Forecasting oil price volatility using spillover effects from uncertainty indices

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Abstract

We consider spillovers between oil price volatility and key uncertainty indicators and we extend the applicability of the spillover index beyond economic inference, by generating forecasts of oil price volatility. The paper shows that spillovers do not contain significant predictive information, raising critical questions regarding the usefulness of the spillover index for forecasting exercises at low sampling frequency; i.e. for monthly data.

JEL codes: C22, C32, C53, Q47.
Keywords: Uncertainty, oil price volatility, forecasting accuracy, spillover effects.

1. Introduction

Since the development of the Diebold and Yilmaz (2009) spillover index and the Baker *et al.* (2016) economic policy uncertainty (*EPU*), many studies have assessed the relationship between the latter and oil prices/volatility (Antonakakis *et al.*, 2014; Kang *et al.*, 2017). Others have examined the predictive information of EPU on oil price/volatility forecasts (Bekiros *et al.*, 2015; Degiannakis and Filis, 2017, 2018). Findings suggest that EPU transmits spillover effects to the oil market and contains predictive information.

However, there are still two important gaps that need to be addressed: *(i)* there exist different layers of uncertainty, EPU aside, which could also transmit spillover effects to oil prices/volatility (e.g. geopolitical uncertainty, financial markets uncertainty, etc.), that have hitherto largely been ignored and *(ii)* studies that investigate spillover effects do not assess their usefulness in predictions. By contrast, we opine that spillover effects should not merely be used for inference, but also for forecasting purposes.

We fill these gaps by *(i)* concentrating on the most important uncertainty indicators and *(ii)* extending the applicability of the spillover index beyond mere inference, to show its usefulness for forecasting purposes. We confine our interest in oil price volatility, given its quality to approximate uncertainty surrounding the oil market. In this letter, we only consider low frequency data (monthly) due to the availability of data for the majority of the uncertainty indices.

Results show that, all different types of uncertainty are linked to OVX, but only spillovers from $USEPU$ contain significant in-sample predictive information. Nonetheless, even these spillovers from $USEPU$ cannot provide any statistically significant incremental forecasting gains. This finding practically questions the effectiveness of spillover effects for volatility forecasts and thus, the usefulness of the spillover index in general. To strengthen our findings further evidence is required that would consider other asset classes (for both returns and volatilities) and also the different magnitudes of spillover effects.

The remainder of the paper is structured as follows. Section 2 presents data and methods, Section 3 discusses empirical findings and Section 4 concludes the study.

2. Data and methods

2.1. Data description

We use monthly data (June, 2007 to February, 2019) for the OVX index (implied volatility index of WTI crude oil prices), the VIX index (implied volatility index of S&P500 index), the US EPU ($USEPU$), the global EPU ($GEPU$), the geopolitical risk index (GR) by Caldara and Iacoviello (2018) and the partisan conflict index (PC) by Azzimonti (2014). The data have been retrieved by CBOE (OVX and VIX), Baker *et al.* (2016) ($USEPU$ and $GEPU$), M. Iacoviello's personal website[1] (GR) and Federal Reserve Bank of Philadelphia (PC). The study period is dictated purely by data availability of the OVX index.

2.2. Methods

Initially, we employ the Diebold and Yilmaz (2012) framework to extract net pairwise spillovers between uncertainty indicators ($VIX_t, USEPU_t, GEPU_t, GR_t, PC_t$) and OVX_t. We start with the generic form of a p-th order, N-variable Vector Autoregressive (*VAR*) model:

$$\boldsymbol{z}_t = \sum_{k}^{p} \boldsymbol{\Theta}_k \boldsymbol{z}_{t-k} + \boldsymbol{e}_t, \tag{1}$$

where, $\boldsymbol{z}_t$ is a vector of $N(=6)$ endogenous variables, $\boldsymbol{\Theta}_k$ with $k = 1$,…, p, are parameter matrices $[N \times N]$ and $\boldsymbol{e}_t \sim (\boldsymbol{0}, \boldsymbol{S})$ is a vector of disturbances, independent over time; although not necessarily *i.i.d.*.[2] Finally, $t = 1$,…, T is the time index. The standard moving average representation of the *VAR* is:

$$\boldsymbol{z}_t = \sum_{b=0}^{\infty} \boldsymbol{A}_b \boldsymbol{e}_{t-b}, \tag{2}$$

