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"Selective Attention in Exchange Rate Forecasting"

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Selective Attention in Exchange Rate Forecasting*

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Abstract

We analyze the exchange rate forecasting performance under the assumption of selective attention. Although currency markets react to a variety of different information, we hypothesize that market participants process only a limited amount of information. Our analysis includes more than 100,000 news articles relevant to the six most-traded foreign exchange currency pairs for the period of 1979–2016. We employ a dynamic model averaging approach to reduce model selection uncertainty and to identify time-varying probability to include regressors in our models. Our results show that considering selective attention improves forecasting results. Specifically, we document a growing impact of foreign trade and monetary policy news on the Euro/United States of America dollar currency pair following the global financial crisis. Overall, our results point to the existence of selective attention in the case of most currency pairs.

Keywords: exchange rate, selective attention, news, dynamic model averaging

JEL Classification: F33, G41, C11

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1. Introduction

The drivers of movements in exchange rates have been the subject of intensive research since the collapse of the Bretton Woods system (Dornbusch, 1976; Frenkel, 1976; Bilson, 1978; Frankel, 1979 and 1984; Taylor, 1995; Frankel and Rose, 1995) and economic fundamentals, along with supply and demand forces, were often shown to be the primary influence in this regard (Engel and West, 2005) when compared with a random walk (Meese and Rogoff, 1983). Advancements in modeling and estimation techniques along with data availability further brought attention to new explanatory variables such as news, sentiment, uncertainty, and online searches (Bloom, 2009 and 2014; Égert and Kočenda, 2014; Jurado et al., 2015; Caporale et al., 2017; Kočenda and Moravcová, 2018; or Wilcoxson et al., 2020).

We target this particular area and contribute to the debate by exploring how variances in exchange rates can be better explained by focusing on attention that market players pay to specific events or policy changes resulting from news announcements. Furthermore, we also argue that the sheer amount of news available creates information overload and the focus on market participants becomes selective (Akerlof, 1991; Carr, 2004; Galai and Sade, 2006; Karlsson et al., 2009). Moreover, Wilcoxson et al. (2020) point out necessity to implement shrinkage and sparsity when employing online searches into the forecasting models.

In the spirit of Kahneman (1973), and based on the prediction performance of our model, our model-driven evidence approach suggests that attention is selective when we narrow our variable set to predictors evidenced as being informative. Both issues are addressed in more detail in the literature review, where they are put into perspective alongside existing theoretical and empirical works. Based on analyzing the exchange rates between the key world currencies and a very large set of explanatory variables, we show that models of smaller sizes with selected types of variables offer better forecast performance than larger models. In this respect, selective attention is shown to play an important role. The above approach as well as results represent the key novelties with which we contribute to the related literature.

In our analysis, we accentuate the issue of information overload and hypothesize that economic agents are overwhelmed by the extent of information they receive, primarily from online sources. Market participants use various channels and devices to obtain information but concurrently, they are equipped with only limited attention and a restricted ability to process data, as noted by Shannon (1948) and, more recently, by Sims (2003, 2006). Festré and Garrouste (2015) discussed the *selective attention* psychology that leads to less than optimal outcomes.

However, empirical research incorporating the notion of a limited amount of information being accepted by market participants is limited.[1]

For our analysis, we chose the exchange rates between the United States dollar (USD) and the Australian dollar (AUD), Canadian dollar (CAD), British pound (GBP), Euro (EUR), Japanese yen (JPY), and New Zealand dollar (NZD). Our selection was motivated by the fact that these currencies represent the entire foreign exchange (FOREX) market well, since they are globally the most actively traded currencies and have for a set time accounted for more than two-thirds of the global FOREX turnover by currency pair (BIS, 2016; Antonakakis, 2012). These currencies also experience substantial volatility and asymmetry spillovers in their propagation (Baruník et al., 2017) and are, thus, good representatives for analyzing large exchange rate movements and the factors influencing them.

We hypothesize that large exchange rate fluctuations can, to a significant extent, be explained by reactions stemming from the attention paid to news announcements. To do so, we constructed several indices based on more than 100,000 published news articles about economic activity, monetary policy, price development, and foreign trade related to the countries representing selected currency pairs. Furthermore, we used Google queries to capture the extent of attention paid to news relevant to our selected currencies. Finally, we used the Chicago Board Options Exchange (CBOE) volatility index (VIX) as a measure of uncertainty present in the market.

We contribute to the literature in two specific ways. First, in our empirical assessment, we explore differences in exchange rate forecasting performance between models containing only macroeconomic fundamentals and those that include factors related to attention. We also employ different estimation techniques (time-varying parameter vector auto-regressive (TVP-VAR) model, dynamic model averaging (DMA), and dynamic model selection (DMS)) and perform several robustness checks. Second, based on this approach, we provide robust evidence that considering selective attention improves forecasting results. Our results delivered several detailed findings but some specific outcomes stood out; e.g., interest rate differential exhibited a decreasing impact on most of the currency pairs, while portfolio rebalancing after the global financial crisis[2] (GFC), represented by stock returns, influenced only the USD, Euro, and the AUD. The Euro/USD exchange rate reacted sensitively to news articles about foreign trade and

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[1] From a psychological point of view, there is room for discussion about selective attention when economic agents decide to accept only a limited amount of information. Such a decision does not lead to optimal behaviour and the agents involved instead behave inattentively. For a detailed review of theoretical and empirical papers concerning the economics of attention, see Festré and Garrouste (2015).

[2] The global financial crisis (GFC) refers to a sever worldwide financial crisis between mid 2007 and early 2009.

monetary policy issues. Overall, however, our results point to the existence of selective attention in the case of the all analyzed currency pairs.

The remainder of this paper is structured as follows. Section two reviews the literature concerning determinants of exchange rate movements and selective attention. Section three introduces data and the methods used. Section four compares differences and estimation errors between our basic and attention models, and time-varying probability for including regressors in the models; robustness analysis employing different estimation techniques is presented in section five. We provide brief conclusions in section six.

2. Literature review

The forecasting ability of exchange rate models was partly undermined by the "Meese–Rogoff Puzzle" (Meese and Rogoff, 1983), which argued that a random walk model provided no worse predictions than time series models including macroeconomic variables. As a result, the relationship between exchange rate models and macroeconomic fundamentals was interrupted to a certain degree, a state characterized by an *exchange rate disconnect puzzle*. According to Sims (1998, p. 344), the "*actual behavior of macroeconomic aggregates shows a combination of real and nominal sluggishness* [and therefore] *macroeconomists should rethink their commitment to modeling behavior as continuous dynamic optimization, with delays and inertia represented as emerging from adjustment costs*". However, advanced modeling methods, new data sources providing rich datasets, new explanatory variables such as news, sentiment, and uncertainty, and processes of integration and globalization enable connecting exchange rates with macroeconomic fundamentals and additional new variables, and improve the quality of the forecasts of these models, which in turn can better explain exchange rate fluctuations in turbulent market environments.

Attention

An investor's attention is a real phenomenon in the internet era characterized by the next-to-unlimited amount of information available. The theory of *behavioral attention* is closely connected with uncertainty as many economic agents make decisions involving a degree of uncertainty and risk. Having formulated information theory, Shannon (1948) stated that people have a limited capacity for working with information and news, even though this information is freely available. Shannon (1948) also emphasized the value of information in the transmission of messages. A limited capacity to process information can be illustrated by consumers who are less satisfied, less confident, and more confused due to an overload of online information (Lee and Lee, 2004). In this regard, attention should be considered as a scarce cognitive source with specific subjective rules for its allocation. In this sense, the *rational inattention* of economic agents causes them to be deliberately inattentive to some news as they simply are not able to absorb all news available to them. The theory of rational inattention is discussed by Sims (2003, 2006, 2010), who mentions the problem of limited attention among economic agents who are unable to absorb all news and make sense of it in times of information overload.

