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NAVIGATING CRUDE OIL VOLATILITY FORECASTS: ASSESSING THE CONTRIBUTION OF GEOPOLITICAL RISK

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ABSTRACT

Media evidence and previous research have established that geopolitical risk is an important driver of crude oil price volatility. In this paper, we assess whether the importance of geopolitical uncertainty is also "translated" into valuable predictive information for oil price volatility forecasts. To do so, we construct a "beauty contest" where we assess the incremental predictive content of geopolitical risk against several other highly important uncertainty indicators, for forecasting horizon up to 22-days ahead. Initially, we use a HAR model which is augmented by each of the uncertainty indicators. Subsequently, we develop a Dynamic Model Averaging (DMA) methodology, where we assess whether the combination of all uncertainty indices (DMA-all), vis-a-vis a DMA model without the geopolitical uncertainty index, exhibits superior predictive performance. Our findings show that geopolitical uncertainty offers superior predictive information when combined with other uncertainty indicators. More importantly, we show that the inclusion of geopolitical uncertainty in a DMA framework generates superior trading profits and risk management measures' predictions, in comparison with benchmark models, especially in longer-run horizons. Several implications are drawn from these results.

Keywords: HAR model, Realized oil price volatility, Geopolitical risk, Dynamic model averaging, Forecasting evaluation, Value-at-Risk, Trading profits

JEL Codes: C10, C22, C53, F30, G17, Q47.

Disclaimer : The views expressed in this paper are those of the authors and not necessarily those of the Bank of Greece.

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1 Introduction

Crude oil plays a crucial role in the global economy since it is considered a key commodity for all economies. According to Vo (2011), a rise in oil price impacts production costs, which can, in turn, affect future inflation. Apart from its significant impact on the macroeconomic environment, oil price shocks can affect financial markets immediately. Furthermore, over the last two decades, the behaviour of oil price fluctuations has changed massively making the market environment rather volatile. Such a regime change in the oil market fluctuations, which affects policy decisions and financial stability, made researchers and policy makers to turn their attention to modelling and forecasting oil price volatility (Ferderer, 1996; Baumeister and Kilian, 2016; Wang et al., 2016; Charles and Darne, 2017; Degiannakis and Filis, 2017; Delis et al., 2022). Coupled with this, the importance of forecasting oil price volatility has been also intensified in recent years due to the financialization of oil market, which originated by the fact that financial institutions to consider oil market as an important investment asset and not a pure consumption asset (Silvennoinen and Thorp, 2013).

The abovementioned developments have also led to the need for a clear understanding of which are the main determinants and predictors of oil price volatility. In this regard, it is widely known that crude oil is characterized by its special geopolitical nature, which differentiates it from other commodities and financial assets. This key characteristic should be taken into account by the relevant stakeholders, namely investors and policy makers.

There are several studies focusing on the impact of geopolitical risk on oil market uncertainty (e.g. Miao et al., 2017; Brandt and Gao, 2019). The motivation of those studies comes from the fact that geopolitical events affect both oil demand and supply, as well as, the uncertainty about the future availability of oil. More specifically, geopolitical tensions, on one hand, can create oil supply shocks due to changes in oil production by the oil producing countries, which result in higher oil price uncertainty (Brown and Huntington, 2017; Bouoiyour et al., 2019; Zhang et al., 2023). From the demand side, geopolitical risk could halt economic activity, leading to abrupt reduction in oil demand and increased oil price volatility (Bouoiyour et al., 2019; Cunado et al., 2020; Mignon and Saadaoui, 2024). Finally, sudden shifts in geopolitical uncertainty could also affect the precautionary demand for oil, which could create abrupt changes in oil prices and volatility. Against this backdrop, this paper extensively examines the predictive information that geopolitical risk offers to the crude oil uncertainty (or else oil price volatility).

Studies on the relationship between geopolitical risk and the oil market have flourished since Caldara and Iacoviello (2018) constructed the geopolitical risk index (GPR)[1] In our paper, we assess the predictive power of the GPR index, along with its two sub-indices of geopolitical threats and acts, for crude oil price volatility forecasts. In a nutshell, we identify which GPR (index or sub-index) provides the most useful information, and at which time-horizons, when generating oil price realized volatility forecasts at short-, mid- and long-term horizons. To provide, though, a meaningful conclusion on the predictive ability of GPR (and its sub-indices) for oil price volatility forecasting, we create a "beauty contest" where additional uncertainty indices are evaluated in our forecasting framework, such as the Economic Policy Uncertainty index (EPU), Financial Stress Index (FSI), the Aruoba-Diebold-Scotti (ADS) Business Condition index, as well as, proxies of financial markets volatility indices (VIX, VXD and VXN). These indices have been chosen as they are the most well–known indices that capture different layers of uncertainty, namely, the uncertainty originating from economic policies, the financial system, the real economy and the financial markets, which could drive changes in the oil market (see, for instance, Apostolakis et al., 2021; Chen et al., 2022; Cross et al., 2022; Fernandez-Perez and López, 2023). In addition, there is ample evi-

[1]The GPR index is based on articles of leading international newspapers covering geopolitical tensions by counting the occurrence of all relevant words. More specifically, this index covers topics that are associated with wars, acts of terrorism and any tension occurred between states, which affects the international relations from a peace perspective. Furthermore, the availability of the GPR index is not confined at the aggregates level. A disentanglement between the effects of adverse geopolitical events from the effects of pure geopolitical risks has been conducted. This disentanglement results in the availability of two sub-indices, namely the geopolitical threats (GPR THREAT) and the geopolitical acts (GPR ACT) indices. The construction of the GPR THREAT index relies on identification of words reflecting explicit mentions of geopolitical risk, military-related tensions, nuclear tensions, war threats and terrorist threats. By contrast, the GPR ACT index is based on identification of words capturing actual adverse geopolitical events, such as the beginning of a war or terrorist acts.

dence of their forecasting ability on oil price volatility. [2]. We note that our aim is not to assess an extensive list of uncertainty indicators but rather to compare the predictive power of the most commonly–used indicators against the GPR indices. We leave the latter for future work.

Overall, this paper contributes to the literature in the following ways. First of all, the main contribution of this paper is the investigation whether the GPR index and its two sub-indices provide predictive power to oil price volatility forecasts. Second, we extend the existing literature by assessing the performance of the GPR indices in an integrated methodological framework, where a variety of uncertainty indicators have been incorporated so to assess the predictive gains from the GPR indices vis-a-vis the other well–known uncertainty indicators, when forecasting oil price volatility. Furthermore, we assess the time-varying contribution of the GPR indices on oil price volatility forecasts, so as to identify the time periods when he highest predictive power is obtained. In this regard, the contribution of the forecasting model specifications that include GPR indices, through a DMA approach, will be assessed. Finally, the forecast evaluation framework is not limited to statistical loss-functions, but economic and risk management evaluations functions are also applied in order to examine the predictive role of GPR indices on oil price volatility in real-world applications.

[2] For instance, EPU has been incorporated in the modelling framework of several forecasting exercising (e.g. Wei et al., 2017; Ma et al., 2019; Wang et al., 2022; Li et al., 2022), showing a superior predictability of oil price volatility. The FSI index provides market-based snapshot of financial markets' stress on a daily basis. The index is constructed based on 33 financial market variables, such as yield spreads, valuation measures and interest rates. According to Nazlioglu et al. (2015) oil market movements are affected by financial stress through its impact on both economic activity and investor behavior. On the one hand, increased financial stress causes economic activity to slow down, which leads to lower energy demand, declining oil prices and higher volatility. On the other hand, increased financial stress seems to cause investors to adjust their portfolios and, therefore, is likely to have an impact on oil price fluctuations, given the financialization of the latter market (Gkillas et al., 2020). Furthermore, the ADS index is designed to track real business conditions at high observation frequency, along with lower frequency economic indicators, such as weekly initial jobless claims, monthly industrial production, quarterly real GDP. Fluctuating business conditions tend to impact the demand for oil and hence the oil prices and its volatility. Finally, motivated by several studies that use implied volatility measures to improve the predictive performance of their realized volatility models (Busch et al., 2011; Gong and Lin, 2018; Lv, 2018), and due to the strong interconnectedness between oil and stock market volatilities (Boldanov et al., 2016; Degiannakis and Filis, 2017), we enhance the list of uncertainty indices that are used as predictors of oil price volatility with the most representative implied volatility indices of the US stock market, namely the CBOE Volatility Index (VIX), the NASDAQ-100 Volatility Index (VXN) and the DJIA Volatility Index (VXD).

The findings of this paper indicate that the GPR indices generate more accurate oil price volatility predictions, relatively to other uncertainty indicators, especially for the mid- and long-run horizons. More importantly, though, our DMA framework strongly suggests that the incorporation of the GPR indices, along with the remaining uncertainty factors, is capable of enhancing the predictive accuracy for oil price volatility. These improved forecasts are also useful for trading and risk management purposes. For instance, the DMA model that incorporates the GPR indices (DMA-all model) generates annualized cumulative trading returns that are approximately 7% higher compared to the DMA model that excludes geopolitical uncertainty (DMA-without GPR model), in the long-run horizons. Finally, the magnitude of trading losses, given the violation of the VaR, are materially lower when the VaR is measured based on the oil price volatility forecasts from the DMA-all model.

The rest of the paper is structured as follows. Section 2 explains the estimation procedure of the realized oi price volatility. Section 3 presents the data that are used in this study, whereas Section 4 details the methodology, which is separated into the individual HAR models and DMA combination modelling framework. Section 5 describes the evaluation framework and Section 6 analyses the findings of the study before we conclude the paper in Section 7.

2 Estimating realized volatility

Realized volatility has been widely used as a proxy for the volatility based on the use of intraday data. In our paper, the estimation of realized volatility is based on the realized standard deviation measure due to its simplicity and the fact that the purpose of this study is not to find the most accurate realized volatility measure. Therefore, we use the most widely used and simple measure compared to alternative measures, such as the realized kernel that is appropriate for capturing market microstructure noise. Therefore, our analysis is based on tick-by-tick data that are aggregated at 10min sampling frequency, which is sufficient to capture the actual but unobservable volatility of the series, while minimizing the microstructure noise of the tick-by-tick data.

Let the returns calculated as $r_{t,j} = log(\frac{p_{t,j}}{p_{t,j-1}})$, where $p_{t,j}$ is the oil price, for $j =$

$1, 2, \ldots, M$, denoting the time of observation within each day, and $t = 1, 2, \ldots, T$ represents the number of days. Thus, the daily realized standard deviation measure is calculated as the sum of squared intraday returns:

$$RV_t = \sqrt{\sum_{j=1}^{M} r_{t,j}^2} \tag{1}$$

It is noted that the realized volatility converges to the integrated volatility as the sampling frequency goes to zero and the number of intraday intervals (M) approaches infinity. In this paper, we are in line with Hansen and Lunde (2005) and we work with annualized realized volatility, which is computed as:

$$ARV_t = RV_t\sqrt{252}. \tag{2}$$

3 Data description

Our study period runs from January 4, 2010 to August 30, 2019[3] and the number of observations is 2494 (trading days). For the estimation of the realized oil price volatility, data of the front-month futures contracts for the WTI crude oil are used. The sampling frequency of the dataset is chosen to be 10 minutes, since, according to the literature, the issue of the autocovariance bias induced by market microstructure noise seems to be minimized when working with such frequencies. The source of the retrieved data is TickData.

In our work, we also use the oil price implied volatility index (OVX) as a key predictive variable, which enters in all models. A number of papers use OVX from the Chicago Board Options Exchange (CBOE) in order to improve the oil price realized volatility forecasts (Haugom et al., 2014; Dutta, 2017). These studies have shown that OVX can explain and predict the future oil market uncertainty. Hence, the use of OVX in the simple HAR model (HAR-OVX) is considered as our benchmark model, where the augmented models are required to improve.

[3] The tick-by-tick WTI oil prices are available to the authors until August 2019. Hence, due to data availability issues, the sample ends at that period.

Figure 1 portrays the annualized realized volatility together with the OVX series, given their close relationship. It is apparent that high values of volatility are observed in 2011 and 2012, which is related to the geopolitical tensions that sparked due to the Libyan uprising. Furthermore, during the 2015-2016 period we observe significant increase in oil price volatility due to the oil price plunge at that period, which was triggered by the global oil supply glut, the de-escalation of geopolitical concerns in the Middle East, as well as, the weak global aggregate demand. Finally, the oil price volatility peaks in late 2018 and early 2019 are related to the US-China trade war, as well as, conflicts between US and Iran. Hence, from Figure 1 we can immediately observe the role of geopolitical tensions on oil price volatility during our sample period.

[FIGURE 1 HERE]

Besides the intraday data used for estimating the daily realized oil price volatility, our dataset includes the daily data of our predictive uncertainty indicators. Our key variables of interest are the GPR index and its sub-indices (GPR THREAT and GPR ACT), which have been retrieved by the relevant website[4]. As already mentioned in the introduction, the GPR indices are based on automated text-search results of the electronic archives of 11 national and international newspapers, which contain search terms that are related to geopolitical risks on daily basis.

Figure 2 depicts the GPR index and its two sub-indices. It is rather interesting that as we move towards the end of our sample period, the GPR index and the GPR THREAT assume higher values, whereas the reverse is true for the GPR ACT. Inspecting both Figures 1 and 2 we can observe that indeed there seems to be some relationship between the peaks in GPR indices and peaks in oil price volatility, which could be translated into predictive gains for the latter.

[FIGURE 2 HERE]

As mentioned in Section 1, our additional predictors of oil price realized volatility include the most well–known uncertainty indices. First, we consider the US Economic Policy Uncertainty Index[5] developed by Baker et al. (2016). Furthermore, we also con-

[4] See https://www.matteoiacoviello.com/gpr.htm for further details.

[5] The data are obtained from https://www.policyuncertainty.com/us_monthly.html.

sider the US Financial Stress Index (FSI) as a potential predictor[6]. Our real-economy uncertainty indicator is the Aruoba- Diebold-Scotti (ADS) Business Condition index and the data are retrieved by the Federal Reserve Bank of Philadelphia[7]. Finally, we use stock market implied volatility indices, as proxies of our financial markets uncertainty, namely the OVX, VIX, VXN and VXD. This dataset is readily available at a daily frequency and is obtained from CBOE for the corresponding implied volatility indices.