where, the $[N \times N]$ coefficient matrices $\boldsymbol{A}_b$ are recursively defined. We employ a generalized framework (i.e. see Koop *et al.*, 1996; Pesaran and Shin, 1998) whereby, no specific ordering is required. The H-step-ahead forecast error variance decompositions (FEVDs) are given by:

$$\boldsymbol{\varphi}_{ij,t}(H) = \frac{\sigma_{jj,t}^{-1} \sum_{t=1}^{H-1} (\boldsymbol{u}_i' \boldsymbol{A}_t \boldsymbol{S} \boldsymbol{u}_j)^2}{\sum_{t=1}^{H-1} (\boldsymbol{u}_i' \boldsymbol{A}_t \boldsymbol{S} \boldsymbol{A}_t' \boldsymbol{u}_i)}, \tag{3}$$

[1] https://www2.bc.edu/matteo-iacoviello/gpr.htm.

[2] *For the estimation of the VAR model, we assume a specific form for mean and variance vector, i.e.* $(\boldsymbol{0}, \boldsymbol{S})$, *but we do not need to specify the distribution of* $\boldsymbol{e}_t$, *as long as the independency over time holds. The assumption of normally distributed errors is required only for the statistical inference.*

where, σ_{jj}^{-1} is the standard deviation of the estimated error term for the j-th equation of the *VAR* model and $\boldsymbol{u}_i$ is a selection vector, which assumes the value of one for element i and zero otherwise. $\boldsymbol{S}$ is the estimated variance matrix of vector $\boldsymbol{e}$. The $\boldsymbol{\varphi}_{ij}(H)$ matrix gives the input of variable j to the FEVD of variable i. The main diagonal corresponds to idiosyncratic effects while, off-diagonal elements, to cross-variable effects. The normalised version of the matrix (i.e. due to $\sum_{j=1}^{N} \boldsymbol{\varphi}_{ij}(H) \neq 1$) is $\widetilde{\boldsymbol{\varphi}}_{ij,t}(H) = \frac{\boldsymbol{\varphi}_{ij,t}(H)}{\sum_{j=1}^{N} \boldsymbol{\varphi}_{ij,t}(H)}$. Our main focus, though, is on the net pairwise spillover effects that can be obtained as:

$$NPWS(H) = \widetilde{\boldsymbol{\varphi}}_{ij,t}(H) - \widetilde{\boldsymbol{\varphi}}_{ji,t}(H). \tag{4}$$

Next, we assess the predictive content of the net pairwise spillover effects on the OVX index. We start from the in-sample estimation, employing the HAR model[3], which is extended in order to include information from the net pairwise spillover effects:

$$\begin{aligned} log(OVX_t) = {} & \alpha_0 + \alpha_1 log(OVX_{t-1}) + \alpha_2 \left(3^{-1} \sum_{n=1}^{3} log(OVX_{t-n})\right) \\ & + \alpha_3 \left(12^{-1} \sum_{n=1}^{12} log(OVX_{t-n})\right) + \alpha_4 log(UNC_{t-1}) \\ & + \alpha_5 d\left(NPWS_{OVX-UNC,t-1} < 0\right) \\ & + \alpha_6 d\left(NPWS_{OVX-UNC,t-1} < 0\right) \times log(UNC_{t-1}) + \varepsilon_t, \end{aligned} \tag{5}$$

where $\varepsilon_t \sim (0, \sigma_\varepsilon^2)$, UNC_t denotes each one of the five alternative uncertainty indicators, $UNC_t\colon \{VIX_t, USEPU_t, GEPU_t, GR_t, PC_t\}$, the $d\left(NSPW_{OVX-UNC,t} < 0\right)$ is a dummy variable that takes the value of one when the uncertainty indicator (UNC_t) is a net transmitter of spillover effects[4] to OVX and zero otherwise.

Next, we proceed with the real out-of-sample forecasting exercise. A recursive approach is used with an initial sample period of 40 monthly observations. The remaining 41 months are used for the real out-of-sample iterated forecasts. We consider *h*-months ahead forecasts for *h*=1,...,12. Henceforth, in order to estimate real out-of-sample forecasts, eq.5 is re-estimated as:

[3] The Heterogeneous AutoRegressive model (HAR) by Corsi (2009) is regarded as the best for modelling and forecasting asset price volatility (Degiannakis and Filis, 2017). Following Degiannakis and Filis (2019) we adjust the simple HAR model for monthly data considering the 1-month, 1-quarter and 1-year lags. For robustness, we estimate distributed lag models as well as autoregressive models, but the findings are qualitatively similar and available upon request.