The psychological stream of literature focuses on the problem of *selective attention* or *selection exposure hypothesis*, i.e., when economic agents pay attention to a limited amount of information or simply ignore some of it. As Carr (2004) states, agents manage the excessive volume of information in a way where they prioritize selected information to process it. This means that they do not behave rationally; rather, they select what information they respond to and what they ignore. The reason for this may be that agents do not adopt optimal decision-making because of procrastination and obedience, and subsequently make selective and incorrect decisions (Akerlof, 1991). Alternatively, the information may be assessed as threatening (Caplin, 2003) or negative (Karlsson et al., 2009) and, as a result, agents refuse to collect additional information. This phenomenon is sometimes called the *ostrich effect*, which is defined by Galai and Sade (2006, p. 2741) as behavior produced when investors try to avoid "apparently risky situations by pretending they do not exist". As such, financial investors look for information differently in periods of financial booms compared with downturns. These differences are characterized, e.g., by the existence of delays in information-seeking processes. Alternatively, investors pay more attention to their portfolios and tend to look for information when financial markets are rising in particular, while they ignore information when markets are in a downturn and they may face potential losses (Karlsson et al., 2009). Furthermore, a growing body of literature on attention adopts Bayes' rules (Schwartzstein, 2014; Whiteley and Sahani, 2012, Mirza et al., 2019) and the cognitive role of the Bayesian model averaging approach (FitzGerald et al., 2014). Concerning this particular literature, we show that attention is selective when agents narrow their attention to predictors believed to be informative, relative to a prediction performance (Kahneman, 1973).

Uncertainty and its measures

We deal with both news and uncertainty in our models, as both phenomena increase the role of selective attention among market participants. The phenomenon of *uncertainty* again became a popular research topic after the GFC and the subsequent economic recession. According to

Bloom (2009, 2014), uncertainty can have an impact on output, employment, and FOREX rate expectations and its volatility, particularly in recessions or negative economic performance.

There is an understandable variation in approaches for how to measure uncertainty, with no single or objective measure denoted as better than others. Researchers use various proxies to capture volatility or the dispersion of macroeconomic, microeconomic, and financial variables, e.g., the *VIX index* (the CBOE volatility index) to measure the market's expectation of future volatility in US equity markets. A second possible proxy is *the appearance of specific words* in newspapers, other publications, and in the media in general, as the media functions as an important actor for conveying news to uncertain economic agents (Bloom, 2014; Égert and Kočenda, 2014; Jurado et al., 2015; Caporale et al., 2017; Griffith et al., 2019). In this respect, Beckmann and Czudaj (2017) studied the impact of economic policy uncertainty on the exchange rate expectations in the US and found that announcements and uncertainty concerning policy decisions were important determinants of exchange rate expectations. Therefore, uncertainty, together with economic policy, may serve as a proxy for unobservable components not included in former theoretical model expectations (see the "scapegoat" theory defined by Bacchetta and van Wincoop, 2013).

Another interesting proxy for uncertainty may be the *frequency* of newspaper articles containing specific words such as "uncertain/uncertainty" and "economy/economics", among others (Baker et al., 2016). However, Jurado et al. (2015) emphasized that these proxies may not be well connected to economic uncertainty and provide a new measure of uncertainty derived from macroeconomic activity. In this sense, they do not study the volatility or dispersion of selected individual variables per se; rather, they attempt to discover whether the predictability of the economy (common variations in uncertainty across a time series) is less or more uncertain. Jurado et al. identified three main episodes of macroeconomic uncertainty in the post-war period (1973–1974, 1981–1982, and 2007–2009) and concluded that this general uncertainty was lower than individual uncertainty (based on individual variables).

Finally, there is also a new possibility for expressing uncertainty in the era of unlimited information and data availability, i.e., the use of *Google Trends data*. This tool measures investor attention based on the intensity of Google searches, i.e., it focuses on the receiver of the news rather than on the sender (the media) of said news. Reed and Ankouri (2018) confirm that Google Trends data serve as information about people's interest for a given currency. Koop and Onorante (2019) cast several macroeconomic variables using US data and confirmed that the inclusion of Google Trends data improved the forecast performance of general macroeconomic aggregates and that using these data in the form of model probabilities rather than regressors can help identify structural changes in the trend behavior of macroeconomic variables, and deal with forecasts following a crisis. Wilcoxson et al. (2020) analyzed Google queries in the process of forecasting exchange rates, confirming that Google Trends data can help to increase the predictive power of exchange rate models. Smith (2012) tested whether Google data can predict the volatility of exchange rates and argued that these data have a degree of predictive power beyond standard models. Kristoufek (2015) studied the dynamic relationship between the price of BitCoin and search queries on Google Trends and Wikipedia, and found a strong bidirectional correlation between these variables that may affect the frequent bubbles connected with the fluctuation of BitCoin price. Yang et al. (2020) focus on China and confirm that Baidu search volume index serves as a factor of investors' attention. Seabold and Coppola (2015) focus on FOREX markets and found that the use of Google Trends data improved the quality of forecasting by approximately 20 percent. Goddard et al. (2015) verified the relationship between investor attention and the dynamics of currency prices using a Google search volume index for main currency pairs and found that changes in investor attention were associated with changes in the holdings of the largest traders in FOREX markets when the causality ran mainly from investor attention to market volatility. Employing Google Trends data in an extended vector autoregressive model of the Polish zloty, Chojnowski and Dybka (2017) included sentiment data from the credit, financial, and price markets that support the evidence indicating the better forecasting power of this model compared with a model based only on fundamental macroeconomic variables or the random walk model. Bulut (2018) used internet search data from Google Trends to capture an information set of decision-makers and concluded that the use of Google Search data concerning current macroeconomic variables, and nowcasting of these variables, should be considered an alternative for proper testing of exchange rate determination models because of the presence of a lag in the availability of the official data to market participants. Accordingly, Bulut (2018) suggests using Google Trends data to nowcast the future exchange rate movement. Bulut and Dogan (2018) used Google Trends data for the forecasting of the USD–Turkish Lira exchange rate using two structural models (purchasing power parity and a monetary model) and found that these out-of-sample forecasts performed better compared with a random walk model.

3. Data and method

We analyzed the forecasting performance of the FOREX models that involved exchange rates for the USD with respect to the six most-traded currencies (CAD, JPY, AUD, EUR, GBP, and

NZD) using quarterly log returns in the period from 1979Q1–2016Q4.[3] We used four groups of exchange rate predictors.[4] First, following Taylor (1995), we defined mainstream macroeconomic imbalances based on inflation differential (consumer price indexes), interest rate differential (three-month interbank interest rate), a monetary and portfolio balance model (M1 monetary aggregates, real gross domestic product, and trade balances).

Second, we argue that foreign currency demand is significantly affected by expectations about future volatility (uncertainty) and portfolio rebalancing, particularly after the GFC beginning in 2007. Therefore, in our models, we included relevant VIX indices (EUVIX, JYVIX, and BPVIX) and stock market return differentials (DAX, Nikkei 225, FTSE 250, SMI PR, TSX, ASX 200, NZX 50)[5].

Third, we focus on the impact of attention that reflects the attractiveness of the topics related to the selected currency pairs. To do so, we used Google Searches, which provided information about the search intensity of selected phrases (Search Volume Index of internet search queries in a range from 0 to 100 provided by Google Trends database).[6]

Fourth, we focus on news about macroeconomic fundamentals related to selected currency pairs. Following Baker et al. (2016), we developed indices calculated as counts of news articles related to four different categories: economic activity, money, price, and trade. We used data from the Proquest Database, which included more than 315 million news articles at the time related to analyzed currency in 3500 English-language newspapers. For each currency pair, we created five indices: (1) *output* (keywords: "GDP", "output", "recession", "production") yielding 21,400 articles; (2) *money* (keywords: "money", "interest rate", "monetary", "central bank") yielding 55,700 articles; (3) *price* (keywords: "price", "inflation", "deflation", "CPI") yielding 33,00 articles; (4) *trade* (keywords: "trade", "export", "import") yielding 25,200 articles; (5) *total* (all keywords) yielding 100,500 articles. We excluded all news including the keywords "US", "USA" or "United States" to avoid the impact of news on the domestic (US) economy; this step correctly isolated the impact of news relevant to the economies of the six currencies being researched.

[3] All exchange rates are quoted against the U.S. dollar, i.e., one unit of a currency in terms of the U.S. dollar. This is a typical approach in the forex literature – any potential domestic (U.S.) shocks are integrated into all currency quotes.

