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OPEC News and Exchange Rate Forecasting Using Dynamic Bayesian Learning

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Abstract

We consider whether a newspaper article count index related to the Organization of the Petroleum Exporting Countries (OPEC), which rises in response to important OPEC meetings and events connected with OPEC production levels, contains predictive power for the foreign exchange rates of G10 countries. The applied Bayesian inference methodology synthesizes a wide array of established approaches to modelling exchange rate dynamics, whereby various vector-autoregressive models are considered. Monthly data from 1996:01 to 2020:08 (given an in-sample of 1986:02 to 1995:12), shows that incorporating the OPEC news-related index into the proposed methodology leads to statistical gains in out-of-sample forecasts.

JEL Codes: C32, C53, Q41

Keywords: OPEC News; Exchange Rate Forecasting; Bayesian Dynamic Learning

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1. Introduction

The foreign exchange market is the largest and most liquid financial market in the world, with an average daily turnover of 6.6 trillion United States (US) dollars in April 2019, up from the 5.1 trillion US recorded in April 2016.[1] Given the importance of currency markets, accurate forecasting of exchange rate returns is paramount not only to investors but also exporters and importers, retailers and consumers, who ultimately make decisions based on the value of domestic currencies. Moreover, policymakers are concerned with pass-through, a major mechanism by which exchange movements affect domestic economic aggregates. In this regard, the literature on the predictability of exchange rate returns is voluminous, to say the least (see for example, Rossi (2013), Christou et al., (2018), Salisu and Ndako (2018), Salisu et al., (2019) for detailed reviews), with a common observation that the task of forecasting exchange rate movements based on wide-array of macroeconomic, financial and behavioural fundamentals, as well as linear and (parametric and semi-or non-parametric) nonlinear econometric models, is an arduous task, as originally indicated by Meese and Rogoff (1983).

Against this backdrop, the objective of our paper is to add to this mass of literature, by analysing the ability of the information content of the Organization of the Petroleum Exporting Countries (OPEC) meetings and events connected with OPEC production levels, to forecast returns on the US dollar-based nominal exchange rates of the G10 countries, over the monthly period 1986:02 to 2020:08[2]. Based on the large number of econometric methods used in existing studies, we rely on a flexible empirical framework, recently developed by Beckmann et al., (2020), which is basically a high-dimensional multivariate time series model. This involves the full cross-section of the nine exchange rates, an exogenous predictor associated with OPEC news, and time variation in coefficients and volatilities, with the associated algorithm choosing these categories in a data-based fashion using dynamic model selection methods, i.e., decisions about specification choices are all made automatically in a time-varying fashion.

At this stage, it is important to understand the underlying motivation for looking at the role of OPEC meetings and events associated with production decisions in forecasting exchange rate returns. OPEC decisions have been shown to have not only first- but also second-moment

[1] Statistics are based on last available data from the Triennial Survey of global foreign exchange market volumes of the Bank for International Settlement (BIS) at: https://www.bis.org/statistics/rpfx19_fx.htm.

[2] The significant role of news in the prediction of return series, although not from the perspective of OPEC news and exchange rate returns, is well documented in the literature (see for example, Narayan (2019), Salisu and Vo (2020) for detailed reviews).

impacts on oil prices (Mensi et al., 2014; Gupta and Yoon, 2018). As outlined in Salisu et al., (2020a), from a theoretical point of view, there are primarily two direct transmission channels from oil prices to exchange rates. Firstly, according to the terms of trade channel, an oil price increase is followed by a depreciation of those currencies in countries with large oil dependence in the tradable sector, since the price level in these countries increases. Secondly, in line with the wealth channel, when oil prices rise, wealth is transferred to oil-exporting countries and this is reflected in an improvement in the current account balance, so that oil-exporting countries' currencies are expected to appreciate while the currencies of oil-importers are expected to depreciate.[3] At the same time, OPEC decisions affect oil market volatility, which translates into overall economic uncertainty (Hailemariam et al., 2019), driving exchange rate movements via a simple hedging motive. As pointed out by Benigno et al., (2012), based on a two-country open-economy theoretical model, an increase in uncertainty does not necessarily lead to a depreciation of a currency: what matters is whether the currency is relatively safer when there is bad news, i.e., an increase in uncertainty. In this respect, uncertainty may improve the hedging properties of a currency leading to an increase in its demand and thereby appreciation. In other words, OPEC decisions act as single sources of information associated with the oil market, capturing movements in both prices and volatility, and in turn do not require us to incorporate information on both the first- and second-moments of oil price simultaneously into the model to forecast exchange rate returns. It is important to incorporate the role of both oil price and its volatility via OPEC decisions, given the persistent uncertainty in the oil market, especially in the wake of the global financial crisis, China-US trade war, and of course the recent outbreak of COVID-19 (Bouri et al., 2020).