[4] According to our estimation of spillover effects, an uncertainty indicator is a net transmitter when the net pairwise spillover index is below zero.

$$
\begin{aligned}
log(OVX_t) = \alpha_0 + \alpha_1 log(OVX_{t-1}) + \alpha_2 \left(3^{-1} \sum\nolimits_{n=1}^{3} log(OVX_{t-n})\right) \\
+ \alpha_3 \left(12^{-1} \sum\nolimits_{n=1}^{12} log(OVX_{t-n})\right) + \alpha_4 log(UNC_{t-h}) \\
+ \alpha_5 d\left(NPWS_{OVX-UNC,t-h} < 0\right) \\
+ \alpha_6 d\left(NPWS_{OVX-UNC,t-h} < 0\right) \times log(UNC_{t-h}) + \varepsilon_t,
\end{aligned} \tag{6}
$$

The forecasts from eq.6 are then compared with the random walk (RW) model ($log(OVX_t) = \alpha_0 + \varepsilon_t$) and the simple HAR model (for $\alpha_4 = \alpha_5 = \alpha_6 = 0$), based on the Mean Squared Predictive Error (MSPE) statistical function.

3. Findings

3.1. Spillover effects

Figure 1 illustrates the net pairwise spillovers between UNC and OVX. Not surprisingly, OVX is mainly a transmitter of shocks to VIX and $GEPU$, especially after the oil price collapse period of 2014-2016 (in line with Antonakakis *et al.*, 2014). The net transmitting character of OVX on these two uncertainty indices can be justified by the fact that increased uncertainty in the oil market can affect stock market behaviour and economic policy uncertainty via several channels, such as the stock valuation channel, monetary channel, fiscal channel, output channel and investment uncertainty channel (see, for instance, Degiannakis *et al.*, 2018; Antonakakis *et al.*, 2017; Antonakakis *et al.*, 2014). Such findings can be also justified by the fact that the oil market has become more financialised over recent years and thus the uncertainties between the oil and stock markets tend to become more interlinked.

Conversely, OVX mainly receives from PC, which could be explained by the impact of the US political disagreement on aggregate investment (Azzimonti, 2018). More particularly, despite the fact that oil is not explicitly included in the discussion about the broader effects of partisan conflict, Azzimonti (2018) makes very clear that there is a negative impact of the US partisan conflict on aggregate investment, which subsequently, can be argued to affect oil prices, given the importance of the US economy to the oil market (Jiang *et al.*, 2020).

As far as $USEPU$ is concerned, evidence suggests that apart from the oil price collapse period, it is a net transmitter of shocks to OVX. Once again, we observe that another US-specific policy-related uncertainty index (following the PC) tends to transmit shocks to OVX. Such finding strengthens the argument that oil market uncertainty tends to be impacted by policy-related conditions in the US.

The impact of GR is less clear as it assumes both roles. Nevertheless, apparently GR transmits spillover effects to OVX during the oil price collapse period. We note that linkages between oil and geopolitical risk have been mentioned in the study by Caldara and Iacoviello (2018), whereby increased levels of geopolitical risk, which are typically associated with turbulence in oil producing countries, tend to amplify uncertainty in the oil market.

[Figure 1 here]

3.2. Modelling and forecasting oil price volatility

Table 1 presents the results from the in-sample modelling of OVX, which is the first step to evaluate the usefulness of spillover effects beyond economic inference. Results suggest that only spillover effects transmitted by $USEPU$ contain useful in-sample predictive information on OVX. A plausible explanation of this may rest on the fact that $USEPU$ is the most inclusive uncertainty index, as it is impacted by US-specific, global and geopolitical events, as well as, by uncertainty in financial markets and conflicts among the US political parties, congress, and the President of the US.

[Table 1 here]

Next, we investigate whether the in-sample gains from spillover effects transmitted by the $USEPU$ improve the accuracy for OVX forecasting. Table 2 provides evidence that, although, $USEPU$ spillover effects provide some forecasting gains, yet these are not statistically significant[5]. Hence, we maintain that the spillover effects do not contain incremental predictive ability, either compared to the RW or the simple HAR model. Thus, the usefulness of spillover effects for forecasting purposes is questionable.

[Table 2 here]

We should note here that the main idea behind the development of the spillover approach was not to identify out-of-sample gains but rather to be used for economic inference. Although in this study we proceed one step further so as to assess whether spillover effects have the ability to identify out-of-sample predictive gains, it may well be the case that their usefulness for economic inference may not translate into forecasting ability. Even more, the fact that we do not observe any out-of-sample forecasting gains could be the result of the specific forecasting framework that we

[5] This is based on the Model Confidence Set of Hansen *et al*. (2011).

utilise, given that we solely capture linear effects. Thus, a different forecasting framework could reveal the predictive ability of spillover effects.