[4] We use publicly available data sources: XE.COM, OECD, Eurostat, FRED, CBOE, Yahoo Finance, and Bloomberg Database. Detailed descriptions of all the regressors are provided in the Appendix, Table A1. All the analyzed time series are transformed by log differences.

[5] All selected stock market indices were transformed to differentials of their log returns against S&P 500.

[6] The normalized search query index at a given point in time is a ratio of the total search volume for each query to the total number of all search queries. We use keywords "Australian Dollar," "Canadian Dollar," "British Pound," "Euro," "Japanese Yen," "New Zealand Dollar," "United States Dollar," with emphasis on the searches in the category "Currency."

We assumed the time-varying reactions of exchange rates to the market information and macroeconomic fundamentals with possible endogeneity biases. Moreover, we hypothesized that market participants were overwhelmed by information and that they paid time-varying selective attention to predictors. Based on these assumptions, we employed dynamic model averaging (DMA) and dynamic model selection (DMS) approaches (Koop and Korobilis, 2012), and estimated time-varying posterior probability to include selected regressors in the model. We employed a Kalman filter to estimate the time-varying parameter model, which is specified in (1)–(2) as:

$$\begin{aligned} y_t &= z_t\theta_t + \varepsilon_t \\ \theta_t &= \theta_{t-1} + \eta_t \end{aligned} \tag{1}$$

where y_t represents the log-returns of the selected currency pair and z_t includes all predictors, lagged returns, and intercept. Furthermore,

$$z_t = \phi + \gamma y_{t-1} + \beta X_{t-1} \tag{2}$$

where *X* represents the vector of macroeconomic fundamentals search volume indices and indices calculated from news articles.

We followed Koop and Korobilis (2012) and defined *K* models as predictors $z_t^{(k)}$ for $k = 1, \ldots, K$. Thus, $z_t^{(k)}$ is a subset of z_t and the set of models (1) is rewritten as

$$\begin{aligned} y_t &= z_t^{(k)}\theta_t^{(k)} + \epsilon_t^{(k)} \\ \theta_t^{(k)} &= \theta_{t-1}^{(k)} + \eta_t^{(k)} \end{aligned} \tag{3}$$

for each currency pair *y*. Thus, we have $K = 2^{m\tau}$ models for *m* explanatory variables in each model and rolling forecasts that employ an estimation of $\hat{\theta}$ using data from $\tau - \tau_0$. Let $L_t \in \{1,2,\ldots,K\}$ denote the model that applies at time *t,* and average weighted DMA point forecasts based on available data in $t-1$ as

$$E(y_t|y^{t-1}) = \textstyle\sum_{k=1}^{K} \pi_{t|t-1,k} z_t^k \hat{\theta}_{t-1}^{(k)}, \tag{4}$$

where $\pi_{t|s,l} = Pr(L_t = l|y^s)$. We calculate the time-varying posterior probability to include the predictors in the model as

$$p(\Theta_{t-1}|y^{t-1}) = \sum_{k=1}^{K} p\left(\theta_{t-1}^{(k)}\middle|L_{t-1} = k, y^{t-1}\right) Pr(L_{t-1} = k|y^{t-1}), \tag{5}$$

where $p\left(\theta_{t-1}^{(k)}\middle|L_{t-1} = k, y^{t-1}\right)$ is given by $\Theta_{t-1}|\mathrm{L}_{t-1} = k, y^{t-1}$.

Finally, we employed DMS based on the averaging over predictive results for every model, selecting the highest value for $\pi_{t|t-1,k}$ at each point in time. Moreover, we followed Raftery et al. (2010) to involve a forgetting factor, which implied that observations in a specific period in the past had weight $0 < \lambda_j < 1$[7]. In addition, as a robustness check, we compared DMA and DMS results with time-varying parameter VAR (TVP-VAR) and reported mean squared forecast error (MSFE), mean absolute forecast error (MAFE), and the sum of predictive likelihoods (log(PL)), which represented predictive density for y_t given data in time $t-1$ (Geweke and Amisano, 2011).

4. Results

Our empirical analysis comprised two main steps. First, we considered selective attention with respect to various predictors and showed that economic agents changed their attention to information content as it related to a specific currency over time. Second, we compared the forecasting performance of models including additional larger models.

Table 1 illustrates overall empirical evidence of time-varying selective attention to different predictors, while more detailed dynamic results are presented in graphical form later in this section. The selective attention to predictors is represented by a posterior probability for including selected predictors in the model. We also show that economic agents narrow their attention to different predictors believed to be informative for the specific currency.

Table 1 illustrates changes in selective attention for three sub-periods: (1) 1980–1984 (shortly after the European Monetary System was established in March 1979); (2) during the period of Great Moderation (1985–2007); (3) after the (GFC) that fully took hold in 2008 (2008–2016). We found that the average posterior probability for paying attention to trade balances, money growth, VIX, and search indexes was below 0.65 for all currency pairs during all selected sub-periods. We thus conclude that only inflation differential, interest rate differential, GDP growth, stock returns, and news can serve as appropriate predictors of the selected currency pairs. Moreover, our results indicate that the average probability of including news in forecasting models is relevant only for the Euro after the GFC.

<...Table 1...>

[7] We follow Koop and Korobilis (2012) and set parameter $\lambda = 0.99$, which ensures that observations five years ago ≈ 80% as much weight as the last period's observation.

In addition, we provide thorough dynamic development details of the posterior probability for each predictor. Figure 1 plots the estimates of the posterior probabilities for individual variables that could be potentially included in the forecasting model; the figures on the left represent estimates for macro fundamentals, volatility indices, and stock return differences, while those on the right indicate the same for news (indices based on article news) and searches (data from the Google Trends database).

Generally, the probability of inclusion in the case of past values of the exchange rate (variable *ER*(*t*-1)) increased over time and approached almost 1 (except for USD/GBP and USD/NZD, in which case the probability increased only before the GFC and again in Japan in 2013 when it reached 0.9); accordingly, we can state that past exchange rate values could fairly substantially influence the current or predicted value of the exchange rate. In the case of the USD/EUR, the increase in probability starting with the initiation of the Euro can be explained by the strong appreciation of the Euro relative to the USD from 2000 to 2008 and then by the GFC. The sudden drop in probability in the case of the USD/NZD pair in 1985 may have been caused by the change of the exchange rate regime (from fixed to floating) in New Zealand in this year. However, the same step, i.e., the change from fixed to floating exchange rate regime in 1983 led to a one-year rise in the probability of *ER*(*t*-1) (and a simultaneous one-year drop in the case of *Inflation diff*) in 1984 for the USD/AUD pair, before decreasing and remaining at the same level in subsequent years (until 1997), as in the case of the USD/NZD. Thus, we could state that the implementation of a floating regime decreased the probability of inclusion of this variable in the forecasting models of these two currency pairs. Interestingly, there was a higher probability increase for the USD/AUD and USD/NZD pairs at approximately 1998, likely as a reaction to the creation of the Euro currency in 1999 and the Asian crisis of 1997 and 1998; however, it remained at a high level only for the USD/AUD case, until the end of the period (in the USD/NDZ case, it became extremely volatile). A strong depreciation of the AUD against the USD in 2003 also increased the probability of the CAD/USD currency pair in this year; this situation continued in subsequent years due to the US budget and current account deficits.

The role of interest rate differential (*IR diff*) was almost negligible in case of the USD/EUR pair and was below 0.5 for the USD/AUD and CAD/USD pairs, and less for the USD/NZD pair (except for the period 1979–1988). The only currency pair in which this variable played a role from the beginning of the analyzed period until approximately 2003 was the JPY/USD combination; however, the probability of inclusion of *IR diff* decreased systematically after 2003. For a limited time, the probability was higher in the case of the USD/GBP pair in the second half of the 1980s, until approximately 1992, when interest rates in the United Kingdom began decreasing, and in case of the USD/EUR pair in 2004 and 2005 (likely as a result of a higher Federal Funds Rate, which was initiated in June 2004 and continued until June 2006 as a reaction to rising house prices and the first signals of a house price bubble); however, the level of probability nonetheless very low. There were also two separate probability jumps in 1980 and 1985 for the USD/NZD pair (which can potentially be explained by the above-mentioned switch from a fixed to a floating exchange rate regime in 1985) with a long-term decreasing tendency in the 1990s (and simultaneously, the increasing tendency of the *ER*(*t*-1) variable).

