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Global economic policy uncertainty aligned: An informative predictor for crude oil market volatility[☆]

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ABSTRACT

This paper constructs an aligned global economic policy uncertainty (GEPU) index based on a modified machine learning approach. We find that the aligned GEPU index is an informative predictor for forecasting crude oil market volatility both in- and out-of-sample. Compared to general GEPU indices without supervised learning, well-recognized economic variables, and other popular uncertainty indicators, the aligned GEPU index is rather powerful and can provide preponderant or complementary information. The trading strategy based on the aligned GEPU index can also generate sizable economic gains. The statistical source of the aligned GEPU index's predictive power is that it can learn both the magnitude and sign of national EPU variables' predictive ability and thus yields reasonable and informative loadings. On the other hand, the economic driving force probably stems from the ability for forecasting the shocks of oil-related fundamentals.

1. Introduction

The prediction of crude oil market volatility is very important and useful for oil-related investors, firms, and organizations in many fields such as risk management and portfolio allocation. Therefore, an extensive body of academic studies investigate how to improve the predictability of crude oil market volatility (see, e.g., Degiannakis & Filis, 2017; Gkillas et al., 2020; Gong & Lin, 2018; Haugom et al., 2014; Kristjanpoller & Minutolo, 2016; Ma, Liao et al., 2019a; Pan et al., 2017; Prokopczuk et al., 2016; Sévi, 2014; Wang et al., 2016; Wei et al., 2017; Zhang et al., 2022, 2019). However, it remains an open question which determinants are informative for predicting oil price volatility. Recently, a growing number of works find that the economic policy uncertainty (EPU), pioneered by Baker et al. (2016), appears to be predictive for oil price volatility (see, e.g., Li et al., 2021; Liang et al., 2020; Ma et al., 2018; Wei et al., 2017). Along the same lines, this paper contributes to the existing literature by originally proposing an aligned global economic policy uncertainty (GEPU) index with supervised learning. Furthermore, we shed new light on the relationship between EPU and crude oil price volatility.

We provide theoretical interpretations of the predictive power of our new GEPU index for future crude oil

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price volatility in three dimensions. First, GEPU contains information on *economics* and finance. Barsky and Kilian (2004) and Kilian (2009) argue that macroeconomic conditions are responsible for the changes of oil price by shifting oil demand. Moreover, Kilian and Hicks (2013) present that unexpected economic growth plays a leading role in driving up crude oil prices.[1] This is because economic growth will lead to an increase in oil demand (Hamilton, 2009). In addition, Ma, Ji et al. (2019b) provide evidence that financial predictor is most powerful for forecasting crude oil market volatility, and oil financialization is becoming the central determinant of crude oil price behavior. In this sense, GEPU is informative for future oil price volatility as it contains information on economics and finance.

Second, GEPU reflects information about *uncertainty*. Uncertainty arises from a wide range of factors such as financial crises, policy changes, political elections, wars, terrorist attacks, geopolitical risk, and financial market volatility. Barsky and Kilian (2004) provide a detailed analysis regarding the effect of uncertainty factors (e.g., political events, wars, and embargo policy) on oil price shocks. Furthermore, it has been well recognized that uncertainty variables are powerful for forecasting crude oil price volatility (see, e.g., Li et al., 2021; Liang et al., 2020; Wei et al., 2017).

Third, GEPU also covers *global* information. Crude oil is a central resource for the global economy instead of a specific country. Therefore, a voluminous literature (see, e.g., Barsky & Kilian, 2004; Hamilton, 2009; Kilian, 2009; Kilian & Hicks, 2013) investigate oil price behavior from a global perspective, mainly involving the Organization of the Petroleum Exporting Countries (OPEC), Organization for Economic Co-operation and Development (OEDC), emerging economies (e.g., China), the Middle East, and the United States, among others. For this motivation, Ratti and Vespignani (2016) and Miao et al. (2017) rely on global factors to predict oil prices. We thus infer that GEPU appears informative for future oil price volatility as it covers global market information.

Apart from the three economic motivations, our newly constructed GEPU index has a statistical learning ability. Specifically, we align individually national EPU indices with the forecast target of crude oil market volatility. Therefore, the resulting GEPU index can learn useful information from the forecast target. Alternatively, Davis (2016) proposes a general GEPU index that is a GDP-weighted average of national EPU indices. We also construct another two general GEPU indices based on the simple mean and principal component analysis (PCA) approaches, which use the equally weighted average and first principal component, respectively, of national EPU indices. The three general GEPU indices can only eliminate the idiosyncratic noises of individual EPU indices but retain their common approximation errors that are not relevant for forecasting crude oil market volatility. To surmount this econometric difficulty, we employ the partial least squares (PLS) approach by Kelly and Pruitt (2013, 2015) to filter out both the irrelevantly idiosyncratic and common error components from the individual EPU proxies, thus extracting the most relevant component that is informative for future oil volatility.

Empirically, we provide evidence that our aligned GEPU index can predict crude oil market volatility both in- and out-of-sample. The predictive power of the aligned GEPU index continues to be significant in long-horizon volatility forecasting, and survives a series of robustness checks, including alternative benchmark models, alternative forecast evaluation methods, different crude oil proxies, and alternative variable sets of national EPU indices. Furthermore, the trading strategy based on the aligned GEPU index can generate sizable economic gains, which is helpful for investors.

The aligned GEPU index dominates the above-mentioned general GEPU indices during the full-sample period. Nonetheless, the predictability of the aligned GEPU index and general GEPU indices is concentrated in cyclical expansions and recessions, respectively, thus providing complementary information across business cycles. This appears helpful for further improving the predictability for oil volatility. In addition, we document that the predictability of the aligned GEPU index is not driven by economic variables related to changes in macroeconomic risks or business-cycle fundamentals. Furthermore, our aligned GEPU index can provide additional and complementary information beyond what is already contained in the existing uncertainty indices. In this sense, the aligned GEPU index is a valuable predictor for oil volatility relative to the existing well-recognized predictors.

We further explore the source of our aligned GEPU index's predictive power for forecasting crude oil market volatility. On the one hand, the statistical source of the predictive power stems from the ability of supervised learning. Specifically, the used PLS approach can learn both the magnitude and sign of national EPU variables' predictive ability and thus yields reasonable and informative loadings on the aligned GEPU index. By contrast, the loadings on the general GEPU indices are irrelevant to the purpose of forecasting oil volatility. On the other hand, many studies attribute oil price behavior to the shocks of oil supply and demand (Barsky & Kilian, 2004; Kilian, 2009; Kilian & Hicks, 2013). We empirically demonstrate that the aligned GEPU index has a better predictive ability for the shocks of oil supply and demand than the general GEPU indices. This is the economic driving force behind the predictability of the aligned GEPU index.

This paper is closely related to the literature on economic policy uncertainty and the predictability of crude oil market volatility (see, e.g., Li et al., 2021; Liang et al., 2020; Ma et al., 2018; Wei et al., 2017). In comparison with the related works, the paper's contribution is threefold. First and most importantly, we use a machine learning approach, PLS, to construct a new GEPU index that aligns national EPU indices toward the purpose of forecasting oil volatility. Furthermore, we document that the aligned GEPU index yields better forecasting performance than the general GEPU indices. Second, we provide a detailed comparison with popular economic variables

[1] Conversely, oil price shock and volatility would also affect economic growth and macroeconomic conditions (see, e.g., Ferderer, 1996; Hamilton, 1983, 1996; Mork, 1989).

and uncertainty indicators and find that the aligned GEPU index remains powerful and useful in the presence of the popular predictors. Third, we provide evidence to explain both the statistical and economic sources of the predictive power of the aligned GEPU index for forecasting oil price volatility.

More broadly, this paper is also related to the studies that use the PLS approach to construct a new predictor for forecasting financial markets. Nearly all the related studies rely on the PLS approach to forecast stock returns (see, e.g., Hoang et al., 2021; Huang et al., 2015; Kelly & Pruitt, 2013; Lin, 2018; Stivers, 2018). Distinct from these studies, this paper focuses on crude oil market and its price volatility. More importantly, since asset price volatility is highly persistent, the lagged volatility variables can predict a large amount of future volatility (see Corsi, 2009; Paye, 2012). Accordingly, the autoregression (AR) model is the most popular and useful benchmark for forecasting aggregate market volatility. In such a framework, we should not align the proxy variables (i.e., national EPU indices) directly towards the forecast target of future market volatility. In doing so, the aligned predictor and AR lags would have overlapping information, thus lowering the predictive power. In light of this issue, we propose a modified PLS approach, in which the learning target is not the dependent variable (i.e., future oil market volatility) but the AR residual (i.e., the unpredictable component). Our empirical evidence suggests that the modified PLS approach generates stronger predictability (e.g., larger in-sample R^2) than the conventional PLS approach.