Figure 3 displays all the above mentioned uncertainty indices, categorized per related class. Interestingly enough, Figure 3 suggests that there are similar peaks in the uncertainty indices and the oil price realized volatility, from Figure 1. For instance, the high values of the FSI, EPU and implied volatility indices in 2011-2012 coincide with the oil price volatility peaks of the same period. Similar observations can be made for the 2015-2016 and 2018-2019 periods. Even more, the trough of the ADS index in early 2019 also coincides with the peak in oil price volatility. Hence, this eye-ball examinations allows us to conclude that these uncertainty indices are also expected to provide predictive gains for oil price volatility forecasts.

[FIGURE 3 HERE]

In Table 1 we present the descriptive statistics of all our variables. We observe that almost none of the variables under consideration is normally distributed, since all variables present positive skewness and excess kurtosis. The only exception is ADS, which seems to be closer to the normal distribution. Another noteworthy point is that, according to the coefficient of variation (CV), the RV seems to be more dispersed compared either to the OVX or the additional implied volatility indices.

[TABLE 1 HERE]

[6]The data is available for download from the Office of Financial Research, https://www.financialresearch.gov/financial-stress-index/.

[7]The ADS index on the web page https://philadelphiafed.org/research-and-data/real-time-center/business-conditions-index.

4 Modelling framework

4.1 Näive and benchmark models

In this paper, we use a simple Random Walk (RW) without a drift, as the most näive model, similarly to the common practice of the related literature (see, Murat and Tokat, 2009; Degiannakis and Filis, 2017; Dutta, 2017, among others). The RW is expressed as follows:

$$log(ARV_t) = log(ARV_{t-1}) + \varepsilon_t, \tag{3}$$

where ARV_t is the annualised realized volatility of the WTI crude oil at day t and ε_t is a white noise.

In addition to the RW, the simple HAR model (HAR-RV) is considered as one of our benchmark models, which is based on the HAR model specification proposed by Corsi (2009). There is a wealth of literature, already cited here, which confirms that the simple HAR-RV model is indeed a benchmark model for oil price volatility forecasting (Busch et al., 2011; Sévi, 2014; Gkillas et al., 2020; Degiannakis and Filis, 2022, to name a few). In our study we choose to use the simple HAR model as a benchmark, for two reasons. First, it is easy to be estimated and, second, according to the literature, it is considered difficult to be beat by extended versions, when referring to the energy markets (e.g., Sévi, 2014; Prokopczuk et al., 2016; Degiannakis and Filis, 2017). However, it is important to note that recent years there have been proposed indeed very promising extended versions of the HAR model, such as that of Jawadi et al. (2020) who consider trading volumes and jumps as significant volatility drivers or the HARQ by Bollerslev et al. (2016) and the SHAR by Patton and Sheppard (2015). The use of such extended versions of the simple HAR model could be applied in future research.

More specifically, the HAR structure captures stylized facts of financial market volatility such as long memory and was motivated by the heterogeneous market hypothesis proposed by Muller et al. (1997). Thus, the main idea of the HAR specification is to use realized volatility aggregated over different time horizons in order to disentangle the information coming from the expectations of different market participants (e.g.

short-term traders and long-term traders). The HAR-RV model is written as follows:

$$
\begin{aligned}
log(ARV_t) = a_0^{(t)} + a_1^{(t)} log(ARV_{t-1}^{(d)}) + a_2^{(t)} log(ARV_{t-1}^{(w)}) \\
+ a_3^{(t)} log(ARV_{t-1}^{(m)}) + \varepsilon_t,
\end{aligned}
\tag{4}
$$

where ε_t is the error term and $a_0^{(t)}, a_1^{(t)}, a_2^{(t)}, a_3^{(t)}$ are the parameters. Moreover, the components of the HAR structure, namely the realized volatilities aggregated over different time horizons, are calculated as follows: $log(ARV_{t-1}^{(d)}) = log(ARV_{t-1})$; $log(ARV_{t-1}^{(w)}) = \left(5^{-1} \sum_{k=1}^{5} log(ARV_{t-k})\right)$; $log(ARV_{t-1}^{(m)}) = \left(22^{-1} \sum_{k=1}^{22} log(ARV_{t-k})\right)$, which is in line with Corsi and Renò (2012).

Despite the fact that the literature has nominated the HAR-RV model as a key benchmark framework for oil price volatility forecasting, some show that the HAR-RV that is augmented with the oil price implied volatility index (OVX) could yield improved forecasts (see, Haugom et al., 2014; Dutta, 2017; Lv, 2018, for instance.). Thus, our HAR-RV model is extended by including the OVX as the key exogenous predictor (HAR-OVX)[8]. The HAR-OVX model is our second benchmark model and its specification is written as:

$$
\begin{aligned}
log(ARV_t) = a_0^{(t)} + a_1^{(t)} log(ARV_{t-1}^{(d)}) + a_2^{(t)} log(ARV_{t-1}^{(w)}) \\
+ a_3^{(t)} log(ARV_{t-1}^{(m)}) + \beta_1^{(t)} log(OVX_{t-1}) + \varepsilon_t,
\end{aligned}
\tag{5}
$$

where $log(OVX_{t-1})$ is the one lagged OVX in logarithmic transformation.

4.2 Augmenting the benchmark model with the GPR indices

Existing studies (already discussed previously in this section) in their search for improving forecasting accuracy, they typically augment a benchmark model with additional predictive factors. Such an approach allows them to assess the incremental predictive gains for each of their chosen predictors. Given that the HAR-OVX model provides significant predictive information to oil price realized volatility, we opted to

[8] An alternative proxy to OVX for oil price volatility is the OPU index, developed by Abiad and Qureshi (2023). However, given the high correlation between these two indices, we opted to use OVX so that our framework is closely related to the current literature that has considered the HAR-OVX model as a key benchmark model for oil price volatility forecasting.

augment eq.5 specification with the additional predictors that reflect the exogenous information of the geopolitical risk[9], such as:

$$
\begin{aligned}
log(ARV_t) = {} & a_0^{(t)} + a_1^{(t)} log(ARV_{t-1}^{(d)}) + a_2^{(t)} log(ARV_{t-1}^{(w)}) \\
& + a_3^{(t)} log(ARV_{t-1}^{(m)}) + \beta_1^{(t)} log(OVX_{t-1}) + \beta_2^{(t)} X_{t-1}^{(GP)} + \varepsilon_t,
\end{aligned} \tag{6}
$$

where GP=GPR, $GPR\ THREAT$ or $GPR\ ACT$[10].

4.3 Augmenting the benchmark model with the other uncertainty indices

Our "beauty contest" requires the estimation of the HAR-OVX model that is extended to include the exogenous information from the remaining competing uncertainty indicators ($OTHER$), which were mentioned in Section 1, such as:

$$
\begin{aligned}
log(ARV_t) = {} & a_0^{(t)} + a_1^{(t)} log(ARV_{t-1}^{(d)}) + a_2^{(t)} log(ARV_{t-1}^{(w)}) \\
& + a_3^{(t)} log(ARV_{t-1}^{(m)}) + \beta_1^{(t)} log(OVX_{t-1}) + \beta_2^{(t)} X_{t-1}^{(OTHER)} + \varepsilon_t,
\end{aligned} \tag{7}
$$

where $OTHER$=EPU, ADS, FSI, $log(VIX)$, $log(VXD)$ or $log(VXN)$[11].

Note that the role of this "beauty contest" is to assess whether the geopolitical uncertainty provides superior predictive ability relatively to other well-known and commonly used uncertainty indicators, which capture different layers of economic and financial uncertainty.

To summarize, we estimate 12 individual models (AR, HAR-RV, HAR-OVX and 9 HAR-OVX-X models) and we obtain their forecasts for 1- up to 22-days ahead horizons. We note that our forecasting framework is not subject to forward-looking bias or any

[9]We reiterate that we augment the HAR-OVX (rather than the HAR-RV) with the GPR indices, given that the literature has suggested that the former is rather superior to the simple HAR-RV.

[10]For robustness purposes, we examined for potential non-linearities and asymmetries in the GPR-oil price volatility relationship. Should they have been existed they would be considered in the out-of-sample forecasts. Nevertheless, our analysis did not find evidence on either a non-linear or an asymmetric relationship.

[11]The logarithmic transformation has been applied to the the implied volatility indices, since the handling of the variables transformations is important to be consistent across all volatility indices (realized or implied).

data leakage, hence we generate out-of-sample forecasts which are always based on the available information set at time t.

4.4 Dynamic model averaging (DMA) approach

The forecasting models that have been explained thus far assume that the predictors which are included in each model remain constant over the study period. Hence, having estimated the individual models, we proceed with the use of an integrated modelling framework that combines the predictive information from the different uncertainty indicators and allows the estimation of time–varying parameters in order to capture potential breaks in our series. Thus, a DMA framework, initially proposed by Raftery et al. (2010), is employed that allows for K models of different specifications to generate forecasts that are optimally aggregated over time. The state-space model[12] consists then of the two following equations:

$$y_t = \boldsymbol{x_t^{(k)}} \boldsymbol{\alpha_t^{(k)}} + \varepsilon_t^{(k)} \quad \text{for} \quad \varepsilon_t^{(k)} \sim N(0, H_t^{(k)}), \tag{8}$$

$$\boldsymbol{\alpha_t^{(k)}} = \boldsymbol{\alpha_{t-1}^{(k)}} + \boldsymbol{u_t^{(k)}} \quad \text{for} \quad \boldsymbol{u_t^{(k)}} \sim N(\boldsymbol{0_{4\times 1}}, \boldsymbol{\Sigma_{u_t}^{(k)}}). \tag{9}$$

where $k = 1, \ldots, K$, y_t denotes the dependent variable $log(ARV_t)$, $\boldsymbol{\alpha_t^{(k)}}$ are the regression parameters of three volatility components that constitute the simple HAR-RV model specification and the errors $\varepsilon_t^{(k)}$ and $\boldsymbol{u_t^{(k)}}$ are mutually independent. Moreover, if there are m predictors in $\boldsymbol{x_t^{(k)}}$, the total number of possible combinations of these predictors is $K = 2^m$. According to the Eq. (8), which is based on the HAR-RV specification, the number of combinations is $K = 2^4 = 16$. This model can be estimated by using the Kalman filter method[13]. One key element that has to be mentioned is that the approximation of the forgetting factor λ, which is used in order to avoid estimating the state covariance matrix $\boldsymbol{\Sigma_{u_t}^{(k)}}$ is replaced by the standardized self-perturbed Kalman filter[14]

[12]This state space form is based on the simple HAR-RV model specification for simplicity reasons. The state space model is of similar fashion for the other models that include uncertainty indicators as predictors of the realized oil price volatility.

[13]More details for each step of the estimation of time-varying parameter models and the combination of those models through the DMA approach can be found in the Appendix.

[14]This methodological part is motivated by the study of Delis et al. (2022), which provides more details on this approximation.

proposed by Grassi et al. (2017). This specific approach avoids the calibration of a design parameter as the perturbation term is scaled by the amount of the uncertainty in the realized oil price volatility data. In this study, the main purpose is to explore the incremental forecasting performance of the models that include both the GPR indices and alternative uncertainty indicators, such as the economic policy uncertainty, contrary to those that do not contain any of the GPR indices. Thus, we implement a DMA modelling approach, as follows:

DMA - without GPR:

$$y_t = \boldsymbol{x_t^{(k)}} \boldsymbol{\alpha_t^{(k)}} + \boldsymbol{x_{t,OTHER}^{(k)}} \boldsymbol{\beta_t^{(k)}} + \varepsilon_t^{(k)} \quad \text{for} \quad \varepsilon_t^{(k)} \sim N(0, H_t^{(k)}), \tag{10}$$

DMA - all:

$$y_t = \boldsymbol{x_t^{(k)}} \boldsymbol{\alpha_t^{(k)}} + \boldsymbol{x_{t,OTHER}^{(k)}} \boldsymbol{\beta_t^{(k)}} + \boldsymbol{x_{t,GP}^{(k)}} \boldsymbol{\gamma_t^{(k)}} + \varepsilon_t^{(k)} \quad \text{for} \quad \varepsilon_t^{(k)} \sim N(0, H_t^{(k)}). \tag{11}$$

An important advantage of this combinative methodology is the ability to extract the weights corresponding to the individual models that include specific group of variables (e.g., GPR indices) as predictors in the DMA-all model. More specifically, the aggregation of these models' weights provides evidence for a higher probability of these specific explanatory variables to be included in the optimal combined forecast of oil price volatility. Hence, through the DMA framework we aim to reveal the corresponding weight of all uncertainty factors (but more importantly of the GPR indices) to oil price volatility forecasts.

5 Forecast evaluation

5.1 Prediction settings

Our in-sample period runs from January 4, 2010 until March 17, 2014. The out-of-sample periods start in March 18, 2014, leaving us with 1408 out-of-sample forecasts for each horizon (1- up to 22-days ahead). Furthermore, we use direct multi-step ahead forecasting approach [15], with 1000 days as our fixed-window length for the rolling estimations.

5.2 Statistical loss functions

Initially we evaluate the forecasting performance of the competing models using two well-known statistical loss functions, namely the Mean Squared Predicted Error (MSPE) and the Mean Absolute Error (MAE), which are defined as:

$$MSPE^{(h)} = \frac{1}{T_1}\sum_{t=1}^{T_1}(ARV_{t+h|t} - ARV_{t+h})^2, \tag{12}$$

and

$$MAE^{(h)} = \frac{1}{T_1}\sum_{t=1}^{T_1}\mid ARV_{t+h|t} - ARV_{t+h}\mid, \tag{13}$$

where $ARV_{t+h|t}$ is the h-days-ahead realized volatility forecast, ARV_{t+h} is the realized volatility at day $t+h$ and T_1 is the number of the out-of-sample data points.