The important capital markets (*Stock ret diff*) for the USD/EUR pair is at the highest level compared with other currency pairs (the value of probability is almost 1 for the analyzed period, which in this case began from 1999), signaling that capital markets played a significant role in the exchange rate movement. This variable was added to the prediction model for this time and explained the variability of the USD/EUR exchange rate. Interestingly, the probabilities became important in the case of USD/GBP, USD/AUD, and USD/NZD pairs in the period following the GFC. This fact may signal the effect of portfolio rebalancing in case of these three currency pairs during the crisis period when traditional macroeconomic variables became less important and capital market variables more important, as investors moved their portfolios to other capital markets (at the time in Europe or the US) to the UK or even to smaller markets in Australia or New Zealand (see also the results of the robustness analysis). In the case of the JPY/USD pair, the probability continuously decreased during this period (the probability was between 0.2 and 0.5 during the 1980s, partly as a reflection of the financial market bubble illustrated by a strongly rising Nikkei stock price index in Japan between 1983 and 1989, when it was eliminated by monetary policy tightening).

Gross domestic product differential (*GDP diff*) probabilities yielded ambiguous results: (1) a stable probability in the case of the USD/EUR pair of approximately 0.5; (2) a rising probability in for the USD/AUD pair throughout the period; (3) fluctuating probabilities for the USD/GBP case in 1984, 1989–1990, and particularly after the GFC; (4) high probability in the case of the CAD/USD pair in the period from 1985–1994, followed by a higher probability after the GFC, too; (5) rapidly fluctuating (higher and lower) probabilities for the USD/NZD pair during the 1980s (likely caused by economic reforms forced by rising unemployment and economic stagnation) and an increasing tendency since then. For the JPY/USD pair, this variable was strongly insignificant, which is not surprising when we consider the long-term economic stagnation in Japan, particularly from 1993–2003.

The highest level of probability for the inflation differential (*Inflation diff*) was estimated for the USD/EUR pair, particularly after 2001, which may reflect the focus on monetary policy in the Euro Area, and in the case of the USD/AUD pair (where economic agents perceived poor results related to combating inflation, particularly in the 1980s and 1990s) showing a slightly decreasing probability after the GFC. Probabilities of approximately 0.5 were also estimated for the JPY/USD pair (which may reflect the fact that inflation/deflation policy in Japan remained at the center of attention of both economic agents and policymakers) but with a decreasing tendency after the policy of quantitative easing was implemented in 2001, which was also the case for the USD/GBP pair. The probability rose in years preceding 1983 in for the USD/NZD pair, with the highest values recorded having been between 8.0 and 0.95 at the end of this period, before falling to almost 0 in 1984, before continuously growing to approximately 0.5 when liberalization tendencies concerning monetary policy and preparation of the inflation targeting regime's implementation (from 1990) began in New Zealand. For the CAD/USD case, the probability was higher during the 1980s but subsequently dropped to a level of approximately 0.4.

Money supply differential (*M1 diff*) had a long-term impact on the JPY/USD exchange rate where the probability increased in 1989 and again in 1995, likely as a result of monetary policy tightening (after the 1980s bubble times, characterized by rising land and stock prices) and then again in 2000 before the implementation of the unconventional monetary policy in Japan. The first policy of quantitative easing introduced in 2001 was replaced by comprehensive monetary easing in 2010. Then, the new policy of quantitative and qualitative easing with yield curve control was applied in April 2013, which may explain the drop in the probability of inclusion of the money supply variable in the forecasting model during this period. The probability of *M1 diff* was higher in the USD/AUD pair in the first half of the 1980s, but it continuously decreased after 1989 (Australia abandoned the money supply targeting regime in 1985) and particularly after 1993, when the first inflation target was set. Generally, the role of the money supply was diminishing throughout this time for all country pairs, reflecting a deflection from the monetary transmission mechanism (which employed a monetary base as an instrument for influencing money supply) to the implementation of inflation targeting regimes instead during the late 1980s and early 1990s. For the USD/EUR and USD/GBP pairs, and from approximately 1990 also the USD/NZD pair, the probability fluctuating was approximately 0.5. We estimated a low probability for the CAD/USD pair.

The probability of the trade balance differential (*TB diff*) was relatively high but very volatile for the JPY/USD case until approximately 2005 when it dropped to almost 0. For the

CAD/USD pair, a higher probability in the second half of the 1980s may have been a reflection of a report by the McDonald Commission in 1985, followed by negotiations of the Canada-US Free Trade Agreement, which had been prepared in 1987 and signed in January 1988. In the USD/EUR pair, the probability was not sufficiently high and reached almost 0. The probability level was stable only for the USD/NZD pair and was estimated at approximately 0.5. However, the probability of this variable appeared to be volatile, with occasional jumps and drops indicated in the case of other country pairs.

The VIX index (*VIX*), which represents the market's expectation of future volatility (generally interpreted as uncertainty), exhibited low probability. The role of news and searches (the figures on the right) can also be assessed as ambiguous; we can see relatively high probabilities of news in case of the USD/EUR, USD/AUD, and also the USD/GBP and USD/NZD pairs throughout the period, and in case of the JPY/USD pair, at the beginning of the period. Moreover, we can see a rising influence of Google searches for the USD/NZD pair and a stable probability for the USD/GBP and CAD/USD pairs, while a high jump was observed for the USD/AUD pair during the GFC, and a short episode of high probability was indicated for the USD/EUR pair in 2005 and 2006 with a subsequent decrease.

In summary, macro fundamentals were observed to play a significant role in the exchange rate determination. However, indices calculated from the counts of newsletter articles related to four different categories (economic activity, money, price and trade) in a given country were also shown to be significant and were rightly included in our models as explanatory determinants. The only two exceptions were the JPY/USD and CAD/USD pairs, which indicated a relatively low level of inclusion probabilities throughout the analyzed period. This result can be interpreted by the fact that Japan is often considered a safe haven for financial investors and, as such, the role of article news and Google searches is limited. In the case of Canada, this outcome was likely the result of either the relatively small importance of this financial market in the world or the fact that the Canadian dollar is recognized as a commodity currency in the shadow of its more important neighbor.

In the next step, we focus on the forecasting performance of our models. Figure 2 shows actual and predicted exchange rate returns employing two different groups of predictors. The first group of predictors only includes the macroeconomic fundamentals (inflation differential, interest rate differential, money growth differential, GDP growth differential, trade balance differential, stock returns differ-ential, and VIX). The second group of predictors is extended for indices calculated from the counts of newsletter articles related to four different categories (economic activity, money, price and trade) in a given country (Proquest data-base) and searches refer to the search volume index of the given currency names (Google Trends data-base). While the left panels in this figure plot the data, the right panels plot the deviations between the actual and predicted values of the individual exchange rate. Actual data were much more volatile compared with predicted data, which could be explained by a fact mentioned by many authors, i.e., that no prediction model can encompass all the variables influencing the exchange rate movement.

A comparison of the forecasting performance of both models showed that extension for news and searches convincingly decreased the absolute deviation of the predicted values compared with actual data for all selected currency pairs.

<...Figure 2...>

In case of the USD/EUR pair, the deviations were the most apparent; while the predictions produced by the first group of predictors deviated less in the first half of the analyzed period, the predictions of the extended group of predictors were more precise in the second half of the period, i.e., in 2006 and particularly after the GFC (with some occasional exceptions, e.g., 2012Q2, 2015Q4, and 2016Q2). The above findings confirmed that the role of news and online searches had increased in recent decades. It also supports the idea that investors are attentive to huge amount of information and that the role of traditional macroeconomic fundamentals is decreasing. The same holds for the USD/AUD pair and partly for the USD/NZD pair; it was observed that the deviation of the prediction was smaller in the second half of the analyzed period and particularly after the GFC (again with some slight exceptions). In the case of some currency pairs (JPY/USD, USD/GBP, and CAD/USD), the situation was not as convincing and both forecasts were almost identical, i.e., extended models did not change the quality of the forecasting model much.