The remainder of the paper is organized as follows. Section 2 presents the variables, models, and data source. Section 3 provides in-sample predictive analysis. Section 4 reports out-of-sample forecasting performance. Section 5 makes several robustness checks. Section 6 provides explanations about the source of predictive power. Finally, Section 7 concludes.

2. Methodology and data

2.1. Realized variance of oil prices and its predictive benchmark

Following the related literature on the prediction of aggregate market volatility (see, e.g., Chen et al., 2016; Christiansen et al., 2012; Nonejad, 2017; Paye, 2012; Wang et al., 2018), we calculate the realized variance (RV) as a proxy for the aggregate oil market volatility. Specifically, RV is calculated by summing all the squared daily market returns in a month,

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

where RV_t is the realized variance for month t, $r_{t,j}$ represents the daily return for the jth trading day in month t, and M_t is the number of all trading days in month t.

The aggregate market volatility calculated by Eq. (1) is typically leptokurtotic and non-Gaussian. Most of the predictive regressions used by this paper are estimated by ordinary least squares (OLS). Nonetheless, the OLS estimator appears to be misleading when regression errors are non-Gaussian. To avoid such an issue, we take the natural logarithm of the original RV, i.e., $LV_t = \ln(RV_t)$, which is approximately Gaussian (see also Chen et al., 2016; Christiansen et al., 2012; Nonejad, 2017; Paye, 2012; Wang et al., 2018; Zhang et al., 2022). That is, we rely on the logarithmic RV, LV_t, to model and forecast the aggregate oil market volatility in the empirical analysis.

The prevailing benchmark model for forecasting aggregate market volatility is the autoregression (AR) model,

$$LV_{t+1} = \alpha + \sum_{\ell=1}^{L} \beta_\ell LV_{t+1-\ell} + \omega_{t+1}, \tag{2}$$

where ω_{t+1} is the regression error. The optimal lag length $L = 2$, which is determined by the Bayesian information criterion (BIC).[2]

Paye (2012), Wang et al. (2018), Zhang et al. (2022), and many others also use the AR benchmark model to predict aggregate market volatility at the monthly frequency. It should be noted that the heterogeneous autoregressive (HAR) model pioneered by Corsi (2009) is a widely used benchmark to predict volatility at the daily frequency (see, e.g., Corsi et al., 2010; Degiannakis & Filis, 2017, 2022; Haugom et al., 2014; Lang et al., 2021; Li et al., 2020; Sévi, 2014; Zhang et al., 2020). While this study is based on the monthly frequency, we also consider the HAR benchmark. Two important findings emerge (see the Internet Appendix for the details). First, the AR benchmark and its extensions outperform the HAR benchmark and its extensions, respectively. This indicates that the AR model is a preferred benchmark in this study, which is consistent with the existing studies on predicting aggregate market volatility at the monthly frequency. Second, regardless of which benchmark (AR or HAR) we choose, our aligned GEPU index always shows the best forecasting performance.

2.2. Construction of the aligned GEPU index

The main purpose of this paper is to construct an aligned GEPU index and use it to improve the predictability of crude oil market volatility. To this end, we rely on the PLS approach developed by Kelly and Pruitt (2013, 2015). Compared to traditional dimension reduction methods such as the PCA, the PLS possesses an additional function of supervised learning. More specifically, the PLS approach can aggregate predictive information that is relevant to the forecast target. The related literature on return predictability (see, e.g., Hoang et al., 2021; Huang et al., 2015; Lin, 2018) use the PLS approach to construct diffusion indices that are aligned with future stock returns (i.e., the forecast target).

It is important to note that we propose a modification to the conventional PLS by learning the information from the unpredictable component (i.e., residual term)

[2] In the robustness check below, we further consider the Akaike information criterion (AIC) and adjusted R^2 to choose the optimal number of AR lags. Our results are not specific to alternative choices of AR lags.

in the AR benchmark model (2) instead of the forecast target (i.e., realized variance). This is because financial market volatility is highly persistent and thereby exhibits strong autocorrelation (Corsi, 2009). As a result, the AR benchmark (that is, the RV lags) can explain and predict a large amount of the future RV component. Given this, we have to add new predictors into the AR benchmark and investigate whether the new predictors can provide useful information that is complementary to that contained in the RV lags. In such a framework, the learning target should be the residual term (i.e., the unpredictable component) in the AR benchmark model (2) instead of the dependent variable of RV.

We show our modified PLS approach through three steps. In the first step, we run N (the number of all the national EPU variables) time-series regressions. Specifically, for each EPU variable from the N cross-national markets in $\{EPU_i\}_{i=1}^{N}$, we run a time-series regression of $EPU_{i,t}$ on a constant and the learning target of ω_{t+1} in Eq. (2) instead of the forecast target of LV_{t+1} as follows.

$$EPU_{i,t} = \pi_{i,0} + \pi_i \omega_{t+1} + u_{i,t}, \tag{3}$$

where π_i is the loading that captures the sensitivity of the ith EPU to the true driver instrumented by the unpredictable component ω_{t+1}.

In the second step, we run T cross-sectional regressions. Specifically, for each time t, we run a cross-sectional regression of $EPU_{i,t+1}$ on a constant and the corresponding loading $\hat{\pi}_i$ estimated in regression (3),

$$EPU_{i,t+1} = \phi_{t+1} + F_{t+1}^{PLS} \hat{\pi}_i + v_{i,t+1}, \tag{4}$$

where the regression coefficient F_{t+1}^{PLS} is the aligned GEPU index (GEPU-PLS hereafter) extracted from N national EPU indices.

In the third step, we forecast crude oil market volatility by regressing LV_{t+1} on a constant, the AR lags, and the PLS index $\hat{F}_t^{PLS}$ estimated in (4),

$$LV_{t+1} = \alpha + \sum_{\ell=1}^{L} \beta_\ell LV_{t+1-\ell} + \psi \hat{F}_t^{PLS} + \varepsilon_{t+1}. \tag{5}$$

Actually, our modified PLS approach includes four steps. Before conducting the above-mentioned three traditional steps in Eq. (3)–(5), we have to run regression (2) to obtain the error term (i.e., the learning target). This additional step is not included by the conventional PLS approach. Furthermore, the learning target in the conventional PLS approach is just the forecast target. That is, the conventional PLS approach replaces ω_{t+1} with LV_{t+1} in Eq. (3).

Finally, it should be noted that we produce our GEPU-PLS index recursively when doing the out-of-sample forecasting exercise. Specifically, we only use all the data available up to month t when forecasting oil market volatility in month $t + 1$. Therefore, there is no look-ahead bias in the out-of-sample test.

2.3. Other variables and their predictive models

To confirm the superiority of our aligned GEPU index based on the novel PLS method, we should compare it with other related uncertainty variables in terms of their predictive ability. First, the raw GEPU proposed by Davis (2016) and provided by the EPU website is a natural benchmark, which is labeled GEPU-website. In addition, as the aligned GEPU index can be regarded as a diffusion index, we should consider other popular diffusion indices such as simple mean and PCA. Specifically, the simple mean index is the equally weighted average of all the individual cross-national EPUs, which is dubbed GEPU-mean. The PCA index is the first principal component extracted from all the individual cross-national EPUs, which is dubbed GEPU-PCA. Compared to the PLS index, the diffusion indices of GEPU-website, GEPU-mean, and GEPU-PCA are completely powerless to learn useful information from the forecast (or learning) target. Given this, we presume that our PLS index with supervised learning can outperform the traditional diffusion indices. While this is not an exhaustive comparison of all diffusion indices, we have considered the three most necessary indices that are closely related to our PLS index.