5.3 Model Confidence Set

Subsequently, we use the Model Confidence Set (MCS), developed by Hansen et al. (2011), in order to further evaluate our forecasts, so as to identify the set of the best models, based on a specific loss function (the MSPE is used in our study[16]).

By implementing the MCS test, we aim to conclude to the final set of the best performing models. In greater detail, under an elimination algorithm, the MCS provides us with the set of models that survive, at a predefined level of significance a. As an initial step, the entire list of models $M = M_0 = \{1,\ldots,m_0\}$ has been used and the following

[15] For technical details, see Marcellino et al. (2006) and Buncic and Gisler (2016).

[16] We also implement the MCS test using MAE as a loss function, which provides qualitatively similar results.

null hypothesis of equal predictive ability has been repeatedly tested:

$$H_{0,M} : E(d_{i,i^*,t}) = 0, \ \forall \ i, i^* \in M, \tag{14}$$

where $d_{i,i^*,t} = \Psi_{i,t} - \Psi_{i^*,t}$ is defined as the evaluation differential for $\forall \ i, \ i^* \in M_0$ and $\Psi_{i,t} = (ARV^{(i)}_{t+h|t} - ARV^{(i)}_{t+h})^2$, where $ARV_{t+h|t}$ denotes the h-days-ahead oil price volatility forecast produced by i model. As a next step, the process is repeated until the null is not rejected any longer. Regarding the required MCS settings[17], the predefined values that we choose are a) the level of significance that we define as $a = 0.1$ and b) a block bootstrap with 10,000 bootstrap replications.

5.4 Economic–based evaluation functions

Apart from the statistical evaluation, we assess our "beauty contest" using economic-based evaluation functions. The choice of these evaluation functions is motivated by several studies that opted to use both economic-based and statistical loss-functions so to provide a complete assessment of their forecasts (see, for instance Lux et al., 2016; Degiannakis and Filis, 2017; Gkillas et al., 2020; Degiannakis and Filis, 2022).

5.4.1 Trading profits

The first economic-based evaluation function is based on the profits generated by trading the USO[18]. Our trading strategy focuses on real-world asset trading and as such the USO can be traded on information from the oil price volatility forecasts. The strategy works as follows. We assume that the trader starts its trading at the last day of our in-sample period. At that day she makes oil price volatility forecasts for up to 22-days ahead, using each of the models detailed in Section 4. Her trading period ends at the last day of our out-of-sample period. If the oil price volatility forecast of model i for time $t+h$ based on information available at time t is higher than that of the actual oil price volatility at time t, the trader takes a short position in USO. If the oil price volatility forecast of model i for time $t+h$ is lower than that of the actual oil price volatility at

[17] For further details see Hansen et al. (2011).

[18] The USO is an exchanged-traded product (ETP) that predominantly holds short-term NYMEX futures contracts on WTI crude oil.

time t, then the position that the trader takes is long. This idea is based on the inverse relationship between the underlying asset and its volatility, which suggests that higher (lower) volatility is related to negative (positive) returns. Hence, when the trader forecasts a higher (lower) volatility, she assumes that the USO will have a price decrease (increase) and hence she takes a short (long) position in the USO. If the $t+h$ forecast is successful (unsuccessful) then she makes a positive (negative) return, which amounts to the difference between the price of the USO_t and the USO_{t+h}. This is repeated for all the trading days of our out-of-sample period. Thus, the model's i cumulative returns, which is the metric for comparing the models, over the out-of-sample period is measured as[19]:

$$r^{(i)} = \sum_{t=1}^{T_1} \left(\frac{(USO_{t+h} - USO_t) d_t^{(i)}}{USO_t} \right), \tag{15}$$

where $d_t^{(i)} = 1$ if $ARV_{t+h|t}^{(i)} \leqslant ARV_t$ and $d_t^{(i)} = -1$ if $ARV_{t+h|t}^{(i)} > ARV_t$.

5.4.2 Risk management loss functions

Additionally, we utilize loss functions based on a risk management application procedure[20]. As a first step, and according to Lopez (1999), we measure the distance between predicted Value–at–Risk (VaR) and actual loss, but only when the loss is greater than the expected outcome according to our risk management measure. Before proceeding to the relevant risk management loss function, we recap what the VaR states.

VaR at a given probability level $(1-p)$, is the predicted amount of financial loss of a portfolio over a given time horizon. If r_t denotes the returns, then[21] in a static manner of thinking VaR is the value $VaR_t^{(1-p)}$ satisfies the condition:

$$p = P\big(r_t \leqslant VaR_t^{(1-p)}\big) = \int_{-\infty}^{VaR_t^{(1-p)}} \frac{1}{\sqrt{2\pi}} exp(-\frac{1}{2} r_t^2) dr_t. \tag{16}$$

[19]In our study, we assume zero transaction costs because we are not focusing on the profits but in comparing the models, which provide oil price volatility forecasts.

[20]Angelidis and Degiannakis (2008), Angelidis et al. (2007), Degiannakis et al. (2013), Sarma et al. (2003), among others, have evaluated forecasting accuracy with risk management loss functions.

[21]Under the assumption of standard normally distributed log-returns.

Naturally, $VaR_t^{(1-p)}$ is the p^{th} percentile of the underlying distribution, or $VaR_t^{(1-p)}$ $= \zeta_p$, where ζ_p is the percentile of the standard normal distribution. But, under a dynamic framework (which of course is much closer to the real world data) that incorporates the ability to predict realized volatility, we have $p = P\big(r_t \leqslant VaR_t^{(1-p)}\big) =$ $\frac{1}{\sigma_t\sqrt{2\pi}}exp(-\frac{r_t^2}{2\sigma_t^2})dr_t$. Hence:

$$VaR_t^{(1-p)} = \zeta_p \sigma_t. \tag{17}$$

Therefore, based on a forecasting model i, the h-days-ahead financial loss prediction of a portfolio at a $(1-p)$ probability level is computed as:

$$VaR_{t+h|t}^{(i)(1-p)} = \frac{\zeta_p}{\sqrt{252}} ARV_{t+h|t}^{(i)}. \tag{18}$$

When a violation of VaR occurs, then we compute the magnitude of the violation as the squared difference between VaR prediction of model i and the loss of our portfolio. For the trading days that there is no violation of the VaR measure the loss is zero. So, the proposed risk management loss function for day t+h is:

$$\psi_{VaR,t+h}^{(i)} = \big(1 + (r_{t+h} - VaR_{t+h|t}^{(i)(1-p)})^2\big) I\big(r_{t+h} < VaR_{t+h|t}^{(i)(1-p)}\big), \tag{19}$$

where $I\big(r_{t+h} < VaR_{t+h|t}^{(i)(1-p)}\big)$ takes the value of 1 if the condition holds and 0 otherwise. Hence, model's i sum of penalty scores is computed as:

$$\Psi_{VaR}^{(i)} = \sum_{t=1}^{T_1} \psi_{VaR,t+h}^{(i)}, \tag{20}$$

where T_1 denotes the number of out-of-sample data points. The proposed loss function considers both the number of violations, in total, and the magnitude of the loss.

Regarding the second step of the risk management application procedure, a similar approach is implemented for an alternative risk management measure, namely the Expected Shortfall (ES). In greater detail, the ES is calculated based on the study of

Degiannakis et al. (2014) using the following formula:

$$ES_{t+h|t}^{(i)(1-p)} = \tilde{k}^{-1} \sum_{i=1}^{\tilde{k}} (VaR_{t+h|t}^{(i)(1-p+ip(\tilde{k}+1)^{-1})}) \tag{21}$$

where $\tilde{k}$ is a large number of slices each with identical probability mass ($\tilde{k} = 1000$). After having obtained ES, we proceed with the corresponding loss function that is motivated by a study of Angelidis and Degiannakis (2007). In this regard, the loss function based on the ES measure for day $t+h$ is computed as follows:

$$\psi_{ES,t+h}^{(i)} = \big(1 + (r_{t+h} - ES_{t+h|t}^{(i)(1-p)})^2\big) I\big(r_{t+h} < VaR_{t+h|t}^{(i)(1-p)}\big). \tag{22}$$

and the final model's i loss function for ES is computed as:

$$\Psi_{ES}^{(i)} = \sum_{t=1}^{T_1} \psi_{ES,t+h}^{(i)}. \tag{23}$$

6 Out-of-sample results

6.1 Statistical loss functions results

6.1.1 Evaluating the predictive role of the GPR indices

We start out analysis with Table 2 that reports the first set of results, which depict whether the GPR index and its sub-indices are capable of providing predictive gains, relatively to the näive (RW) and benchmark models (HAR-RV and HAR-OVX) of our study. Table 2 reports the actual forecast errors of the RW and HAR-RV models, whereas the performance ratio of each corresponding model relative to the benchmark HAR-RV model is presented in the last four rows of the each loss-function. A ratio that takes a value below 1 denotes that the corresponding model outperforms the HAR-RV model.

[TABLE 2 HERE]

Evidently, the HAR-RV model can indeed outperform the RW model at all horizons. However, as noted in Section 3, the HAR-OVX is indeed superior to the HAR-RV, showing that the OVX can provide predictive gains for the oil price realized volatility. Our key interest, though, lies on the performance of the HAR-OVX models that are augmented with the GRP index (HAR-OVX-GPR), and its sub-indices, namely, HAR-OVX-GPR THREAT and HAR-OVX-GPR ACT. We can observe that although all three geopolitical uncertainty indices improve the HAR-OVX model, it is mainly the HAR-OVX-GPR and HAR-OVX-GPR THREAT mainly that seem to constantly offer predictive gains at all horizons (at least based on the MSPE loss-function). Hence, Table 2 clearly provides evidence in favour of the predictive information that is included in the geopolitical indices and thus, the importance of geopolitical tensions on the behaviour of oil price volatility.

6.1.2 Evaluating the predictive role of the GPR indices vis-a-vis other well–known uncertainty indices

However, as mentioned in Section 1, a key interest of the present study is whether the usefulness of geopolitical uncertainty indices on oil price volatility forecasts can survive a "beauty contest" against other commonly-used uncertainty indices. Table 3 provides the statistical loss function values of the other competing uncertainty indicators, which are compared to the respective ones of the HAR-OVX-GPR model. Thus, values below 1 suggest that a competing model outperforms the HAR-OVX-GPR model.

[TABLE 3 HERE]

Table 3 suggests that the majority of those models present higher MSPE and MAE values relative to the HAR-OVX-GPR model for almost all horizons, apart from the 1-day ahead. The only exception is the HAR-OVX-EPU, which seems to perform better. In addition, the HAR-OVX-VXD seems to perform marginally better at the 5-days ahead horizon, as well. These findings suggest that the enhanced predictability of oil price realized volatility, using information that reflects the US economic policy uncertainty, might be statistically superior to the GPR information, which will be assessed using the MCS test. In any case, the findings that EPU index seems to outperform the HAR-OVX-GPR, is justified by the fact that EPU index does not only cover policy-related uncertainty issues but it also covers concerns regarding geopolitical tensions.

6.1.3 Evaluating the predictive role of the GPR indices in a DMA framework

Our final set of results concerns the DMA methodological framework that combines information of the entire set of predictors. The results are shown in Table 4, which once again reports the performance ratios of the DMA models relatively to the HAR-OVX-GPR model. We observe that both DAM-without-GPR and DMA-all exhibit improved forecasting power relatively to the HAR-OVX-GPR, for the horizons up to 10-days ahead. Nevertheless, the DMA-all seems to be the model that outperforms all other models in short- and mid-run horizons (especially in terms of MSPE). Comparing two DMA models we note that the GPR indices are important in improving the oil price volatility forecasts, even when all other uncertainty indices are also considered, as the DMA-all is the best performing model. However, this better performance does not hold for the 22-days ahead, where the HAR-OVX-GPR remains the best performing model.

[TABLE 4 HERE]

6.2 Model Confidence Set procedure results

Having evaluated the competing models based on the MSPE and MAE, we proceed with the MCS results, which are reported in Table 5.

[TABLE 5 HERE]

It is evident from Table 5 that the two DMA models are the best performing models at almost the horizons up to 15-days ahead. The DMA-all maintains its position among the best performing models for the 22-days ahead horizon. Furthermore, we note that the HAR-OVX models that are augmented with the uncertainty indices, other than the GPR, are among the set of the best performing models for the 15-days ahead horizon. Nevertheless, the DMA-all is the model with the highest probability across all horizons, suggesting that a model that combines all uncertainty indicators, including the GPR indices, provide indeed significant superior predictive ability.

Another interesting observation that is extracted from Table 5 is that the HAR-OVX-GPR ACT is the only model with exogenous information that does not belong to the best set of models at any forecasting horizon, which may suggest that the geopolitical threats, as opposed to the acts, are more important in the behaviour and thus forecast of oil price volatility, especially in the longer run horizons (22-days ahead). Finally, concerning again the longer run horizon, we note that the economic policy uncertainty is considered an important factor that provides superior predictions for the oil price realized volatility.

Overall, the statistical evaluation of the competing models suggests that the GPR indices are capable of offering important predictive information when combined with other uncertainty indicators, for all horizons. Even more, the GPR index, as well as, the GPR THREAT index also offer superior predictive ability in the 22-days ahead horizon.

6.3 DMA weights

Delving deeper on the impact of geopolitical uncertainty on oil price volatility, it is important to extend the analysis of the DMA-all model focusing on the weights that each group of uncertainty indices assumes in the model (as shown in eq.A.11), over the out-of-sample forecasting period. Put it simply, it is important to identify the contribution of the GPR indices (compared to the other uncertainty indices) to the DMA model, which is computed by averaging all possible combinations of model specifications. Regarding the weight given to each individual model, it relies on the idea that a model that had better forecasting performance in the past, receives higher weight at time t. Therefore, after producing the model averaging during the out-of-sample period, we aggregate the weights of the models that include GPR indices as explanatory variables. Equivalently, we proceed with the weights calculation of the remaining uncertainty indices, grouped as economic-based (EPU, ADS and FSI) and stock market-based uncertainties (VIX, VXD and VXN). Figures 4 to 8 depict these weights for all forecasting horizons.

