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Which exogenous driver is informative in forecasting European carbon volatility: Bond, commodity, stock or uncertainty?

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A R T I C L E I N F O

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A B S T R A C T

This study relies on 45 exogenous drivers to improve the accuracy in forecasting EUA volatility. Several popular linear and nonlinear predictive regressions, including individual factor analysis, the combination forecast method, the diffusion index model and the supervised learning method, are used to generate volatility forecasts at the monthly frequency. Our empirical results reveal that the diffusion index model and combination forecast method can hardly drive the EUA volatility in a data-rich world owing to worse forecasting performance of individual factors; however, the supervised learning method can successfully predict the EUA volatility. Additionally, the WilderHill new energy global innovation index, Euro corporate bond return spread, GSCI gold index and Euro Area government bond yield spread can extremely drive EUA volatility in terms of individual factor analysis, frequency of variable selection and factor importance. Our findings provide crucial implications to market participants and emission companies, who should pay more attention to the price movement of European bond market, gold and clean energy.

1. Introduction

The European Union Emissions Trading System (EU ETS) is the first carbon trading market worldwide and aims to reduce carbon emissions (Alberola et al., 2008; Chevallier, 2009). The European Union Allowances (EUA) represents the carbon emission permit and can be traded directly. Specifically, the CO_2 emissions of a firm exceed (less than) their allowances, which can buy (sell) more (excess) of them. Since the inception of the EUA futures contract, the volatility of EUA has recently received increasing attention from academic, carbon-intensive companies and the government. Accurately forecasting EUA volatility can help investors or emission companies economically hold market timing strategies to buy or sell their emission permits and help regulators efficiently guide the development of the carbon market. Therefore, it is significantly attractive for investors and managers to discover the predictive factors, as this will further ascertain the dynamics of carbon volatility. This study mainly sheds light on the information content of 45 exogenous drivers, including 8 bond-related, 12 commodity-related, 11 equity-related and 14 uncertainty-related factors, using combination forecasting, diffusion indexing and supervised learning methods.

Existing studies have recorded that a large set of exogenous variables can drive the volatility of the European carbon market (see, for example, Chevallier, 2010; Byun and Cho, 2013; Dutta, 2018; Dai et al., 2022; Liu et al., 2021) or carbon allowance price (see, for example, Paolella and Taschini, 2008; Chevallier, 2011c; Fan et al., 2017; Tan et al., 2021; Ren et al., 2022a, 2022b; Wen et al., 2022).[1] Furthermore, numerous studies focus on the linkage or spillover effect between carbon allowances and other markets, such as market fundamentals (Christiansen et al., 2005),

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[1] The literature employs various econometric and statistical models to investigate the carbon prices, returns and volatility, such as, GARCH-type models (Chevallier, 2009; Feng et al., 2011; Byun and Cho, 2013; Dutta, 2018; Liu et al., 2021), HAR-RV model (Chevallier and Sévi, 2011), and machine learning methods (Zhu et al., 2018).

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fossil energy markets (Zhang and Sun, 2016), clean energy markets (Dutta et al., 2018), nonenergy markets (Tan et al., 2020), equity markets (Chevallier, 2009) and market uncertainty (Ye et al., 2021; Wen et al., 2022). Undoubtfully, accurately modeling the volatility of carbon plays a vital role in recognizing the carbon price dynamics and controlling market risk. However, in practice, it is extremely complicated for investors and market participants to accurately forecast it because the volatility dynamics of carbon allowances easily break the structure caused by the EU ETS regulation.

Motivated by previous investigations of the European carbon market, our study aims to concentrate on three questions to extend the literature on EUA volatility forecasting. *First, which exogenous predictor can more influentially drive EUA volatility?* According to the arguments of Benz and Trück (2009), the carbon price is directly determined by the supply and demand of the carbon allowance.[2] To this end, existing studies have shown the correlation between the price of carbon allowances and demand factors, including weather (Mansanet-Bataller et al., 2007), macroeconomics (Chevallier, 2011c), crude oil (Byun and Cho, 2013), gas (Wang and Guo, 2018), coal (Byun and Cho, 2013), electricity (Aatola et al., 2013), nonenergy commodities (Tan et al., 2020), equity (Dutta et al., 2018), bonds (Chevallier, 2010; Ren et al., 2022b) and economic policy uncertainty (Dai et al., 2022). Specifically, Byun and Cho (2013) explore the forecasting ability of Brent oil, coal, and electricity natural gas and argue that energy volatility can increase forecasting performance. However, previous studies, i.e., Byun and Cho (2013), Tan et al. (2020), Dai et al. (2022) and others, commonly focus on the predictive content from single class factors (energy, financial, uncertainty factors), and few studies investigate carbon volatility forecasting through a large set of predictors. It is well known that the more categories of predictors there are, the more predictive information there is. As such, to fill this research gap, our study considers 45 exogenous drivers to explore their forecasting performance and ascertain which predictor can drive EUA volatility efficiently.

Second, how do investors and researchers use information extracted from various predictors in practice? In a data-rich environment, market participants can derive a huge amount of information from the Internet, social media and other channels. However, investors cannot consider all the information owing to investors' limited attention. Existing studies regularly introduce dimensionality reduction methods to extract comprehensive information from a large number of predictors and avoid overfitting issues (Neely et al., 2014; Huang et al., 2015; Zhang et al., 2019; Huang et al., 2021; Wang et al., 2022; Zhang et al., 2022). Specifically, Wang et al. (2022) employ principal component analysis (PCA), partial least squares regression (PLS) and scaled PCA (SPCA) to extract the common information from global economic conditions and news-based uncertainty indexes to predict the realized variance of natural gas and clean energy stock volatility. In accordance with the previous volatility forecasting literature, our investigation develops a diffusion index from the PCA, PLS and SPCA models to examine their predictive information content in EUA volatility. Furthermore, forecast combination is another popular method to incorporate information from considerable variables (Rapach et al., 2010; Zhang et al., 2019; Wang et al., 2022). As such, we also consider the three popular combination methods, that is, mean combination forecasts (MCF), median combination forecasts (MECF), and trimmed combination forecasts (TCF), to incorporate the information and overcome the model uncertainty (Rapach et al., 2010).

Third, does the supervised learning method help to improve the accuracy of EUA volatility forecasting? The complex features of EUA volatility, such as high volatility, nonlinear dynamics and instability (Alberola et al., 2008; Chevallier, 2011a, 2011b; Feng et al., 2011), which lead to accurate forecasting and modeling of carbon volatility remain challenging. OLS regression is a prevailing tool for time-series prediction, but Bishop and Nasrabadi (2006) argue that the performance is poor when many potential explanatory variables exist in regression. However, the machine learning algorithm can ignore the limitation of a number of explanatory variables, which provides new opportunities for market participants and researchers to predict the price or volatility in energy finance (Ghoddusi et al., 2019). Three popular supervised learning methods, which are widely used in financial markets, are used to explore their performance in the European carbon market, including the least absolute shrinkage and selection operator (LASSO) of Tibshirani (1996), elastic net (ELN) of Zou and Hastie (2005) and support vector regression (SVR) of Vapnik (1999). LASSO and ELN rely on the penalty function to select the influential factors and minimize the sum-of-squares error, thereby improving the accuracy of volatility forecasting (Zhang et al., 2019; Plakandaras and Ji, 2022; Wang et al., 2022). Professor Vapnik first proposed the support vector machine (SVM) to solve classified issues; later, based on the SVM, Vapnik (1999) developed the SVR to deal with function fitting problems. SVR relies on the structural risk minimization principle, resulting in this method facing small samples and overcoming local optimal solution problems, which is one of the main advantages (Awad and Khanna, 2015).

To measure the volatility of the European carbon market, existing studies prefer GARCH-type models (Chevallier, 2009; Feng et al., 2011; Byun and Cho, 2013; Dutta, 2018; Liu et al., 2021); however, realized volatility (RV) has been widely used in the field of volatility forecasting because of its obvious advantages, such as less macroeconomic noise and ease of implementation (Corsi, 2009; Chevallier and Sévi, 2011; Wang et al., 2022; Zhang et al., 2022). Additionally, Chevallier and Sévi (2011) argue that the HAR-RV model of Corsi (2009) performs superior to the GARCH model in forecasting the volatility of EUA. Considering the data frequency of macroeconomic variables and various uncertainty indexes (basically, monthly or quarterly), following the strands of literature in financial volatility forecasting (such as Paye, 2012; Wang and Guo, 2018; Wang et al., 2022; Zhang et al., 2022), our study employs the realized volatility at monthly frequency to model the volatility in the European carbon emission market.

We consider the following 4 groups of exogenous drives of EUA volatility that have been included in the work of Chevallier (2011a), Byun and Cho (2013), Tan et al. (2021), Ren et al. (2022a), Wen et al. (2022) and others: 1) commodity-related factors (energy and metal commodity); 2) bond-related factors; 3) stock-related factors; and 4) uncertainty-related factors. These 45 exogenous drivers of carbon volatility are determined by the following potential theoretical illustration. First, undoubtfully, energy-related factors can directly affect carbon prices through energy consumption and emissions, while metal commodity-related factors can also drive the volatility of carbon emissions by material cost, production and transportation (Chevallier, 2009). Second, the bond yield spread and risk-free yield can always reflect the domestic economic conditions . Specifically, during the period of economic prosperity, the return of bonds will become lower, whereas carbon emissions will increase owing to increasing production activities and energy consumption. Third, financial activities can influence the volatility of carbon prices through the financing costs of related corporates and technology upgradation . In our study, we consider the stock market indexes from 11 industrial countries around the world to measure financial activities. Finally, the uncertainty-related factors consist of the following parts: 1) the global new energy index; 2) the implied volatility of the S&P 500 index and WTI crude oil; 3) the news-based policy uncertainty index of the global and European areas; and 4) the news-based uncertainty index of the climate. More details can be found in Section 3. Empirically, our findings are as follows. First, the Wilder Hill new energy global innovation index (NEGI), Euro corporate bond return spread (ECBRS), GSCI gold index (GDI) and Euro Area government bond yield spread (EGYS) can drive EUA volatility in terms of individual factor analysis, frequency of variable selection and factor

[2] EU ETS regulation and policy are always classified as the supply factor of carbon allowance. In our study, we mainly focus on the exogenous drivers from demand of carbon allowance owing to the supply factor is hardly to quantify.

importance. Second, the diffusion index model (PCA, PLS and SPCA) and combination forecast method (MCF, MECF and TMCF) hardly improve the accuracy of volatility forecasting in the European carbon market because the majority of individual predictors show limited forecasting performance. Third, being of interest, the supervised learning method (ELN, LASSO and SVR) can significantly predict the EUA volatility because of their advantages. Specifically, variable selection (ELN and LASSO) can achieve a bias-variance tradeoff, and SVR can better fit small samples, nonlinear features and high-dimensional regression, resulting in superior forecasting performance. Finally, the results of economic value analysis indicate that the supervised learning method can obtain higher realized utility than competing models.