Overall, the results of this study pave the path for a new strand in the relevant literature, as they practically suggest that spillover analysis – although important to the extent that we attain a better understanding of the underlying interrelations within a network of variables, may not always be useful when it comes to out-of-sample forecasting. The specific questions that emerge from our analysis of this particular topic and deserve further investigation in the future relate to (i) the extent to which a rather inclusive index (e.g., $USEPU$) performs better vis-à-vis indices that capture individual components of uncertainty and (ii) whether the framework of analysis per se (e.g., the specific asset class or forecasting framework) is restrictive and does not actually support the generalisation of the findings.

4. Conclusion

We generated forecasts of OVX based on net spillovers between the variable itself and key uncertainty indicators. Findings provide strong evidence that spillovers do not generate real out-of-sample forecasting gains at low sampling frequency, casting doubt on the overall effectiveness of the spillover approach. Nonetheless, given that our findings, on this rather novel approach, are conditional on the specific question under investigation, we maintain that additional evidence is required, considering different asset classes (e.g. exchange rates), different sampling frequency (i.e. daily data) and alternative forecasting frameworks.

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TABLES

Table 1: The extended HAR model from eq.5.

	Uncertainty indicators				
	VIX	USEPU	GEPU	GR	PC
α_0	0.7465**	2.3548***	0.7955*	0.2603	1.6879
α_1	1.0696***	1.0241***	1.0741***	1.0867***	0.9911***
α_2	-0.3241	-0.2657	-0.2754	-0.2521	-0.2711
α_3	0.0158	0.0532	0.0906	0.0343	-0.0012
α_4	0.0359	-0.3581***	-0.0825	0.0391	-0.1643
α_5	1.2481	-1.9705*	-0.7068	0.1147	0.5481
α_6	-0.5274	0.4045*	0.1369	-0.0237	-0.0776
Adjusted R^2	0.7897	0.7971	0.7698	0.7657	0.7883
F-statistic	43.5763***	45.5252***	38.9093***	38.0486***	43.2081***
DW	1.8946	2.0591	1.9223	1.9006	1.9351
AIC	-0.6833	-0.7188	-0.5927	-0.5751	-0.6764

Note: DW is the Durbin-Watson statistic, AIC is the Akaike Information Criterion. The F-statistic tests the null hypothesis that all the coefficients (excluding intercept) are statistically equal to zero and it is computed as: $F=\frac{R^2/(k-1)}{(1-R^2)/(T-k)}$. VIX, USEPU, GEPU, GR and PC denote the uncertainty indices for the S&P500, US economic policy uncertainty, global economic policy uncertainty, geopolitical risk and partisan conflict, respectively.
*, **, *** denote significance at 10%, 5% and 1% level, respectively.

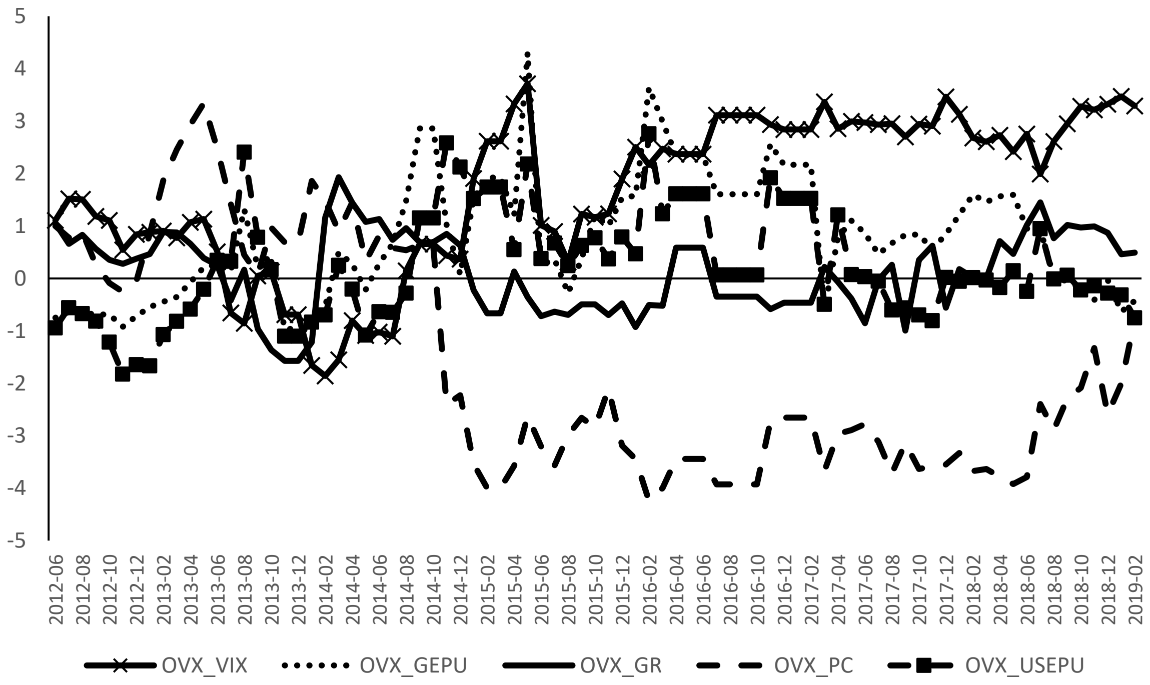
Table 2: MSPE results based on the real out-of-forecasts; forecasting period: October 2015 – February 2019.