[FIGURES 4 TO 8 HERE]

According to Figures 4–8, it is observed that the incorporation of the GPR indices in the DMA model is time-varying with a large break occurred at the end of 2015 - beginning of 2016, which is related to the de-escalation of the geopolitical tensions of that period, as already mentioned in Figure 1. Nevertheless, a finding that repeats it-self across almost all horizons is that the GPR indices are the most important contributors at the DMA-all model during the period 2014-2015, as well as, in the middel of 2017. In both periods the global economy experienced a series of geopolitical tensions, which explains this finding. For instance, in 2014 we experienced events such as the Russian invasion in Crimea, tensions in Gaza Strip, civil unrest in Egypt, as well as, the start of the second Libyan civil war. In addition, in 2017 we had a series of events in the Middle-East from ISIS, such as bombings in Tehran (Iran) and Karbala (Iraq) or the battle of Mosul (Iraq), to highlight a few.

Regarding the remaining groups of uncertainty variables, we highlight the fact that the stock market-related uncertainty group assumes very high weights in almost all periods and across all forecast horizons, with the exception being the year 2017. This is justified by the increased financialization of the crude oil market. Nevertheless, the high aggregated weight of the last group of uncertainty indices (EPU, ADS and FSI), further confirms that uncertainty related to the oil market fundamentals continues to provide important predictive information.

6.4 Economic–based evaluations functions - results

We extend our analysis through the use of two economic-based evaluation criteria, a simple trading game and a risk management evaluation process, as presented in Section 5.4.

6.4.1 Trading profits

Starting with the trading strategy, Tables 6 and 7 report the incremental profits/losses of each different forecasting model vis-a-vis the HAR-RV and the HAR-OVX models, respectively. Recall that if the oil price volatility forecast of model i for time $t+h$ is higher (lower) than that of the actual oil price volatility at time t, the trader takes a short (long) position in USO.

[TABLES 6 AND 7 HERE]

It becomes clear that both DMA models (DMA-without GPR and DMA-all) exhibit materially improved incremental profits compared to both HAR-RV and HAR-

OVX models. This is particularly evident for the 1- and 5-days ahead forecast horizons, when an investor that uses the forecasts from the DMA models for 1- and 5-days ahead trading, can earn about 25% higher annualized profits relative to an investor that is using the HAR-RV or HAR-OVX models for her trading decisions. For the medium and longer run horizons we observe that the superior DMA-all profitability diverges away even compared to the DMA-without GPR, which is suggestive of the fact that this incremental profitability is related to the incorporation of GPR indices in the DMA framework. Furtheremore, the HAR-OVX-GPR model is also showing materially improved profits at the medium and longer run horizons (although comparable to the HAR-OVX-EPU and the HAR-OVX-VXN models).

Next, Figures 9 to 13 show the cumulative profits from USO trading over the out-of-sample period and across the different forecasting horizons. To avoid any complexity we show the cumulative trading profits for the two DMA models, as well as, the HAR-OVX models that are augmented with the GPR indices.

[FIGURES 9 TO 13 HERE]

Based on Figures 9 to 13 we can clearly observe that the DMA-all is the models that constantly exhibits the higher cumulative trading profits, with the only exception being the 1-day ahead trading, where the DMA-all shows a marginally lower profitability compared to the DMA-without GPR model. Another interesting observation is that as we move towards the longer run horizons, the HAR-OVX with the GPR indices seems to outgrow the returns generated by the DMA-without GPR model. This finding further confirms that the use of GPR indices in a DMA framework is capable of offering not only statistically superior forecasts but also superior trading profits, which also confirms the added-value of the GPR indices in oil price volatility forecasting.

6.4.2 Risk management loss function results

In the final part of our analysis, we assess whether the superior performance of the GPR indices, when these are incorporated in the DMA framework, is also apparent in a risk management exercise. To do so, we employ both VaR and ES forecasting exercises of the daily oil price returns. These risk management loss functions, proposed by Lopez (1999) and Angelidis and Degiannakis (2007), measure the magnitude of the distance between the predicted risk measure (VaR or ES) and the potential losses in the events that the VaR is violated. Therefore, contrary to the trading profits evaluation framework, the optimal values of this loss functions are the lowest, since the estimated measures refer to investment losses. The results of the average $\Psi^{(i)}_{VaR}$ values, relative to those of the HAR-RV and HAR-OVX models, over the entire out-of-sample period and across the different forecasting horizons, are presented in Tables 8 and 9, whereas the relevant results for ES are included in Tables 10 and 11.

[TABLES 8 AND 9 HERE]

[TABLES 10 AND 11 HERE]

From Tables 8 and 9 we note that the added-value of the DMA-all model, or of the HAR-RV-GPR models is not evident for the 1- and 5-days horizons, since the HAR-OVX models which are extended with other uncertainty indices exhibit better performance from a risk management perspective. By contrast, from the 15- to the 22-days ahead horizons the DMA-all exhibits the best risk management performance. Regarding the $\Psi^{(i)}_{ES}$ values presented in Tables 10 and 11, the results can be interpreted in a qualitatively similar manner. More specifically, the DMA model including GPR and the other uncertainty indicators reduces the loss, compared to the remaining models, at the longest horizon. Moreover, it is noted that the performance of the DMA-all is better than that of the benchmark models, namely the HAR-RV and HAR-OVX, for all forecasting horizons. To summarize, we conclude that the incorporation of the GPR indices in a DMA forecasting framework is capable of improving the risk management performance of the investors, at least in the longer run horizons.

Overall, the findings from the economic-based evaluation framework suggest that the forecasts should be evaluated based on a specific criterion that serves the interest of the end-user, rather than solely based on statistical-loss functions, which ignore the purpose for generating the forecasts. Put it simply, should an end-user needs the oil price volatility forecasts so to trade the USO, then she should focus on the DMA-all model. By contrast, should she needs the oil price volatility forecasts for risk management purposes, then the DMA-all would only serve her if she has a long-run investment horizon.

These findings corroborate the results obtained by Degiannakis and Filis (2022) who show that the evaluation of the oil price volatility forecasts is more economically useful when it is performed using criteria that match the purpose of the forecasts. More specifically, Degiannakis and Filis (2022) point out that a forecasting model may be superior for a particular trading strategy (e.g., trading the asset) but it may not be useful for a different trading strategy (e.g., trading straddles on the asset).

7 Conclusion

Our study assesses the predictive content of the GPR index, and its sub-indices, for oil price realized volatility forecasts, for horizons up to 22-days ahead. To do so, we initially use a HAR model which is augemented with the GPR indices. However, to show that the predictive information from the GPR indices is indeed valuable, we construct a "beauty contest" where the forecasting performance is evaluated against the performance of several other well-known uncertainty indicators that have been commonly used for oil price volatility forecasting. Subsequently, we combine the information of all uncertainty indicators, including GPR indices, using a DMA methodology (DMA-all) and we compare its performance against a DMA model which does not include the GPR indices. Our evaluation framework includes both the use of statistical loss-functions, as well as, economic-based criteria, namely, a trading game and a risk management framework.

Our results suggest that geopolitical risk indices are important predictors for the WTI crude oil price volatility, across all horizons. Put is simply, we show that the geopolitical tensions are functioning as early-warning triggers for oil price uncertainty. This is particularly evident in the DMA-all model, where its performance is superior to the HAR models, but also to the DMA-without the GPR indices model. Regarding the alternative uncertainty indicators' performance, it is highlighted that EPU offers predictive gains in the longer run horizons, which could be justified by the fact that EPU also include information regarding geopolitical tensions. More importantly, though, our economic-based evaluation criteria show that the DMA-all model generates the highest trading profits across all horizons, whereas the HAR-OVX-GPR also exhibits significant profits in the longer run horizons. Finally, from a risk management perspective, we find that the the incorporation of the GPR indices in a DMA forecasting framework improves the VaR and ES predictions, at least in the longer run horizons.

Such findings have important implications for professional forecasters, investors and risk managers that develop modelling and forecasting frameworks for oil price volatility. Hence, end-users of oil price volatility forecasts should implement models that use geopolitical uncertainty indices along with information extracted from a large variety of uncertainty indicators, so that they can generate economically useful forecasts.

Some interesting directions for future research could include the implementation of additional combination techniques, which may improve the incremental predictive content of the GPR indices. Another obvious direction is the use of alternative geopolitical uncertainty indicators (e.g. the BlackRock Geopolitical Risk Indicator or the indices developed by BBVA Research) in similar forecasting frameworks, as well as, additional economic-based evaluation criteria (e.g. different trading or hedging strategies), given that these are important to the end-users of oil price volatility forecasts.

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References

Abiad, A. and I. A. Qureshi (2023). The macroeconomic effects of oil price uncertainty. *Energy Economics 125*, 106839.

Angelidis, T., A. Benos, and S. Degiannakis (2007). A robust var model under different time periods and weighting schemes. *Review of Quantitative Finance and Accounting 28*, 187–201.

Angelidis, T. and S. Degiannakis (2007). Backtesting var models: A two-stage procedure. *Journal of Risk Model Validation 1*(2), 27–48.

Angelidis, T. and S. Degiannakis (2008). Volatility forecasting: Intra-day versus inter-day models. *Journal of International Financial Markets, Institutions and Money 18*(5), 449–465.

Apostolakis, G. N., C. Floros, K. Gkillas, and M. Wohar (2021). Financial stress, economic policy uncertainty, and oil price uncertainty. *Energy Economics 104*, 105686.

Baker, S., N. Bloom, and S. Davis (2016). Measuring Economic Policy Unvertainty. *Quarterly Journal of Economics 131*(4), 1593–1636.

Baumeister, C. and L. Kilian (2016). Forty years of oil price fluctuations: Why the price of oil may still surprise us. *Journal of Economic Perspectives 30*(1), 139–160.

Boldanov, R., S. Degiannakis, and G. Filis (2016). Time-varying correlation between oil and stock market volatilities: Evidence from oil-importing and oil-exporting countries. *International Review of Financial Analysis 48*, 209–220.

Bollerslev, T., A. J. Patton, and R. Quaedvlieg (2016). Exploiting the errors: A simple approach for improved volatility forecasting. *Journal of Econometrics 192*(1), 1–18.

Bouoiyour, J., R. Selmi, S. Hammoudeh, and M. E. Wohar (2019). What are the categories of geopolitical risks that could drive oil prices higher? acts or threats? *Energy Economics 84*, 104523.

Brandt, M. W. and L. Gao (2019). Macro fundamentals or geopolitical events? a textual analysis of news events for crude oil. *Journal of Empirical Finance 51*, 64–94.

Brown, S. P. and H. G. Huntington (2017). Opec and world oil security. *Energy Pol-*

icy 108, 512–523.

Buncic, D. and K. I. Gisler (2016). Global equity market volatility spillovers: A broader role for the United States. *International Journal of Forecasting 32*(4), 1317–1339.

Busch, T., B. J. Christensen, and M. Ø. Nielsen (2011). The role of implied volatility in forecasting future realized volatility and jumps in foreign exchange, stock, and bond markets. *Journal of Econometrics 160*(1), 48–57.

Caldara, D. and M. Iacoviello (2018). Measuring Geopolitical Risk. *International Finance Discussion Paper 2018*(1222), 1–66.

Charles, A. and O. Darne (2017). Forecasting crude-oil market volatility: Further evidence with jumps. *Energy Economics 67*, 508–519.

Chen, Y., G. Qiao, and F. Zhang (2022). Oil price volatility forecasting: Threshold effect from stock market volatility. *Technological Forecasting and Social Change 180*, 121704.

Corsi, F. (2009). A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics 7*(2), 174–196.

Corsi, F. and R. Renò (2012). Discrete-time volatility forecasting with persistent leverage effect and the link with continuous-time volatility modeling. *Journal of Business and Economic Statistics 30*(3), 368–380.

Cross, J. L., B. H. Nguyen, and T. D. Tran (2022). The role of precautionary and speculative demand in the global market for crude oil. *Journal of Applied Econometrics 37*(5), 882–895.

Cunado, J., R. Gupta, C. K. M. Lau, and X. Sheng (2020). Time-varying impact of geopolitical risks on oil prices. *Defence and Peace Economics 31*(6), 692–706.

Degiannakis, S., P. Dent, and C. Floros (2014). A monte carlo simulation approach to forecasting multi-period value-at-risk and expected shortfall using the figarch-skt specification. *The Manchester School 82*(1), 71–102.

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

Finance 76, 28–49.

Degiannakis, S. and G. Filis (2022). Oil price volatility forecasts: What do investors need to know? *Journal of International Money and Finance 123*, 102594.

Degiannakis, S., C. Floros, and P. Dent (2013). Forecasting value-at-risk and expected shortfall using fractionally integrated models of conditional volatility: International evidence. *International Review of Financial Analysis 27*, 21–33.

Delis, P., S. Degiannakis, and G. Filis (2022). What matters when developing oil price volatility forecasting frameworks? *Journal of Forecasting 41*(2), 361–382.

Dutta, A. (2017). Modeling and forecasting oil price risk: the role of implied volatility index. *Journal of Economic Studies 44*(6), 1003–1016.

Ferderer, J. P. (1996). Oil price volatility and the macroeconomy. *Journal of Macroeconomics 18*(1), 1–26.

Fernandez-Perez, A. and R. López (2023). The effect of macroeconomic news announcements on the implied volatility of commodities: The role of survey releases. *Journal of Futures Markets 43*(11), 1499–1530.

Gkillas, K., R. Gupta, and C. Pierdzioch (2020). Forecasting realized oil-price volatility: The role of financial stress and asymmetric loss. *Journal of International Money and Finance 104*, 102137.

Gong, X. and B. Lin (2018). The incremental information content of investor fear gauge for volatility forecasting in the crude oil futures market. *Energy Econ. 74*, 370–386.

Grassi, S., N. Nonejad, and P. S. De Magistris (2017). Forecasting With the Standardized Self-Perturbed Kalman Filter. *Journal of Applied Econometrics 32*(2), 318–341.

Hansen, P. and A. Lunde (2005). A forecast comparison of volatility models: Does anything beat a GARCH (1,1)? *Journal of Applied Econometrics 20*(7), 873–889.