To the best of our knowledge, this is the first attempt[4] to analyse the ability of OPEC meetings and events connected with OPEC production levels, as captured by a newspaper article count index related to OPEC, developed by Plante (2019), to forecast G10 nominal exchange rate returns based on dynamic Bayesian learning methods.

The remainder of the paper is organized as follows: Section 2 outlines the data and the methodology; Section 3 presents the results; with Section 4 concluding the paper.

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[3] See for example, Lizardo and Mollick (2010), who provide detailed evidence that US dollar exchange rates are affected by the price of crude oil.

[4] The only somewhat related paper is Ayadi et al., (2020), which, *inter alia*, provide in-sample evidence of the effect of OPEC decisions on the volatility of the Canadian dollar. Given that here we concentrate on exchange rate returns only, the above-mentioned paper provides us with the motivation to forecast exchange rate volatility due to OPEC decisions as an area for future research.

2. Data and Methodology

All our model configurations are vector autoregressive (VAR) models (or extensions thereof) that involve a cross-section of exchange rates as dependent variables, and the variable capturing OPEC decisions as the exogenous predictor. We use the common set of G10 currencies: the Australian dollar (AUD), the Canadian dollar (CAD), the Euro (EUR), the Japanese yen (JPY), the New Zealand dollar (NZD), the Norwegian krone (NOK), the Swedish krona (SWK), the Swiss franc (SWF), the Great Britain pound sterling (GBP) and the US dollar (USD). All currencies are expressed in US dollars, that enter the model as discrete returns, with the data derived from the Main Economic Indicators (MEI) database of the Organisation for Economic Co-operation and Development (OECD). Thus, we have nine exchange rates, each relative to the US dollar, entering our VAR.

The sample runs from 1986:02 until 2020:08, driven by the data availability of the newspaper-based index related to OPEC (OPEC1), as developed by Plante (2019). In this paper, the author introduce a newspaper (the Financial Times, the Houston Chronicle, the New York Times and the Wall Street Journal) article count index related to OPEC that rises in response to important OPEC meetings and events connected with OPEC production levels.[5] Note that we work with the growth rates of this index, i.e., GOPEC1, to mimic shocks originating from OPEC-related news, with these variable capturing changes in information.[6] The 9 exchange rate returns and GOPEC1 are plotted in Figure A1, and summarized in Table A1 in the Appendix of the paper. As can be seen, Norway has the highest mean returns, while the Euro has the lowest, and New Zealand has the highest volatility, while Canada has the lowest. All variables are non-normal, barring the Euro exchange rate returns and GOPEC1, based on the Jarque-Bera test of normality.

The time-varying parameter VAR model in this study is specified as:

$$y_t = x_t\beta_t + \varepsilon_t,\ \ \varepsilon_t \sim N(0, \Sigma_t) \tag{1}$$

$$\beta_{t+1} = \beta_t + u_t,\ \ \varepsilon_t \sim N(0, \Omega_t) \tag{2}$$

where y_t is a 9×1 vector containing observations of the US dollar-based foreign exchange rates; x_t is a matrix in which each row contains predetermined variables in each VAR equation i, i.e.,

[5] The index is available for download from the website of Dr. Michael D. Plante at: https://sites.google.com/site/michaelplanteecon/research.

[6] Our basic findings, outlined in the next section, remain the same with log-level data of the OPEC index, but the growth rate of this variable performs better than the log-level version of the same. Complete details of the results based on log-level data are available upon request from the authors.

an intercept, the lagged exogenous OPEC variable, and lagged dependent variables. β_t is assumed to follow a multivariate random walk process without a drift, with the covariance matrix Ω_t. The model parameters are initialized with an expected value of 0 and a covariance matrix of Ω_0, i.e., $\beta_0 \sim N(0, \Omega_0)$. Let $\Omega_{0,i}$ represent the block of Ω_0 associated with the coefficients in equation i, and $\Omega_{0.i,ij}$ is the diagonal elements of $\Omega_{0,i}$. Given this, it is specified that:

$$\Omega_{0.i,ij} = \begin{cases} \gamma_1 s_i^2, & for\ intercepts \\ \frac{\gamma_2}{r^2}, & for\ coefficients\ on\ own\ lag\ (r = 1, \dots, p) \\ \frac{\gamma_3 s_i^2}{r^2 s_j^2}, & for\ coefficients\ on\ cross\ lag\ (r = 1, \dots, p)\ of\ variable\ i \neq j \\ \gamma_4 s_i^2, & for\ coefficients\ on\ the\ exogenous\ variable \end{cases} \tag{3}$$