In addition to the related diffusion indices that are based on global EPUs, we further consider some popular economic variables and uncertainty indicators to investigate whether the predictive power of our aligned GEPU index is driven by these omitted variables, which are related to business-cycle fundamentals or changes in macroeconomic risks. Specifically, we consider 14 commonly adopted economic variables from Welch and Goyal (2008): (1) log dividend-price ratio (DP), (2) log dividend yield (DY), (3) log earnings-price ratio (EP), (4) log dividend-payout ratio (DE), (5) stock return variance (SVAR), (6) book-to-market ratio (BM), (7) net equity expansion (NTIS), (8) treasury bill rate (TBL), (9) long-term yield (LTY), (10) long-term return (LTR), (11) term spread (TMS), (12) default yield spread (DFY), (13) default return spread (DFR), and (14) inflation (INFL).[3] In addition, the considered uncertainty variables include financial uncertainty (FU), macro uncertainty (MU), real uncertainty (RU), monetary policy uncertainty (MPU), geopolitical risk (GPR), and CBOE volatility index (VIX).[4]

To investigate the in- and out-of-sample predictability of various predictors, we estimate the predictive regression models as follows.

$$LV_{t+1} = \alpha + \sum_{\ell=1}^{L} \beta_\ell LV_{t+1-\ell} + \varphi X_t + \varepsilon_{t+1}, \tag{6}$$

where X_t is one of the considered predictors, including GEPU-PLS, GEPU-website, GEPU-mean, and GEPU-PCA, six alternative uncertainty variables, and fourteen economic variables. Consistent with regression (5), regression (6) is an augmented AR model. Paye (2012) and Wang et al. (2018) also rely on this framework to explore the predictability of a potential predictor.

[3] We lag inflation for an extra month to account for the delay in releases of the CPI.

[4] See Jurado et al. (2015), Baker et al. (2016), Caldara and Iacoviello (2022), and Ludvigson et al. (2021) for more details about the considered uncertainty variables.

2.4. Data source

First, our dependent variable is the realized variance of crude oil market, which is calculated based on daily crude oil prices. We collect the price data from the homepage of the U.S. Energy Information Administration (EIA) at https://www.eia.gov/.

Second, the most important explanatory variable is the GEPU index proposed by Davis (2016). The data are available from the EPU website at http://www.policyuncertainty.com/.[5] In terms of the individual EPU indices, we consider 15 countries: Brazil, Canada, Chile, China, France, Germany, Ireland, Italy, Japan, Russia, South Korea, Spain, Sweden, the United Kingdom, and the United States.[6] The reason why we choose the 15 specific countries is that their EPU data and the GEPU-website data are available as early as January 1997. In doing so, we can obtain a relatively long sample period spanning from January 1997 to December 2019.

The 14 economic variables of Welch and Goyal (2008) are available from Amit Goyal's webpage at http://www.hec.unil.ch/agoyal/. The uncertainty data of FU, MU, RU are updated by Sydney Ludvigson at https://www.sydneyludvigson.com/. The MPU and GPR data are also available from the EPU website. The VIX data are collected from *Yahoo!* Finance at https://finance.yahoo.com/. Finally, we use the volume of crude oil production and consumption to explore the economic source of predictive power for oil market volatility in Section 6.2 and the data are also available at the homepage of the EIA.[7]

3. In-sample predictive analysis

3.1. In-sample estimation results

To investigate the in-sample predictability of various GEPU indices, we run the predictive regression model in (6). The corresponding in-sample estimation results are reported in Table 1, Panel A. The coefficient estimate on our aligned GEPU (i.e., GEPU-PLS) is positive and statistically significant at the 1% level. An increase in GEPU-PLS of one standard deviation (2.73) leads to a 15.18% increase in oil market RV, which is economically significant. By contrast, the coefficient estimates on other competing GEPU indices are all insignificant.

In addition, we calculate the incremental R^2 (ΔR^2), defined as the in-sample R^2 of an augmented AR model of interest minus the in-sample R^2 of the AR benchmark, to measure the incremental information of the new predictor beyond that already contained in the AR lags (i.e., lagged RVs). We find that the ΔR^2 for GEPU-PLS is 3.15%, which is sizable relative to the counterparts of GEPU-website, GEPU-mean, and GEPU-PCA, ranging from 0.20% to 0.32%. In a word, the aligned GEPU index shows powerful in-sample predictability for crude oil market volatility, while the general GEPU indices fail to improve the explanatory ability of the AR model.

There remain two important issues. First, how is the predictive ability of the conventional GEPU-PLS whose learning target is RV instead of its error term? We report the in-sample estimation results of the conventional GEPU-PLS in Panel B of Table 1. Not surprisingly, the conventional GEPU-PLS exhibits a slight decline relative to our modified GEPU-PLS with respect to coefficient significance and ΔR^2. This evidence suggests that the modified PLS approach, in which the learning target is the error term in the AR benchmark model instead of RV, is not only theoretically reasonable but also practically useful. Nonetheless, the conventional GEPU-PLS continues to surpass the competing GEPU variables of GEPU-website, GEPU-mean, and GEPU-PCA.

Second, the GEPU-PLS index has a look-ahead bias when we use the full-sample data to construct it.[8] To avoid this issue, we recursively calculate $\hat{F}_t^{PLS}$ (the GEPU-PLS index at time t) based on the data no later than time t. In the study, we rely on the data in the first 10 years as the initial training sample to recursively calculate the look-ahead bias-free GEPU-PLS index. Panel C of

Table 1
In-sample estimation results for various GEPU indices.

GEPU indices	φ	t-stat	ΔR^2 (%)
Panel A: Major GEPU indices			
GEPU-website	−0.08	−1.32	0.25
GEPU-mean	−0.08	−1.51	0.32
GEPU-PCA	−1.30	−1.14	0.20
GEPU-PLS	5.56***	4.65	3.15
Panel B: Conventional GEPU-PLS aligned with the dependent variable instead of its residual term			
GEPU-PLS	8.25***	4.33	2.75
Panel C: Look-ahead bias-free GEPU-PLS			
GEPU-PLS	4.55**	2.16	1.09

This table reports the in-sample results for the following augmented AR model.

$$LV_{t+1} = \alpha + \sum_{\ell=1}^{L} \beta_\ell LV_{t+1-\ell} + \varphi X_t^{GEPU} + \varepsilon_{t+1},$$

where LV_{t+1} is the logarithmic realized variance in month t + 1, and X_t^{GEPU} denotes one of the considered GEPU indices. The regression coefficients of φ, its Newey–West t-statistics, and incremental R^2 (ΔR^2) are reported. Specifically, ΔR^2 is defined as the in-sample R^2 of the above augmented AR model minus the in-sample R^2 of the AR benchmark. $**$ and $***$ indicate significance at the 5% and 1% levels, respectively. The full-sample period is from January 1997 to December 2019 (Note that the look-ahead bias-free GEPU-PLS index uses the first 10 years as the initial training sample period).

5 The EPU website provides two versions for the GEPU index - one based on current-price GDP measures and one based on PPP-adjusted GDP. In the applications below, we use the former to represent the GEPU-website index. Of course, the results are qualitatively similar for alternative versions. In addition, it should be noted that the two versions for GEPU-website both have a look-ahead bias as they are measured based on the current price of GDP. Even then, our GEPU-PLS index can outperform the GEPU-website index.

6 In the robustness check below, we alternatively consider an extended variable set for national EPU indices and obtain qualitatively similar results.

7 Due to data constraints, we use the volume data of crude oil production and consumption in the United States.

8 It should be noted that the GEPU-PLS index has no look-ahead bias in the out-of-sample test because we recursively generate the index. In addition, the GEPU-website and GEPU-PCA also have a look-ahead bias. Even though, they show little in-sample predictability.

Table 1 reports the corresponding in-sample results. The look-ahead bias-free GEPU-PLS index delivers a smaller ΔR^2at 1.09% and its coefficient t-statistic decreases by more than 50%. This is intuitive since we have ruled out the look-ahead information. Nonetheless, in comparison with the general GEPU indices (i.e., GEPU-website, GEPU-mean, and GEPU-PCA), the look-ahead bias-free GEPU-PLS index remains powerful for the in-sample predictability of oil market volatility. Its ΔR^2 is still considerable and its slope estimate continues to be both statistically and economically significant.

Finally, it is of interest to explore the forecasting power of our aligned GEPU index in relation to that of the general GEPU indices. To this end, we run the following bivariate predictive regressions based on our aligned GEPU index and a control variable.[9]

$$LV_{t+1} = \alpha + \sum_{\ell=1}^{L} \beta_\ell LV_{t+1-\ell} + \varphi X_t + \psi \hat{F}_t^{PLS} + \varepsilon_{t+1}. \tag{7}$$

The coefficient of interest is the regression slope ψ on $\hat{F}_t^{PLS}$. Here, X_t is one of the general GEPU indices, such as GEPU-website, GEPU-mean, and GEPU-PCA; and in Section 3.2, X_t denotes one of the economic variables; in Section 3.3, X_t denotes one of the uncertainty variables except for GEPUs.