Hansen, P., A. Lunde, and J. M. Nason (2011). The Model Confidence Set. *Econometrica 79*(2), 453–497.

Haugom, E., H. Langeland, P. Molnár, and S. Westgaard (2014). Forecasting volatility of the U.S. oil market. *Journal of Banking and Finance 47*(1), 1–14.

Jawadi, F., Z. Ftiti, and W. Louhichi (2020). Forecasting energy futures volatility with threshold augmented heterogeneous autoregressive jump models. *Econometric Reviews 39*(1), 54–70.

Li, X., Y. Wei, X. Chen, F. Ma, C. Liang, and W. Chen (2022). Which uncertainty is powerful to forecast crude oil market volatility? new evidence. *International Journal of Finance & Economics 27*(4), 4279–4297.

Lopez, J. A. (1999). Methods for evaluating value-at-risk estimates. *Economic review 2*, 3–17.

Lux, T., M. Segnon, and R. Gupta (2016). Forecasting crude oil price volatility and value-at-risk: Evidence from historical and recent data. *Energy Economics 56*, 117–133.

Lv, W. (2018). Does the OVX matter for volatility forecasting? Evidence from the crude oil market. *Physica A: Statistical Mechanics and its Applications 492*, 916–922.

Ma, R., C. Zhou, H. Cai, and C. Deng (2019). The forecasting power of epu for crude oil return volatility. *Energy Reports 5*, 866–873.

Marcellino, M., J. H. Stock, and M. W. Watson (2006). A comparison of direct and iterated multistep AR methods for forecasting macroeconomic time series. *Journal of Econometrics 135*, 499–526.

Miao, H., S. Ramchander, T. Wang, and D. Yang (2017). Influential factors in crude oil price forecasting. *Energy Economics 68*, 77–88.

Mignon, V. and J. Saadaoui (2024). How do political tensions and geopolitical risks impact oil prices? *Energy Economics 129*, 107219.

Muller, U. A., M. M. Dacorogna, R. D. Dav, B. Olsen, O. V. Pictet, and J. von Weizsacker (1997). Volatilities of different time resolutions - Analyzing the dynamics of market components. *Journal of Empirical Finance 4*, 213–239.

Murat, A. and E. Tokat (2009). Forecasting oil price movements with crack spread futures. *Energy Economics 31*(1), 85–90.

Nazlioglu, S., U. Soytas, and R. Gupta (2015). Oil prices and financial stress: A volatility spillover analysis. *Energy Policy 82*(1), 278–288.

Patton, A. J. and K. Sheppard (2015). Good volatility, bad volatility: Signed jumps and the persistence of volatility. *Review of Economics and Statistics 97*(3), 683–697.

Prokopczuk, M., L. Symeonidis, and C. Wese Simen (2016). Do Jumps Matter for Volatility Forecasting? Evidence from Energy Markets. *Journal of Futures Markets 36*(8), 758–792.

Raftery, A. E., M. Kárný, and P. Ettler (2010). Online prediction under model uncertainty via dynamic model averaging: Application to a cold rolling mill. *Technometrics*, 52–66.

Sarma, M., S. Thomas, and A. Shah (2003). Selection of value-at-risk models. *Journal of Forecasting 22*(4), 337–358.

Sévi, B. (2014). Forecasting the volatility of crude oil futures using intraday data. *European Journal of Operational Research 235*(3), 643–659.

Silvennoinen, A. and S. Thorp (2013). Financialization , crisis and commodity correlation dynamics. *Journal of International Financial Markets, Institutions Money 24*, 42–65.

Vo, M. (2011). Oil and stock market volatility: A multivariate stochastic volatility perspective. *Energy Economics 33*(5), 956–965.

Wang, J., X. He, F. Ma, and P. Li (2022). Uncertainty and oil volatility: Evidence from shrinkage method. *Resources Policy 75*, 102482.

Wang, Y., F. Ma, Y. Wei, and C. Wu (2016). Forecasting realized volatility in a changing world: A dynamic model averaging approach. *Journal of Banking and Finance 64*, 136–149.

Wei, Y., J. Liu, X. Lai, and Y. Hu (2017). Which determinant is the most informative in forecasting crude oil market volatility: Fundamental, speculation, or uncertainty? *Energy Economics 68*, 141–150.

Zhang, Z., Y. Wang, J. Xiao, and Y. Zhang (2023). Not all geopolitical shocks are alike: Identifying price dynamics in the crude oil market under tensions. *Resources Policy 80*, 103238.

Descriptive statistics

	RV	OVX	GRP	GRP THREAT	GRP ACT
Mean	27.90	33.19	112.26	120.72	67.06
Median	25.31	31.68	90.07	93.59	43.53
Maximum	99.03	78.97	725.02	822.62	871.97
Minimum	4.38	14.50	0.00	0.00	0.00
Std. Dev.	12.59	10.31	82.08	93.87	98.62
Skewness	1.63	0.87	1.78	1.79	2.66
Kurtosis	6.92	3.93	8.24	7.91	13.55
Coeff. Var.	0.45	0.31	0.73	0.78	1.47
Observations	2494	2494	2494	2494	2494

	EPU	ADS	FSI	VIX	VXD	VXN
Mean	104.62	-0.09	-0.60	16.94	16.07	18.99
Median	89.60	-0.12	-0.66	15.58	14.82	17.55
Maximum	490.89	0.92	2.41	48.00	41.45	46.63
Minimum	3.32	-0.80	-1.81	9.14	7.58	10.31
Std. Dev.	60.86	0.30	0.79	5.70	4.86	5.40
Skewness	1.56	0.39	1.03	1.71	1.76	1.56
Kurtosis	6.58	3.21	4.07	6.70	6.88	5.98
Coeff. Var.	0.58	-3.41	-1.33	0.34	0.30	0.28
Observations	2494	2494	2494	2494	2494	2494

Table 1: Descriptive statistics of the variables. This table presents the descriptive statistics of the variables that have been used in the empirical analysis for forecasting realized oil price volatility. RV = WTI oil price realized volatility, OVX = CBOE oil implied volatility, GPR = geopolitical risk index, GPR THREAT = geopolitical risk threats index, GPR ACT = geopolitical risk acts index, EPU = US Economic policy uncertainty index, ADS = Aruoba-Diebold-Scotti Business Condition index, FSI = US Financial stress index, VIX = S/P500 implied volatility index, VXN = Nasdaq100 implied volatility index, VXD = DJIA implied volatility index.

MSPE

Days-ahead	1	5	10	15	22
RW	74.928	112.953	141.735	153.329	187.927
HAR-RV	58.720	87.505	106.993	121.403	143.100
HAR-OVX	0.910	0.944	0.960	0.968	0.964
HAR-OVX-GPR	0.906	0.930	0.952	0.955	0.953
HAR-OVX-GPR THREAT	0.907	0.931	0.952	0.957	0.956
HAR-OVX-GPR ACT	0.906	0.943	0.962	0.964	0.958

MAE

Days-ahead	1	5	10	15	22
RW	6.102	7.434	8.354	8.648	9.631
HAR-RV	5.191	6.357	6.998	7.515	8.209
HAR-OVX	0.954	0.958	0.980	0.983	0.970
HAR-OVX-GPR	0.956	0.959	0.982	0.985	0.974
HAR-OVX-GPR THREAT	0.956	0.958	0.982	0.987	0.975
HAR-OVX-GPR ACT	0.955	0.961	0.980	0.981	0.969

Table 2: MSPE and MAE results across all forecasting horizons - bechmark model and geopilitical uncertainty indices. The first two rows of each panel report the MSPE and MAE loss functions for RW and HAR-RV. The remaining four rows report the loss functions of the remaining models relatively to the HAR-RV. A ratio below 1 suggests that the respective model outperforms the HAR-RV model, in terms of MSPE and MAE, respectively.

MSPE

Days-ahead	1	5	10	15	22
HAR-OVX-EPU	0.987	1.000	0.980	0.987	0.984
HAR-OVX-ADS	1.004	1.018	1.018	1.027	1.026
HAR-OVX-FSI	0.993	1.012	1.015	1.028	1.030
HAR-OVX-VIX	0.995	1.007	1.004	1.019	1.025
HAR-OVX-VXD	0.993	0.995	1.005	1.015	1.022
HAR-OVX-VXN	0.995	1.009	1.001	1.012	1.010

MAE

Days-ahead	1	5	10	15	22
HAR-OVX-EPU	0.992	0.998	0.985	0.990	0.983
HAR-OVX-ADS	0.998	1.002	1.005	1.009	1.006
HAR-OVX-FSI	0.996	1.003	1.002	1.006	1.006
HAR-OVX-VIX	0.988	0.998	1.006	1.009	1.015
HAR-OVX-VXD	0.987	0.990	0.995	1.005	1.008
HAR-OVX-VXN	0.993	1.003	1.008	1.009	1.013

Table 3: MSPE and MAE results across all forecasting horizons - uncertainty indices. Values represent the loss functions (MSPE and MAE) of each model relative to the to the HAR-OVX-GPR. A ratio below 1 suggests that the respective model outperforms the HAR-OVX-GPR model, in terms of MSPE and MAE, respectively.

MSPE

Days-ahead	1	5	10	15	22
DMA-without GPR	0.935	0.891	0.926	0.967	1.007
DMA-all	0.931	0.879	0.912	0.959	1.009

MAE

Days-ahead	1	5	10	15	22
DMA-without GPR	0.971	0.959	0.966	0.980	1.007
DMA-all	0.971	0.962	0.967	0.980	1.023

Table 4: MSPE and MAE results across all forecasting horizons - DMA framework. Values represent the loss functions (MSPE and MAE) of each model relative to the to the HAR-OVX-GPR. A ratio below 1 suggests that the respective model outperforms the HAR-OVX-GPR model, in terms of MSPE and MAE, respectively.

MCS test

Days-ahead	1	5	10	15	22
RW	0.000	0.000	0.000	0.000	0.000
HAR-RV	0.000	0.001	0.000	0.002	0.000
HAR-OVX	0.014	0.007	0.005	0.003	0.025
HAR-OVX-GPR	0.015	0.007	0.013	0.005	**0.226**
HAR-OVX-GPR THREAT	0.015	0.007	0.013	0.067	**0.177**
HAR-OVX-GPR ACT	0.015	0.007	0.003	0.067	0.079
HAR-OVX-EPU	0.027	0.007	0.029	**0.104**	**1.000**
HAR-OVX-ADS	0.015	0.006	0.000	**0.104**	0.002
HAR-OVX-FSI	0.024	0.007	0.000	**0.153**	0.000
HAR-OVX-VIX	0.027	0.007	0.013	**0.244**	0.025
HAR-OVX-VXD	0.027	0.007	0.013	**0.244**	0.025
HAR-OVX-VXN	0.027	0.007	0.013	**0.408**	0.079
DMA-without GPR	**0.532**	**0.270**	**0.102**	**0.443**	0.079
DMA-all	**1.000**	**1.000**	**1.000**	**1.000**	**0.226**

Table 5: The results of the MCS test for different forecasting horizons. Figures in bold denote the model that belongs to the confidence set of the best performing models.

Incremental annualized cumulative returns vs the HAR-RV (%)

Days-ahead	1	5	10	15	22
RW	-11.212	-21.742	-16.033	-14.530	-8.297
HAR-OVX	0.575	-3.713	-2.192	-0.507	2.545
HAR-OVX-GPR	8.665	-1.147	1.214	3.417	4.457
HAR-OVX-GPR THREAT	6.652	-3.147	1.321	2.077	3.810
HAR-OVX-GPR ACT	4.847	-1.661	-2.088	0.523	4.845
HAR-OVX-EPU	8.645	-3.452	-0.476	2.391	5.039
HAR-OVX-ADS	-1.938	-4.737	-4.604	-3.156	-1.132
HAR-OVX-FSI	5.341	0.745	-3.549	-5.559	-0.002
HAR-OVX-VIX	0.261	2.271	-1.348	0.879	1.011
HAR-OVX-VXD	4.153	-0.242	-0.995	0.956	0.615
HAR-OVX-VXN	7.466	-0.291	0.160	2.290	5.368
DMA-without GPR	25.746	7.110	0.360	-2.057	2.088
DMA-all	23.889	8.008	2.159	4.960	9.670

Table 6: The annualized cumulative trading returns when implementing a trading strategy on USO. The numbers refer to the incremental annualized cumulative trading returns relative to the HAR-RV model.

Incremental annualized cumulative returns vs the HAR-OVX (%)					
Days-ahead	1	5	10	15	22
RW	-11.787	-18.029	-13.841	-14.023	-10.842
HAR-RV	-0.575	3.713	2.192	0.507	-2.545
HAR-OVX-GPR	8.090	2.566	3.406	3.924	1.912
HAR-OVX-GPR THREAT	6.077	0.566	3.513	2.584	1.265
HAR-OVX-GPR ACT	4.272	2.051	0.103	1.030	2.301
HAR-OVX-EPU	8.071	0.261	1.716	2.899	2.494
HAR-OVX-ADS	-2.513	-1.024	-2.412	-2.649	-3.677
HAR-OVX-FSI	4.767	4.458	-1.357	-5.051	-2.547
HAR-OVX-VIX	-0.314	5.984	0.844	1.386	-1.534
HAR-OVX-VXD	3.578	3.471	1.197	1.463	-1.929
HAR-OVX-VXN	6.891	3.422	2.352	2.797	2.823
DMA-without GPR	25.171	10.823	2.551	-1.550	-0.457
DMA-all	23.314	11.721	4.350	5.467	7.126

Table 7: The annualized cumulative trading returns when implementing a trading strategy on USO. The numbers refer to the incremental annualized cumulative trading returns relative to the HAR-OVX model.