In summary, we consider selective attention and employ a dynamic model averaging approach to reduce model selection uncertainty. Our results show significant changes of posterior probability to select specific predictors into the models and confirm increasing forecasting performance of extended models. The results point to the existence of selective attention.

5. Robustness analysis

As an additional step, we checked the sensitivity of our analyses in two ways, with respect to the detailed news grouping and based on estimation techniques.

First, we focused on possible heterogeneous selective attention to specific macroeconomic news and differentiated among four groups of news: (1) output and productivity; (2) money and monetary policy; (3) prices; (4) trade. Figure 3 presents estimations of probabilities of the extended model, where the panels on the right include probabilities for individual categories of news (output, price, money and trade) and Google searches. The probabilities for all categories were relatively stable and very often at the same level for almost all country pairs in the analyzed period except for the USD/EUR pair, where the probabilities differed significantly and partly so in the case of the USD/AUD pair. High volatility for all categories was apparent at the start of the analyzed period in for the USD/NZD pair before economic reforms in New Zealand were adopted. The probability of news in the "price" category was relatively volatile and high in the case of the USD/EUR pair (particularly in 2001 and then in 2005–2010, when the probability was higher than 0.8). News in the "money" category was also volatile for the USD/EUR pair, however, the opposite trend (except for 2006–2008) was observed when the probabilities rose and fell together. In 2008, the probability of Google searches jumped to almost 1 for the USD/AUD pair, to 0.7 for the USD/NZD pair, to 0.6 for the USD/GBP pair, or fluctuated between 0.2 and 0.45 for the CAD/USD pair. On the other hand, the probability dropped in the years preceding 2008 in Japan, which confirmed the fact that Japan is often regarded as an investment safe haven. We cannot say that there is one category (compared with others) with the highest or lowest probability in this period as the probabilities varied based on time. For example, the lowest probability for the "output" category among other categories was estimated for the USD/EUR and JPY/USD pairs, while the highest probability for the same category was estimated for the CAD/USD pair. On the other hand, the highest probability for news in the "trade" category was observed for the USD/EUR and JPY/USD pairs in the second half of the period, while it was lowest for the CAD/USD pair from 1988. In the USD/AUD pair, the highest probability was estimated for news in the "price" category (the probability increased before the inflation target regime was adopted).

When we summarized the results of this step of our analysis, it became evident that the decomposition of one general index of news into four individual categories did not deliver any considerable refinement to our previous results, except for the USD/EUR currency pair. Thus, we concluded that the USD/EUR exchange rate had been significantly influenced by news about prices during the years 2006–2008, when the ECB decided to start increasing its policy rates because their monetary analysis indicated upward risks to price stability. Following the GFC, the impact of the news was primarily observed for trade and output success.

<...Figure 3...>

Second, we compared the forecasting performance of three different groups of models using DMA, DMS, and TVP-VAR by reporting MAFEs, MSFEs, and the sum of predictive likelihoods (log(PL)). We considered the same lag (1) as in the previous analyses. Our results in Table 2 show an increase in the forecasting performance of extended models (that included article news and Google searches) when DMA and DMS methods specifically were employed.

<...Table 2...>

To summarize the results of the analyses, the inclusion of news articles and Google searches in the prediction models using DMA/DMS methods led to more precise predictions for most currency pairs. Compared with the TVP-VAR approach, forecasting errors decreased because we reduced the uncertainty of model selection following the assumption of selective attention, and kept models to smaller sizes. We take these results as evidence that selective attention impacted the performance of currency pair predictions.

We also showed that splitting news articles into individual groups did not help to increase the forecasting performance of the all exchange rates, except for the EUR/USD and JPY/USD pairs.

6. Conclusions

Recent empirical models explaining the determination of exchange rates often fail to predict the future value of exchange rates, even when they include traditional theory-based variables. In this paper, we contribute to the debate on factors that impact exchange rate fluctuations by including factors related to the attention given to specific events or policy changes in the form of news announcements and online searches. We followed a relevant stream of the literature and argued that market participants suffered from significant information overload and were prone to be rationally inattentive or selective to only specific information.

Our approach is novel in the sense that we used both macroeconomic and online data based on more than 100,000 published news articles about economic activity, monetary policy, price development, and foreign trade related to the countries represented in the selected currency pairs.

Moreover, our results point to the presence of selective attention for the all reviewed currency pairs. We employed dynamic model averaging and dynamic model selection methods to estimate the time-varying posterior probability as a means for including specific predictors in our models. We confirmed significant changes in predictor selection because economic agents narrow their attention to different predictors believed to be informative for the specific currency. We then produced one-step-ahead forecasts at each point in time. Our results show that considering selective attention improves forecasting results of large models.

In addition, a comparison of our point forecasts using actual data confirmed the importance of predictors related to news articles and Google Trends data searches. When compared with models that included only macroeconomic fundamentals, the forecasting performance increased after we included indices constructed from news articles and Google Trends data searches. One of our key results also pointed at the growing impact of foreign trade and monetary policy news on the Euro/USD exchange rate following the GFC.

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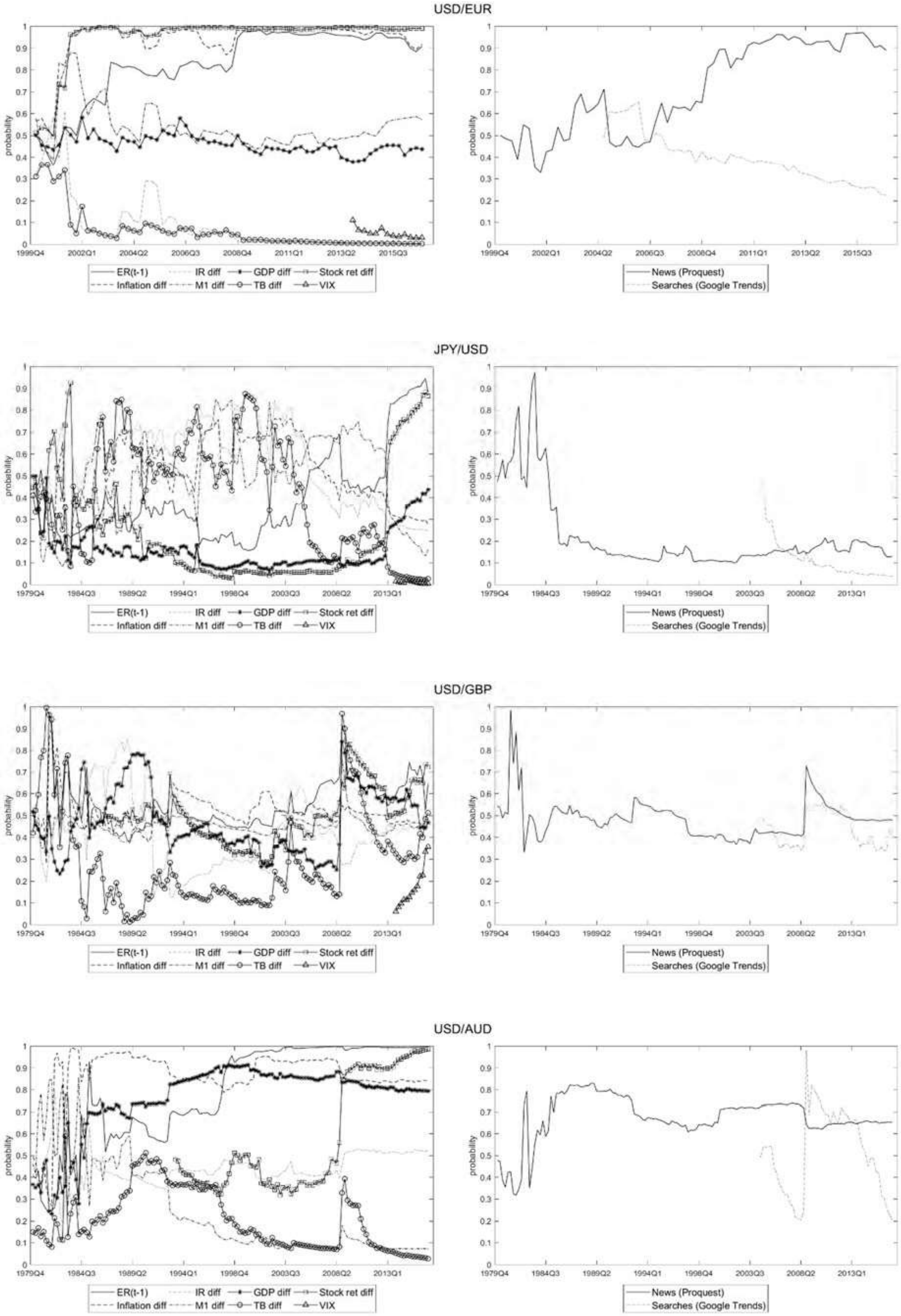
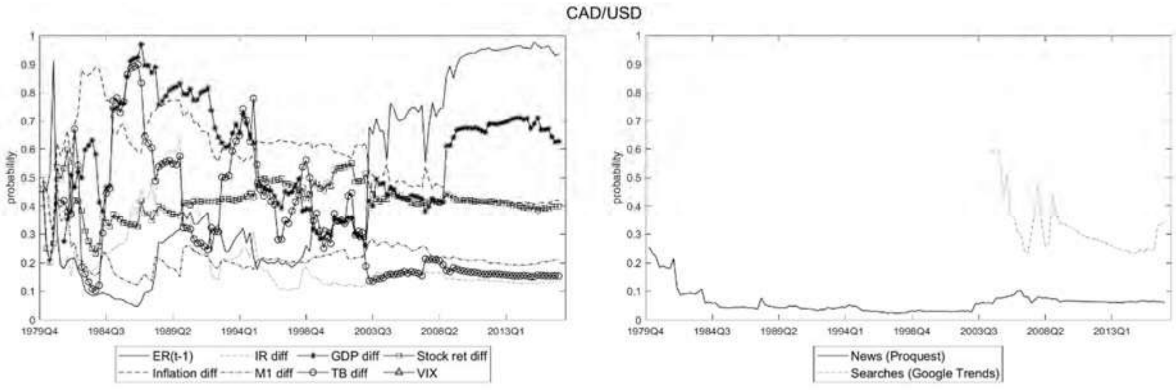
Table 1: The average posterior probability of including predictors into the models.