Table 2 reports the in-sample results of the bivariate predictive regressions between the aligned GEPU index and general GEPU indices. In comparison with the results reported in Table 1, Panel A, we obtain two interesting observations. First, the magnitude of GEPU-PLS's coefficients, significance levels, and ΔR^2s barely change. The estimates of regression slope ψ remain significantly positive and economically large. The resulting ΔR^2 ranges from 3.15% to 3.16%, which is almost the same as the one reported in Table 1, Panel A. Second, the magnitude of the general GEPU indices' coefficients and significance levels become smaller. For instance, the regression slope (its Newey–West t-statistic) of the GEPU-website changes from −0.08 (−1.32) reported in Table 1, Panel A, to 0.00 (0.03) reported in Table 2. Overall, the above-mentioned results suggest that the aligned GEPU-PLS empirically dominates the general GEPU indices in forecasting crude oil market volatility, and the general GEPU indices cannot provide complementary information that is useful to improve the in-sample predictability of the aligned GEPU-PLS.

Table 2
Comparison with general GEPU indices.

General GEPU indices	φ	t-stat	ψ	t-stat	ΔR^2 (%)
GEPU-website	0.00	0.03	5.57***	4.55	3.15
GEPU-mean	0.02	0.31	5.70***	4.55	3.16
GEPU-PCA	0.30	0.27	5.66***	4.61	3.16

This table reports the in-sample results for the following augmented AR model.

$$LV_{t+1} = \alpha + \sum_{\ell=1}^{L} \beta_\ell LV_{t+1-\ell} + \varphi X_t + \psi \hat{F}_t^{PLS} + \varepsilon_{t+1},$$

where LV_{t+1} is the logarithmic realized variance in month $t+1$, X_t denotes one of the general GEPU indices, and $\hat{F}_t^{PLS}$ is the aligned GEPU index generated by the PLS approach. The regression coefficients of φ and ψ, their Newey–West t-statistics, and incremental R^2 (ΔR^2) are reported. Specifically, ΔR^2 is defined as the in-sample R^2 of the above augmented AR model minus the in-sample R^2 of the AR benchmark. *** indicates significance at the 1% levels. The full-sample period is from January 1997 to December 2019.

3.2. Comparison with economic variables

In this subsection, we compare the in-sample predictability of the aligned GEPU-PLS index with economic variables and investigate whether its in-sample predictability stems from omitted economic variables related to changes in macroeconomic risks or business-cycle fundamentals. First, we run the univariate regression (6) with controls for alternative economic variables. The corresponding estimation results are reported in Panel A of Table 3. Out of the 14 individual economic variables, only log earnings-price ratio (EP), stock return variance (SVAR), long-term yield (LTY), long-term return (LTR), and default return spread (DFR) yield powerful regression slopes that are statistically significant at the 10% or better significance levels. Furthermore, only 2 economic variables, namely LTR and DFR, generate considerable ΔR^2 greater than 1%. By contrast, none of the 14 economic variables exhibits a higher significance level or greater ΔR^2 than the aligned GEPU-PLS index.

We then run the bivariate regression in Eq. (7) based on our aligned GEPU-PLS index and one of the individual economic variables. Also, the corresponding estimation results are reported in Panel A of Table 3. The estimates of the slope ψ on GEPU-PLS are in the range between 5.13 and 7.36, all of which are positive and sizable, similar with the results of the univariate regression including only GEPU-PLS reported in Table 1, Panel A. Moreover, the slope ψ continues to be statistically significant at the 1% level when augmented by the individual economic variables. The resulting ΔR^2s for the bivariate regressions range from 3.15% to 4.42%, which are substantially greater than those reported in the univariate regressions based on the individual economic variables alone. The results indicate that the in-sample predictability of the aligned GEPU-PLS index is not driven by macroeconomic fundamentals and this new predictor can provide substantial uncertainty forecasting information complementary to that already contained in the economic fundamentals.

3.3. Comparison with other uncertainty indicators

In this subsection, we compare the in-sample predictability of the aligned GEPU-PLS index with other popular uncertainty indicators. The motivation is that we wonder whether the predictive ability of the aligned GEPU indicator is a substitute for or is complementary to uncertainty indicators. Similar to the comparison with economic variables, we run both the univariate and bivariate regression models with other popular uncertainty indicators.

[9] Note that in this paper, the bivariate (univariate) predictive regression refers to the AR model that further includes two (one) predictors.

Table 3
Comparison with economic variables and uncertainty indicators.

Variables	Univariate regression			Bivariate regression				
	φ	t-stat	ΔR^2 (%)	φ	t-stat	ψ	t-stat	ΔR^2 (%)
Panel A: Economic variables								
DP	−0.11	−0.52	0.08	0.21	0.97	6.26***	4.38	3.39
DY	−0.17	−0.90	0.20	0.16	0.77	6.13***	4.31	3.29
EP	−0.20*	−1.72	0.66	−0.12	−1.36	5.26***	4.30	3.37
DE	0.11	1.26	0.29	0.13	1.52	5.66***	4.67	3.54
SVAR	17.14***	3.80	0.97	10.99	1.55	5.13***	3.98	3.53
BM	−0.57	−1.09	0.25	0.24	0.43	5.81***	4.40	3.18
NTIS	−0.85	−0.35	0.04	−5.37**	−2.27	7.36***	5.13	4.42
TBL	0.02	1.32	0.31	−0.01	−0.35	5.75***	4.42	3.17
LTY	0.04*	1.81	0.58	−0.02	−0.57	6.04***	4.01	3.20
LTR	0.03***	2.86	1.39	0.03**	2.35	5.13***	4.45	4.01
TMS	0.00	−0.11	0.00	0.00	−0.03	5.56***	4.66	3.15
DFY	0.12	1.06	0.30	0.19*	1.78	6.02***	4.89	3.89
DFR	−0.05***	−3.40	1.14	−0.04**	−2.53	5.20***	4.34	3.85
INFL	0.02	0.21	0.01	0.02	0.21	5.56***	4.65	3.16
Panel B: Alternative uncertainty variables								
FU	0.79***	3.44	2.41	0.55**	2.02	4.43***	3.15	4.19
MU	1.74***	3.08	2.54	1.88***	3.75	5.93***	4.89	6.11
RU	1.87	1.64	0.91	2.54**	2.37	6.25***	4.84	4.77
MPU	0.08	1.19	0.30	0.01	0.07	5.53***	4.28	3.15
GPR	0.07	1.36	0.36	0.10**	2.21	5.88***	4.85	3.83
VIX	0.31***	2.98	1.42	0.11	0.80	4.92***	3.22	3.27

This table reports the in-sample results for both the univariate AR model,

$$LV_{t+1} = \alpha + \sum_{\ell=1}^{L} \beta_\ell LV_{t+1-\ell} + \varphi X_t + \varepsilon_{t+1},$$

and the bivariate AR model,

$$LV_{t+1} = \alpha + \sum_{\ell=1}^{L} \beta_\ell LV_{t+1-\ell} + \varphi X_t + \psi \hat{F}_t^{PLS} + \varepsilon_{t+1},$$

where LV_{t+1} is the logarithmic realized variance in month t + 1, X_t denotes one of the competing predictors, including 14 popular economic variables (see Panel A) and 6 alternative uncertain indicators (see Panel B), and $\hat{F}_t^{PLS}$ is the aligned GEPU index generated by the PLS approach. The regression coefficients of φ and ψ, their Newey–West t-statistics, and incremental R^2 (ΔR^2) are reported. Specifically, ΔR^2 is defined as the in-sample R^2 of the above augmented (univariate or bivariate) AR model minus the in-sample R^2 of the AR benchmark. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The full-sample period is from January 1997 to December 2019.

The corresponding results are reported in Panel B of Table 3. The univariate regression results suggest that the financial uncertainty (FU), macro uncertainty (MU), and CBOE volatility index (VIX) have strong forecasting ability with significant coefficients and large ΔR^2s greater than 1%. Nonetheless, the aligned GEPU index continues to outperform all the uncertainty indicators, with a more significant coefficient and larger ΔR^2.

The bivariate regression results show that the macro uncertainty (MU), real uncertainty (RU), and geopolitical risk (GPR) yield larger regression coefficients with better significance levels. Furthermore, the joint ΔR^2 for the bivariate regression based on GEPU-PLS and MU (RU, GPR) is larger than the sum of the single ΔR^2s for their univariate counterparts. These results imply that the predictive ability between GEPU-PLS and MU (RU, GPR) are nearly perfectly complementary to each other, in line with their relatively low correlations (which are unreported, but available upon request).