Our study contributes in three ways to the literature of modeling and forecasting EUA volatility. First, different from previous studies (such as Chevallier, 2009; Feng et al., 2011; Byun and Cho, 2013; Dutta, 2018; Liu et al., 2021), we construct the realized volatility of EUA at the monthly frequency and introduce some prevailing time series models to generate volatility forecasts, which provide new insight to forecast EUA volatility. Second, numerous studies focus on EUA future price predictability (e.g., Byun and Cho, 2013; Dutta, 2018; Dai et al., 2022; Liu et al., 2021), and our study extends their work by exploring whether the 45 exogenous drivers can more influentially drive EUA volatility. Accurately forecasting volatility is beneficial for investors and emission companies in portfolio diversification, derivatives pricing, hedging and financial risk management. Third, many influential studies, i.e., Rapach et al. (2010), Neely et al. (2014), Zhang et al. (2019), Huang et al. (2021), argue that the combination forecast method (MCF, MECF and TMCF) and diffusion index model (PCA, PLS and SPCA) can successfully predict asset return or volatility. We introduce previous methods and explore whether the combination forecast method and diffusion index model can help to improve the accuracy of EUA volatility forecasting. Furthermore, in addition to the combination forecast method and diffusion index model, we empirically examine the forecasting ability of supervised learning methods (ELN, LASSO and SVR) along the lines of rapid development of machine learning methods in energy finance (Ghoddusi et al., 2019). To the best of our knowledge, our study is the first to compare the abovementioned predictive regressions, which are widely used in the literature of energy volatility forecasting and can offer more comprehensive insight to accurately predict volatility under a method-rich environment in the EUA futures market.

The remainder of the paper is organized as follows. Section 2 presents the methodology. Section 3 describes the dataset of EUA volatility and 45 exogenous drivers. Section 4 presents the empirical analysis. Concluding remarks are given in Section 5.

2. Methodology

2.1. Benchmark model

The existing studies consider the GARCH-type model to measure the volatility of carbon (Chevallier, 2009; Feng et al., 2011; Byun and Cho, 2013; Dutta, 2018; Liu et al., 2021). However, Chevallier and Sévi (2011) argue that the HAR-RV model of Corsi (2009) performs better than the GARCH model in forecasting the volatility of EUA. As such, our study employs realized volatility (RV) to model carbon price volatility. Furthermore, Corsi (2009) indicates that the HAR-RV model can be simplified as an autoregressive model (AR (22)), which is widely used in the forecasting area and can be directly defined as

$$\mathrm{RV}_{t+1} = \beta_0 + \sum_{i=1}^{p} \beta_i \mathrm{RV}_{t-i+1} + \varepsilon_{t+1}, \tag{1}$$

where RV_t is the realized volatility at the monthly frequency and can be expressed as the sum of daily squared returns, $\mathrm{RV}_t = \sum_{j=1}^{M} r_{t,j}^2$, where M is the number of trading days for a specific month t, and $r_{t,\,j}$ represents the j^{th} day return of month t. ε_{t+1} is the disturbance term. To obtain the optimal lag order p, different from Chevallier and Sévi (2011), we consider the AIC information criteria. The results indicate that the optimal p is equal to 2.

To examine which individual predictors can successfully drive the volatility of carbon prices, we extend model (1) with 45 exogenous variables, defined as

$$\mathrm{RV}_{t+1} = \beta_0 + \sum_{i=1}^{p} \beta_i \mathrm{RV}_{t-i+1} + \varphi_\alpha \boldsymbol{X}_{t,\alpha} + \varepsilon_{t+1}, \tag{2}$$

where $\boldsymbol{X}_{t,\,\alpha}$ denotes the α^{th} variable in month t, and φ_α is the regression coefficient for the α^{th} variable.

2.2. Combination forecast method

Inspired by Rapach et al. (2010), the combination forecast method can incorporate the information from various predictors and avoid model uncertainty. In accordance with previous studies of volatility forecasting, we apply three methods of combination forecasting, which can be defined as

$$\widehat{\mathrm{RV}}_{c,t+1} = \sum_{i=1}^{N} \omega_{i,t} \widehat{\mathrm{RV}}_{i,t+1}, \tag{3}$$

where $\{\omega_{i,\,t}\}_{i=1}^{N}$ denotes the ex ante combined weight of the N individual forecasts formed at month t. $\widehat{\mathrm{RV}}_{i,t+1}$ is the volatility forecasts generated from Eq. (2), and $\widehat{\mathrm{RV}}_{c,t+1}$ represents the combination forecasts. We consider simple averaging combination methods, including the mean, median and trimmed mean. Specifically, the mean combination forecasts (MCF) set $\omega_{i,\,t} = 1/N$ in Eq. (3), the median combination forecasts (MECF) develop by the median of $\{\widehat{\mathrm{RV}}_{i,t+1}\}_{i=1}^{N}$, and the trimmed combination forecasts (TMCF) set $\omega_{i,\,t} = 0$ for the largest and smallest values of N individual forecasts and $\omega_{i,\,t} = 1/(N-2)$ for the remaining forecasts in Eq. (3).

2.3. Diffusion index model

The diffusion index model aims to extract comprehensive information from various predictors and overcome overfitting issues and is widely used in the area of forecasting in financial markets (Neely et al., 2014; Zhang et al., 2019; Huang et al., 2021; Wang et al., 2022; Zhang et al., 2022). The diffusion index models we consider differences in how comprehensive information is extracted and can be organized into the following two classes:

First, we consider the principal component extracted from bond-related predictors, commodity-related predictors, stock-related predictors, uncertainty-related predictors and all predictors. Specifically, the regression with the diffusion index extracted from the principal component analysis (PCA) model can be written as

$$\mathrm{RV}_{t+1} = \beta_0 + \sum\nolimits_{i=1}^{p} \beta_i \mathrm{RV}_{t-i+1} + \sum_{k=1}^{K} \gamma_k F_{k,t}^{\mathrm{PCA}} + \varepsilon_{t+1}, \tag{4}$$

where $F_{k,\,t}^{\mathrm{PCA}}$ denotes the principal component extracted from $\boldsymbol{X}_{i,\,t}$. To select K and in accordance with Neely et al. (2014), we used adjustedR^2.

Recently, Huang et al. (2021) modified the PCA model in terms of scaling each variable by its coefficients from the following regression: $\mathrm{RV}_{t+1} = \alpha_i + \beta_i \boldsymbol{X}_{i,\,t} + \varepsilon_{t+1}$, where β_i is the scaled coefficient. Subsequently, we perform PCA on $\{\beta_1 \boldsymbol{X}_{1,\,t}, \beta_2 \boldsymbol{X}_{2,\,t}, \ldots, \beta_i \boldsymbol{X}_{i,\,t}\}$ to extract the target-specific diffusion index. Specifically, the scaled-PCA model (SPCA) can be written as

$$\mathrm{RV}_{t+1} = \beta_0 + \sum\nolimits_{i=1}^{p} \beta_i \mathrm{RV}_{t-i+1} + \sum_{k=1}^{K} \gamma_k F_{t}^{\mathrm{SPCA}} + \varepsilon_{t+1}, \tag{5}$$

where the optimal K is determined by the adjusted R^2.

Second, Huang et al. (2015) argue that the partial least squares model (PLS) can also successfully construct comprehensive information from various factors. Specifically, the N time-series regression of the individual predictor ($\boldsymbol{X}_{i,\,t}$) and EUA volatility ($\boldsymbol{X}_{i,\,t} = \alpha_{i,\,0} + \alpha_i \mathrm{RV}_{t-1} + \varepsilon_{i,\,t}$) is used to obtain the estimated coefficient α_i. The diffusion index of the PLS model (F_t^{PLS}) extracted from various predictors can be defined as

$$\boldsymbol{X}_{i,t} = \varphi_{i,0} + F_t^{PLS}\widehat{\alpha}_i + \varepsilon_{i,t}, \tag{6}$$

where the estimated coefficient of $\widehat{\alpha}_i$ denotes the PLS diffusion index. The PLS can be presented as

$$\mathrm{RV}_{t+1} = \beta_0 + \sum\nolimits_{i=1}^{p}\beta_i \mathrm{RV}_{t-i+1} + \beta_{\mathrm{pls}}F_t^{\mathrm{PLS}} + \varepsilon_{t+1}. \tag{7}$$

2.4. Supervised learning methods

In recent years, the rapid development of machine learning methods has provided novel opportunities in energy finance (Ghoddusi et al., 2019). According to the difference in algorithms, we divide the three supervised learning methods considered in this study into two sets.

First, variable selection, such as LASSO and ELN, is one of the most popular supervised learning methods in the forecasting literature (Zhang et al., 2019; Wang et al., 2022; Zhang et al., 2022). The variable selection relies on the penalty function, which can set the coefficients of unimportant variables to (to) zero to achieve the reduction dimension. Specifically, the coefficient results estimated from LASSO ($\widehat{\beta}_{\mathrm{LASSO}}$) and ELN ($\widehat{\beta}_{\mathrm{EN}}$) can be expressed as

$$\widehat{\beta}_{\mathrm{LASSO}} = \underset{\beta}{\mathrm{argmin}}\left(\frac{1}{2(t-1)}\sum_{l=1}^{t-1}\left(\mathrm{RV}_{t+1} - \beta_0 - \sum_{i=1}^{K}\beta_i \boldsymbol{X}_{i,t}\right)^2 + \lambda\sum_{i=1}^{K}|\beta_i|\right), \tag{8}$$

$$\widehat{\beta}_{\mathrm{EN}} = \underset{\beta}{\mathrm{argmin}}\left(\begin{array}{c}\dfrac{1}{2(t-1)}\displaystyle\sum_{l=1}^{t-1}\left(\mathrm{RV}_{t+1} - \beta_0 - \sum_{i=1}^{K}\beta_i \boldsymbol{X}_{i,t}\right)^2 \\ +\lambda\displaystyle\sum_{i=1}^{K}\left((1-\alpha)\beta_i^2 + \alpha|\beta_i|\right)\end{array}\right), \tag{9}$$

where λ (α) is the tuning parameter that can control the shrinkage estimators in terms of penalty strictness. Obviously, LASSO only relies on the L_1 penalty functions (λ), whereas ELN relies on both the L_1 and L_2 penalty functions (λ and α). In particular, α is a positive constant ($\alpha \in [0, 1]$); when $\alpha = 1$, the ELN is exactly the same as LASSO. To obtain the optimal choice of α and λ, we consider the same algorithm as Zhang et al. (2019) to determine the optimal value before generating the volatility forecasts.[3]

Second, Ghoddusi et al. (2019) review the usage of machine learning methods in energy finance and find that the support vector machine is one of the most popular techniques. To generate volatility forecasts, we consider the SVR method, which is faster than common SVMs in terms of global solutions by various linear regressions (Zhang and Zhang, 2018). Mathematically, assuming a set of training points $\{(x_i, y_i)\}_{i=1}^{N}$ with input data $x_i \in R^n$ and output data $y_i \in R^n$, the decision function is written as

$$y(z) = \omega^T\kappa(z) + b, \tag{10}$$

where ω is the weight vector and $\kappa(z)$ represents the nonlinear function that maps the input space to a higher-dimensional feature space. Minimizing the structural risk, we can obtain the optimal coefficient estimation from the following optimization problem:

$$\begin{aligned} &min\frac{1}{2}\|w\|^2 + \frac{c}{2}\sum_{i=1}^{l}\xi_i^2 \\ &\mathrm{s.t.}\, y_i = \omega^T\kappa(z_i) + \xi_i + b, i \in [1, l], \end{aligned} \tag{11}$$

where c is the regularization constant and ξ_i represents the training error. For the kernel function of SVR in this study, we consider the radial basis function (RBF) in accordance with Zhang and Zhang (2018).