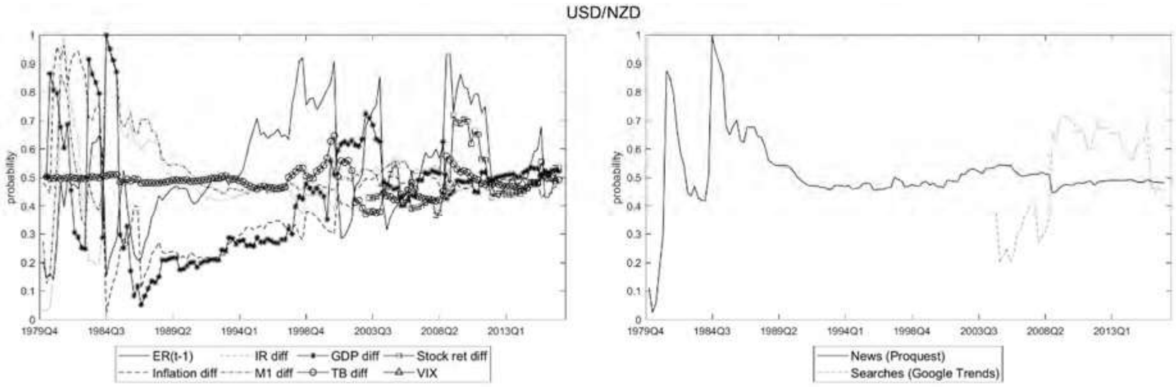
Currency	Period	Predictors									
		Exchange rate (lag 1)	Inflation differential	Interest rate differential	GDP growth differential	Trade balance differential	M1 growth differential	Stock return differential	VIX	News	Google searches
EUR	2000–2007	0.696	0.901	0.178	0.490	0.115	0.582	0.910	–	0.520	0.536
	2008–2016	0.944	0.972	0.014	0.435	0.015	0.505	0.989	0.052	0.883	0.340
JPY	1980–1984	0.311	0.375	0.455	0.238	0.301	0.243	0.495	–	0.616	–
	1985–2007	0.313	0.620	0.690	0.124	0.548	0.555	0.130	–	0.150	0.236
	2008–2016	0.661	0.374	0.316	0.211	0.128	0.475	0.410	0.011	0.171	0.070
GBP	1980–1984	0.584	0.584	0.443	0.418	0.574	0.466	–	–	0.539	–
	1985–2007	0.497	0.519	0.423	0.441	0.161	0.450	0.438	–	0.463	0.405
	2008–2016	0.655	0.492	0.403	0.572	0.446	0.467	0.641	0.171	0.516	0.446
AUD	1980–1984	0.426	0.697	0.401	0.390	0.183	0.611	–	–	0.494	–
	1985–2007	0.799	0.905	0.423	0.817	0.244	0.236	0.398	–	0.722	0.403
	2008–2016	0.994	0.848	0.509	0.817	0.115	0.088	0.887	–	0.652	0.560
CAD	1980–1984	0.237	0.667	0.243	0.485	0.321	0.283	0.365	–	0.134	–
	1985–2007	0.340	0.608	0.231	0.566	0.416	0.212	0.434	–	0.045	0.407
	2008–2016	0.924	0.422	0.138	0.653	0.165	0.205	0.410	–	0.066	0.288
NZD	1980–1984	0.404	0.700	0.462	0.638	0.500	0.520	–	–	0.502	–
	1985–2007	0.527	0.337	0.507	0.365	0.480	0.526	0.442	–	0.525	0.309
	2008–2016	0.612	0.471	0.485	0.504	0.489	0.488	0.520	–	0.485	0.596

Note: Posterior probability of inclusion of predictors in TVP-VAR models. “News” refers to the indices calculated as counts of newsletter articles related to four different categories (economic activity, money, price and trade) in a specific country (Proquest database). Google searches represent the search volume index of the given currency names (Google Trends database).

Figure 1: Time-varying posterior probabilities of including predictors into the models.