Forecasting horizons	RW	HAR	HAR_{USEPU}	$\frac{HAR_{USEPU}}{RW}^{a}$	$\frac{HAR_{USEPU}}{HAR}^{a}$
1	139.0763	47.7326	51.3075	0.3689	1.0749
2	141.0662	104.3545	90.2990	0.6401	0.8653
3	136.9169	132.7897	139.1503	1.0163	1.0479
4	133.6481	138.8830	127.5426	0.9543	0.9183
5	107.5744	123.7463	173.3988	1.6119	1.4012
6	83.0601	99.5721	140.8121	1.6953	1.4142
7	77.5165	97.9840	123.1823	1.5891	1.2572
8	74.8428	98.0214	121.8113	1.6276	1.2427
9	75.3276	98.6540	135.0965	1.7935	1.3694
10	75.7115	118.3759	131.8561	1.7416	1.1139
11	73.2832	150.8982	118.5396	1.6176	0.7856
12	71.3890	162.0641	358.2310	5.0180	2.2104

$^{\alpha}$ A ratio below one suggests that the HAR_{USEPU} model performs better relatively to the RW or the *HAR* model.

FIGURES

Figure 1: Net pairwise spillover effects between OVX and uncertainty indicators.



Note: OVX is a net transmitter (receiver) of spillover effects when the line is above (below) the zero line.

A. Supplementary material (for the benefit of the reviewers)

As we mentioned in footnote 3 of the paper, the results remain qualitatively similar with those of the HAR model, even when we estimate the in-sample and real out-of-sample forecasts based on autoregressive or distributed lag models. In this supplementary material we present these results for the benefit of the reviewers.

Autoregressive (*AR*) model:

$$\begin{aligned} log(OVX_t) = \alpha_0 + \alpha_1 log(UNC_{t-h}) + \ \alpha_2 d\big(NPWS_{OVX-UNC,t-h} < 0\big) \\ + \alpha_3 d\big(NPWS_{OVX-UNC,t-h} < 0\big) \times log(UNC_{t-h}) + e_t, \\ e_t = \alpha_4 e_{t-1} + \varepsilon_t \\ \varepsilon_t \sim (0, \sigma_\varepsilon^2) \end{aligned} \quad (7)$$

Table A.1: Estimated results from autoregressive model.

	Uncertainty indicators				
	VIX	USEPU	GEPU	GR	PC
α_0	3.3774***	4.1537***	3.4382***	3.0397***	2.4159**
α_1	0.0175	-0.1641	-0.0045	0.0778	0.1911
α_2	0.895	-2.1939**	-0.7404	0.4395	1.3241
α_3	-0.3442	0.4686**	0.1462	-0.0854	-0.248
α_4	0.8669***	0.8702***	0.8623***	0.8687***	0.8518***
Adjusted R^2	0.7575	0.7689	0.7561	0.7565	0.7572
F-statistic	50.3677***	53.5856***	49.9702***	50.1088***	50.2924***
DW	1.7241	1.7044	1.7481	1.7156	1.7733
AIC	-0.6329	-0.6808	-0.6272	-0.6288	-0.6331

Note: DW is the Durbin-Watson statistic, AIC is the Akaike Information Criterion. VIX, USEPU, GEPU, GR and PC denote the uncertainty indices for the S&P500, US economic policy uncertainty, global economic policy uncertainty, geopolitical risk and partisan conflict, respectively.