3. Data

3.1. Carbon price series

To measure carbon prices, we consider the ICE ECX EUA (denoted by EUA) continuous settlement price, which has the most liquid futures contracts in the carbon emission trading market. We collect the daily closing price of EUA from the WIND database to construct a time series of RV at monthly frequency ranges from July 2008 to October 2021, containing 160 months. The period extends the sample period of Tan et al. (2021), and similar to the numerous studies of EUA, we neglect Phase I of the European Union Emissions Trading System because the price movements in this period were mainly driven by changing regulation and policy.

3.2. Predictors

Following the existing studies in modeling the price or volatility of EUA, such as Chevallier (2011a), Byun and Cho (2013), Tan et al. (2021), Ren et al. (2022a, 2022b) and others, the 45 exogenous drivers can be classified into 4 groups, including commodity-related factors, bond-related factors, equity-related factors, and uncertainty-related factors. First, we consider 8 bond-related factors, i.e., (i) US corporate bond yield spread (UCBYS); (ii) Euro corporate bond return spread (ECBRS); (iii) euro area 3-month 3 A bond yield (EBY3 M); (iv) US 3-month treasury rate (UTB3 M); (v) euro area 10-year 3 A government bond yield (EBY10 M); (vi) US 10-year treasury rate (UTB10 M); (vii) euro area government bond yield spread (EGYS); (viii) US government bond yield spread (UGYS). The European bond-related factors are collected from ECB, and the rest can be found in FRED.

Second, as for the commodity-related factors, inspired by the work of Chevallier (2011a) and Ren et al. (2022a), we conclude 5 energy commodities, i.e., (i) the monthly realized volatility of NYMEX natural gas futures (USGAS); (ii) ICE UK natural gas futures (UKGAS); (iii) ICE Coal Rotterdam futures (CRF); (iv) ICE Brent oil futures (BOF); (v) GSCI Natural gas index (NGI), and 7 metal commodities (nonenergy), i.e., (i) The realized volatility at the monthly frequency of the GSCI gold index (GDI); (ii) the GSCI silver index (SLI); (iii) the GSCI aluminum index (ALI); (iv) the GSCI copper index (COI); (v) the GSCI lead index (LEI); (vi) the GSCI nickel index (NII); and (vii) the GSCI zinc index (ZII). All commodity price series are collected from the Wind database (except the USGAS from EIA).[4]

Third, the stock indexes of 11 industrial countries are used to explore the predictive content of financial activities, which include (i) All Ordinaries Index (AORD); (ii) AEX index (AEX); (iii) FTSE 100 index (FTSE); (v) FTSE MIB index (FTMIB); (vi) CAC 40 index (FCHI); (vii) DAX index (GDAXI); (viii) Nikkei 225 index (N225); (ix) Shanghai Composite Index (SSEC); (x) Swiss Stock Market Index (SSMI); (xi) STOXX Europe 600 index (SXXP); and (xii) S&P 500 index (INX). We sum the daily realized volatility collected from the Realized Library

[4] Considering the different units of some predictors, we convert the foreign currencies into Euros.

[3] The detailed algorithm can be found in Zhang et al. (2019).

Table 1
Variable description.

Category	Predictors	Strat to end	Database	Calculated methods
Bond-related factors	US corporate bond yield spread (UCBYS)	July 2008–October 2021	FRED	Calculated as difference between Moody's BAA-and AAA-rated US corporate bond yields
	Euro corporate bond return spread (ECBRS)	July 2008–October 2021	ECB	Calculated as difference between FISE EURO BBB and AAA bonds
	Euro area 3-month 3 A bond yield (EBY3 M)	July 2008–October 2021	ECB	–
	US 3-month treasury constant maturity rate (UTB3 M)	July 2008–October 2021	FRED	–
	Euro area 10-year 3 A government bond yield (EBY10 M)	July 2008–October 2021	ECB	–
	US 10-year Treasury constant maturity rate (UTB10 M)	July 2008–October 2021	FRED	–
	Euro Area government bond yield spread (EGYS)	July 2008–October 2021	ECB	Calculated as difference between EURO 10-year and 1-year yield
	US government bond yield spread (UGYS)	July 2008–October 2021	FRED	Calculated as difference between US 10-year and 1-year yield
Commodity-related factors	NYMEX natural gas (USGAS)	July 2008–October 2021	EIA	Calculated as monthly realized volatility
	ICE-UK natural gas futures (UKGAS)	July 2008–October 2021	Wind	
	ICE-Coal Rotterdam futures (CRF)	July 2008–October 2021	Wind	
	ICE-Brent oil futures (BOF)	July 2008–October 2021	Wind	
	GSCI Natural gas index (NGI)	July 2008–October 2021	Wind	
	GSCI gold index (GDI)	July 2008–October 2021	Wind	
	GSCI silver index (SLI)	July 2008–October 2021	Wind	
	GSCI aluminum index (ALI)	July 2008–October 2021	Wind	
	GSCI copper index (COI)	July 2008–October 2021	Wind	
	GSCI lead index (LEI)	July 2008–October 2021	Wind	
	GSCI nickel index (NII)	July 2008–October 2021	Wind	
	GSCI zinc index (ZII)	July 2008–October 2021	Wind	
Equity-related factors	All Ordinaries Index (AORD)	July 2008–October 2021	Realized Library	Calculated as the sum of daily rv5
	AEX index (AEX)	July 2008–October 2021	Realized Library	
	FTSE 100 index (FTSE)	July 2008–October 2021	Realized Library	
	FTSE MIB index (FTMIB)	July 2008–October 2021	Yahoo! Finance	Calculated as monthly realized volatility
	CAC 40 index (FCHI)	July 2008–October 2021	Realized Library	Calculated as the sum of daily rv5
	DAX index (GDAXI)	July 2008–October 2021	Realized Library	
	Nikkei 225 index (N225)	July 2008–October 2021	Realized Library	
	Shanghai Composite Index (SSEC)	July 2008–October 2021	Realized Library	
	Swiss Stock Market Index (SSMI)	July 2008–October 2021	Realized Library	
	STOXX Europe 600 index (SXXP)	July 2008–October 2021	Realized Library	
	S&P 500 index (INX)	July 2008–October 2021	Realized Library	
	WilderHill new energy global innovation index (NEGI)	July 2008–October 2021	Bloomberg	Calculated as log difference of NEGI
	WilderHill clean energy index (CEI)	July 2008–October 2021	Bloomberg	Calculated as log difference of CEI
Uncertainty-related factors	CBOE Volatility index (VIX)	July 2008–October 2021	CBOE website	Calculated as log of VIX
	CBOE Oil volatility index (OVX)	July 2008–October 2021	CBOE website	Calculated as log of OVX
	US Equity market volatility index (UEMV)	July 2008–October 2021	EPU website	Calculated as log of UEMV
	Climate policy uncertainty index (CLPU)	July 2008–October 2021	EPU website	Calculated as log of CLPU

(*continued on next page*)

Table 1 (*continued*)

Category	Predictors	Strat to end	Database	Calculated methods
	Germany economic policy uncertainty index (GMEPU)	July 2008–October 2021	EPU website	Calculated as log of GMEPU
	Italy economic policy uncertainty index (IEPU)	July 2008–October 2021	EPU website	Calculated as log of IEPU
	UK economic policy uncertainty index (UKEPU)	July 2008–October 2021	EPU website	Calculated as log of UKEPU
	France economic policy uncertainty index (FEPU)	July 2008–October 2021	EPU website	Calculated as log of FEPU
	Spain economic policy uncertainty index (SEPU)	July 2008–October 2021	EPU website	Calculated as log of SEPU
	US economic policy uncertainty index (USEPU)	July 2008–October 2021	EPU website	Calculated as log of USEPU
	European economic policy uncertainty index (EEPU)	July 2008–October 2021	EPU website	Calculated as log of EEPU
	Global economic policy uncertainty index (GEPU)	July 2008–October 2021	EPU website	Calculated as log of GEPU

Notes: EIA: https://www.eia.gov/; FRED: https://fred.stlouisfed.org/; ECB: https://www.ecb.europa.eu/; Realized Library: https://realized.oxford-man.ox.ac.uk; CBOE website: https://www.cboe.com/; EPU website: http://www.policyuncertainty.com/.

(except the FTMIB[5]) to construct the monthly stock-related factors.

Finally, considering the influence of investor sentiment and market conditions, we use 14 uncertainty-related factors to explore their forecasting performance, including: (i) WilderHill new energy global innovation index (NEGI); (ii) WilderHill clean energy index (CEI)[6];(iii) CBOE Volatility index (VIX); (v) CBOE Oil volatility index (OVX); (vi) US Equity market volatility index (UEMV); (vii) Climate policy uncertainty index (CLPU); (viii) Germany economic policy uncertainty index (GMEPU); (ix) Italy economic policy uncertainty index (IEPU); (x) UK economic policy uncertainty index (UKEPU); (xi) France economic policy uncertainty index (FEPU); (xii) Spain economic policy uncertainty index (SEPU); (xii) US economic policy uncertainty index (USEPU); (xiii) European economic policy uncertainty index (EEPU); (xv) Global economic policy uncertainty index (GEPU). All the uncertainty-related predictors are scaled by the logarithm to eliminate the influence of different magnitudes. The details and construction of predictors considered in our study can be found in Table 1.

Table 2 shows descriptive statistics of all predictors and RV of EUA reporting mean, standard deviation, skewness, kurtosis, the statics of Jarque-Bera test, the statics of augmented Dickey-Fuller test. Undoubtfully, the stationarity of time series is extremely important in the forecasting process. Being of interest, we employ the augmented Dickey-Fuller (ADF) test to examine the existence of a unit root, and the results indicate that all the time series are stationary.

4. Out-of-sample forecasting results

4.1. Forecasting and evaluation methods

To measure the out-of-sample performance of exogenous drivers, we first consider one of the most popular methods, the out-of-sample R^2 test of Campbell and Thompson (2008), which can evaluate the percent reduction of mean squared predictive error (MSPE) of the competing model ($\text{MSPE}_{\text{model}}$) relative to the benchmark ($\text{MSPE}_{\text{bench}}$). The R^2_{OOS} measure is defined as:

$$R^2_{oos} = 1 - \frac{\text{MSPE}_{\text{model}}}{\text{MSPE}_{\text{bench}}}, \tag{12}$$

where $\text{MSPE}_i = \frac{1}{\delta}\sum_{t=1}^{\delta}\left(\text{RV}_t - \widehat{\text{RV}}_{t,i}\right)^2 (i = \text{model}, \text{bench})$, *and* δ represents the length of the out-of-sample window period. Obviously, a positive value of R^2_{oos} indicates that the extended models have lower MSPE than the benchmark, suggesting superior forecasting performance. To assess the significant difference between competing models and benchmarks, we introduce a one-sided test, the MSPE-adjusted statistic proposed by Clark and West (2007), with the null hypothesis that the MSPE of the benchmark is less than or equal to that of the competing models.

Furthermore, we also consider another loss function, the mean absolute forecast error (MAFE), to weaken the influence of outliers. The RMAFE gains can be defined as

$$\text{RMAFE gains} = 1 - \frac{\text{MAFE}_{\text{model}}}{\text{MAFE}_{\text{bench}}}, \tag{13}$$

where $\text{MAFE}_i = \frac{1}{\delta}\sum_{t=1}^{\delta}\frac{\left|\text{RV}_t - \widehat{\text{RV}}_{t,i}\right|}{\text{RV}_t}, (i = \text{model}, \text{bench})$. Similar to R^2_{oos}, a positive RMAFE gains suggests that the competing model can yield greater forecasting accuracy.

