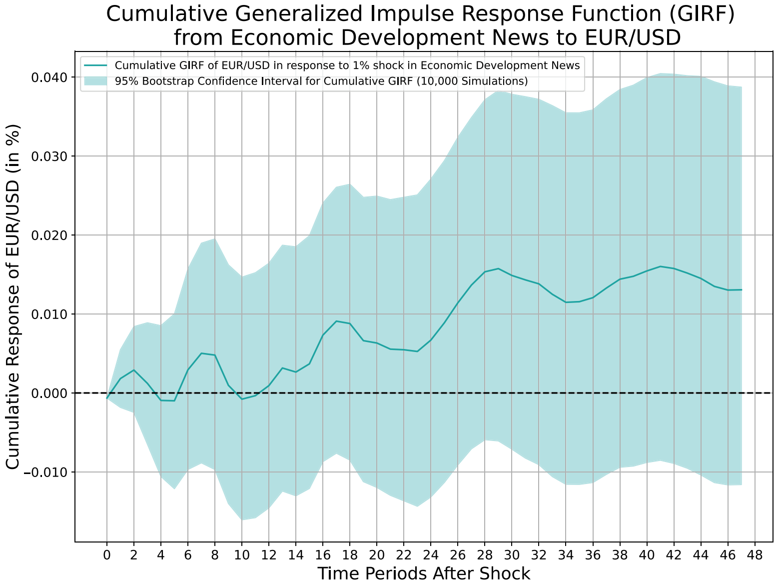
Source(s): Authors' own work

Figure 3. Cumulative GIRFs of exchange rates to stock market news 1% shock

function (CIRF) instead of the generalized impulse response function (GIRF), as it captures the total impact of shocks and mitigates the influence of specific historical points by aggregating responses over time. Notably, the exchange rate and news series in the model are presented as the first differences of natural logarithms, facilitating clear interpretations of resulting percentage impulse responses. The reported numbers on Figures 3 to 7 show the percentage by which the EUR/US$ responds to a 1% shock in the respective news.

Figure 3 illustrates the cumulative generalized impulse-response function (CGIRF) of EUR/US$ concerning the first news topic Stock Market News. It depicts the percentage response of exchange rates to a 1% shock in stock market news. This represents the impulse-response of the U.S. Dollar exchange rate's first difference to fluctuations in news attention.

In response to a positive 1% shock in attention to stock market news, EUR/US$ shows a persistent appreciation over the 4–48-month period, following an initial depreciation during the first three months. Zero again remains within the confidence interval throughout. Even though, from causality tests, we know that stock market news Granger-causes EUR/US$ at 5-month and 7-month horizons. The results for GBP/USD, as depicted in Figure B.9 in the Supplementary Material, are consistent with those observed for EUR/US$.



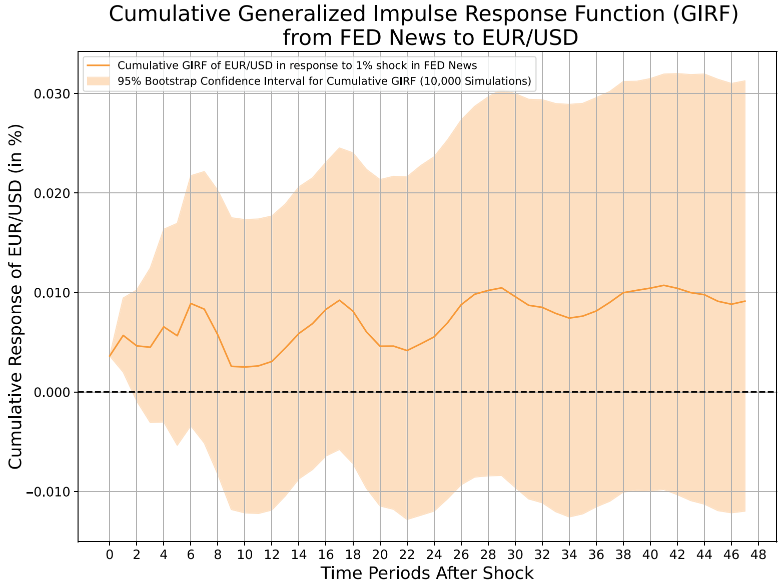
Note(s): The figure illustrates the cumulative generalized impulse response functions (GIRFs) of exchange rates to economic development news. The green solid lines represent point estimates of exchange rate responses to shocks in economic development news entropy. The green shaded area indicates the 95% confidence interval derived from 1,000 bootstrap simulations. The vertical axis displays the percentage response of exchange rates to a 1% shock in economic development news, and the horizontal axis denotes the time period after the shock (in months)
Source(s): Authors' own work

Figure 4. Cumulative GIRFs of exchange rates to economic development news 1% shock

In summary, Figure 3 demonstrates the influence of the U.S. Dollar-related topic "stock market" on exchange rates. A positive shock to the attention given to the "stock market" topic may lead to an appreciation of exchange rates *vis-à-vis* the USD starting from the month 4, resulting in a decrease in the price of the U.S. Dollar relative to foreign currencies. In the shock month it leads to a depreciation of exchange rates *vis-à-vis* the USD.