VaR loss function vs HAR-RV

Days-ahead	1	5	10	15	22
RW	0.075	0.046	-0.139	-0.552	0.136
HAR-OVX	-0.197	-0.179	-0.063	-0.146	0.021
HAR-OVX-GPR	-0.214	-0.203	-0.051	-0.262	-0.076
HAR-OVX-GPR THREAT	-0.244	-0.186	-0.069	-0.236	-0.067
HAR-OVX-GPR ACT	-0.178	-0.139	-0.085	-0.195	-0.034
HAR-OVX-EPU	-0.182	-0.163	-0.026	-0.148	-0.058
HAR-OVX-ADS	-0.210	-0.142	-0.085	-0.177	0.106
HAR-OVX-FSI	-0.170	-0.140	-0.106	-0.101	0.028
HAR-OVX-VIX	-0.296	-0.312	-0.115	-0.095	-0.025
HAR-OVX-VXD	-0.307	-0.422	-0.107	-0.226	0.049
HAR-OVX-VXN	-0.331	-0.269	-0.055	-0.106	0.056
DMA-without GPR	-0.160	-0.360	-0.313	-0.315	-0.056
DMA-ALL	-0.213	-0.345	-0.297	-0.326	-0.120

Table 8: The values refer to the magnitude of trading losses, $\Psi^{(i)}_{VaR}$ (see eq.20), of each model relative to the HAR-RV. The lower the number the lower the losses that a HAR-OVX-X model suffers relatively to the HAR-RV

VaR loss function vs HAR-OVX

Days-ahead	1	5	10	15	22
RW	0.272	0.225	-0.076	-0.405	0.115
HAR-RV	0.197	0.179	0.063	0.146	-0.021
HAR-OVX-GPR	-0.017	-0.024	0.012	-0.116	-0.097
HAR-OVX-GPR THREAT	-0.047	-0.007	-0.006	-0.090	-0.088
HAR-OVX-GPR ACT	0.019	0.040	-0.022	-0.049	-0.055
HAR-OVX-EPU	0.014	0.016	0.037	-0.002	-0.079
HAR-OVX-ADS	-0.013	0.038	-0.022	-0.031	0.085
HAR-OVX-FSI	0.027	0.039	-0.043	0.045	0.007
HAR-OVX-VIX	-0.099	-0.132	-0.052	0.051	-0.046
HAR-OVX-VXD	-0.111	-0.243	-0.044	-0.079	0.029
HAR-OVX-VXN	-0.134	-0.090	0.008	0.040	0.035
DMA-without GPR	0.037	-0.181	-0.250	-0.168	-0.077
DMA-ALL	-0.017	-0.166	-0.234	-0.179	-0.140

Table 9: The values refer to the magnitude of trading losses, $\Psi^{(i)}_{VaR}$ (see eq.20), of each model relative to the HAR-OVX. The lower the number the lower the losses that a HAR-OVX-X model suffers relatively to the HAR-OVX.

ES loss function vs HAR-RV

Days-ahead	1	5	10	15	22
RW	0.116	0.083	-0.076	-0.281	0.173
HAR-OVX	-0.112	-0.096	-0.033	-0.113	-0.029
HAR-OVX-GPR	-0.122	-0.108	-0.026	-0.136	-0.059
HAR-OVX-GPR THREAT	-0.119	-0.108	-0.026	-0.136	-0.048
HAR-OVX-GPR ACT	-0.108	-0.090	-0.035	-0.107	-0.053
HAR-OVX-EPU	-0.096	-0.076	-0.021	-0.088	-0.097
HAR-OVX-ADS	-0.109	-0.077	-0.023	-0.125	-0.003
HAR-OVX-FSI	-0.092	-0.058	-0.045	-0.090	-0.028
HAR-OVX-VIX	-0.161	-0.152	-0.098	-0.133	-0.118
HAR-OVX-VXD	-0.159	-0.197	-0.127	-0.196	-0.077
HAR-OVX-VXN	-0.168	-0.171	-0.080	-0.141	-0.072
DMA-without GPR	-0.134	-0.209	-0.185	-0.181	-0.056
DMA-ALL	-0.134	-0.198	-0.167	-0.172	-0.097

Table 10: The values refer to the magnitude of trading losses, $\Psi_{ES}^{(i)}$ (see eq.23), of each model relative to the HAR-RV. The lower the number the lower the losses that a HAR-OVX-X model suffers relatively to the HAR-RV

ES loss function vs HAR-OVX

Days-ahead	1	5	10	15	22
RW	0.229	0.179	-0.044	-0.168	0.203
HAR-RV	0.112	0.096	0.033	0.113	0.029
HAR-OVX-GPR	-0.010	-0.011	0.007	-0.023	-0.030
HAR-OVX-GPR THREAT	-0.007	-0.012	0.007	-0.023	-0.019
HAR-OVX-GPR ACT	0.004	0.006	-0.002	0.005	-0.023
HAR-OVX-EPU	0.016	0.020	0.012	0.025	-0.067
HAR-OVX-ADS	0.003	0.020	0.010	-0.012	0.026
HAR-OVX-FSI	0.020	0.038	-0.012	0.023	0.001
HAR-OVX-VIX	-0.048	-0.056	-0.065	-0.020	-0.089
HAR-OVX-VXD	-0.046	-0.101	-0.094	-0.084	-0.048
HAR-OVX-VXN	-0.055	-0.075	-0.047	-0.029	-0.042
DMA-without GPR	-0.021	-0.113	-0.152	-0.068	-0.027
DMA-ALL	-0.022	-0.102	-0.134	-0.059	-0.068

Table 11: The values refer to the magnitude of trading losses, $\Psi_{ES}^{(i)}$ (see eq.23), of each model relative to the HAR-OVX. The lower the number the lower the losses that a HAR-OVX-X model suffers relatively to the HAR-OVX.

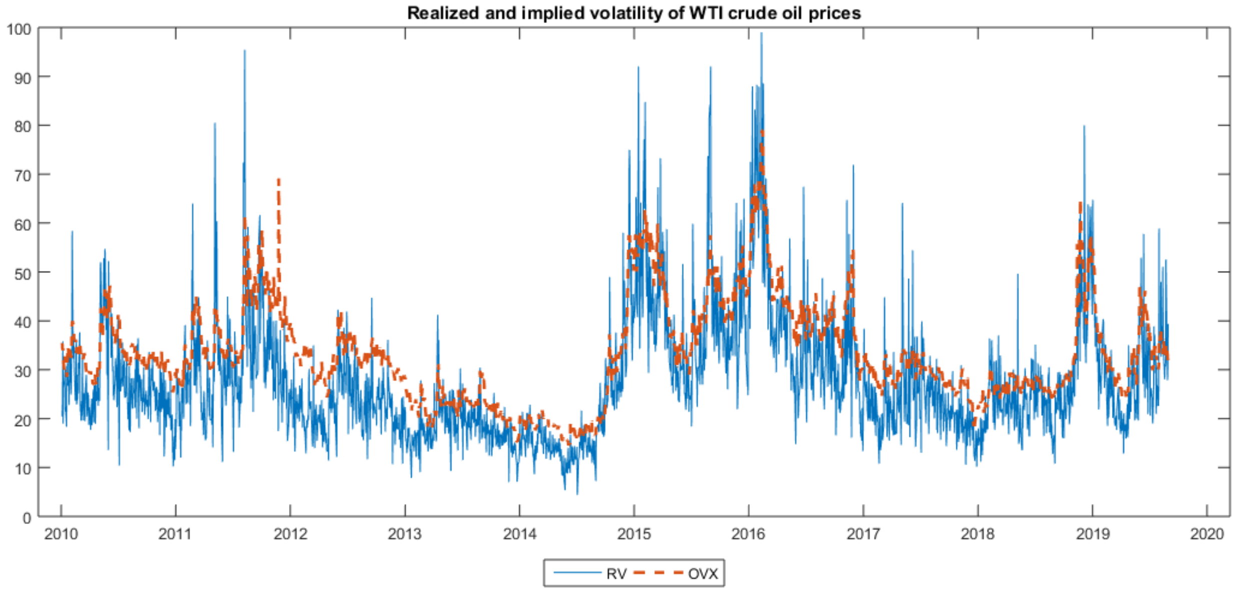

Figure 1: Realized and implied volatility of WTI crude oil prices.

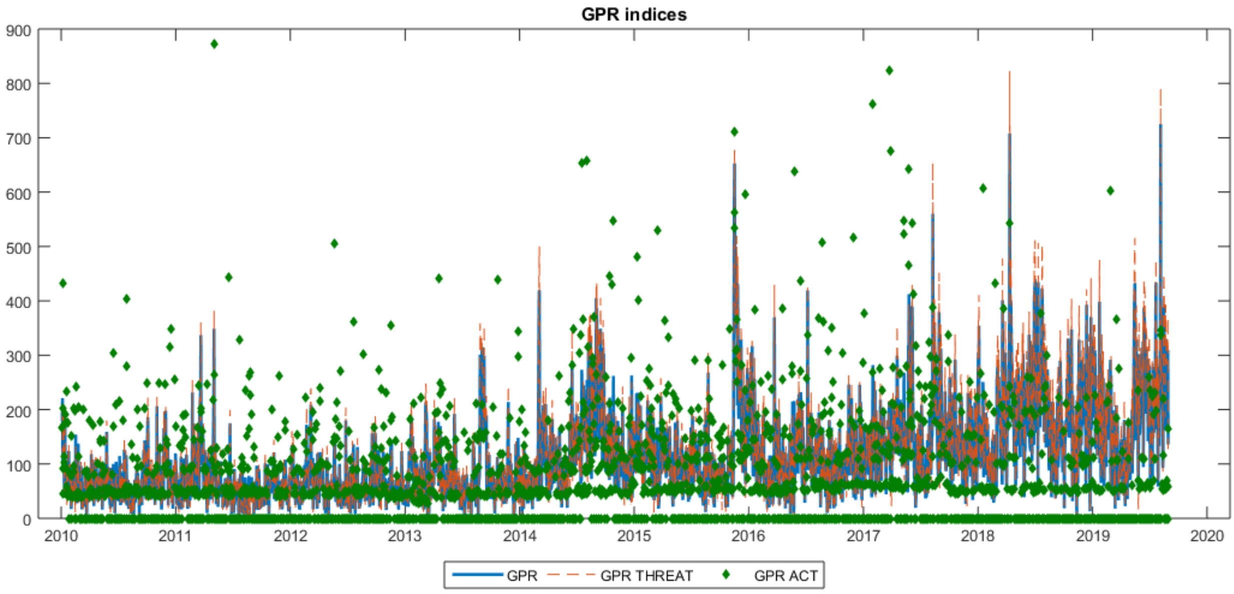

Figure 2: Geopolitical risk indices. GPR = geopolitical risk index, GPR THREAT = geopolitical risk threats index, GPR ACT = geopolitical risk acts index.

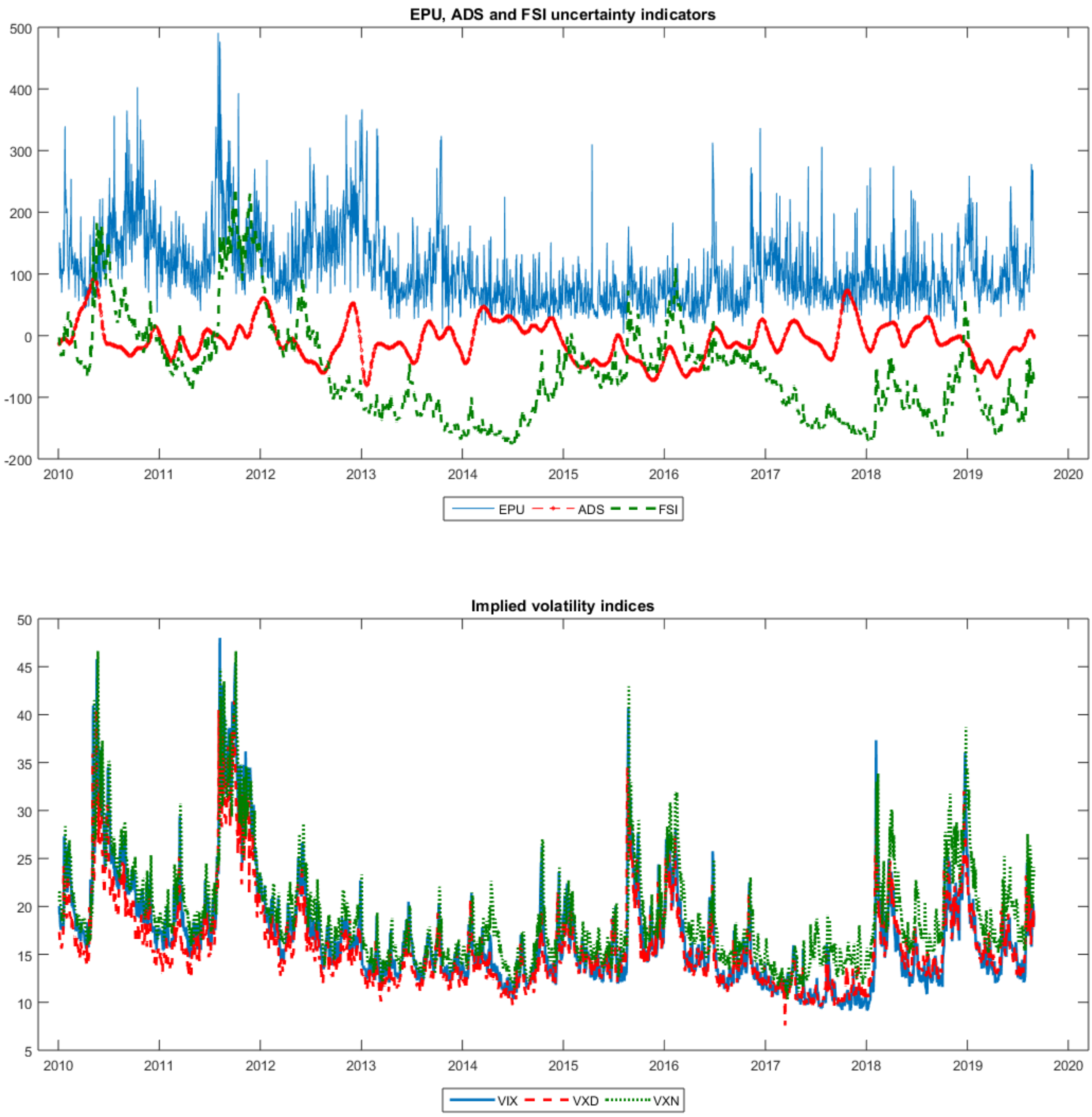

Figure 3: These figures depict the alternative uncertainty indicators, namely the EPU, ADS and FSI as well as the VIX, VXD and VXN, which are the major implied volatility indices of the US stock market. EPU = US Economic policy uncertainty index, ADS = Aruoba-Diebold-Scotti Business Condition index, FSI = US Financial stress index, VIX = S/P500 implied volatility index, VXN = Nasdaq100 implied volatility index, VXD = DJIA implied volatility index.