4.2. Forecasting performance

4.2.1. Forecasting performance of individual predictors

After cleaning or constructing data, the full sample period covers from July 2008 to October 2021, containing 60 months. Recursive forecasting methods are used to generate volatility forecasts. We set July 2008 to December 2017 as the estimation period, and the first forecast is generated in January 2018.

To ascertain which predictor can more influentially drive EUA volatility (*Question 1*), we first assess the forecasting performance of individual predictors. Table 3 reports the evaluation results of one-month-ahead volatility forecasting using the individual predictors. Some interesting findings emerge. First, we can observe that the UCBYS, ECBRS, EBY3 M and EGYS yield positive Roos and RMAFE, and the values of the remaining predictors in Panel A are negative. The adjusted MSPE statistic and its p values show that ECBRS and EBY3 M can significantly outperform peers. Second, as shown in Panel B, surprisingly, the energy-related predictors (except CRF) can weaken the forecasting accuracy, and the GDI and NII can successfully predict EUA future volatility in terms of Roos and RMAFE. Third, the stock-related factors seem to contain less predictive information in EUA volatility because the extended models with stock-related factors always generate negative Roos and RMAFE. Finally, for uncertainty-related factors, only

[5] The series of FTMIB covers from June 2009 to October 2021 in Realized Library. To match full sample period, we collect the daily close price of FTMIB from Yahoo! Finance for constructing monthly realized volatility.

[6] The NEGI and CEI can reflect the global development of clean energy, new energy, renewable energy and decarbonization. The movement of NECI and CEI index always along with the change of the carbon emission, resulting in the uncertainty of European carbon emission market. As such, we classify the NEGI and CEI in the uncertainty groups.

Table 2
Descriptive statistics.

Factors	Mean	Std.Dev	Skewness	Kurtosis	JB-stat	ADF	Factors	Mean	Std.Dev	Skewness	Kurtosis	JB-stat	ADF
EUA	4.899	0.943	0.168	0.188	0.877	−6.081 ***	FTSE	0.003	0.005	6.402	48.956	16,052.433 ***	−8.037 ***
USGAS	0.021	0.021	3.623	20.130	2870.556 ***	−7.634 ***	FTMIB	0.006	0.009	5.049	32.538	7278.867 ***	−8.864 ***
UKGAS	0.022	0.031	2.975	9.866	836.245 ***	−6.825 ***	FCHI	0.003	0.004	5.456	36.511	9106.531 ***	−7.869 ***
CRF	0.006	0.011	3.862	18.182	2450.877 ***	−9.399 ***	GDAXI	0.003	0.004	5.706	41.584	11,656.993 ***	−7.421 ***
BOF	0.012	0.023	5.910	41.305	11,574.107 ***	−6.114 ***	N225	0.002	0.003	5.640	40.833	11,250.390 ***	−7.428 ***
NGI	0.021	0.053	11.384	138.175	122,842.949 ***	−12.577 ***	SSEC	0.003	0.004	3.592	17.061	2151.661 ***	−4.840 ***
GDI	0.003	0.003	3.021	10.466	919.510 ***	−6.315 ***	SSMI	0.002	0.004	6.941	57.990	22,283.936 ***	−9.071 ***
SLI	0.009	0.011	3.065	11.583	1080.153 ***	−6.722 ***	SXXP	0.003	0.006	5.255	34.205	8030.010 ***	−7.715 ***
ALI	0.004	0.003	2.514	7.909	553.234 ***	−7.880 ***	INX	0.002	0.005	5.928	41.888	11,883.143 ***	−7.083 ***
COI	0.006	0.008	6.635	59.560	23,329.733 ***	−7.155 ***	NEGI	0.003	0.077	−0.868	2.482	57.487 ***	−10.218 ***
LEI	0.008	0.010	3.880	21.466	3268.181 ***	−6.402 ***	CEI	−0.001	0.111	−0.741	2.214	44.299 ***	−11.472 ***
NII	0.010	0.011	5.282	36.953	9260.518 ***	−7.457 ***	VIX	2.929	0.380	0.823	0.343	18.309 ***	−4.378 ***
ZII	0.007	0.007	3.515	20.049	2829.862 ***	−6.988 ***	OVX	3.571	0.374	0.663	1.644	27.641 ***	−3.595 ***
UCBYS	−0.005	0.149	1.372	13.017	1103.786 ***	−7.330 ***	UEMV	2.967	0.343	1.101	1.893	53.266 ***	−5.948 ***
ECBRS	0.002	0.008	−0.085	2.014	24.623 ***	−11.351 ***	CLPU	4.675	0.635	−0.304	0.623	4.562 *	−6.297 ***
EBY3 M	−0.031	0.148	−3.815	24.879	4243.544 ***	−7.674 ***	GMEPU	5.133	0.412	0.154	0.006	0.630	−5.939 ***
UTB3 M	−0.012	0.137	−5.624	44.111	12,987.117 ***	−9.015 ***	IEPU	4.761	0.349	−0.479	0.964	11.374 **	−6.940 ***
EBY10 M	−0.030	0.187	−0.125	0.170	0.519	−13.677 ***	UKEPU	5.560	0.463	0.261	−0.293	2.470	−4.082 ***
UTB10 M	−0.016	0.204	−1.148	5.444	217.394 ***	−9.495 ***	FEPU	5.445	0.340	−0.235	0.220	1.648	−6.955 ***
EGYS	0.002	0.184	1.331	4.777	186.957 ***	−11.040 ***	SEPU	4.768	0.365	−0.185	−0.167	1.158	−7.938 ***
UGYS	−0.001	0.144	−0.374	5.518	191.616 ***	−9.220 ***	USEPU	4.991	0.373	0.694	0.561	14.307 ***	−5.449 ***
AORD	0.002	0.004	5.534	36.786	9254.891 ***	−7.862 ***	EEPU	5.236	0.297	−0.005	0.256	0.296	−5.140 ***
AEX	0.001	0.003	8.512	86.854	49,077.650 ***	−8.860 ***	GEPU	5.059	0.364	0.521	−0.468	8.719 ***	−3.418 ***

Notes: We employ several statistics, including the sample mean (Mean), standard deviation (Std. dev.), skewness, kurtosis, Jarque-Bera statistic (JB-stat), and augmented Dickey-Fuller test (ADF). Asterisks ***, **and * denote rejections of the null hypothesis at the 1%, 5% and 10% levels.

Table 3
Individual factor analysis.

Predictors	Roos	AMSPE	RMAFE (%)	Predictors	Roos	AMSPE	RMAFE (%)
Panel A: Bond-related factors							
UCBYS	3.291	1.249	1.095	EBY10 M	−2.124	−1.220	−0.297
ECBRS	3.252	2.595 ***	3.785	UTB10 M	−1.671	−0.648	−1.328
EBY3 M	3.061	1.571 *	2.540	EGYS	1.222	0.910	3.529
UTB3 M	−2.775	−0.853	−1.325	UGYS	−0.513	−1.366	−1.278
Panel B: Commodity-related factors							
USGAS	−2.105	−1.319	−0.406	SLI	−0.052	0.448	0.029
UKGAS	−1.753	−1.381	−3.358	ALI	−1.628	−1.447	−2.538
CRF	0.145	0.275	0.185	COI	1.426	2.769	1.312
BOF	−6.092	−1.102	−3.324	LEI	−0.186	−1.880	−0.246
NGI	−0.278	−2.151	−0.289	NII	0.482	2.607 ***	0.669
GDI	7.041	1.543 *	4.432	ZII	−1.378	−3.107	−2.429
Panel C: Equity-related factors							
AORD	−0.400	−1.649	−0.270	N225	−1.449	−1.933	−2.586
AEX	−1.999	−1.756	−1.876	SSEC	−0.755	−0.508	−4.331
FTSE	−0.497	−2.136	−0.574	SSMI	−1.517	−2.312	−1.710
FTMIB	−0.619	−1.019	−0.393	SXXP	−0.632	−1.890	−0.531
FCHI	−0.134	−0.686	0.106	INX	−0.321	−0.542	−0.095
GDAXI	−2.308	−2.350	−2.953				
Panel D: Uncertainty-related factors							
NEGI	7.626	2.593 ***	25.307	IEPU	−4.294	−1.172	−2.643
CEI	2.059	1.661 **	8.173	UKEPU	−4.268	−2.349	−5.859
VIX	−1.702	−0.947	−1.708	FEPU	−1.331	−1.764	−1.957
OVX	−2.415	−1.202	−1.384	SEPU	−0.930	−2.174	−1.014
UEMV	−2.068	−1.145	−1.981	USEPU	−7.401	−1.299	−6.709
CLPU	−1.590	−1.437	−1.269	EEPU	−5.952	−2.008	−7.721
GMEPU	−11.107	−1.237	−12.686	GEPU	−17.483	−2.066	−21.388

***Notes*:** The table presents the evaluation of the out-of-sample performance of models on the basis of the out-of-sample R^2 test and RMAFE for individual factor analysis. The first out-of-sample forecast begins in January 2018, and the forecasting window covers 46 months.

Table 4
Forecasting performance of diffusion methods and forecast combinations.

Model	Roos	AMSPE	RMAFE (%)	Model	Roos	AMSPE	RMAFE (%)
Panel A: Bond-related factors							
PCA	−1.496	−0.196	−2.425	MCF	0.233	0.395	−0.333
PLS	1.304	0.973	−0.411	MECF	0.573	1.031	−0.183
SPCA	−0.071	−0.068	−0.059	TMCF	0.209	0.385	−0.262
Panel B: Commodity-related factors							
PCA	0.398	0.788	0.167	MCF	0.665	0.567	0.188
PLS	2.949	0.536	−2.735	MECF	−0.102	−0.603	−0.077
SPCA	3.943	0.779	0.025	TMCF	0.334	0.456	0.079
Panel C: Equity-related factors							
PCA	−0.362	−1.278	−0.333	MCF	−0.214	−0.629	−0.175
PLS	1.897	1.909 **	1.865	MECF	−0.135	−1.004	−0.133
SPCA	0.247	0.366	−0.255	TMCF	−0.275	−1.106	−0.246
Panel D: Uncertainty-related factors							
PCA	−2.005	−0.131	−0.673	MCF	−0.507	−0.312	0.244
PLS	−1.914	0.163	1.225	MECF	−0.867	−1.009	−0.333
SPCA	−2.653	−0.306	−1.063	TMCF	−0.599	−0.425	−0.078
Panel E: All factors							
PCA	−0.107	−0.276	0.060	MCF	0.090	0.254	0.026
PLS	−0.507	0.648	−0.042	MECF	−0.090	−0.800	−0.021
SPCA	−2.888	−0.400	−1.200	TMCF	0.028	0.117	−0.043

***Notes*:** The table presents the out-of-sample performance for the diffusion index model and combination forecast method. The first out-of-sample forecast begins in January 2018, and the forecasting window covers 46 months.

Table 5
Forecasting performance of the supervised learning method.