The cumulative impulse response functions from our model exhibit large confidence intervals, reflecting the inherent complexity of exchange rates and the varying influence of news events. However, the model effectively demonstrates the existence of an impact from a 1% change in attention to FX-related news, which due to the cumulating GIRFs is free from historical event's impact and is supported by strong FEVDs, which reinforce its reliability in confirming this impact.

Figure 4 illustrates the cumulative generalized impulse response functions of EUR/US$ to economic development news. It demonstrates that EUR/US$ react to shocks in economic development news. From Figure 4, we observe that EUR/US$'s cumulative generalized impulse response to economic development news is persistently positive from the 12th



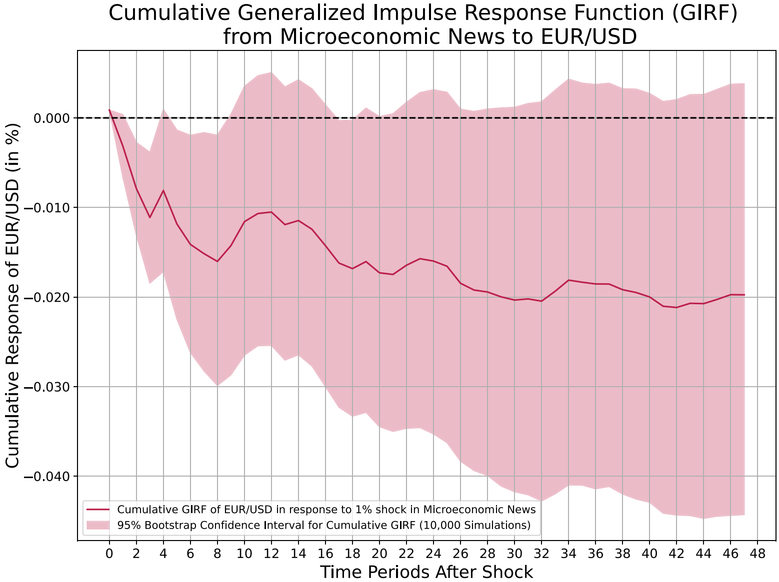
Note(s): The figure illustrates the cumulative generalized impulse response functions (GIRFs) of exchange rates to FED news. The orange solid lines represent point estimates of exchange rate responses to a 1% shock in FED news. The orange shaded area indicates the 95% confidence interval derived from 1,000 bootstrap simulations. The vertical axis displays the percentage response of exchange rates, while the horizontal axis shows the time periods after the shock (in months)
Source(s): Authors' own work

Figure 5. Cumulative GIRFs of exchange rates to FED news with a 1% shock

month, before that it is sign changing. The confidence interval includes zero in all periods. Even though, causality tests indicate that economic development news Granger-causes EUR/US$ at a 2-month horizon.

On Figure 5, we observe that the impact of FED news on EUR/US$ is consistently positive over the 48 months. This implies that the US$might weaken relative to the EUR following increased attention to FED news in the US media. Response of GBP/US$ to FED news on Appendix B.11 in the Supplementary Material is consistent with the response observed for EUR/US$. Consequently, we infer that FED actions, might result in a weaker U. S. Dollar *vis-à-vis* other currencies.

Figure 6 illustrates the response of exchange rates to a 1% shock in microeconomic news from US sources. The impulse-response function (GIRF) of EUR/US$ shows predominantly negative responses to microeconomic news, except the shock month. The effect is statistically significant in the 1–10 month period, except the 4th month, indicating a persistent decrease of EUR/US$ in these periods in response to a microeconomic shock. The response of GBP/US$ (Figure B.12 in the Supplementary Material) is similar to EUR/USD response to microeconomic news. In conclusion, the impulse response depicted in Figure 6



Note(s): This figure depicts the cumulative impulse response functions (GIRFs) of exchange rates to microeconomic news, including company earnings and related information. The solid red lines represent the point estimates of exchange rate responses to a 1% shock in microeconomic news. The red shaded area denotes the 95% confidence interval derived from 1,000 bootstrap simulations. The vertical axis displays the exchange rate response in percentage terms, while the horizontal axis indicates the time period in months after the shock