The bivariate regression results also show that the financial uncertainty (FU), monetary policy uncertainty (MPU), and CBOE volatility index (VIX) yield smaller regression coefficients with no or worse significance levels. Furthermore, the joint ΔR^2 for the bivariate regression based on GEPU-PLS and FU (MPU, VIX) is smaller than the sum of the single ΔR^2s for their univariate counterparts. These results imply that GEPU-PLS empirically dominates FU, MPU, and VIX in terms of predicting crude oil market volatility. This can be attributed to their high correlations (unreported, but available upon request).

In sum, the aforementioned evidence suggests that the new aligned GEPU index can provide additional and complementary uncertainty information beyond what is already contained in the existing uncertainty indices for forecasting crude oil market volatility.

4. Out-of-sample forecasting results

4.1. Out-of-sample forecasting performance

Since our sample period is not very long, we use an expanding estimation window to generate out-of-sample forecasts of crude oil market volatility. The initial estimation sample period is from January 1997 to December 2006, totaling 10 years. Accordingly, the out-of-sample evaluation period runs from January 2007 to December 2019, totaling 13 years. By doing so, we have a desirable trade-off between the in-sample estimation period that has a relatively large sample to accurately estimate initial regression slopes and the out-of-sample period that is long enough for the evaluation. Again, note that we produce our GEPU-PLS index recursively when doing the out-of-sample forecasting exercise. Specifically, we only use all the data available up to month t when forecasting oil market volatility in month $t + 1$. Therefore, there is no look-ahead bias in the out-of-sample test.

In terms of forecast evaluation, we follow the literature on forecasting aggregate market volatility (Christiansen et al., 2012; Paye, 2012; Wang et al., 2018; Zhang et al., 2022) and rely on the out-of-sample R^2 (R^2_{OS}) statistic.[10] The R^2_{OS} measures the proportional reduction in the mean squared predictive error (MSPE) of a forecasting model of interest relative to that of the AR model. Statistically, the R^2_{OS} statistic is computed by the following expression.

$$R^2_{OS} = 1 - \frac{\sum_{t=p}^{T-1}\left(LV_{t+1} - \widehat{LV}^{M}_{t+1}\right)^2}{\sum_{t=p}^{T-1}\left(LV_{t+1} - \widehat{LV}^{B}_{t+1}\right)^2}, \tag{8}$$

where p is the number of observations in the initial estimation sample, T is the number of observations over the whole sample, LV_{t+1} is the true value of the logarithmic RV in month $t + 1$, $\widehat{LV}^{M}_{t+1}$ and $\widehat{LV}^{B}_{t+1}$ are the forecasts of a forecasting model of interest and the AR benchmark, respectively. A positive R^2_{OS} implies that the corresponding predictive model yields more accurate forecasts than the AR benchmark model, while a negative value indicates the opposite. Furthermore, the statistical significance for R^2_{OS} is tested by the adjusted MSPE statistic proposed by Clark and West (2007) (CW statistic or CW-stat hereafter). The CW statistic tests the null hypothesis that the MSPE of the AR benchmark is lower than or equal to the MSPE of a predictive regression model against the upper-tail alternative hypothesis that the MSPE of the AR benchmark is higher than the MSPE of a predictive regression model.

Table 4 reports the out-of-sample forecasting results for the augmented AR models with various GEPU indices. Consistent with the in-sample predictability results reported in Panel A of Table 1, the out-of-sample results show that our aligned GEPU-PLS index substantially enhances forecast accuracy with a large and significant R^2_{OS} of 2.99%. Nonetheless, all the general GEPU indices (i.e., GEPU-website, GEPU-mean, and GEPU-PCA) yield negative R^2_{OS}s, suggesting that they lower the out-of-sample predictability of the AR benchmark. In short, the aligned GEPU-PLS index outperforms the general GEPU indices, as well as the AR benchmark, and can significantly predict crude oil market volatility out-of-sample.

Table 4
Out-of-sample forecasting performance.

GEPU indices	R^2_{OS} (%)	CW-stat	p-value
GEPU-website	−3.58	0.09	0.46
GEPU-mean	−2.63	0.46	0.32
GEPU-PCA	−2.72	0.42	0.34
GEPU-PLS	2.99***	2.75	0.00

This table reports the out-of-sample forecasting performance for the augmented AR model with one of the GEPU indices. The out-of-sample performance is evaluated by the R^2_{OS} statistic. A positive R^2_{OS} implies that the corresponding predictive model outperforms the AR benchmark, while a negative value indicates the opposite. The statistical significance for R^2_{OS} is tested by the Clark and West (2007) statistic (CW-stat). *** indicates significance at the 1% level. The initial estimation sample period is from January 1997 to December 2006, while the out-of-sample evaluation period runs from January 2007 to December 2019.

4.2. Business cycles

It is of interest to examine the predictability of the GEPU indices over business-cycle expansions and recessions. To this end, we follow related literature (see, e.g., Huang et al., 2015; Jiang et al., 2019; Neely et al., 2014; Pan et al., 2020; Rapach et al., 2010; Wang et al., 2019) and calculate the R^2_{OS} statistic separately during expansions ($R^2_{OS,\mathrm{EXP}}$) and recessions ($R^2_{OS,\mathrm{REC}}$),

$$R^2_{OS,c} = 1 - \frac{\sum_{t=p}^{T-1} I^{c}_{t+1}\left(LV_{t+1} - \widehat{LV}^{M}_{t+1}\right)^2}{\sum_{t=p}^{T-1} I^{c}_{t+1}\left(LV_{t+1} - \widehat{LV}^{B}_{t+1}\right)^2} \text{ for } c = \mathrm{EXP}, \mathrm{REC}, \tag{9}$$

where I^{EXP}_{t+1} (I^{REC}_{t+1}) is an indicator that takes a value of one when month t+1 is in an NBER-dated expansion (recession) period and zero otherwise.

Table 5 reports the forecasting results over business cycles. The aligned GEPU index generates significantly positive R^2_{OS} during business-cycle expansions but negative R^2_{OS} during business-cycle recessions. However, we observe an opposite pattern for the general GEPU indices. In other words, the predictability of the aligned GEPU index is concentrated in expansions, while the predictability of the general GEPU indices is concentrated in recessions. It is a helpful finding because we can rely on the opposite forecasting patterns to further improve the out-of-sample predictability. More specifically, we find that the aligned GEPU index and its competing predictors (i.e., the general GEPU indices) provide complementary information across business cycles.[11] If the complementary predictive ability can persist in the future, we can rely on the aligned GEPU index and the general GEPU indices during expansions and recessions, respectively. Undoubtedly, this would help improve the out-of-sample forecasting performance of crude oil market volatility.

[10] We also consider the loss function of Quasi-Likelihood (QLIKE) suggested by Patton (2011) to evaluate the out-of-sample forecasting performance. The results are robust and reported in the Internet Appendix.

[11] We should note that, in terms of the whole sample, the results reported in Table 2 suggest that the aligned GEPU-PLS index dominates the general GEPU indices and the general GEPU indices cannot provide complementary information that is useful to improve the full-sample predictability of the aligned GEPU-PLS.

Table 5
Out-of-sample forecasting performance over business cycles.

GEPU indices	Expansion			Recession		
	R^2_{OS} (%)	CW-stat	p-value	R^2_{OS} (%)	CW-stat	p-value
GEPU-website	−6.86	−1.05	0.85	13.41**	1.86	0.03
GEPU-mean	−6.90	−1.07	0.86	19.49**	2.06	0.02
GEPU-PCA	−7.12	−1.15	0.88	20.04**	2.07	0.02
GEPU-PLS	4.26***	2.92	0.00	−3.60	−0.14	0.56

This table reports the out-of-sample forecasting performance over business cycles for the augmented AR model with one of the GEPU indices. The R^2_{OS} statistic is calculated separately based on the forecasts during cyclical expansions and recessions. A positive R^2_{OS} implies that the corresponding predictive model outperforms the AR benchmark, while a negative value indicates the opposite. The statistical significance for R^2_{OS} is tested by the Clark and West (2007) statistic (CW-stat). ** and *** indicate significance at the 5% and 1% levels, respectively. The initial estimation sample period is from January 1997 to December 2006, while the out-of-sample evaluation period runs from January 2007 to December 2019.

Table 6
Long-horizon forecasting performance.