Model	Roos	AMSPE	RMAFE (%)
Panel A: Elastic Net			
ELN-Bond	10.002	2.127 **	6.365
ELN-Commodity	9.300	2.149 **	4.409
ELN-Stock	11.107	2.334 ***	7.300
ELN-Uncertainty	13.908	2.322 **	6.945
ELN-All	8.016	1.769 **	5.557
Panel B: LASSO			
LASSO-Bond	10.667	2.003 **	6.728
LASSO-Commodity	13.504	2.262 **	7.659
LASSO-Equity	12.882	2.167 **	7.365
LASSO-Uncertainty	14.132	2.350 ***	7.152
LASSO-All	13.269	2.242 **	7.176
Panel C: SVR			
SVR-Bond	14.581	2.888 ***	10.017
SVR-Commodity	8.807	2.839 ***	7.599
SVR-Equity	13.230	3.366 ***	9.933
SVR-Uncertainty	10.809	3.302 ***	5.547
SVR-All	17.859	3.391 ***	9.964

***Notes*:** The table presents the out-of-sample performance for the supervised learning method. ELN-i ($i \in$ (Bond, Commodity, Equity, Unceratinty, All)) represents the volatility forecasts generated from the ELN model with *i*-realted predictors. For example, ELN-B indicates the ELN model with bond-related predictors. The first out-of-sample forecast begins in January 2018, and the forecasting window covers 46 months.

NEGI and CEI can yield significant and positive Roos and RMAFE, suggesting that these two indexes can drive the volatility of EUA futures.

Overall, the forecasting performance of individual predictors indicates that 6 of 45 predictors can significantly predict EUA volatility, including ECBRS, EBY3 M, GDI, NII, NEGI and CEI. Both the ECBRS and EBY3 M are bond-related predictors; as discussed before, the corporate or government bond yield can reflect the economic conditions in the European area, which in turn has implications for carbon emissions. The NEGI and CEI can drive the EUA volatility because the development of new or clean energy (such as solar, wind, and hydrogen energy) can reduce the usage or fossil fuels (such as crude oil and coal) to achieve the goal of decarbonization. Furthermore, the remaining 39 predictors show limited forecasting performance, which may be caused by the following reasons: i) similar to findings of previous studies, e.g., Rapach et al. (2010) and Zhang et al. (2019), the individual predictor hardly consistently maintains powerful predictive ability during the long term or during changing market conditions due to uncertainty; ii) the superior forecasting performance of predictors will become disappointing and lose empirical support over time (Goyal et al., 2021).

4.2.2. Comprehensive information and forecasting performance

To address *Question 2 (How do investors and researchers use information extracted from various predictors in practice?)* and overcoming the model uncertainty, we further considered the comprehensive information extracted from various predictors included in our study.[7] Table 4 reports the evaluation results of the combination forecast (MCF, MECF and TMCF) and diffusion index models (PCA, PLS and SPCA). Surprisingly, we find that the PLS model with stock-related factors can significantly outperform the benchmark and individual predictors, and the remaining models hardly improve the accuracy of EUA volatility forecasting. Our findings are different from those of previous studies, which argue that the comprehensive information extracted from various studies exhibits powerful predictive ability for asset volatility or return for the following reasons: i) The worse forecasting performance of individual predictors leads to the disappointing results of diffusion models and combination forecasts. However, compared with the results of individual predictor analysis, the negative value of comprehensive becomes close to zero (especially for uncertainty-related factors), suggesting that comprehensive information slightly improves the accuracy compared to individual predictors. ii) The diffusion index relies on the statistical principal component of various predictors; however, the weight of each predictor is not determined by the importance or influence of the predictor on EUA volatility. Although the SPCA method needs to scale each predictor by its coefficient, some predictors may exert a nonlinear impact on EUA volatility.

4.2.3. Supervised learning and forecasting performance

Next, we further explore whether the supervised learning method can help to forecast EUA volatility to answer *Question 3 (Does the supervised learning method help to improve the accuracy of EUA volatility forecasting)*? The out-of-sample performance of ELN, LASSO and SVR are shown in Table 5. Obviously, the three supervised learning methods considered in this study can consistently yield the positive values of Roos and RMAFE, suggesting that the supervised learning methods can significantly predict the EUA volatility compared to the competing models in our study. We can observe several findings. First, as shown in Panel A, the ELN model with bond-related predictors, commodity-related factors, stock-related factors, uncertainty-related factors and all factors can reduce in MSPE by 10.002%, 9.300%, 11.107%, 13.908% and 8.016%, respectively, suggesting that the ELN model can significantly outperform the benchmark. The results of the LASSO model are similar to those of ELN. Notably, the uncertainty-related predictors under the variable selection methods (LASSO and ELN) can generate the largest value of Roos, implying that the uncertainty-related factors contain more predictive content for forecasting EUA volatility than other groups, even all predictors. Second, different from the variable selection methods, the support vector regression with all predictors can significantly reduce the MSPE between 8.807% and 17.859%. For the SVR model, considering all predictors can generate a higher value than competing models.

Subsequently, to examine whether our findings are robust over time, we consider the cumulative squared forecast error (CSFE) to graph the forecast evaluation, which is defined as

$$\mathrm{CSFE}_i = \sum_{t=1}^{\delta}\left(\left(\widehat{\mathrm{RV}}_{i,t}^{i,\mathrm{model}} - \mathrm{RV}_t\right)^2 - \left(\widehat{\mathrm{RV}}_{i,t}^{i,\mathrm{bench}} - \mathrm{RV}_t\right)^2\right), \tag{14}$$

where $i = (\mathrm{ELN}, \mathrm{LASSO}\text{ and }\mathrm{SVR})$, and $\widehat{\mathrm{RV}}_{i,t}^{i,\mathrm{model}}$ represents the forecasts generated from model i in month t. Obviously, the negative value of CSFE shows that the competing model can beat the benchmark.

Figs. 1–3 plot the CSFE of ELN, LASSO and SVR. Some interesting findings need to be highlighted here. First, a visible downward trend emerges around January 2020 for variable selection models (ELN and LASSO) with bond-related factors, commodity-related factors, equity-related factors and uncertainty-related factors. Additionally, both the ELN and LASSO models can generate a smaller CSFE than peers based on the Y-axis magnitude when only considering uncertainty-related factors. Second, the graph of bond-related, commodity-related and stock-related factors shows a positive CSFE value (or close to 0) from January 2019 to October 2019, suggesting weak forecasting performance over this period. The SVR model with all factors can outperform peers. Third, the supervised learning models (LASSO, ELN and SVR) consistently perform well at the end of the out-of-sample period (after July 2020).

The superior performance of supervised learning methods is likely due to the following reasons. First, mathematically, variable selection (ELN and LASSO) tends to be more biased than OLS, which will further

[7] To ensure the comparability, we consider the exactly same forecasting method (recursive method) and forecasting window (the last 46 months) with individual factor analysis. Additionally, following the Neely et al. (2014), we determine the K (the number of diffusion indexes used in the predictive regressions) by the adjusted R^2.

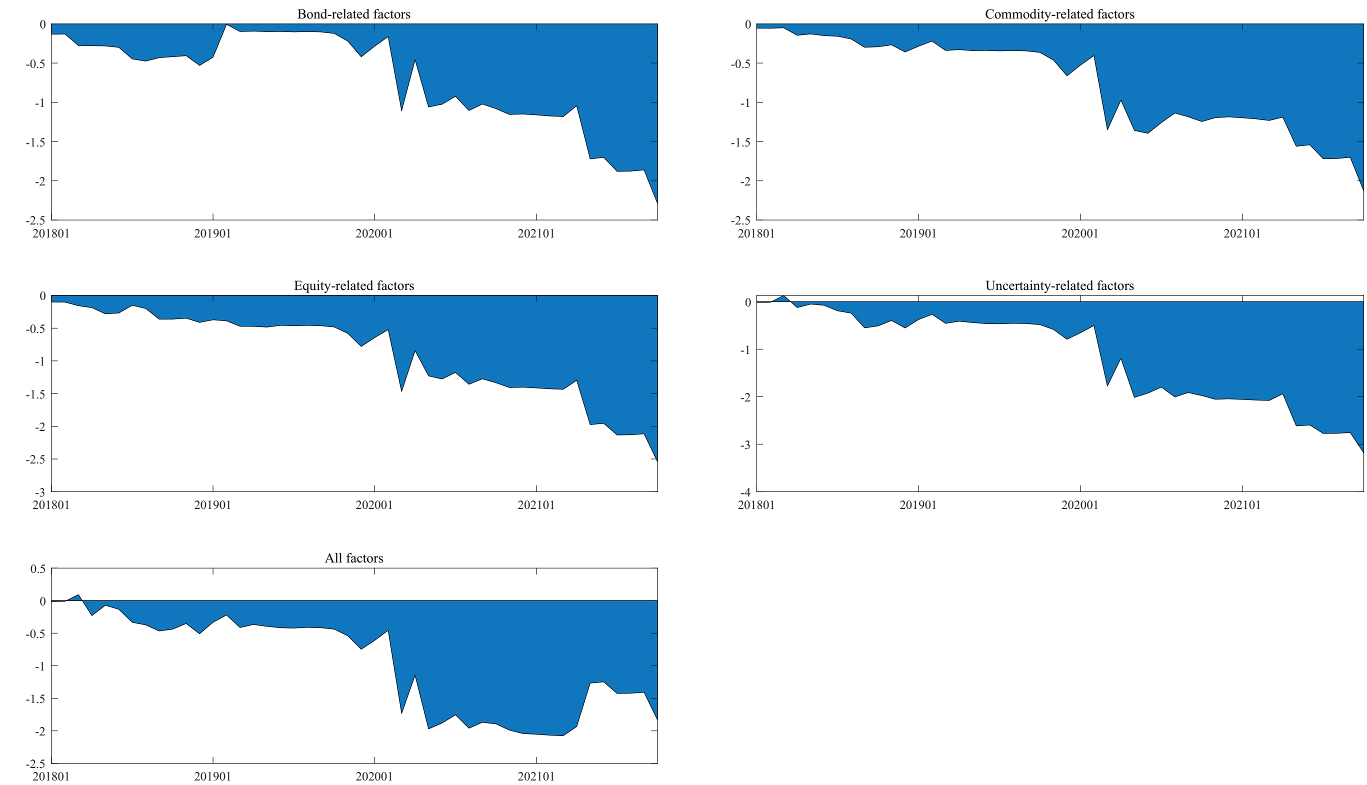

Fig. 1. CSFE of elastic net-type models.
Notes: This figure plots the CSFE of ELN regressions.