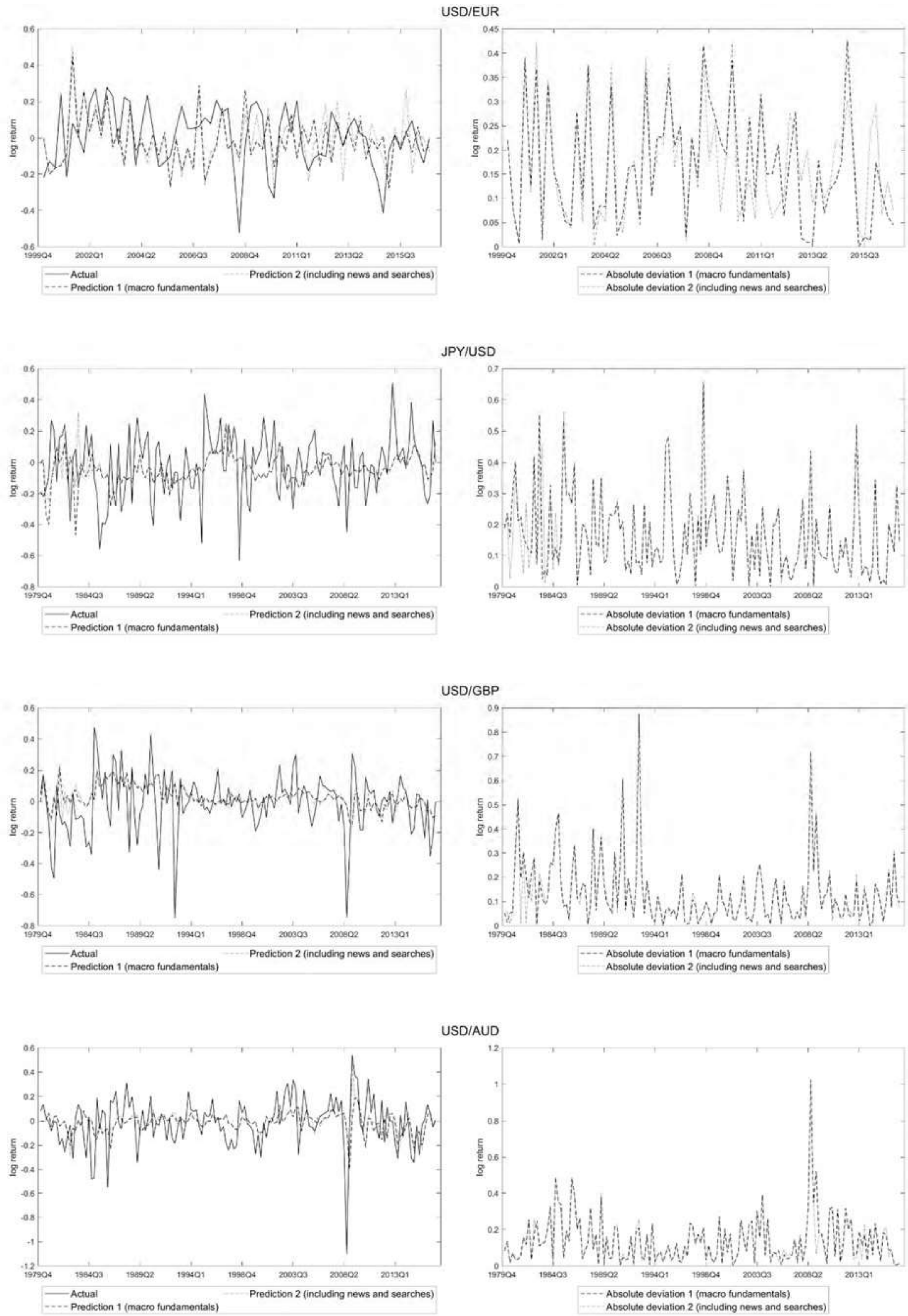


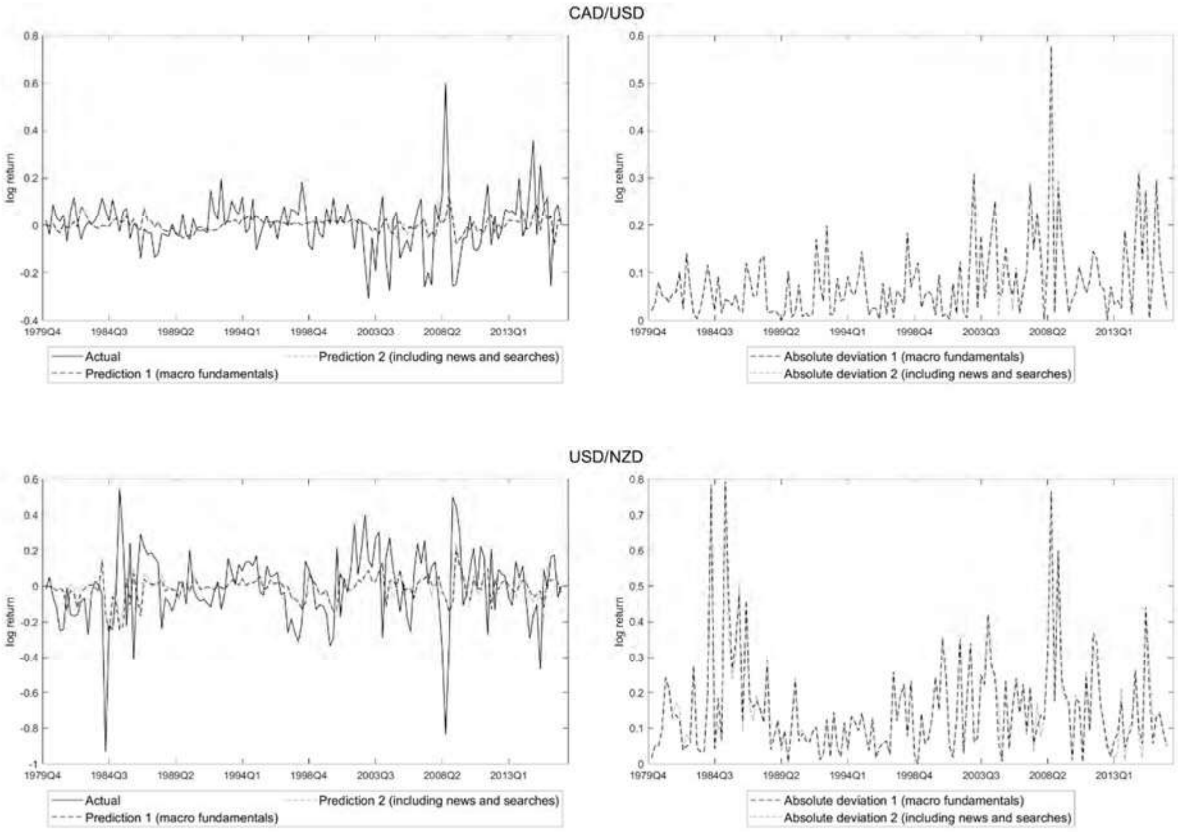




Note: The time-varying posterior probabilities of different predictors being included into the TVP-VAR models. We estimated all our models using the referred predictors presented in two figures for each currency. The figures on the left show posterior probability of macroeconomic fundamentals (inflation differential, interest rate differential, money growth differential, GDP growth differential, trade balance differential, stock returns differential, and VIX), where-as the figures on the right show posterior probability of news and Google searches. News refers to the indi-ces calculated as counts of newsletter articles related to four different categories (economic activity, mon-ey, price and trade) in a given country (Proquest database). Searches represent the search volume index of the given currency names (Google Trends database).

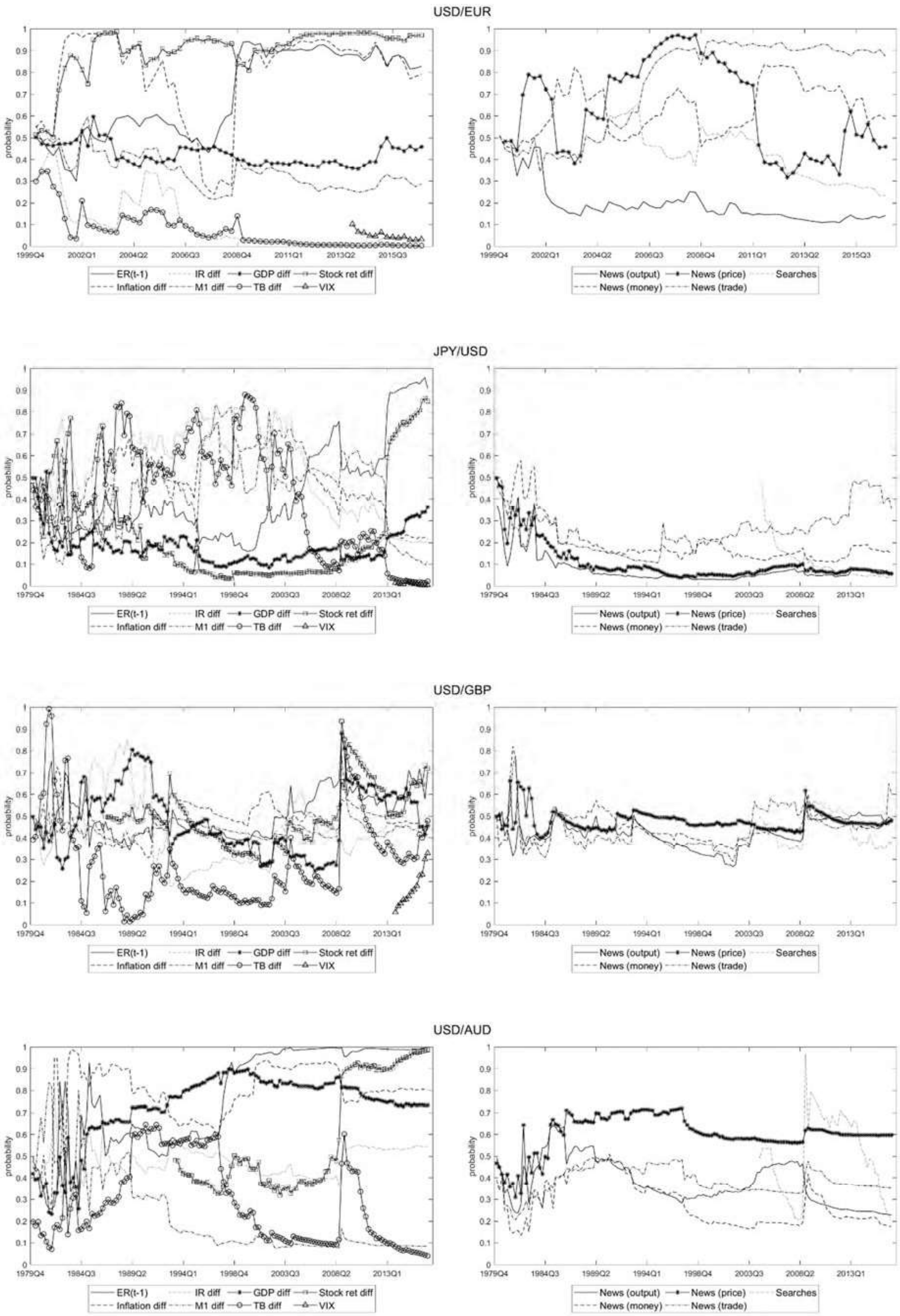
Figure 2: Forecasting performance of model extension.