*, **, *** denote significance at 10%, 5% and 1% level, respectively.

Table A.2: MSPE results from the real out-of-forecasts based on the autoregressive model. Forecasting period: October 2015 – February 2019.

Forecasting horizons	RW	AR	AR_{USEPU}	$\frac{AR_{USEPU}}{RW}^{a}$	$\frac{AR_{USEPU}}{AR}^{a}$
1	139.0763	42.0779	52.0353	0.3741	1.2366
2	141.0662	80.5150	75.8224	0.5375	0.9417
3	136.9169	94.7294	91.3651	0.6673	0.9645
4	133.6481	94.7242	95.2508	0.7127	1.0056
5	107.5744	80.2114	78.5932	0.7306	0.9798
6	83.0601	63.2619	65.3242	0.7865	1.0326
7	77.5165	60.8114	64.7823	0.8357	1.0653
8	74.8428	61.1766	61.4119	0.8205	1.0038
9	75.3276	62.4810	65.0116	0.8631	1.0405
10	75.7115	73.9098	79.1759	1.0458	1.0713
11	73.2832	86.7276	92.0832	1.2565	1.0618
12	71.3890	89.6272	95.3667	1.3359	1.0640

[α] A ratio below one suggests that the AR_{USEPU} model performs better relatively to the *RW* or the *AR* model.

Distributed lag (*DL*) model:

$$\begin{aligned} log(OVX_t) = {} & \alpha_0 + \alpha_1 log(UNC_{t-h}) + \alpha_2 d\left(NPWS_{OVX-UNC,t-h} < 0\right) \\ & + \alpha_3 d\left(NPWS_{OVX-UNC,t-h} < 0\right) \times log(UNC_{t-h}) \\ & + \alpha_4 log(OVX_{t-1}) + \varepsilon_t, \\ & \varepsilon_t \sim (0, \sigma_\varepsilon^2) \end{aligned} \quad (8)$$

Table A.3: Estimated results from the distributed lag model.

	Uncertainty indicators				
	VIX	USEPU	GEPU	GR	PC
α_0	0.5816**	2.3782***	0.8227**	0.0691	1.1674
α_1	0.0165	-0.3705**	-0.0713	0.0702	-0.1095
α_2	0.9835	-1.7649**	-0.6928	0.2358	0.5972
α_3	-0.4119	0.3612**	0.1315	-0.049	-0.1021
α_4	0.8205***	0.8214***	0.8650***	0.8800***	0.8050***
Adjusted R^2	0.7698	0.7884	0.7621	0.7588	0.7681
F-statistic	67.0455***	74.6001***	64.2762***	63.1447***	66.4045***
DW	1.6877	1.9356	1.7926	1.7679	1.8161
AIC	-0.7137	-0.7981	-0.6809	-0.6672	-0.7062

Note: DW is the Durbin-Watson statistic, AIC is the Akaike Information Criterion. VIX, USEPU, GEPU, GR and PC denote the uncertainty indices for the S&P500, US economic policy uncertainty, global economic policy uncertainty, geopolitical risk and partisan conflict, respectively.
*, **, *** denote significance at 10%, 5% and 1% level, respectively.

Table A.4: MSPE results from the real out-of-forecasts based on the DL. Forecasting period: October 2015 – February 2019.

Forecasting horizons	*RW*	*DL*	DL_{USEPU}	$\frac{DL_{USEPU}}{RW}^{a}$	$\frac{DL_{USEPU}}{DL}^{a}$
1	139.0763	42.7974	43.7381	0.3145	1.0220
2	141.0662	83.4373	76.9663	0.5456	0.9224
3	136.9169	99.6763	113.5156	0.8291	1.1388
4	133.6481	100.8561	101.3804	0.7586	1.0052
5	107.5744	86.3938	94.3582	0.8771	1.0922
6	83.0601	68.7852	71.9800	0.8666	1.0464
7	77.5165	66.1093	68.1611	0.8793	1.0310
8	74.8428	65.7583	77.9542	1.0416	1.1855
9	75.3276	65.9992	140.6598	1.8673	2.1312
10	75.7115	80.1259	113.4930	1.4990	1.4164
11	73.2832	97.6687	98.4676	1.3437	1.0082
12	71.3890	102.0121	123.9249	1.7359	1.2148

[α] A ratio below one suggests that the DL_{USEPU} model performs better relatively to the *RW* or the *DL* model.