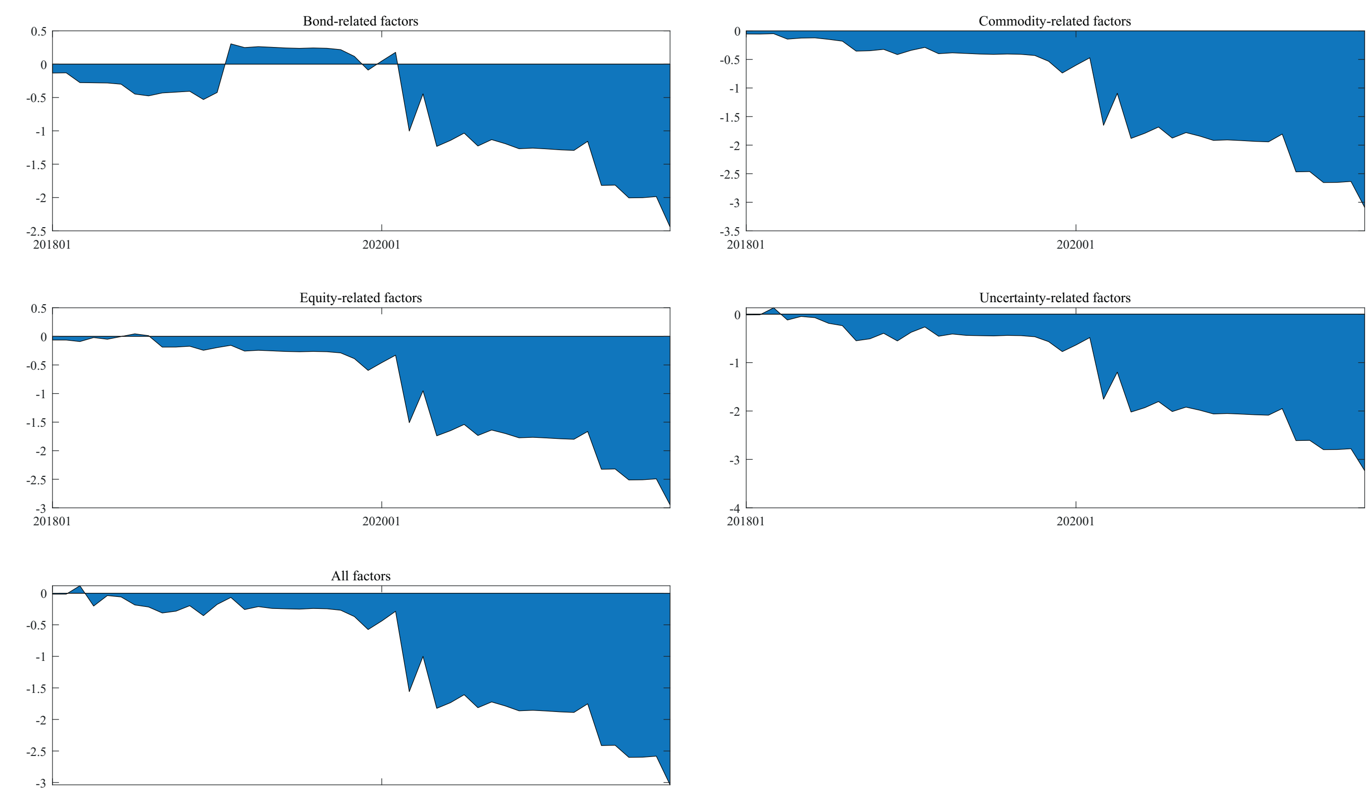

Fig. 2. CSFE of the LASSO-type model.
Notes: This figure plots the CSFE of ELN regressions.

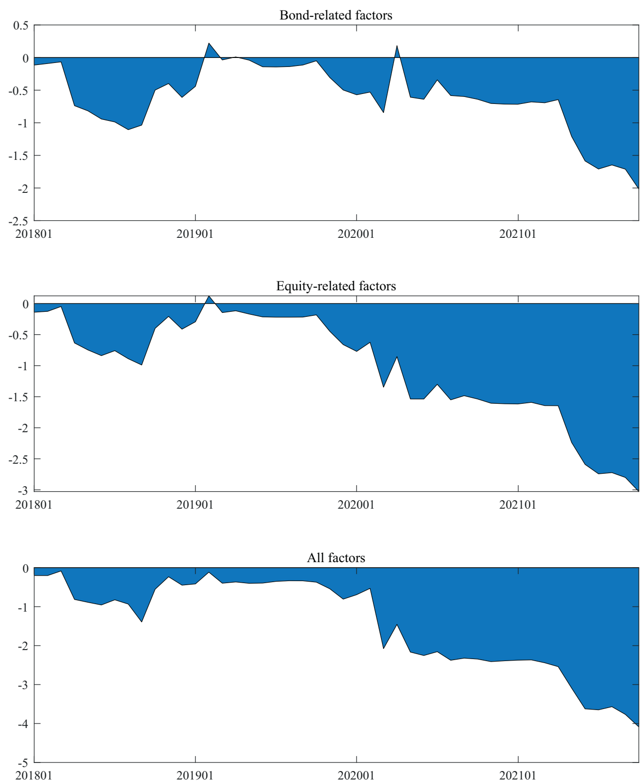

Fig. 3. CSFE of the SVR-type model.
Notes: This figure plots the CSFE of ELN regressions.

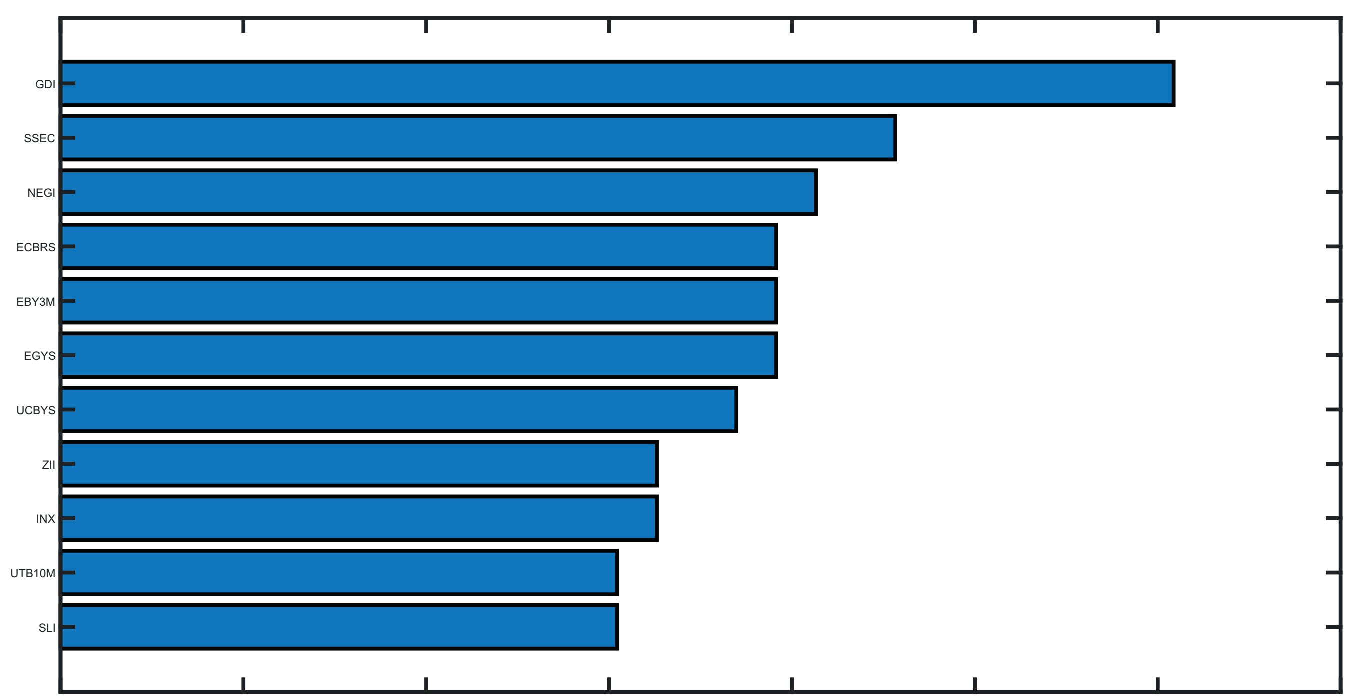

Fig. 4. Factor selection frequencies of ELN.
Notes: This figure plots factor selection frequencies from ELN.

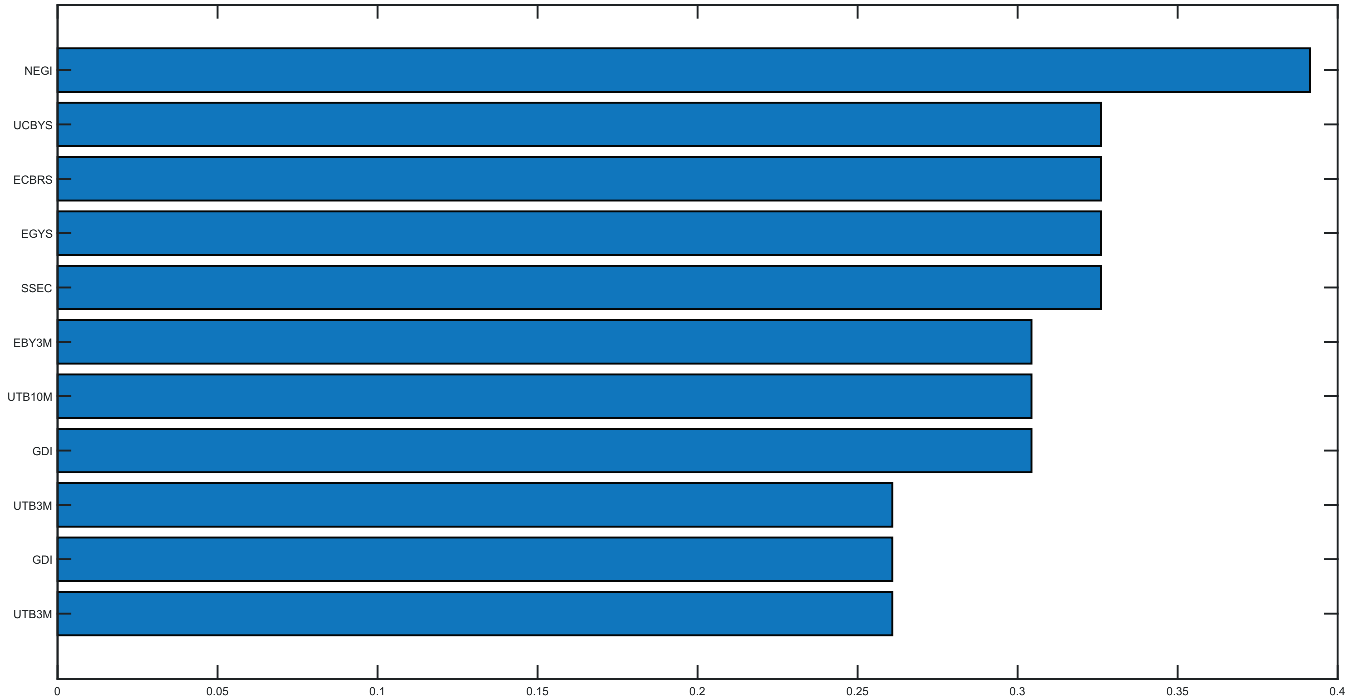

Fig. 5. Factor selection frequencies of LASSO.
Notes: This figure plots factor selection frequencies from LASSO.