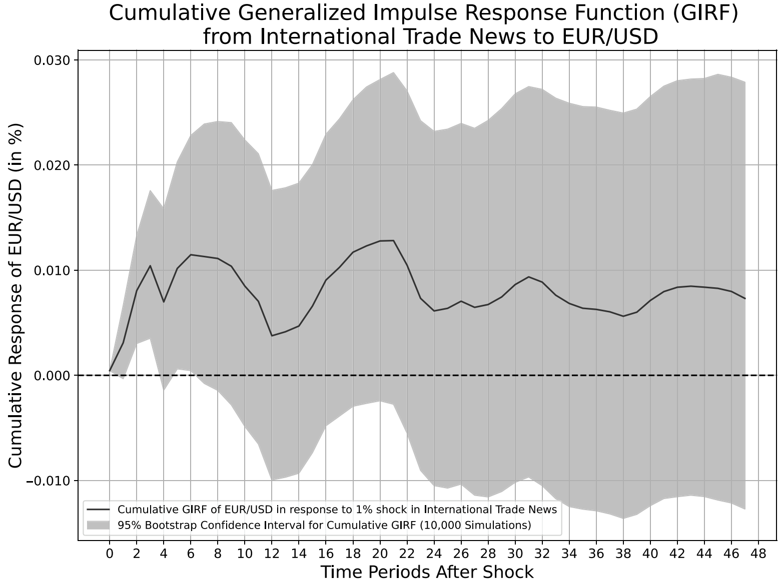
Source(s): Authors' own work

Figure 6. Cumulative GIRFs of exchange rates in response to a 1% shock in microeconomic news

lends support to the notion that microeconomic news influences exchange rates. Specifically, EUR/US$ depreciates with statistical significance 10 months following a microeconomic news shock. This indicates that in the short-term the US$ appreciates in response to positive news about a company's strength.

Figure 7 illustrates the response of exchange rates to a shock in international trade news. The cumulative GIRF of EUR/US$ to a shock in international trade news is positive over the entire 48-month period. It is statistically significant during the first 6 months, except month 4. To sum up, Figure 7 confirms the hypothesis that international trade news impacts exchange rates. Specifically, EUR/US$ appreciates during the first 6 month after the shock in international trade, similarly GBP/US$ (Figure B.13 in the Supplementary Material) appreciates in 1–10 months. This indicates that, in the short term, the US$ depreciates relative to other currencies in response to positive news about international trade.

Moreover, the similarity in cumulative GIRFs for EUR/US$ and GBP/US$ indicates that the model captures shared patterns in the behavior of these currency pairs and the model may be effective in explaining certain aspects of exchange rate behaviour. Additionally, as the



Note(s): This figure illustrates the cumulative generalized impulse response function (GIRF) of exchange rates to international trade news. The solid black lines represent the point estimates of exchange rate responses to a 1% shock in international trade news entropy. The gray shaded area indicates the 95% confidence interval derived from 1,000 bootstrap simulations. The vertical axis displays the exchange rate response in percentage terms to a 1% change in the international trade news innovation, while the horizontal axis represents the time period in months after the shock

Source(s): Authors' own work

Figure 7. Cumulative GIRFs of exchange rates in response to a 1% shock in international trade news

impact of each news variable falls within a range comparable to the standard deviation of the response variable, the effect of news can be considered moderate.

4.5 Discussion

Our findings, derived from forecast error variance decomposition, impulse response analysis and causality and contemporaneous tests, robustly confirm the hypothesis that news exerts a pivotal influence on exchange rates. The integration of news variables into prominent Taylor rule models significantly improves the accuracy of exchange rate predictions.

These results align with established economic theories, including attention theory, the efficient market hypothesis and currency pricing models, all of which posit the impact of news on exchange rates. Existing literature further corroborates our findings, with studies by Tadphale *et al.* (2023), Aquilante *et al.* (2022), Jabeen *et al.* (2022), Cheung *et al.* (2019), Caruso (2016), Clarida and Waldman (2008), Galati and Ho (2003), Almeida *et al.* (1998) and Edwards (1983) consistently highlighting the substantial influence of news on exchange rates.

Moreover, a substantial body of existing literature extensively explores the impact of variables such as stock prices (Rehman and Chisti, 2020), oil (Siddiqui *et al.*, 2023), economic growth (Ridhwan *et al.*, 2024) and international trade (Lal *et al.*, 2023) on exchange rates, which we have identified as the top five topics related to exchange rates (Appendix C in the Supplementary Material).