where γ_i, i=1, 2, 3, 4, are the shrinkage intensity parameters and s_i^2represents the residual variance of the respective variable i. We set the lag length p=6 as in Beckmann et al. (2020). Instead of one shrinkage parameter for all VAR coefficients, the model allows for multiple shrinkage parameters. We use a grid of values, i.e., $\gamma \in \{0; 0.1; 0.5; 0.9\}$ for the shrinkage parameters. The choices of grids for γ allow for the algorithm to choose for the exclusion of model elements, such as VAR lags or the exogenous variable, or to select other informative prior choices in different model specifications. The prior covariance matrix Ω_0 is assumed to be diagonal. If the diagonal elements of Ω_0 are chosen to be small, the respective coefficients are shrunk to 0, which allows for a mechanism to exclude certain model elements in model specifications. The dynamics of Σ_t and Ω_t are controlled by the decay factors δ and λ, which are set to 0.97 and 1, respectively. When δ=1 (similarly for λ), all available historical observations are used equally to update volatilities (and parameters). In contrast, recent observations are giving more weight when a decay factor has a value of less than one.[7]

To allow for the exclusion of model elements and different levels of shrinkage intensity, our empirical study fixes the values of δ and λ and considers a grid of values for each of γ_1, γ_2, γ_3, and γ_4. A dynamic model learning (DML) procedure is employed to evaluate the individual model specification, and automatically select the specification with the highest discounted joint log-predictive likelihood (*DPL*) at each point in time. The *DPL* is calculated as:

$$DPL_{\tau|\tau-1,m} = \prod_{t=1}^{\tau-1} [p_m(y_{\tau-t} | y^{\tau-t-1})]^{\alpha^t} \tag{4}$$

[7] See Beckmann et al., (2020) for further details about the specification choices.

where $p_m(y_{\tau-t}|y^{\tau-t-1})$ represents the predictive likelihood of the model specification m in period t. Subscript $\tau|\tau-1$ refers to the estimates of DPL made at time τ given the information available at time $\tau-1$. The model specification m receives a higher DPL if it has performed well in the recent past. The discount factor α is used to control for the degree of exponential decay of the predictive likelihood in the past.[8] At time τ, the best forecast model specification is selected, which produces the highest production of predictive likelihoods in the past from t-1,…, τ.

3. Results

The forecast evaluation period runs from 1996:01 to 2020:08, i.e., 296 observations, with the start date corresponding to that chosen by Beckmann et al., (2020). As in this paper, the in-sample covers 1986:02 (after transformation into growth rates) to 1995:12, and the statistical criterion we use is the average joint predictive log-likelihood (PLL) shown in Table 1. Note that, the "DML without own/cross-lags and NO REGRESSORS" is the (heteroskedastic) random walk (RW) model. As can be seen from the table, including GOPEC1 outperforms the RW model, while the DML with own- and cross-lags but no GOPEC1 outperforms not only the RW model, but the RW model with the OPEC news-related variable included too. This suggests the importance of own- and cross-lags in forecasting exchange rate returns – an observation also made by Carriero et al., (2009), in terms of emphasizing the role of dynamic co-movements in currencies, while forecasting exchange rates with a large Bayesian VAR model. But more importantly, when we include the GOPEC1 variable into the model with both own- and cross-lags, we obtain the most accurate forecasts, which in turn highlights the need for not only own- and cross-lags in forecasting exchange rate returns of the G10 countries, but also the information content of the growth in the newspaper articles count index related to OPEC meetings and events.

[INSERT TABLE 1]

In Figure 1, the coloured dots show which blocks of variables are included at each point in time. In contrast, blank spaces in the graph depict the time-varying sparsity induced by DML,

[8] A grid of values, i.e., $\alpha \in \{0.5;\ 0.7;\ 0.8;\ 0.9;\ 0.99;\ 1\}$ are considered in this study. Higher values of α are associated with slower switching between models. If $\alpha = 1$, no discounting is applied and the DPL is proportional to the marginal likelihood.

i.e., periods where a block of variables is not selected. We find that the figure highlights the importance of primarily own-lags, besides the intercept, with the role of GOPEC1 becoming important post the global financial crisis, and to some extent the cross-lags.