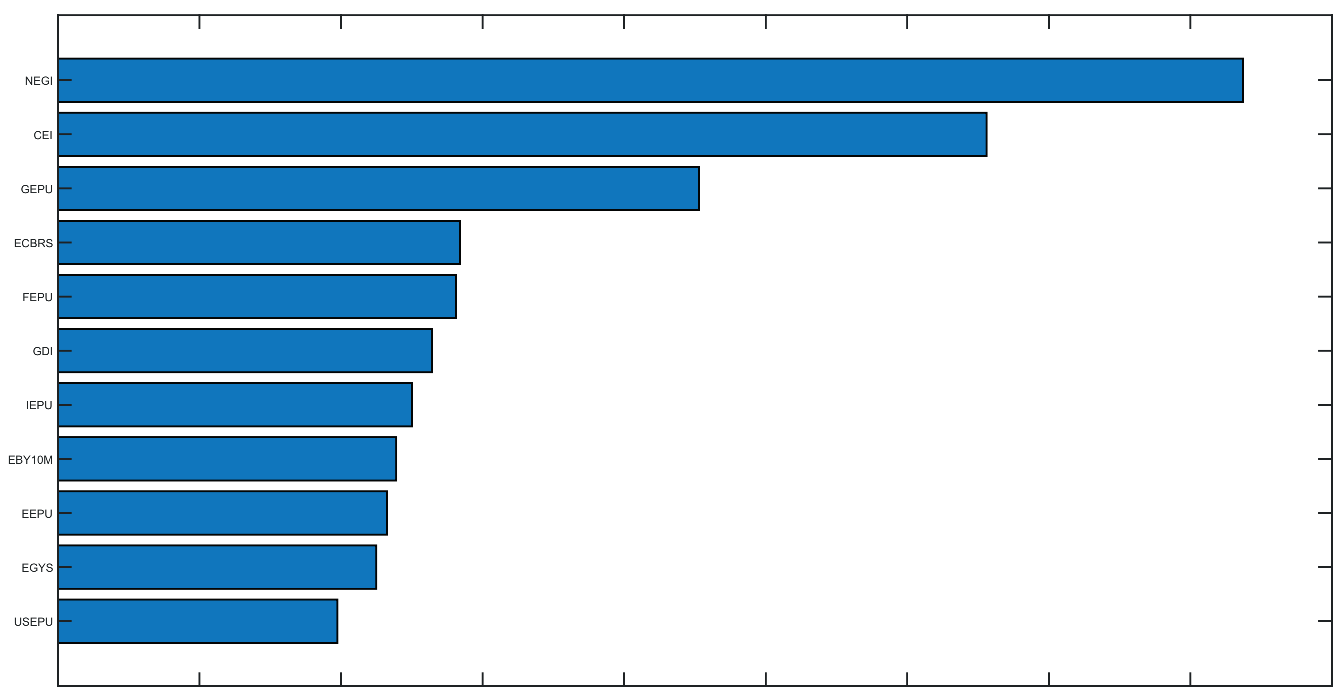

Fig. 6. Factor importance formed by the SVR model.
Notes: This figure plots the factor importance formed by the SHapley Additive explanation method (SHAP) proposed by Lundberg and Lee (2017).

reduce the variance, leading to superior forecasting performance (Plakandaras and Ji, 2022). Furthermore, different from the diffusion index roughly extracted from various predictors, on the basis of the comprehensive information, the variable selection can set the coefficients of useless or unimportant variables to 0. However, we can also observe that the forecasting performance of variable selection is not determined by a number of predictors. Second, as a popular machine learning method, SVR exhibits huge advantages in terms of a small sample, nonlinear feature and high-dimension regression, resulting in superior forecasting performance.

4.3. Model interpretability

As the model uncertainty and changing conditions, the individual predictor analysis is likely unconvinced for market participants and investors. To convincingly address *Question 1*, this subsection further ascertain which factor can more efficiently drive EUA volatility using variable selection frequencies and factor importance to interpret the model.

More specifically, ELN and LASSO can choose the valuable variables and set the coefficient of useless variables to (become) 0. Regarding variable selection methods, we list the coefficient of each variable over the out-of-sample period to calculate the selection frequencies for each variable. Figs. 4 and 5 plot the selection frequencies from ELN and LASSO, respectively. Some interesting findings emerge. First, the GDI, SSEC, NEGI, ECBRS, EBY3 M, EGYS, UCBYS, ZII, INX, UTB10 M, and SLI are the top 11 predictors most frequently selected by ELN; however, LASSO prefers to select the following factors: NEGI, UCBYS, ECBRS, EGYS, SSEC, EBY3 M, UTB10 M, GDI and UTB3 M. Second, we can observe that the 5 bond-related factors with high select frequencies are selected from ELN and LASSO simultaneously, that is, ECBRS, EBY3 M, EGYS, UCBYS, and UTB10 M, suggesting that the bond-related factors can powerfully drive the EUA volatility. Finally, the GDI and NEGI are the predictors most frequently selected by ELN and LASSO, which provides empirical evidence that the GDI and NEGI play an extremely important role in forecasting EUA volatility.

The difference in the algorithm between variable selection and SVR, i.e., linear and nonlinear, leads to the different model interpretability methods. To determine the importance of each predictor, we use the SHapley Additive explanation method (SHAP) proposed by Lundberg and Lee (2017), which relies on the game theoretically optimal Shapley values. Specifically, SHAP can access the contribution of each predictor to the EUA volatility forecasts. A larger SHAP value indicates the irreplaceable importance of predictors. Fig. 6 shows the average SHAP value over the out-of-sample period. Notably, we can observe an obvious difference between variable selection and SVR. First, the results of factor importance indicate that NEGI, CEI, GEPU, ECBRS, FEPU, GDI, IEPU, EBY10 M, EEPU, EGYS, and USEPU are the top 11 important factors. The 7 uncertainty-related factors are likely to dominate the EUA volatility forecasting by using the SVR model. Second, NEGI, ECBRS, GDI and EGYS play a considerably significant role in forecasting EUA volatility in terms of the results of variable selection frequencies and factor importance.

Table 6
Economic gains.

Model	Realized utility (%)				
	Bond	Commodity	Equity	Uncertainty	All
Bench	3.023	3.023	3.023	3.023	3.023
PCA	2.984	3.028	3.023	3.062	3.022
SPCA	2.997	3.185	3.055	2.981	3.050
PLS	3.020	3.118	3.061	3.038	3.033
Mean	3.012	3.045	3.027	3.022	3.028
Median	3.021	3.021	3.023	3.024	3.022
TMC	3.013	3.033	3.023	3.029	3.028
ELN	3.159	3.176	3.195	3.228	3.142
LASSO	3.175	3.217	3.221	3.229	3.205
SVR	3.184	3.048	3.140	3.130	3.255

Notes: The table presents the economic gains of volatility forecasts generated from all regressions.

4.4. Portfolio exercise

Compared with the statistical forecasting performance of exogenous drivers, market participants and policy-makers pay more attention to the economic gains of the forecasting model. To measure the portfolio exercise, we employ the realized utility framework of Bollerslev et al. (2018), which only relies on volatility forecasts ($\widehat{\mathrm{RV}}$). Specifically, a mean-variance investor assigns ω_t of his/her asset to risky asset with r_{t+1} and $(1-\omega_t)$ to risk-free asset with r_t^f. The expected utility with a constant conditional Sharpe ratio can be written as

$$U(x_t) = W_t\left(x_t SR\sqrt{E_t(\mathrm{RV}_{t+1})} - \frac{\gamma}{2}x_t^2 E_t(\mathrm{RV}_{t+1})\right), \tag{15}$$

where γ denotes the investor's relative risk aversion, $E_t(\mathrm{RV}_{t+1}) = Var(r_{t+1}^e)$, where r_{t+1}^e is the excess return, $r_{t+1} - r_t^f$, and the constant Sharpe ratio, $\mathrm{SR} \equiv E_t\left(r_{t+1}^e\right)/\sqrt{E_t(RV_{t+1})}$. To obtain the optimal portfolio, the investor allocates his/her $x_t^* = E_t(r_{t+1}^e)/(\gamma E_t(\mathrm{RV}_{t+1}))$ wealth to the risky asset, or alternatively, $\omega_t^* = \frac{SR/\gamma}{\sqrt{E_t(\mathrm{RV}_{t+1})}}$, where SR/γ denotes the optimal risk target. Hence, the expected utility regarding the optimal target portfolio can be defined as

$$U(\omega_t^*) = \frac{SR^2}{2\gamma}W_t = \frac{1}{2}\times SR\times\frac{SR}{\gamma}W_t, \tag{16}$$

where 1/2 refers to half of the expected return not lost to the disutility of risk, and $SR\times\frac{SR}{\gamma}$ is the expected excess return. However, the investor cannot observe $E_t(\mathrm{RV}_{t+1})$ in practice. As a result, the volatility forecast ($\widehat{\mathrm{RV}}_{t+1}$) replaces $E_t(\mathrm{RV}_{t+1})$, resulting in the average expected utility of

$$\overline{U}(\widehat{\mathrm{RV}}_{t+1}) = \frac{1}{\delta}\sum_{t=1}^{\delta}\frac{SR^2}{\gamma}\left(\frac{\sqrt{\mathrm{RV}_{t+1}}}{\sqrt{\widehat{\mathrm{RV}}_{t+1}}} - \frac{1}{2}\frac{\mathrm{RV}_{t+1}}{\widehat{\mathrm{RV}}_{t+1}}\right). \tag{17}$$

Along the lines of Bollerslev et al. (2018), we set the annualized Sharpe ratio and the coefficient of relative risk aversion as $SR = 0.4$ and $\gamma = 2$, respectively. Consequently, $U(x_t^*) = 4\ \%\ W_t$, implying that the investor would be willing to pay 4% of his/her wealth to gain access to the ω_t^* portfolio of the risky asset rather than simply investing in the risk-free asset. In other words, a risk model that perfectly predicts the RV delivers a realized utility of 8%–4% = 4%.

Table 6 reports the results of realized utility for volatility forecasts generated from various regressions. Columns 2–6 of Table 6 represent the average utility of the forecasting model incorporating bond-related, commodity-related, stock-related, uncertainty-related and all factors, respectively. As shown in Table 6, we can observe several findings. First, the PCA, SPCA and PLS models with commodity-related factors can generate utilities of 3.028%, 3.185% and 3.118%, respectively, relative to that of the benchmark of 3.023%, suggesting that the diffusion index extracted from commodity-related factors can slightly obtain additional economic gains. Second, realized utility generated from combination forecast methods (MCF, MECF and TMCF) are close to that of benchmark, implying the combination forecast method hardly improves economic gains. Finally, being of interest, supervised learning methods can generate significantly higher realized utility than peers. Specifically, the realized utilities of variable selection methods (ELN and LASSO) with uncertainty-related factors and SVR with all predictors are 3.228%, 3.229% and 3.255%, respectively. The results of the portfolio exercise provide empirical evidence that variable selection methods (ELN and LASSO) with uncertainty-related factors and SVR with all predictors can achieve higher economic gains than peers in practice.

Table 7
Results of the alternative forecasting window.

Model	Bond		Commodity		Equity		Uncertainty		All	
	Roos	RMAFE (%)	Roos	RMAFE (%)	Roos	RMAFE (%)	Roos	RMAFE (%)	Roos	RMAFE (%)
PCA	0.081	−0.848	0.104	0.229	−0.315	−0.374	−1.985	−2.164	−0.203	−0.092
SPCA	1.687	1.057	1.381	−0.925	1.044	0.837	−1.121	−0.663	−0.766	−1.866
PLS	−0.094	−0.032	2.256	1.325	0.261	−0.888	−2.128	−2.160	−2.258	−2.334
Mean	0.255	−0.080	0.217	0.192	−0.202	−0.297	−0.594	−0.515	−0.037	−0.195
Median	0.501	−0.045	−0.116	−0.031	−0.202	−0.204	−1.266	−0.942	−0.146	−0.086
TMC	0.408	0.046	0.087	0.114	−0.232	−0.299	−0.539	−0.666	−0.025	−0.200
ELN	6.348 **	3.510	7.761 **	3.797	6.567 **	3.648	7.970 **	4.794	6.247 **	4.440
LASSO	6.697 **	3.714	9.909 ***	5.489	8.322 ***	4.223	8.477 **	5.164	8.256 **	4.863
SVR	9.074 **	8.090	9.872 ***	8.749	10.328 ***	8.664	11.963 ***	7.495	19.186 ***	12.044

Notes: The table presents the out-of-sample performance for the diffusion index model, combination forecast method and supervised learning method. The first out-of-sample forecast begins in January 2016, and the forecasting window covers 70 months.