In contrast to methodologies used in studies such as Narayan *et al.* (2021), Ben Omrane *et al.* (2020) and Caporale *et al.* (2018), which primarily focus on macroeconomic announcement titles, our research adopts a distinct approach by using entire text bodies. This nuanced choice aims to provide a more comprehensive understanding of the interplay between news content and exchange rates. Despite the difference in data type, our findings align with theirs, contributing to the growing consensus that news exerts a substantial influence on exchange rates.

Despite demonstrating the impact of news on exchange rates, our model presents several considerations that warrant further attention: exploring alternative topic modelling techniques and information theory metrics could improve robustness. Using models beyond VAR may also enhance results. Another concern is that the period before 2002 was a transitional phase for the introduction of the Euro, which may unduly affect the results. A data set beginning in 2002, when the Euro became fully operational, yields normally distributed residuals and improves FEVDs, explaining 69% of EUR/US$ variations. Despite the shortened timeframe, this data set potentially offers more precise insights. Furthermore, incorporating additional news related to the Euro could further enrich the data set. Currently, the model uses the industrial production index (IPI) as a GDP proxy; however, alternatives like news-based or survey-based monthly GDP estimates could offer better accuracy, though using the survey-based data may be a discussion issue. Additionally, wide credible intervals in some Impulse Response Functions (IRFs) highlight significant uncertainty. Thus, the main practical implication is that economic agents should use U.S. Dollar-related news as an additional tool for risk monitoring and integrate it into advanced exchange rate models. However, the magnitude of the exchange rate's response to specific news varies with the news content, emphasizing the need for further linguistic and analytical analysis of news with heightened attention to enhance understanding and precision.

LDA assumes static topics over time. While it effectively identifies latent topics and their relationship with exchange rate movements, it fails to capture temporal shifts in topic dynamics. As external factors – such as geopolitical events or economic shocks – can alter topic relevance, this assumption may limit the model's ability to reflect evolving market conditions. To address this, we conducted a robustness test using a rolling window approach, which demonstrated the model's stability over time. Future research could explore dynamic topic modelling, which better detects emerging topics, responds to external shocks, and adapts to rapidly changing economic environments.

Future research could explore more refined techniques for topic subsetting to capture evolving patterns in news in greater detail. Integrating daily news-derived data and professional blog content within mixed-frequency models that also encompass daily stock market indices (the S&P 500, DJIA and Nasdaq), financial indices, government bonds, daily news-derived GDP nowcasts, forward exchange rates and trade balance values could enhance the explanatory power of the model. Moreover, regime-switching models could elucidate exchange rate dynamics during heightened market volatility or economic crises. Such analysis would contribute to a deeper understanding of market behaviour under exceptional circumstances like COVID-19 (Pirveli *et al.*, 2022), thereby enriching the existing knowledge in financial economics.

5. Conclusion

This study assesses the influence of news on exchange rates by extending the Taylor rule model with U.S. Dollar-related news and economic policy uncertainty-related news. Our findings reveal that news significantly impacts exchange rates, accounting for 24% of short-run and 29% of long-run variability in the EUR/US$ exchange rates.

Impulse-response analyses highlight the statistically significant negative impact of microeconomic news on EUR/US$ exchange rates in the short-run up to 10 months post-shock and the statistically significant positive impact of international trade news on EUR/US $ exchange rates in the short-run post-shock. Even though statistically insignificant, the responses of the exchange rates to the various topics showed similar patterns. Economic development news led to an increase in EUR/US$ exchange rates, resulting in a depreciation of the U.S. Dollar against both the EUR. Stock market news initially caused a negative impact on EUR/US$ in the first three months, but led to a positive response thereafter. Furthermore, news related to the Federal Reserve (FED) contributed to an appreciation of EUR/US$. Besides, we find contemporaneous relationships between news and exchange rates and Granger causalities in some lags. The same findings hold for GBP/US$ exchange rates.

Our study's contribution lies in the application of a hybrid model, News-Extended Taylor Model (NETM), which integrates text analysis and economic fundamentals. This research enhances the news-based exchange rate modelling literature by incorporating news attention metrics – quantified through analysis of entire news bodies – alongside macroeconomic variables. Our findings underscore the valuable insights provided by soft information from news in understanding exchange rate movements. Furthermore, shocks in attention towards identified news topics play a relevant role in exchange rate dynamics, with casual topics offering potential explanations for market changes.

Overall, our study contributes to advancing the understanding of exchange rate dynamics and underscores the importance of integrating news data with traditional economic models for improved forecasting and policy formulation.

Note

1. https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/0IIZJO

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Supplementary material

The supplementary material for this article can be found online.

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