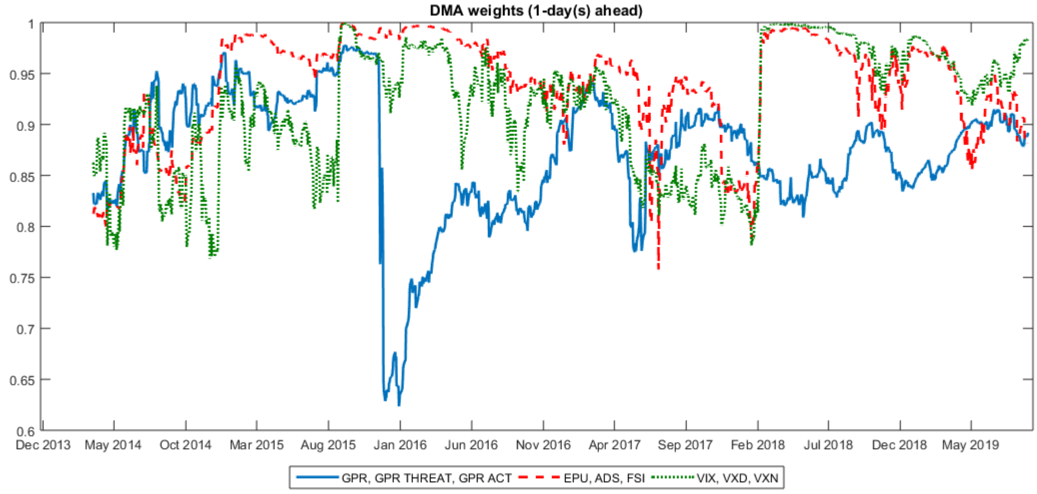

Figure 4: DMA weights for 1-day ahead horizon. This figure shows the aggregation of the weights that correspond to the model specifications with the set of explanatory variables to include at least one of each category's indicators.

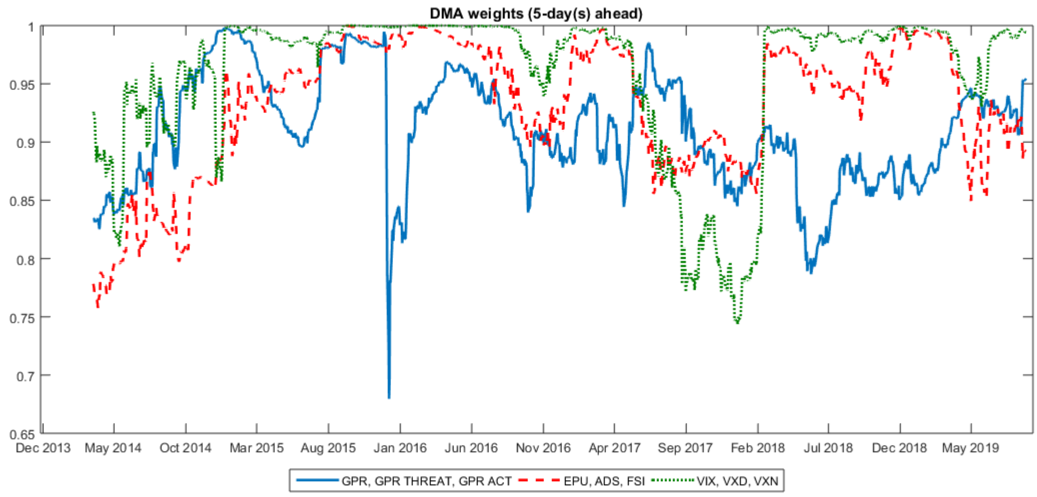

Figure 5: DMA weights for 5-days ahead horizon. This figure shows the aggregation of the weights that correspond to the model specifications with the set of explanatory variables to include at least one of each category's indicators.

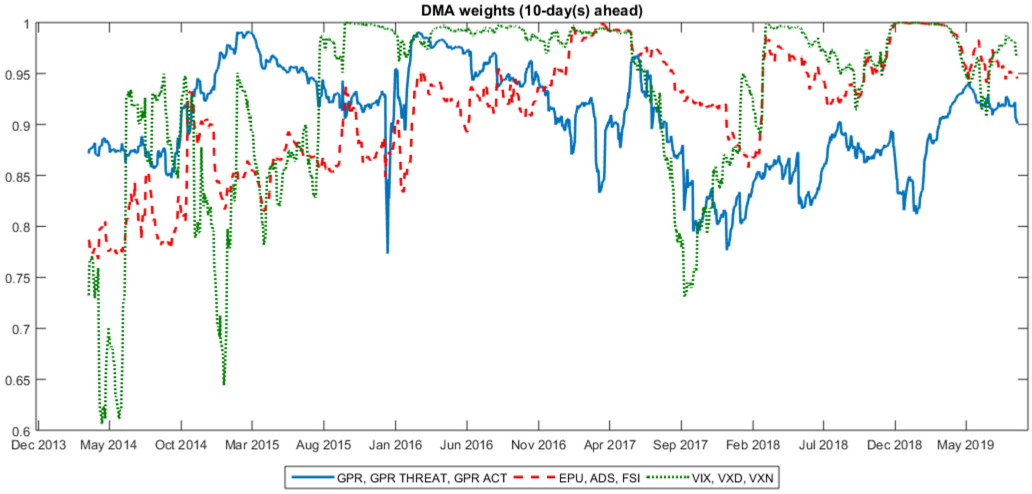

Figure 6: DMA weights for 10-days ahead horizon. This figure shows the aggregation of the weights that correspond to the model specifications with the set of explanatory variables to include at least one of each category's indicators.

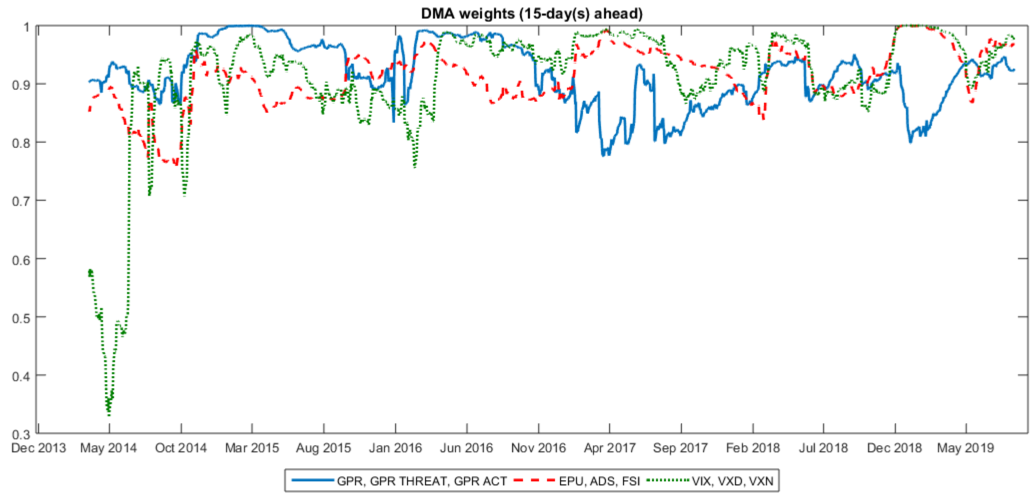

Figure 7: DMA weights for 15-days ahead horizon. This figure shows the aggregation of the weights that correspond to the model specifications with the set of explanatory variables to include at least one of each category's indicators.

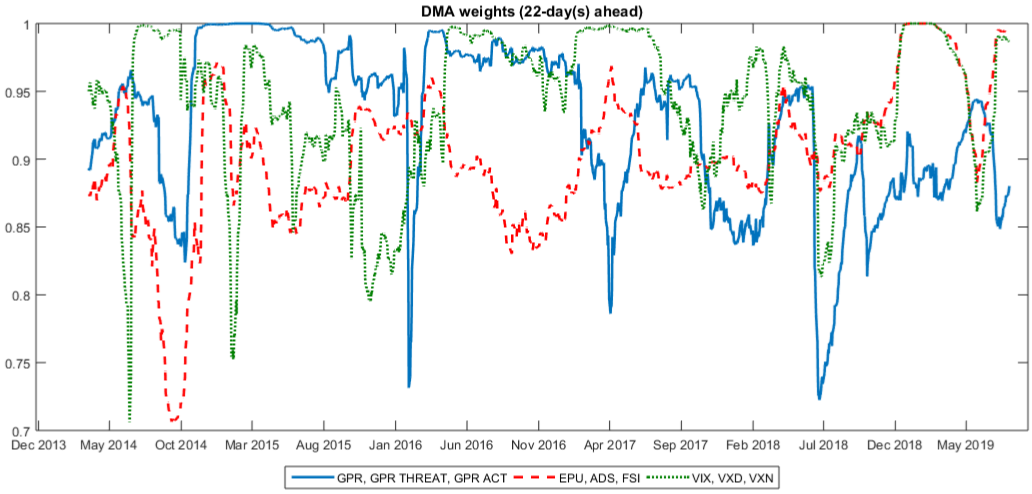

Figure 8: DMA weights for 22-days ahead horizon. This figure shows the aggregation of the weights that correspond to the model specifications with the set of explanatory variables to include at least one of each category's indicators.

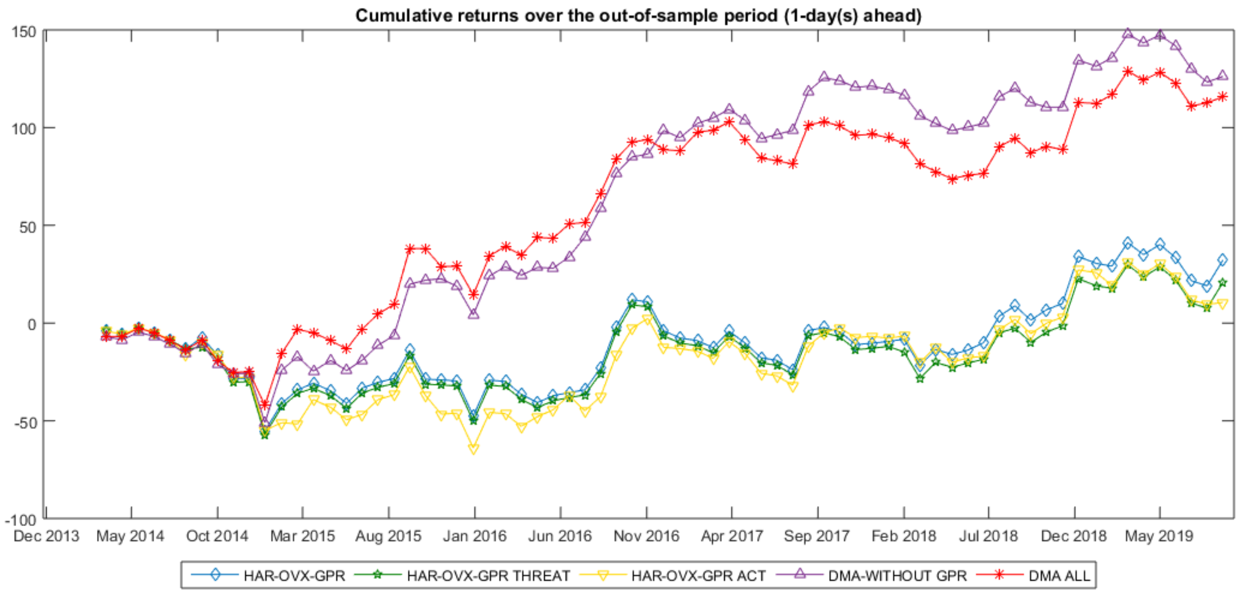

Figure 9: Cumulative trading returns when forecasting oil price realized volatility - 1-day ahead horizon.

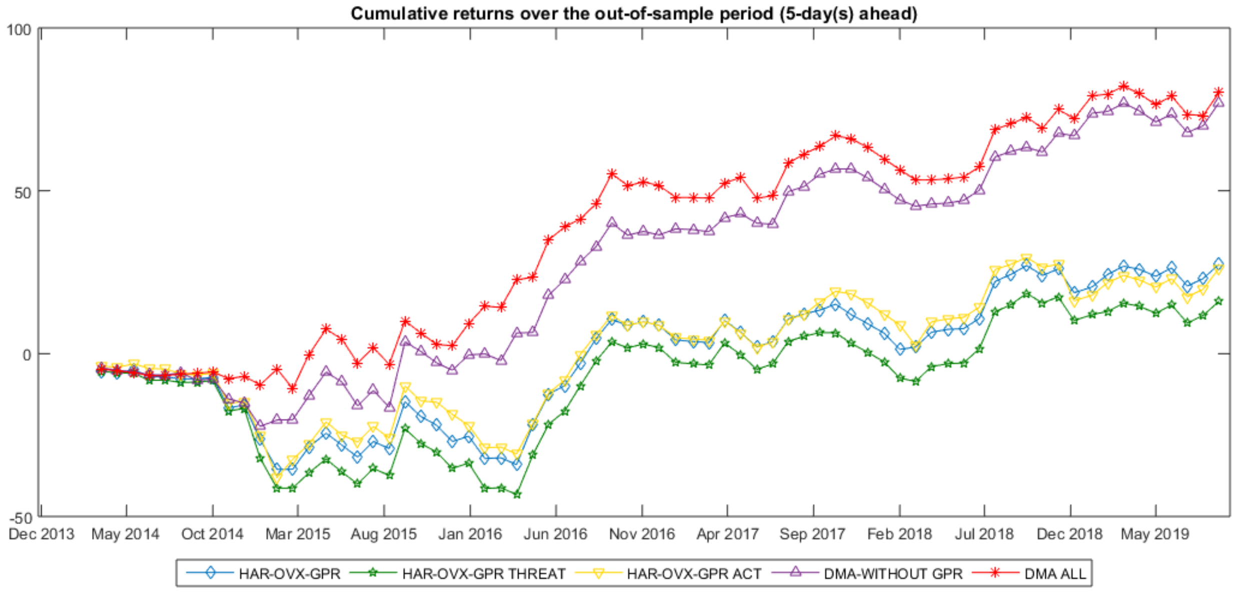

Figure 10: Cumulative trading returns when forecasting oil price realized volatility - 5-days ahead horizon.

