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Abstract

We consider spillovers between oil price volatility and key uncertainty indicators. Adding to existing studies, we extend the applicability of the spillover index beyond economic inference, by generating forecasts of oil price volatility. Findings suggest that spillover effects do not contain significant predictive information. This in turn, raises critical questions regarding the usefulness of the spillover index for such task. However, it is critical to collect further evidence for the support of our findings.

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

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 each uncertainty indicator ($VIX_t, USEPU_t, GEPU_t, GR_t, PC_t$) 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 $\boldsymbol{e}_t \sim (0, S)$ is a vector of disturbances, independent over time (although not necessarily *i.i.d.*). Finally, $t = 1$,…, T is the time index. The standard moving average representation of *VAR* is:

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

where, $N \times N$ coefficient matrices $\boldsymbol{A}_b$ are recursively defined and $\boldsymbol{A}_0$ is the $N \times N$ identity matrix. We employ a generalized framework (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:

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

where, σ_{jj}^{-1} is the standard deviation of the error term (estimation) for the j-th equation of the *VAR* model and $\boldsymbol{u}_i$ is a selection vector, which assumes the value of

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

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., because: $\sum_{j=1}^{N}\boldsymbol{\varphi}_{ij}(H) \neq 1$) 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, using a simple HAR model[2], which we extend to include information from the net pairwise spillover effects:

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

where $\varepsilon_t \sim (0, \sigma_\varepsilon^2)$, UNC_t denotes each of the five alternative uncertainty indicators, $UNC_t\colon \{VIX_t, USEPU_t, GEPU_t, GR_t, PC_t\}$, the $d\big(NSPW_{OVX-UNC,t} < 0\big)$ is a dummy variable that takes the value of one when the uncertainty indicator (UNC_t) is a net transmitter of spillover effects[3] to OVX and zero otherwise.

Following the in-sample estimation of eq.5, 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:

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

[2] 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 a distributed lag model and an autoregressive model. Results are qualitatively similar and available upon request.

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

The forecasts from eq.6 are then compared to a simple random walk (RW) ($log(OVX_t) = \alpha_0 + \varepsilon_t$) and simple HAR model (for $\alpha_4 = \alpha_5 = \alpha_6 = 0$), based on the well-established Mean Squared Predictive Error (MSPE) loss 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). Conversely, OVX mainly receives from PC, which could be explained by the impact of political disagreement on aggregate investment (Azzimonti, 2018). 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. The impact of GR is less clear as it assumes both roles. Nevertheless, it transmits spillover effects to OVX during the oil price collapse period.

[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.

[Table 1 here]

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 establish whether the in-sample gains from spillover effects transmitted by the $USEPU$ improve the accuracy for OVX forecasting. Table 2 suggests that $USEPU$ spillover effects provide some forecasting gains, yet these are not statistically significant[4]. Hence, we maintain that the spillover effects do not contain any incremental predictive ability, either compared to the RW or the simple

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

HAR model. Thus, the usefulness of spillover effects beyond economic inference is questionable.

[Table 2 here]

4. Conclusion

We generate forecasts of OVX based on net spillovers between the variable itself and key uncertainty indicators. Findings suggest that spillovers do not generate significant real out-of-sample forecasting gains, casting doubt on the overall effectiveness of the spillover approach. Nonetheless, to further the support of such findings, additional evidence is required, considering different asset classes and the spillover magnitudes.

References

Antonakakis, N., Chatziantoniou, I. & Filis, G. (2014). Dynamic spillovers of oil price shocks and economic policy uncertainty. *Energy Economics*, *44*, 433-447.

Azzimonti, M. (2018). Partisan conflict and private investment. *Journal of Monetary Economics,* 93, 114-131.

Azzimonti, M. (2014). *Partisan conflict.* Federal Reserve Bank of Philadelphia. Working paper series, No. 14-19.

Baker, S.R., Bloom, N. & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4), 1593-1636.

Bekiros, S., Gupta, R. & Paccagnini, A. (2015). Oil price forecastability and economic uncertainty. *Economics Letters*, 132, 125-128.