GEPU indices	Quarterly		Semiyearly		Yearly	
	R^2_{OS} (%)	CW-stat	R^2_{OS} (%)	CW-stat	R^2_{OS} (%)	CW-stat
GEPU-website	−6.51	0.08	−9.88	−0.04	−10.19	0.18
GEPU-mean	−3.86	0.54	−5.49	0.61	−9.28	0.51
GEPU-PCA	−3.42	0.55	−4.58	0.68	−7.62	0.57
GEPU-PLS	1.94***	2.63	2.91***	2.90	4.90***	2.93

This table reports the long-horizon forecasting performance for the augmented AR model with one of the GEPU indices. The out-of-sample performance is evaluated by the R^2_{OS} statistic. A positive R^2_{OS} implies that the corresponding predictive model outperforms the AR benchmark, while a negative value indicates the opposite. The statistical significance for R^2_{OS} is tested by the Clark and West (2007) statistic (CW-stat). *** indicates significance at the 1% level. The initial estimation sample period is from January 1997 to December 2006, while the out-of-sample evaluation period runs from January 2007 to December 2019.

4.3. Long-horizon performance

In this paper, we focus on the predictability of various GEPU indices for the monthly horizon, while it is equally important to examine the predictability over longer horizons. Therefore, we further forecast crude oil market volatility over the quarterly, semiyearly, and yearly horizons and report the corresponding results in Table 6.

The aligned GEPU index continues to yield significantly positive R^2_{OS}s over longer horizons, while the general GEPU indices yield negative ones. Furthermore, the out-of-sample forecasting gain of the aligned GEPU index increases with the horizon length, and the forecasting power for the general GEPU indices decreases with the horizon length. This finding suggests that our aligned GEPU index is persistent and has a long-run effect on crude oil market volatility. It is important to stress that the GEPU-PLS index used to predict long-horizon volatility is aligned to the corresponding long-horizon target instead of the monthly target. This helps the GEPU-PLS index gather more useful information for forecasting long-horizon volatility.

4.4. Economic significance

The aforementioned analyses focus on out-of-sample evaluation from a statistical perspective. Nonetheless, investors are more interested in economic significance. We follow Degiannakis and Filis (2022) and investigate the economic value of oil price volatility forecasts. Degiannakis and Filis (2022) propose several trading strategies based on the forecasts of oil price volatility. We adopt one strategy that is most suitable for this study. Specifically, we take a long (short) position in the CBOE Crude Oil Volatility Index (OVX) at the beginning of month $t + 1$ if we expect an increase (decrease) in oil price volatility. We close the position at the market close in each trading month. Consequently, the trading strategy can realize a return in month $t + 1$ as follows.

$$\eta_{t+1} = \begin{cases} r_{t+1}, & \text{if } \widehat{LV}_{t+1} > LV_t; \\ -r_{t+1}, & \text{if } \widehat{LV}_{t+1} \leq LV_t, \end{cases} \tag{10}$$

where $r_{t+1} = p^{closing}_{t+1}/p^{opening}_{t+1} - 1$, $p^{opening}_{t+1}$ and $p^{closing}_{t+1}$ are the opening and closing prices, respectively, of OVX in month $t + 1$. It should be noted that many related studies may consider a realized return as $r^*_{t+1} = p^{closing}_{t+1}/p^{closing}_{t} - 1$. We recommend our version because when we obtain the volatility forecast for month $t + 1$, we have already used the closing information in month t.[12] Therefore, it is too late to take a position at the closing of month t.

In addition to the AR benchmark, we further consider a well-known trading strategy, namely buy-and-hold. In the buy-and-hold strategy, we just take a long position in OVX and hold it throughout the entire sample period. The OVX data are available at *investing.com*. The sample period spans from July 2008 to December 2019.

Table 7 reports the trading results. The buy-and-hold strategy, AR benchmark, and the competing models based on the general GEPU indices generate average returns below 13.69% per annum. By contrast, our aligned GEPU-PLS index produces the largest average return at 17.46%. We

12 Although we provide a preferred suggestion, the results are qualitatively similar for alternative versions of realized returns.

Table 7
Economic significance.

Models	Avg ret (%)	Std dev (%)	SRatio
Buy-and-hold	13.13	61.83	0.21
AR benchmark	11.48	62.96	0.18
GEPU-website	8.19	63.00	0.13
GEPU-mean	13.69	62.92	0.22
GEPU-PCA	13.69	62.92	0.22
GEPU-PLS	17.46	62.84	0.28

This table reports the economic value of various trading strategies. The buy-and-hold strategy takes a long position in OVX and holds it throughout the entire sample period. In terms of the oil volatility forecasting models, we take a long (short) position in OVX at the beginning of the next month if the volatility forecast is larger (smaller) than the current volatility level. We then close the position at the market close in each trading month. The average return (Avg ret), standard deviation (Std dev), and Sharpe ratio (SRatio) are reported. The returns are annualized and in percentage. The sample period spans from July 2008 to December 2019.

Table 8
Out-of-sample forecasting performance based on alternative AR benchmark.

GEPU indices	R^2_{OS} (%)	CW-stat	p-value
GEPU-website	−3.53	0.04	0.49
GEPU-mean	−2.78	0.40	0.35
GEPU-PCA	−2.83	0.38	0.35
GEPU-PLS	1.88**	2.31	0.01

This table reports the out-of-sample forecasting performance for the augmented AR model with one of the GEPU indices. In particular, we rely on the AIC and adjusted R^2 (rather than the BIC) to choose the number of AR lags in this table. The out-of-sample performance is evaluated by the R^2_{OS} statistic. A positive R^2_{OS} implies that the corresponding predictive model outperforms the AR benchmark, while a negative value indicates the opposite. The statistical significance for R^2_{OS} is tested by the Clark and West (2007) statistic (CW-stat). ** indicates significance at the 5% level. The initial estimation sample period is from January 1997 to December 2006, while the out-of-sample evaluation period runs from January 2007 to December 2019.

further take risk into consideration. The standard deviation of the aligned GEPU-PLS index is the second smallest among all the strategies. Moreover, the strategy based on the GEPU-PLS index yields the largest Sharpe ratio. In sum, the aligned GEPU-PLS index shows better forecasting performance in both the statistical and economic senses.

5. Robustness checks

5.1. Alternative AR benchmark models

All the predictors are separately added into the AR benchmark model. Therefore, the model specification of the AR benchmark is central to the forecasting tests. With this in mind, we employ alternative information criteria to determine the optimal lag length for the AR model. The BIC suggests that the optimal lag length $L = 2$. We additionally consider the Akaike information criterion (AIC) and adjusted R^2, both suggesting that the optimal number of AR lags is 3.

We repeat the forecasting procedure based on the new AR model with three lags. Table 8 reports the corresponding out-of-sample results. The reported R^2_{OS}s and their significance levels are qualitatively similar to the counterparts in Table 4. That is, the aligned GEPU-PLS index can improve the out-of-sample predictability of the AR benchmark, while the general GEPU indices would lower the predictability. Thereby, our results are not specific to alternative choices of AR lags.

5.2. Directional accuracy

Following Degiannakis and Filis (2017), we use the Direction-of-Change (DoC) test to evaluate the out-of-sample forecasting performance. Degiannakis and Filis (2017) stress that the DoC is central to market timing and asset allocation. Specifically, the DoC measures the proportion of a model that correctly predicts the direction of the volatility movement. Let D_t be a dummy variable that takes the value of one if a model correctly predicts the direction of volatility movement in month t, and zero otherwise. Accordingly, this dummy variable is expressed as

$$D_t = \begin{cases} 1 & \text{if } LV_t > LV_{t-1} \text{ and } \widehat{LV}_t > LV_{t-1} \\ 1 & \text{if } LV_t < LV_{t-1} \text{ and } \widehat{LV}_t < LV_{t-1} \\ 0 & \text{otherwise,} \end{cases} \quad (11)$$

where LV_t is the true value of the logarithmic RV in month t and $\widehat{LV}_t$ is the forecast of a forecasting model of interest. Further, the DoC rate is defined as $1/(T-p)\sum_{t=p+1}^{T} D_t$, that is, the proportion of forecasts that correctly predict the direction of the volatility movement. To examine the statistical significance of the DoC rate, we employ a non-parametric test proposed by Pesaran and Timmermann (1992), which tests the null hypothesis that the DoC rate of a model of interest is equal to or lower than the DoC rate of random walk against the alternative hypothesis that the DoC rate of a model of interest is higher than the DoC rate of random walk.