Table 8
Results of the DM test.

Model	Bond		Commodity		Equity		Uncertainty		All	
	DM1	DM2	DM1	DM2	DM1	DM2	DM1	DM2	DM1	DM2
PCA	−0.600	−1.257	1.121	0.660	−1.780	−1.181	−1.492	−0.286	−0.579	0.235
SPCA	0.883	−0.142	−0.059	−0.758	1.152	2.187 **	−0.027	0.372	−0.052	−0.011
PLS	0.519	−0.168	0.923	0.014	−0.930	−0.254	−1.455	−0.435	−1.526	−0.495
Mean	0.620	−0.452	0.586	0.439	−1.436	−0.603	−0.365	0.291	0.136	0.096
Median	1.223	−0.345	−0.103	−0.518	−1.016	−1.029	−1.583	−0.593	−0.948	−0.204
TMC	0.680	−0.437	0.576	0.290	−1.546	−1.031	−0.849	−0.098	−0.232	−0.171
ELN	1.566 *	1.484 *	1.727 **	1.370 *	1.626 *	1.948 **	1.796 **	1.377 *	1.097	1.094
LASSO	1.433 *	1.378 *	1.817 **	1.746 **	1.600 *	1.686 **	1.835 **	1.418 *	1.755 **	1.423 *
SVR	1.777 **	1.121	2.115 **	1.537 *	2.283 **	1.595 *	1.868 **	0.851	2.115 **	1.364 *

Notes: The table presents the results of the DM test for the diffusion index model, combination forecast method and supervised learning method. The first out-of-sample forecast begins in January 2018, and the forecasting window covers 46 months.

4.5. Robustness check

4.5.1. Alternative out-of-sample period

The forecasting performance is sensitive to the length of the out-of-sample period. This subsection considers another window to reconfirm our empirical findings. We extend the previous forecasting window, and the first forecast is generated on January 2016 and contains 70 months. The out-of-sample performance of the alternative out-of-sample period is shown in Table 7. The variable selection (ELN and LASSO) and SVR model can yield the significant and positive value of Roos and RMAFE (%), suggesting that the supervised learning methods can consistently successfully predict the EUA volatility. The empirical results confirm that our findings are robust to the forecasting window.

4.5.2. Alternative evaluation method

Another popular evaluation method, the Diebold-Mariano (DM) test of Diebold and Mariano (1995), is widely used to examine the paired difference between benchmark and competing models. To evaluate the DM statistic, we consider the following two loss functions, heteroskedasticity-adjusted mean square error (HMSE) and heteroskedasticity-adjusted mean absolute error (HMAE), defined as

$$\mathrm{HMSE} = \delta^{-1}\sum_{t=1}^{\delta}\left(1-\widehat{\mathrm{RV}}_t/\mathrm{RV}_t\right)^2, \tag{18}$$

$$\mathrm{HMAE} = \delta^{-1}\sum\nolimits_{t=1}^{\delta}\left|1-\widehat{\mathrm{RV}}_t/\mathrm{RV}_t\right|, \tag{19}$$

where δ is the length of the out-of-sample period. The DM statistic can be expressed as

$$\mathrm{DM}_i = \frac{\overline{d}}{\sqrt{\mathrm{Var}(d)}}, \tag{20}$$

where $\overline{d} = \frac{1}{\delta}\sum_{t=1}^{\delta} d_t$, d_t denotes the differential of the HMSE and HMAE, $\mathrm{Var}(d)$ is the variance of d_t, and $i = (\mathrm{HMSE}, \mathrm{HMAE})$. The null hypothesis of the DM test is no difference between the benchmark and competing models.

Table 8 reports the results of the DM test. We can observe that the

Table 9
Results of multiple forecast horizons.

Regressions	$H=3$		$H=6$		$H=12$	
	Roos	AMSPE	Roos	AMSPE	Roos	AMSPE
MCF	−0.775	−2.265	−0.987	−2.524	−1.290	−2.470
MECF	3.312**	2.260	3.188**	1.967	0.028	1.130
TMCF	−0.589	0.904	−2.058	0.463	−6.142	−0.656
PCA	0.196	0.752	−0.013	0.068	−0.697	−1.352
PLS	0.304	1.009	0.137	0.383	−0.550	−0.963
SPCA	0.206	0.725	0.004	0.114	−0.684	−1.175
ELN	16.120	2.644 ***	19.360	2.700 ***	31.683	3.563 ***
LASSO	14.615	2.597 ***	19.622	2.873 ***	28.431	3.502 ***
SVR	37.353	3.335 ***	46.624	3.498 ***	59.158	3.868 ***

Notes: This table reports the multistep-ahead evaluation results.

Table 10
Results of agriculture-related predictors.

Regressions	Roos	AMSPE	Regressions	Roos	AMSPE
Panel A: Agriculture-related predictors					
PCA	−0.131	−0.239	MCF	0.101	0.350
PLS	−0.359	−0.429	MECF	−5.531	−0.229
SPCA	−0.396	−0.492	TMCF	0.101	0.350
ELN	10.554	2.237 **	LASSO	12.263	2.394 ***
SVR	12.622	3.013 ***			
Panel B: All predictors					
PCA	−0.230	−1.041	MCF	0.001	0.046
PLS	−0.172	0.786	MECF	−0.136	−1.535
SPCA	−0.230	−1.041	TMCF	−0.014	0.006
ELN	12.577	2.264 **	LASSO	8.759	1.696 **
SVR	18.179	3.222 ***			

Notes: This table shows the evaluation results of agriculture-related predictors. The first out-of-sample forecast begins in January 2018, and the forecasting window covers 46 months.

DM1 statistics of variable selection (ELN and LASSO) and SVR are positive under the HMSE loss function (except ELN with all predictors), suggesting that the supervised learning methods can significantly reject the null hypothesis. Additionally, supervised learning methods (ELN, LASSO and SVR) can also reject the null hypothesis under the HMAE loss function (except SVR with bond-related factors, SVR with uncertainty-related factors and ELN with all factors). The DM results are consistent with the out-of-sample R^2 test and RMAFE gains, implying that supervised learning methods can improve the accuracy in forecasting EUA volatility.

4.5.3. Multiple forecast horizons

Our study further explores the performance of predictive regressions for 3-month, 6-month, and 12-month forecasting horizons because market participants concentrate not only on short-term but also on medium- and long-term performance.[8] Theoretically, for multiple-step-ahead horizon forecasting, we replace the left-hand side of predictive regressions with $\mathrm{RV}_{t+1,h} = \frac{1}{h}\sum_{i=1}^{n}\mathrm{RV}_{t+1}$. Table 9 reports the evaluation results of multiple-horizon-ahead volatility forecasting. Obviously, we can observe that supervised learning methods, including ELN, LASSO and SVR, can obtain positive and significant values of Roos for 3-month-ahead, 6-month-ahead, and 12-month-ahead horizons, suggesting that supervised learning methods can consistently improve the accuracy of EUA volatility forecasting.

4.5.4. Extending the number of predictors

In this subsection, we further consider the 10 exogenous agriculture-related predictors to reconfirm the superior performance of supervised learning methods.[9] Specifically, along the lines of Tan et al. (2022), the following agriculture-related predictors are included in our study: GSCI cocoa index (GCOC), GSCI coffee index (GCOF), GSCI corn index (GCOR), GSCI cotton index (GCOT), GSCI soybeans index (GCSY), GSCI sugar index (GCSU), GSCI wheat index (GCWH), GSCI feeder index (GCFD), GSCI lean hogs index (GCLH) and GSCI live cattle index (GCLC). Similarly, we calculate the realized volatility at the monthly frequency of these 10 agriculture-related predictors. Table 10 reports the evaluation results of agriculture-related predictors. The results of Panel An indicate that the diffusion models and combination methods cannot improve the accuracy of volatility forecasting, while the supervised learning methods can significantly outperform peers. Furthermore, Panel B shows the evaluation results of all predictors, including 8 bond-related, 12 commodity-related, 11 equity-related, 14 uncertainty-related and 10 agriculture-related factors. Obviously, the ELN, LASSO and SVR can yield positive and significant values of Roos, which reconfirms our previous findings that supervised learning methods can successfully predict EUA volatility. Overall, our results are robust to the number of exogenous drivers.

5. Summary and concluding remarks

This study mainly sheds light on the role of various exogenous drivers in forecasting EUA volatility using combination forecasting methods, diffusion index models and supervised learning methods. We consider 45 exogenous factors that can be classified into the following classes: 8 bond-related factors, 12 commodity-related factors, 11 equity-related factors and 14 uncertainty-related factors. The aim of this research is to address the following questions. *Questions 1(Q1): Which exogenous predictor can more influentially drive EUA volatility? Question 2 (Q2): How do investors and researchers use information extracted from various predictors in practice? Questions 3(Q3): Does the supervised learning method help to improve the accuracy of EUA volatility forecasting?*

Several interesting findings are highlighted here. First, we first assess the forecasting performance of individual factors to address *Q1*. The empirical results show that ECBRS, EBY3 M, NII, GDI, NEGI and CEI can strongly drive EUA volatility. Second, in terms of the overfitting issue, we further consider the diffusion index models (PCA, PLS and SPCA) and combination forecasting methods (MCF, MECF and TMCF), which can incorporate the comprehensive information extracted from 45 exogenous drivers, to solve *Q2*. The results show that the diffusion index models and combination forecast methods hardly improve the accuracy in forecasting EUA volatility because few individual factors can successfully predict EUA volatility. Third, we further explore the forecasting performance of supervised learning methods (ELN, LASSO and SVR) to provide the answer to *Q3*. Our results indicate the superior forecasting performance of variable selection (ELN and LASSO) and SVR for EUA volatility. Furthermore, to further ascertain which exogenous variables can influentially drive EUA volatility (*Q1*), we employ the variable selection frequencies and factor importance to interpret the model. We find that the NEGI, ECBRS, GDI and EGYS play a considerably significant role in forecasting EUA volatility in terms of the results of variable selection frequencies and factor importance. Finally, we further assess the incremental realized utilities of the combination forecast method, diffusion index model and supervised learning method for market participants and policy makers. Our findings provide strong evidence that the supervised learning method can achieve higher economic gains than competing models in practice.

The above findings provide crucial implications to participants in the European carbon market. Investors or emission companies can obtain statistically significant improvements in forecasting EUA volatility when using various exogenous drivers, such as the Wilder Hill new energy global innovation index (NEGI), Euro corporate bond return spread (ECBRS), GSCI gold index (GDI) and Euro Area government bond yield spread (EGYS), meaning that they should pay more attention to the price movement of the European bond market, gold and clean energy. In this regard, our conclusions matter to academics, as well as portfolio and risk managers in their quest to more accurately predict EUA volatility. Our forecast analysis also concerns policymakers and central bankers who are becoming more interested in the volatility of EUA as some of them consider launching their own carbon emission markets. Future studies could examine the volatility transmission channels from financial markets (such as fossil energy, clean energy and equity markets) to carbon markets.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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