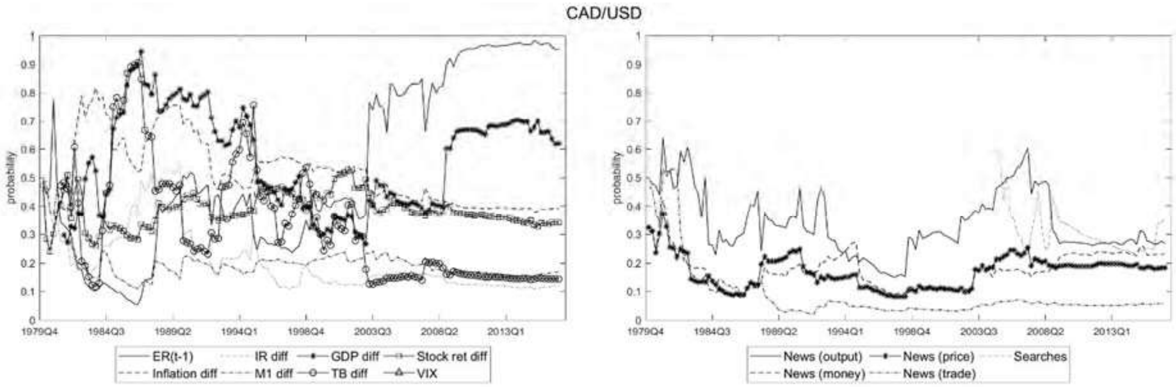




Note: The forecasting performance of different model extensions, where two different TVP-VAR models were estimated by a Dynamic Model Averaging (DMA) approach. The first group of models only included the macroeconomic fundamentals (inflation differential, interest rate differential, money growth differential, GDP growth differential, trade balance differential, stock returns differential, and VIX). The second group of models are extended for indices calculated from the counts of newsletter articles related to four different categories (economic activity, money, price and trade) in a given country (Proquest data-base) and searches refer to the search volume index of the given currency names (Google Trends data-base).

Figure 3: Time-varying posterior probabilities of including predictors into the extended models.





Note: Time-varying posterior probabilities of the inclusion of attention-related predictors into the TVP-VAR extended models. We estimate our models using the predictors [list the predictors] present-ed in two figures for each currency. On the left, figures show posterior probability of macroeconomic fun-damentals. On the right, figures show posterior probability of news and searches. News refers to the indi-ces calculated as counts of newsletter articles that are related to four different categories (economic activi-ty/output, money, price and trade) in a given country (Proquest database). Searches represent the search volume index of the given currency names (Google Trends database).

Table 2: Forecasting performance summary.

Currency	Model	TVP-VAR			DMA			DMS		
		MAFE	MSFE	log(PL)	MAFE	MSFE	log(PL)	MAFE	MSFE	log(PL)
EUR	Macro fundamentals	10.647	1.720	0.326	10.947	1.668	1.467	10.711	1.628	1.827
	Incl. news & searches	11.138	1.817	0.040	10.848	1.648	1.379	10.653	1.617	1.566
	Extended models	12.072	1.882	1.176	10.632	1.600	1.797	10.435	1.595	2.190
JPY	Macro fundamentals	25.045	2.701	0.364	23.711	2.506	4.274	26.123	2.826	6.459
	Incl. news & searches	25.851	2.775	-0.723	23.575	2.478	3.555	24.871	2.679	4.599
	Extended models	25.743	2.793	-2.024	23.561	2.464	3.389	26.180	2.839	5.613
GBP	Macro fundamentals	22.758	2.683	-4.482	19.315	2.287	-6.610	19.796	2.278	-4.827
	Incl. news & searches	23.163	2.720	-4.525	18.976	2.267	-6.595	19.433	2.286	-5.190
	Extended models	24.928	3.012	-5.120	19.606	2.335	-6.997	20.761	2.420	-5.027
AUD	Macro fundamentals	24.605	2.906	2.993	20.540	2.357	0.251	20.873	2.404	0.212
	Incl. news & searches	25.303	3.199	3.937	19.979	2.288	-0.160	20.292	2.321	0.173
	Extended models	25.899	3.263	4.884	20.339	2.326	0.076	20.953	2.377	-0.291
CAD	Macro fundamentals	11.604	1.460	-0.357	10.687	1.344	-0.370	10.975	1.358	-0.210
	Incl. news & searches	11.572	1.461	-0.405	10.764	1.350	-0.349	11.104	1.367	-0.135
	Extended models	12.050	1.518	-0.194	10.667	1.347	-0.317	11.183	1.373	-0.152
NZD	Macro fundamentals	24.959	2.971	2.412	22.694	2.560	0.504	22.971	2.582	0.872
	Incl. news & searches	25.690	3.020	2.687	22.520	2.524	0.299	23.143	2.613	0.017
	Extended models	26.278	3.083	2.176	22.829	2.594	0.860	24.076	2.799	1.103

Note: The table compares the forecasting performance of three different groups of models: TVP-VAR model, a group of TVP-VAR models that are estimated by a Dynamic Model Averaging approach, and a group of TVP-VAR models that are estimated by a Dynamic Model Selection approach. The forecasting performance of each of the selected groups of models is presented by using three different groups of predictors. The first group of predictors includes macroeconomic fundamentals only (inflation differential, interest rate differential, money growth differential, GDP growth differential, trade balance differential, stock returns differential, and VIX). The second group of predictors is extended for indices calculated as counts of newsletter articles in the selected country and search volume index of the referred currency name (Google Trends database), denoted as “Incl. news & searches”. The third group of predictors (denoted as “Extended models”) differentiate between four different categories of news that are related to economic activity, money, price and trade.

Appendix

Table A1. Definitions of macroeconomic fundamentals.

Name and source	Definition
GDP OECD http://stats.ukdataservice.ac.uk/Index.aspx?DataSetCode=MEI	Gross domestic product at a constant price and value that is seasonally adjusted, using the national currency for all countries except for Japan, which used USD (fixed PPPs) (main economic indicators, October 2017).
CPI OECD http://stats.ukdataservice.ac.uk/Index.aspx?DataSetCode=MEI	Consumer price index (Main economic indicators, October 2017).
Interest rate OECD http://stats.ukdataservice.ac.uk/Index.aspx?DataSetCode=MEI	Three-month or 90-day rates and yields for all countries except for Japan (certificates of deposit), interbank rates in percentage (Main economic indicators, October 2017).
M1 OECD http://stats.ukdataservice.ac.uk/Index.aspx?DataSetCode=MEI Bank of England for the United Kingdom	Monetary aggregate M1, value, seasonally adjusted, national currency (Main economic indicators, October 2017).
Export, Import OECD http://stats.ukdataservice.ac.uk/Index.aspx?DataSetCode=MEI	The total exported and imported value of goods that are seasonally adjusted in national currency (Main economic indicators, October 2017).