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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.

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

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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 website¹ (*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 ($VIX_b, USEPU_b, GEPU_b, GR_b, PC_b$) and OVX_t . We start with the generic form of a p -th order, N -variable Vector Autoregressive (*VAR*) model:

$$\mathbf{z}_t = \sum_k^p \boldsymbol{\Theta}_k \mathbf{z}_{t-k} + \mathbf{e}_t, \quad (1)$$

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

$$\mathbf{z}_t = \sum_{b=0}^{\infty} \mathbf{A}_b \mathbf{e}_{t-b}, \quad (2)$$

where, the $[N \times N]$ coefficient matrices \mathbf{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:

$$\phi_{ij,t}(H) = \frac{\sigma_{jj}^{-1} \sum_{l=1}^{H-1} (\mathbf{u}'_i \mathbf{A}^l \mathbf{S} \mathbf{u}_j)^2}{\sum_{l=1}^{H-1} (\mathbf{u}'_i \mathbf{A}_l \mathbf{S} \mathbf{A}'_l \mathbf{u}_i)}, \quad (3)$$

where, σ_{jj}^{-1} is the standard deviation of the estimated error term for the j -th equation of the *VAR* model and \mathbf{u}_i is a selection vector, which assumes the value of one for element i and zero otherwise. \mathbf{S} is the estimated variance matrix of vector \mathbf{e} . The $\phi_{ij}(H)$ 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 $\sum_{j=1}^N \phi_{ij}(H) \neq 1$) is $\tilde{\phi}_{ij,t}(H) = \frac{\phi_{ij,t}(H)}{\sum_{j=1}^N \phi_{ij,t}(H)}$. Our main focus, though, is on the net pairwise spillover effects that can be obtained as:

$$NPWS(H) = \tilde{\phi}_{ij,t}(H) - \tilde{\phi}_{ji,t}(H). \quad (4)$$

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 model³, which is extended in order to include information from the net pairwise spillover effects:

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. $(0, \mathbf{S})$, but we do not need to specify the distribution of \mathbf{e}_t , as long as the independency over time holds. The assumption of normally distributed errors is required only for the statistical inference.

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.

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

where $\varepsilon_t \sim (0, \sigma_\varepsilon^2)$, UNC_t denotes each one of the five alternative uncertainty indicators, $UNC_t \in \{VIX_b, USEPU_b, GEPUB, GR_b, PC_t\}$, the $d(NPWS_{OVX-UNC,t} < 0)$ is a dummy variable that takes the value of one when the uncertainty indicator (UNC_t) is a net transmitter of spillover effects⁴ 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 $h=1, \dots, 12$. Henceforth, in order to estimate real out-of-sample forecasts, Eq. (5) is re-estimated as:

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

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

Fig. 1 illustrates the net pairwise spillovers between UNC and OVX . Not surprisingly, OVX is mainly a transmitter of shocks to VIX and $GEPUB$, 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 specifically, 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.

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.

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 significant⁵. 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.

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

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

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

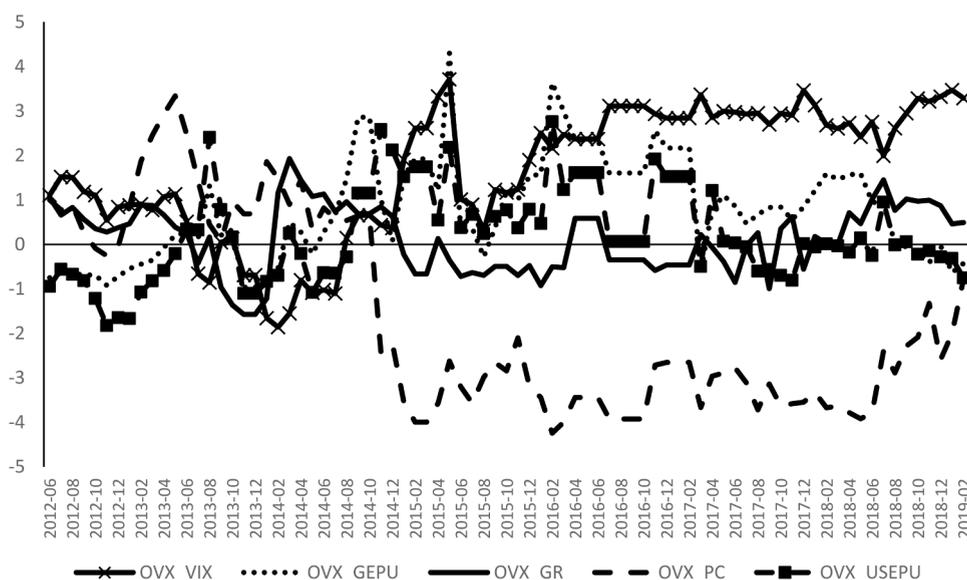


Fig. 1. Net pairwise spillover effects between OVX and uncertainty indicators. Note: OVX is a net transmitter (receiver) of spillover effects when the line is above (below) the zero line.

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.

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 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

Table 2

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

Forecasting horizons	RW	HAR	HAR_{USEPU}	$\frac{HAR_{USEPU}^a}{RW}$	$\frac{HAR_{USEPU}^a}{HAR}$
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

^aA ratio below one suggests that the HAR_{USEPU} model performs better relatively to the RW or the HAR model.

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.

Declarations of Competing Interest

None.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:[10.1016/j.frl.2020.101885](https://doi.org/10.1016/j.frl.2020.101885).

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