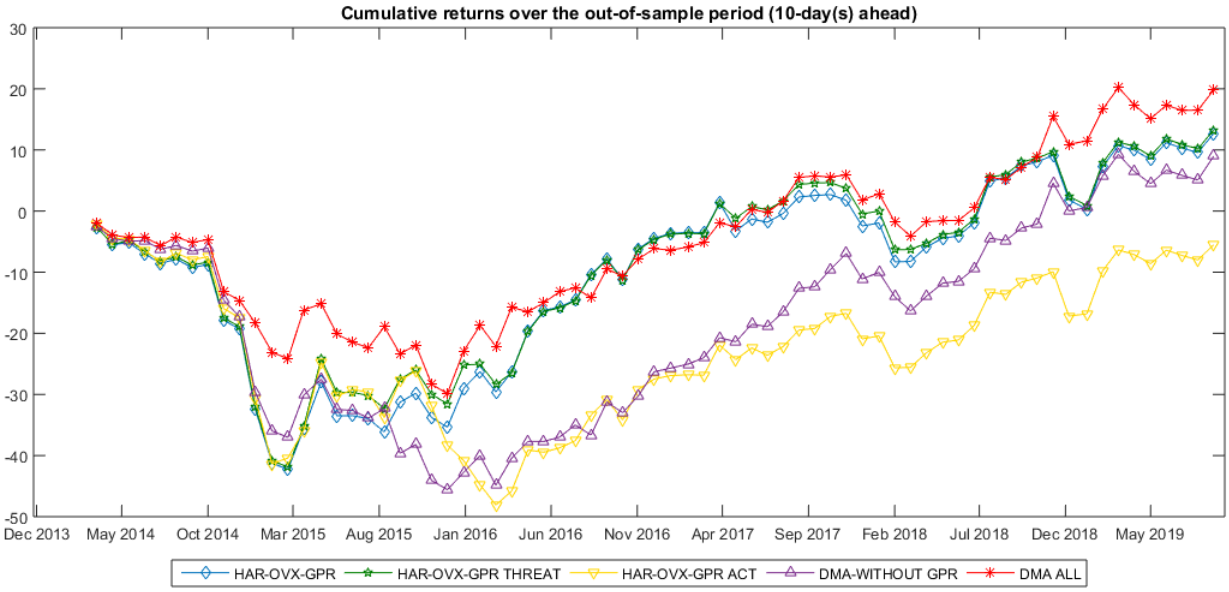

Figure 11: Cumulative trading returns when forecasting oil price realized volatility - 10-days ahead horizon.

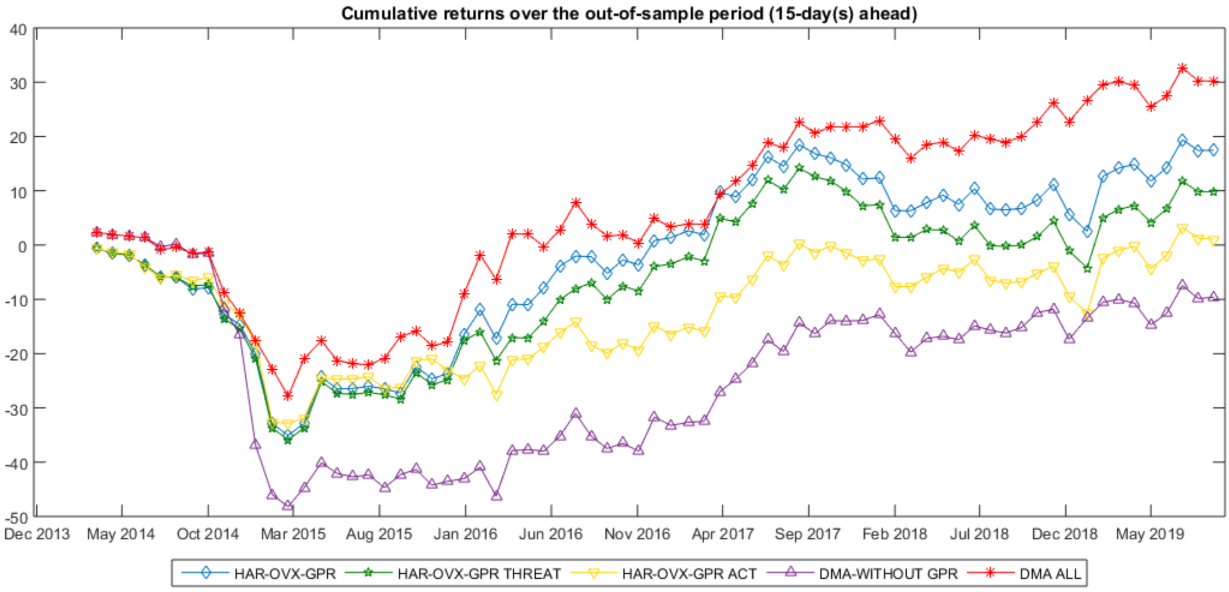

Figure 12: Cumulative trading returns when forecasting oil price realized volatility - 15-days ahead horizon.

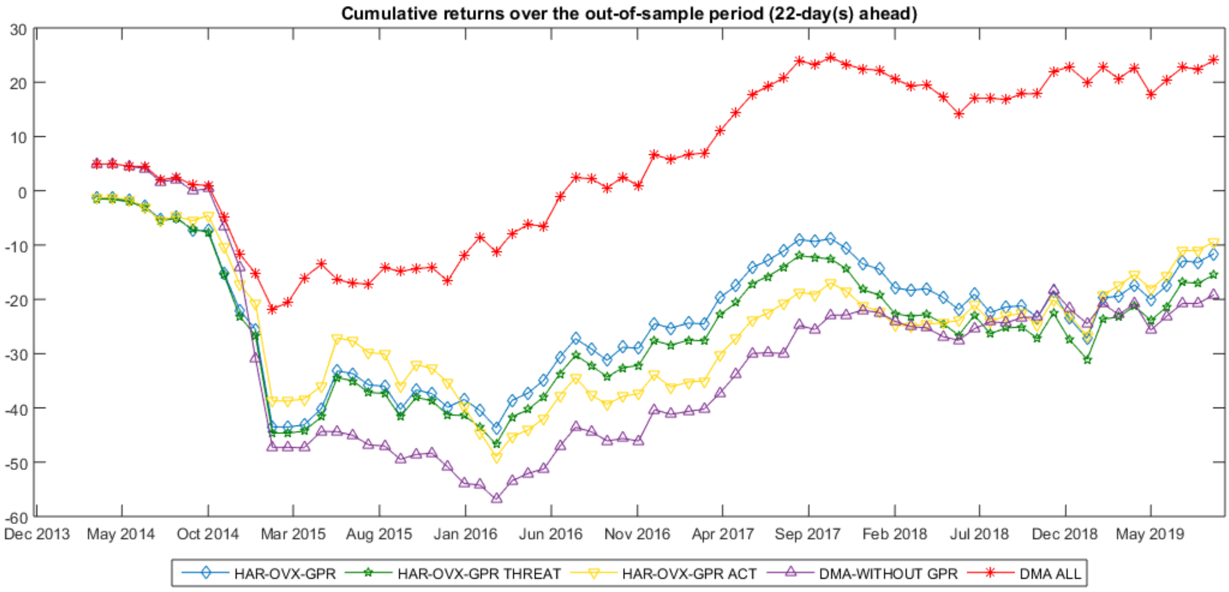

Figure 13: Cumulative trading returns when forecasting oil price realized volatility - 22-days ahead horizon.

Appendix DMA approach

In this part, we concentrate on the one-step ahead forecasting procedure in order to show the updating steps of the DMA approach in detail. Regarding multi-period ahead forecasting, the idea is similar because the whole framework of the DMA approach is based on the Eq. (17), which describes how the direct forecasts are obtained.

The main methodological approach of the updating equations of the TVP model is based on the Kalman filter, which begins with the result:

$$(\boldsymbol{\alpha}_{\boldsymbol{t-1}} \mid y^{t-1}) \sim N(\hat{\boldsymbol{\alpha}}_{\boldsymbol{t-1}}, \boldsymbol{\Sigma}_{\boldsymbol{t-1|t-1}}), \tag{24}$$

The Kalman filtering process proceeds as follows:

$$(\boldsymbol{\alpha}_{\boldsymbol{t}} \mid y^{t-1}) \sim N(\hat{\boldsymbol{\alpha}}_{\boldsymbol{t-1}}, \boldsymbol{\Sigma}_{\boldsymbol{t|t-1}}), \tag{25}$$

where $\boldsymbol{\Sigma}_{\boldsymbol{t|t-1}} = \boldsymbol{\Sigma}_{\boldsymbol{t-1|t-1}} + \boldsymbol{\Sigma}_{\boldsymbol{u_t}}$.

Since we are motivated by the approach that Grassi et al. (2017) proposed, the updating equation of $\boldsymbol{\Sigma}_{\boldsymbol{t|t-1}}$ is perturbed by a function of the squared prediction errors, which is shown in the updating steps. At this step, we assume the following:

$$\boldsymbol{\Sigma}_{\boldsymbol{t|t-1}} = \boldsymbol{\Sigma}_{\boldsymbol{t-1|t-1}}. \tag{26}$$

At this point, we have to mention that due to the fact that we use the aforementioned approach, we no longer have to estimate $\boldsymbol{\Sigma}_{\boldsymbol{u_t}}$. Kalman filter procedure is completed by the updating equation:

$$(\boldsymbol{\alpha}_{\boldsymbol{t}} \mid y^{t}) \sim N(\hat{\boldsymbol{\alpha}}_{\boldsymbol{t}}, \boldsymbol{\Sigma}_{\boldsymbol{t|t}}), \tag{27}$$

where

$$\hat{\boldsymbol{\alpha}}_{\boldsymbol{t|t}} = \hat{\boldsymbol{\alpha}}_{\boldsymbol{t|t-1}} + \boldsymbol{\Sigma}_{\boldsymbol{t|t-1}} \boldsymbol{x}_{\boldsymbol{t}}' (\hat{H}_t + \boldsymbol{x}_{\boldsymbol{t}} \boldsymbol{\Sigma}_{\boldsymbol{t|t-1}} \boldsymbol{x}_{\boldsymbol{t}}')^{-1} (y_t - \boldsymbol{x}_{\boldsymbol{t}} \hat{\boldsymbol{\alpha}}_{\boldsymbol{t-1}}), \tag{28}$$

and

$$\boldsymbol{\Sigma_{t|t}} = \boldsymbol{\Sigma_{t|t-1}} - \boldsymbol{\Sigma_{t|t-1}}\boldsymbol{x_t'}(\hat{H}_t + \boldsymbol{x_t}\boldsymbol{\Sigma_{t|t-1}}\boldsymbol{x_t'})^{-1}\boldsymbol{x_t}\boldsymbol{\Sigma_{t|t-1}} + \beta \cdot max\left[0, FL\left(\frac{\varepsilon_t^2}{\hat{H}_t} - 1\right)\right] \cdot I, \quad (29)$$

where $\varepsilon_t = y_t - \boldsymbol{x_t}\boldsymbol{\hat{\alpha}_{t-1}}$ and the estimated error variance is calculated by the following[22]:

$$\hat{H}_t = \kappa \hat{H}_{t-1} + (1-\kappa)\varepsilon_t^2. \quad (30)$$

Recursive forecasting is implemented by using the predictive distribution,

$$(y_t \mid y^{t-1}) \sim N(\boldsymbol{x_t}\boldsymbol{\hat{\alpha}_{t-1}}, \hat{H}_t + \boldsymbol{x_t}\boldsymbol{\Sigma_{t|t-1}}\boldsymbol{x_t'}). \quad (31)$$

After having estimated each individual model of the K combinations under the TVP approach, which is explained analytically in the previous part, the DMA averages the forecasts obtained by the individual models using $\pi_{t|t-1,k}$ as weights for $k = 1, \ldots, K$ over the out-of-sample period. Those DMA forecasts can be expressed as:

$$E(y_t \mid y^{t-1}) = \sum_{k=1}^{K} \pi_{t|t-1,k}\boldsymbol{x_{t-1}^{(k)}}\boldsymbol{\hat{\alpha}_{t-1}^{(k)}} \quad (32)$$

where $\boldsymbol{\hat{\alpha}_{t-1}^{(k)}}$ are the Kalman filter estimates of the state-space model at time $t-1$.

At this point, probability in the forecasting model has to be determined. As proposed by Raftery et al. (2010), the relation between $\pi_{t|t-1,k}$ and $\pi_{t-1|t-1,k}$ is described as:

$$\pi_{t|t-1,k} = \frac{\pi_{t-1|t-1,k}^{\alpha}}{\sum_{l=1}^{K} \pi_{t-1|t-1,l}^{\alpha}} \quad (33)$$

where $0 < \alpha \leqslant 1$ is a forgetting factor[23], which is constant and smaller than 1.

[22]The design parameters β and κ are set as 1e-10 and 0.94, respectively.

[23]In this study, we follow Koop and Korobilis (2012) in setting $\alpha = 0.99$.

The updating equation is defined as follows:

$$\pi_{t|t,k} = \frac{\pi_{t|t-1,k} f_k(y_t \mid y^{t-1})}{\sum_{l=1}^{K} \pi_{t|t-1,l} f_l(y_t \mid y^{t-1})} \tag{34}$$

where $f_k(y_t \mid y^{t-1})$ is the predictive density of model k. The main idea of this updating equation is that a model, which had a better forecasting performance in the past, will receive higher weight at time t.

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