Caldara, D. & Iacoviello, M. (2018). Measuring geopolitical risk. *FRB International Finance Discussion Paper*, 1222.

Corsi, F. (2009). A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics*, 7, 174–196.

Degiannakis, S. & Filis, G. (2017). Forecasting oil price realized volatility using information channels from other asset classes. *Journal of International Money and Finance*, 76, 28-49.

Degiannakis, S. & Filis, G. (2018). Forecasting oil prices: High-frequency financial data are indeed useful. *Energy Economics*, 76, 388-402.

Degiannakis, S. & Filis, G. (2019). Forecasting European economic policy uncertainty. *Scottish Journal of Political Economy*, 66(1), 94-114.

Diebold, F. X. & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, 119(534), 158-171.

Diebold, F. X. & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1), 57-66.

Hansen, P.R., Lunde, A. & Nason, J.M. (2011). The model confidence set. *Econometrica*, *79*(2), 453-497.

Kang, W., de Gracia, F. P. & Ratti, R. A. (2017). Oil price shocks, policy uncertainty, and stock returns of oil and gas corporations. *Journal of International Money and Finance*, 70, 344-359.

Koop, G., Pesaran, M. H. & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics,* 74(1), 119-147.

Pesaran, H.H. & Shin, Y. (1998). Generalised impulse response analysis in linear multivariate models. *Economics Letters,* 58(1), 17-29.

TABLES

Table 1: Estimated results 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. 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.

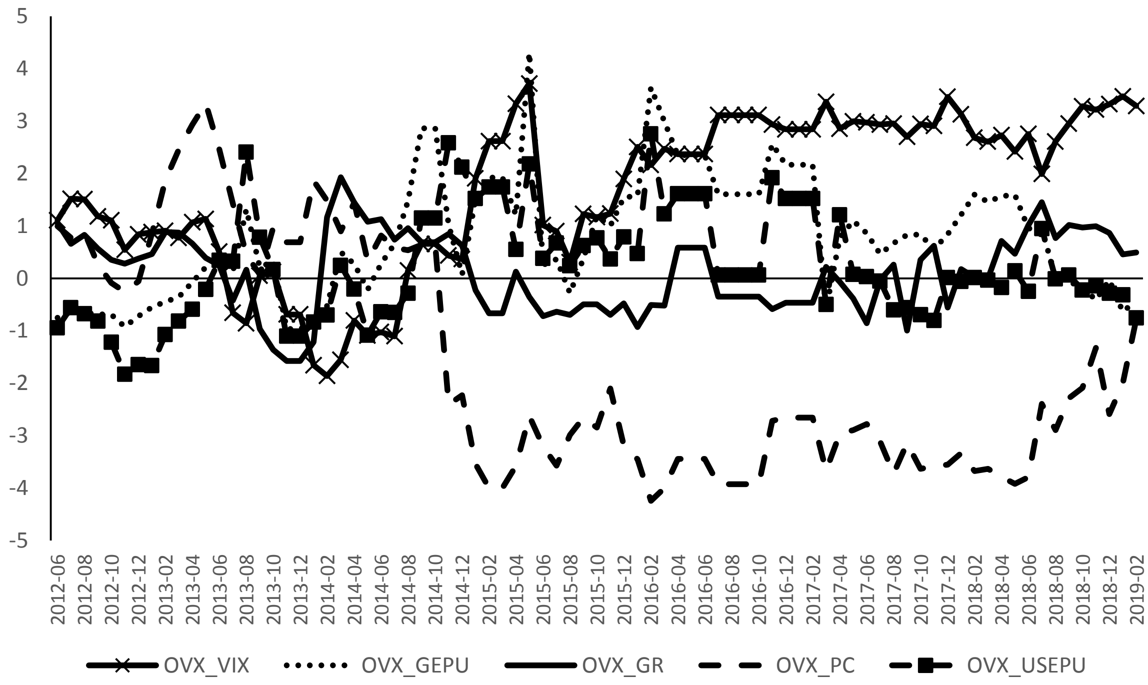
Table 2: MSPE results from the real out-of-forecasts. Forecasting period: October 2015 – February 2019.

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