Table 9 reports the DoC results for the AR benchmark and its augmented models with various GEPU indices. Two findings emerge. First, we reject the null hypothesis of no directional accuracy at the 1% significance level for all the forecasting models, suggesting the success of the AR benchmark and its augmented models in the directional prediction. Second and more importantly, the aligned GEPU-PLS index can help the corresponding augmented AR model yield a substantially larger DoC rate than the AR benchmark, while the general GEPU indices have no such ability. Therefore, the DoC results are in line with the R^2_{OS} results reported in Table 4. The aligned GEPU-PLS index exhibits substantially higher directional accuracy.

5.3. Alternative crude oil proxies

The focus of this paper is on the predictability of the volatility of WTI prices. However, Brent is an equally popular benchmark in oil pricing. Given this, we additionally use the predictors and corresponding models to forecast the Brent oil market volatility.

Table 10 reports the corresponding results. Overall, the predictability results are qualitatively similar for alternative oil proxies (i.e., WTI and Brent). Specifically, the

Table 9
Directional accuracy.

Models	DoC rate	PT-stat	*p*-value
AR benchmark	0.55***	2.93	0.00
GEPU-website	0.55***	2.79	0.00
GEPU-mean	0.54***	2.66	0.00
GEPU-PCA	0.54***	2.53	0.01
GEPU-PLS	0.58***	2.85	0.00

This table presents the out-of-sample forecasting results regarding directional accuracy. The considered forecasting models include the AR benchmark and its augmented model with one of the GEPU indices. The Direction-of-Change (DoC) rates, PT statistics (PT-stat) of Pesaran and Timmermann (1992), and *p*-values are reported. The DoC rate is defined as the proportion of forecasts that correctly predict the direction of the volatility movement. Statistical significance for the DoC rate is based on the *p*-value of the PT statistic. *** indicates significance at the 1% level. The initial estimation sample period is from January 1997 to December 2006, while the out-of-sample evaluation period runs from January 2007 to December 2019.

aligned GEPU-PLS index generates a large and significant coefficient estimate and sizable in- and out-of-sample R^2s, suggesting powerful in- and out-of-sample predictive ability. By contrast, the general GEPU indices generate small coefficient estimates with no significance level, negligible in-sample R^2s, and negative R^2_{OS}s, suggesting little, if any, predictive power. Thereby, our forecasting results are robust to alternative crude oil proxies.

5.4. An extended variable set for global economic policy uncertainties

The competing predictor of GEPU-website is a GDP-weighted average of national EPU indices for 21 countries: Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the United Kingdom, and the United States. However, the focus of this paper is on 15 out of the 21 national EPU indices. This is because the rest national EPU indices are not available during the whole period of the GEPU-website index. For instance, the data of the EPU index for the Netherlands are available not earlier than March 2003, while the GEPU-website index begins from January 1997. Even though, we still try to use all the 21 national EPU indices to construct the GEPU-mean, GEPU-PCA, and GEPU-PLS indices. To this end, we follow Davis (2016) and impute missing values for the rest 6 countries by using a regression-based method.

Table 11 reports the forecasting results based on an extended variable set including 21 national EPU indices. In short, we observe robust results for both WTI and Brent. The aligned GEPU index remains informative and powerful for forecast crude oil market volatility both in- and out-of-sample, while all the general GEPU indices exhibit little, if any, in- and out-of-sample predictive power.

6. Predictability source and explanations

In this section, we provide explanations about the source of our aligned GEPU index's predictive power from both the statistical and economic perspectives. By doing so, we can further reduce the concern of data mining and make the forecasting results more convincing.

6.1. Statistical source

First, we report the correlations for various GEPU indices in Table 12. The correlations among the general GEPU indices (i.e., GEPU-website, GEPU-mean, and GEPU-PCA) are extremely high, above 0.95, implying that the general GEPU indices contain similar and overlapping information. By contrast, the correlations between the aligned GEPU index and the general GEPU indices are lower and negative, implying that the aligned GEPU index can provide complementary information beyond what is contained in the general GEPU indices. This finding echoes the business-cycle predictability results reported in Table 5, that is, the aligned GEPU index and general GEPU indices contain complementary information and show better forecasting performance over cyclical expansions and recessions, respectively.

Second and more importantly, we plot the loadings for the national EPU indicators on the GEPU-PLS and GEPU-PCA indices in Fig. 1. Fig. 1 also depicts the partial correlation between the future oil market volatility and each national EPU variable, with the effect of the AR lags removed. That is, we calculate the correlation by controlling for the lagged volatility variables. This is reasonable because each the GEPU index is used as an additional predictor embedded in the augmented AR model. We are thus interested in the predictive information beyond what is already contained in the AR lags. Since asset price volatility is highly persistent, the AR lags likely provide the most information for future volatility (see Corsi, 2009; Paye, 2012). In this sense, the partial correlations measure the degree of complementary information that is useful for forecasting the crude oil market volatility beyond what is already contained in the control variables (i.e., the AR lags).

Fig. 1 shows that the individually national EPU variables load nearly uniformly on the GEPU-PCA index, which is in line with the loadings on the GEPU-mean index.[13] This explains why the correlation between the GEPU-mean and GEPU-PCA indices is as high as 0.99. By contrast, the national EPU variables load quite differently on the GEPU-PLS index. Some of the estimated loadings are positive, while the others are negative. More importantly, the signs of the loadings on the GEPU-PLS index are consistent with the signs of the corresponding partial correlations. Furthermore, the magnitudes of the loading and partial correlation for a specific national EPU are closely associated. For instance, Russia (Chile) yields both the most negative (positive) loading and partial correlation. This important finding indicates that the aligned GEPU-PLS index generates reasonable loadings according to the predictive power of the individual EPU variables. Therefore, the aligned GEPU-PLS index can aggregate useful information from the individual EPU variables. However, the loadings (or weights) for the individual EPU variables on the general GEPU indices are not associated with the

13 Apparently, the national EPU variables load completely uniformly on the GEPU-mean index, so that we do not depict the equal loadings for the sake of brevity.

Table 10
Forecasting performance for Brent.

GEPU indices	In-sample estimation			Out-of-sample evaluation		
	φ	t-stat	ΔR^2 (%)	R^2_{OS} (%)	CW-stat	p-value
GEPU-website	−0.04	−0.78	0.08	−3.47	−0.39	0.65
GEPU-mean	−0.05	−1.08	0.15	−2.52	0.07	0.47
GEPU-PCA	−1.02	−0.97	0.13	−2.39	0.11	0.46
GEPU-PLS	5.80***	4.35	2.85	2.63***	2.55	0.01

This table reports the in- and out-of-sample results for forecasting the Brent oil market volatility. The predictive regression model is the following augmented AR model.

$$LV_{t+1} = \alpha + \sum_{\ell=1}^{L} \beta_\ell LV_{t+1-\ell} + \varphi X_t^{GEPU} + \varepsilon_{t+1},$$

where LV_{t+1} is the logarithmic realized variance for Brent in month $t + 1$, and X_t^{GEPU} denotes one of the considered GEPU indices. The reported in-sample results include the regression coefficients of φ, its Newey–West t-statistics, and incremental R^2 (ΔR^2). Specifically, ΔR^2 is defined as the in-sample R^2 of the above augmented AR model minus the in-sample R^2 of the AR benchmark. The out-of-sample performance is evaluated by the R^2_{OS} statistic. A positive R^2_{OS} implies that the corresponding predictive model outperforms the AR benchmark, while a negative value indicates the opposite. The statistical significance for R^2_{OS} is tested by the Clark and West (2007) statistic (CW-stat). *** indicates significance at the 1% level. The full-sample period is from January 1997 to December 2019, while the out-of-sample evaluation period runs from January 2007 to December 2019.

Table 11
Forecasting performance for an extended GEPU variable set.