[INSERT FIGURE 1]

We conduct two more analyses. Note that, in addition to the benchmark index (OPEC1), Plante (2019) develops another index (OPEC2), whereby the raw number of articles written about OPEC is divided by the total number of articles produced by the four newspapers over the same time period, with data available from 1986:01 to 2016:12. Given that Beckmann et al., (2020) cover the same sample period, we firstly conduct a comparative analysis of the performance of the growth rates of these two OPEC indexes, i.e., GOPEC1 and GOPEC2 with the predictors used by these authors over the out-of-sample period 1996:01 to 2016:12, based on an in-sample of 1986:02 to 1995:12. The PLLs are reported in Table A2 in the Appendix of the paper.[9] As can be seen, besides the RW model, GOPEC1 outperforms all predictors, including the growth in oil price, barring stock returns. But GOPEC2 does not outperform GOPEC1, and does equally as well as oil returns. Our results highlight that we can obtain forecasting gains for the exchange rate returns by including the role of both oil price and its volatility via the newspaper index associated with OPEC meetings and decisions. Secondly, along the lines of Plante et al. (2019), we create another index based on Google search volume data[10] using the search term "OPEC" covering the period 2004:01 to 2020:09. Using the growth rate of this index (GGSVI), and in- and out-of-sample periods of, respectively, 2004:01 to 2008:03 and 2008:04 to 2020:09, we find, as shown in Table A2 in the Appendix of the paper, that GGSVI outperforms the RW model, with the PLL being 23.47 relative to 23.40. Again, this result suggests that an alternative internet search-based index that contains information on OPEC decisions can also beat the historical mean model.

4. Conclusion

In this paper, we analyse the ability of the information content of a newspaper articles count index related to OPEC meetings and events connected with its production levels to forecast

[9] To make our results based on the GOPEC1 and GOPEC2 perfectly comparable with those obtained by Beckmann et al., (2020) with the alternative predictors and the RW model they use, we use the same exchange rate returns as these authors, derived from a different source (DataStream).

[10] A number of studies suggest using Google search volume for constructing news-based indexes for return predictability (see Salisu et al., (2020b) for a review).

returns on the US dollar-based nominal exchange rates of the G10 countries, over the monthly period 1996:01 to 2020:08, with an in-sample of 1986:02 to 1995:12. Based on the large number of econometric methods used in existing studies, we rely on a flexible high-dimensional multivariate time series model involving the full cross-section of the nine exchange rates, the exogenous predictor associated with OPEC news, and time variation in coefficients and volatilities. We find that incorporating the growth of the OPEC index in the proposed methodology leads to statistical gains in out-of-sample forecasts. Given this finding, investors, exporters and importers, retailers and consumers, and policymakers can improve the accuracy of currency forecasts for making their respective decisions by including the role of the OPEC index, which drives both oil price and/or returns and their volatility (as indicated by existing studies relating OPEC news and the oil market), based on the Bayesian learning model, where decisions about specification choices are made automatically in a time-varying manner.

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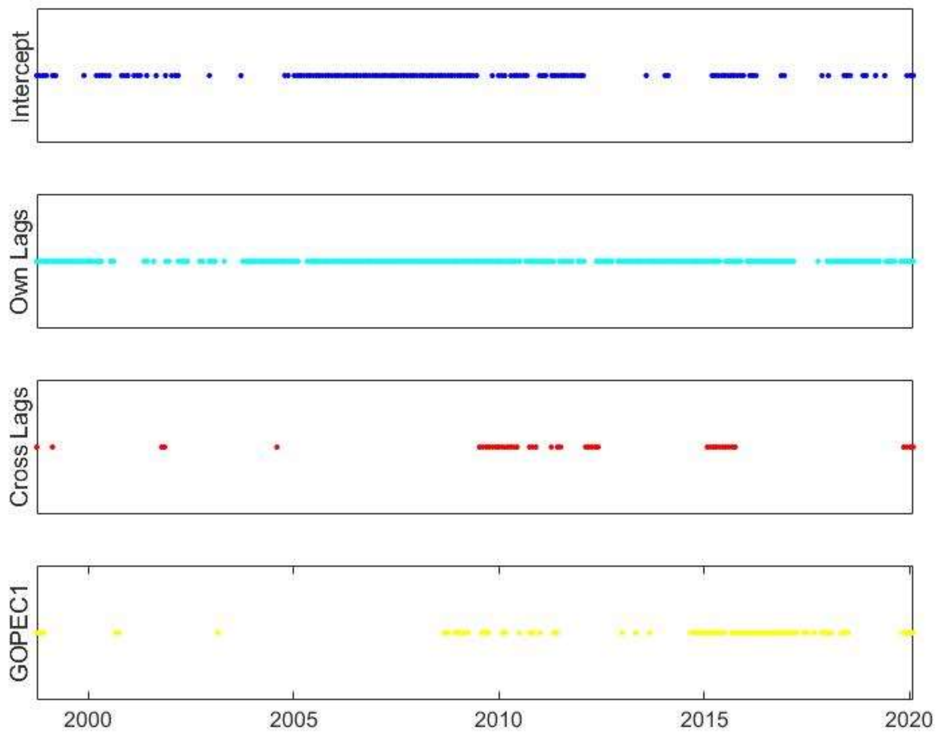
TABLE 1. Evaluation of Forecasting Results Using Newspaper-Based OPEC Index (GOPEC1): 1996:01-2020:08 (In-Sample: 1986:02-1995:12)