GEPU indices	In-sample estimation			Out-of-sample evaluation		
	φ	t-stat	ΔR^2 (%)	R^2_{OS} (%)	CW-stat	p-value
Panel A: WTI						
GEPU-website	−0.08	−1.32	0.25	−3.58	0.09	0.46
GEPU-mean	−0.08	−1.04	0.17	−3.52	0.18	0.43
GEPU-PCA	−0.80	−0.74	0.09	−3.36	0.24	0.40
GEPU-PLS	5.72***	4.87	3.24	0.88**	2.27	0.01
Panel B: Brent						
GEPU-website	−0.04	−0.78	0.08	−3.47	−0.39	0.65
GEPU-mean	−0.05	−0.79	0.08	−3.04	−0.14	0.56
GEPU-PCA	−0.61	−0.62	0.05	−3.06	−0.09	0.54
GEPU-PLS	7.15***	5.20	3.51	3.52***	2.65	0.00

This table reports the in- and out-of-sample results for forecasting the WTI (Panel A) and Brent (Panel B) oil market volatility. The predictive regression model is the following augmented AR model.

$$LV_{t+1} = \alpha + \sum_{\ell=1}^{L} \beta_\ell LV_{t+1-\ell} + \varphi X_t^{GEPU} + \varepsilon_{t+1},$$

where LV_{t+1} is the logarithmic realized variance in month $t + 1$, and X_t^{GEPU} denotes one of the considered GEPU indices. The reported in-sample results include the regression coefficients of φ, its Newey–West t-statistics, and incremental R^2 (ΔR^2). Specifically, ΔR^2 is defined as the in-sample R^2 of the above augmented AR model minus the in-sample R^2 of the AR benchmark. The out-of-sample performance is evaluated by the R^2_{OS} statistic. A positive R^2_{OS} implies that the corresponding predictive model outperforms the AR benchmark, while a negative value indicates the opposite. The statistical significance for R^2_{OS} is tested by the Clark and West (2007) statistic (CW-stat). ** and *** indicate significance at the 5% and 1% levels, respectively. The full-sample period is from January 1997 to December 2019, while the out-of-sample evaluation period runs from January 2007 to December 2019.

individual variables' predictive ability, so that the general GEPU indices are not informative for forecasting crude oil market volatility.

In short, our modified PLS approach can learn both the magnitude and sign of individual variables' predictive ability and thus yields reasonable and informative loadings. This impressive property is the statistical source of the predictive power of the aligned GEPU-PLS index.

6.2. Economic source

In this subsection, we provide economic explanations about the source of the aligned GEPU-PLS index's predictive power for crude oil market volatility. Similar to Rapach et al. (2010), Huang et al. (2015), and Jiang et al. (2019), we associate the predictors' predictive power with related fundamentals. Crude oil prices are essentially

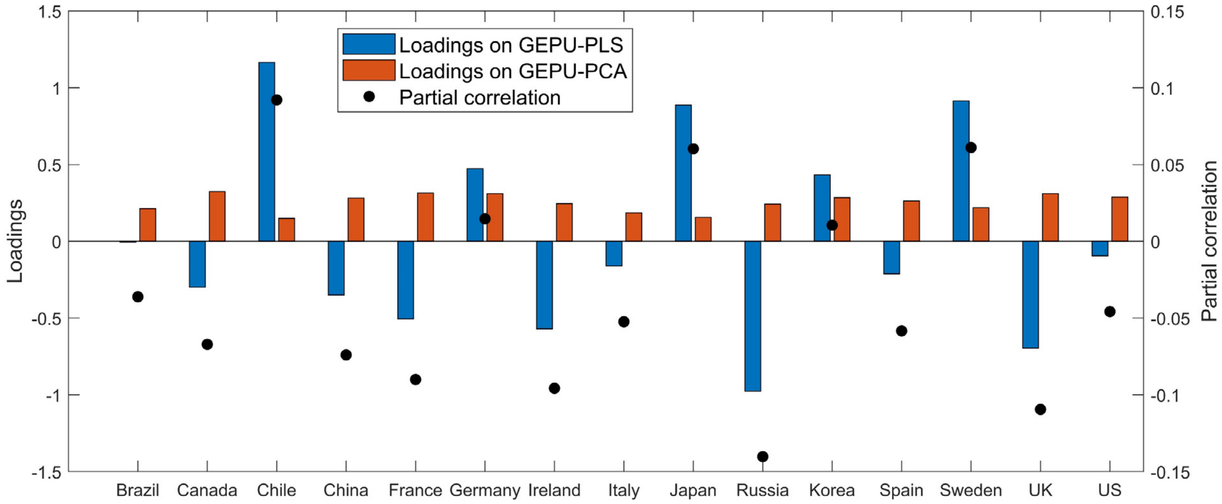

Fig. 1. Partial correlation and loadings for national EPU variables.
The blue and red bars depict the loadings for the 15 national EPU indicators on the GEPU-PLS and GEPU-PCA indices, respectively. The black dots depict the partial correlation between the future oil market volatility and each national EPU variable, with the effect of the AR lags removed. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 12
GEPU indices' correlations.

Variables	GEPU-website	GEPU-mean	GEPU-PCA	GEPU-PLS
GEPU-website	1.00			
GEPU-mean	0.96	1.00		
GEPU-PCA	0.95	0.99	1.00	
GEPU-PLS	−0.24	−0.35	−0.28	1.00

This table reports the correlations for various GEPU indices, including GEPU-website, GEPU-mean, GEPU-PCA, and GEPU-PLS. The sample period is from January 1997 to December 2019.

driven by the supply and demand of crude oil (Barsky & Kilian, 2004; Kilian, 2009; Kilian & Hicks, 2013). Further, the shocks of oil's supply and demand would contribute to the volatility of crude oil prices. Therefore, a powerful predictor is more likely to predict the shocks. We use the volume of newly produced crude oil products and consumption of petroleum products to represent oil's supply and demand. The shocks are estimated by the following regression.

$$y_{t+1} = \alpha + \beta y_t + \eta_{t+1}, \tag{12}$$

where y_{t+1} represents the level of oil's production and consumption in month t + 1 and η_{t+1} is the regression error term, representing the unpredictable component, i.e., the shock of y_{t+1}. We further investigate whether the GEPU predictors can predict the shocks via the following regressions.

$$\eta_{t+1} = \alpha + \beta X_t^{GEPU} + \varepsilon_{t+1}, \tag{13}$$

where X_t^{GEPU} is one of the considered GEPU predictors, including GEPU-website, GEPU-mean, GEPU-PCA, and GEPU-PLS. The regression coefficient of interest is the slope β on X_t^{GEPU}.

Table 13 reports the corresponding regression results. The estimated regression slope β on the aligned GEPU predictor is statistically significant, while the ones on the general GEPU predictors show no or lower significance levels. Furthermore, the aligned GEPU predictor generates larger R^2s than the general ones, suggesting better explanatory ability for the shocks of oil fundamentals. In a word, we document that the economic driving force behind the predictability of the aligned GEPU predictor probably stems from the relatively good ability for forecasting the shocks of oil fundamentals.

7. Conclusion

In this paper, we propose an aligned GEPU index using a modified PLS approach with supervised learning. This new predictor can significantly predict crude oil market volatility both in- and out-of-sample. In addition, the trading strategy based on the aligned GEPU index can generate sizable economic gains, which is helpful for investors. Furthermore, we find that the aligned GEPU-PLS index dominates the general GEPU indices of GEPU-website, GEPU-mean, and GEPU-PCA over the full sample period. Nonetheless, the aligned GEPU-PLS index and the general GEPU indices can provide complementary information across business-cycle expansions and recessions, respectively. In addition, we document that the in-sample predictability of the aligned GEPU-PLS index is not driven by economic fundamentals. The new aligned GEPU index can provide additional and complementary information beyond what is already contained in the existing uncertainty indices. We further provide explanations about the source of our aligned GEPU index's predictive power for forecasting crude oil market volatility. From a statistical perspective, we demonstrate that the modified PLS approach can learn both the magnitude and sign of national EPU variables' predictive ability and thus yields reasonable and informative loadings on the aligned GEPU-PLS index. On the other hand, we document that the economic driving force behind the predictability of the aligned GEPU index probably stems from the relatively good ability for forecasting the shocks of oil-related fundamentals.

Table 13
GEPU and the shocks of oil fundamentals.

Variables	Panel A: Crude oil production			Panel B: Crude oil consumption		
	β	t-stat	R^2 (%)	β	t-stat	R^2 (%)
GEPU-website	1.46	1.24	0.41	−2.11	−0.62	0.15
GEPU-mean	1.57	1.64	0.59	−1.86	−0.65	0.14
GEPU-PCA	3.35*	1.68	0.64	−7.70	−1.32	0.59
GEPU-PLS	−3.84**	−2.03	0.83	−13.01**	−2.42	1.67

This table reports the estimation results of the following predictive regression.

$$\eta_{t+1} = \alpha + \beta X_t^{GEPU} + \varepsilon_{t+1},$$

where η_{t+1} is the shock of crude oil production or consumption in month $t + 1$ and X_t^{GEPU} is one of the considered GEPU predictors. The regression coefficients of β, its Newey–West t-statistics, and R^2s are reported. * and ** indicate significance at the 10% and 5% levels, respectively. The sample period is from January 1997 to December 2019.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ijforecast.2022.07.002.

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