Alternative sets of regressors	PLL
DML with GOPEC1	24.22
Type of restrictions: VAR lags	
DML with own-/cross-lags and NO GOPEC1 ($\gamma_4 = 0$)	24.19
DML without own-/cross-lags ($\gamma_2 = \gamma_3 = 0$) and GOPEC1	24.17
DML without own-/cross-lags ($\gamma_2 = \gamma_3 = 0$) and NO REGRESSORS	24.08

Note: GOPEC1: the growth of OPEC1; see Beckmann et al., (2020) and the associated online Appendix for further details.

FIGURE 1. Inclusion of Blocks of Variables



Note: The figure displays which blocks of variables are included at each point in time over the out-of-sample period; included means the respective γ_i is not 0.

APPENDIX:

TABLE A1. Summary Statistics

	VARIABLE									
STATISTIC	AUSTRALIA	CANADA	EURO	GREAT BRITAIN	JAPAN	NEW ZEALAND	NORWAY	SWEDEN	SWITZERLAND	GOPEC1
Mean	-0.0001	-0.0001	-0.0007	0.0002	-0.0015	-0.0006	0.0004	0.0003	-0.0020	-0.0057
Median	-0.0016	-0.0006	-0.0005	-0.0004	0.0003	-0.0008	0.0006	-0.0001	-0.0017	0.0141
Maximum	0.1798	0.1089	0.0787	0.1097	0.0797	0.1063	0.1314	0.1094	0.1123	1.9161
Minimum	-0.0727	-0.0617	-0.0641	-0.0673	-0.1027	-0.0742	-0.0571	-0.0713	-0.0808	-2.0129
Std. Dev.	0.0262	0.0162	0.0235	0.0232	0.0260	0.0263	0.0252	0.0255	0.0259	0.6938
Skewness	0.9978	0.4827	0.1084	0.6506	-0.3189	0.2112	0.5173	0.4761	0.0422	-0.0942
Kurtosis	8.2027	8.1895	3.3300	5.2055	3.8695	3.7320	4.6677	4.4529	4.1323	2.9438
Jarque-Bera	536.9210	481.7918	2.6955	113.3856	20.1079	12.3516	66.6017	52.1795	22.2930	0.6682
Probability	0.0000	0.0000	0.2598	0.0000	0.0000	0.0021	0.0000	0.0000	0.0000	0.7160
Observations	415									

Note: This table presents the summary statistics of monthly returns covering nine exchange rates and as well as monthly growth rate of the OPEC news-related index (OPEC1) of Plante (2019).

TABLE A2. Evaluation of Forecasting Results: 1996:01-2016:12 (In-Sample: 1986:02-1995:12)

Alternative sets of regressors	PLL
DML with UIP	22.01
DML with OIL	22.03
DML with INT_DIFF	22.02
DML with STOCK_GROWTH	22.06
DML with PPP	22.00
DML with MON	22.03
DML with ASTAY	22.03
DML with GOPEC1	22.04
DML with GOPEC2	22.03
DML without own-/cross-lags ($\gamma_2 = \gamma_3 = 0$) and NO REGRESSORS	21.72

Note: UIP: the uncovered interest rate parity; OIL: the percentage change in the nominal oil price; INT_DIFF: the difference between long- and short-term interest rates; STOCK_GROWTH: the percentage change in stock prices over the past 12 months; GOPEC1: the growth of OPEC1; GOPEC2: the growth of OPEC2; PPP: purchasing power parity; MON: the monetary model; ASTAY: an asymmetric Taylor Rule. See note to Table 1.

TABLE A3. Evaluation of Forecasting Results Using Google Search Volume Index (GSVI): 2008:04-2020:09 (In-Sample: 2004:02-2008:03)

Alternative sets of regressors	PLL
DML with GGSVI	23.47
DML without own-/cross-lags ($\gamma_2 = \gamma_3 = 0$) and NO REGRESSORS	23.40

Note: GGSVI: the growth of GSVI. See note to Table 1.

FIGURE A1. Data Plots