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Clean energy stock returns forecasting using a large number of predictors: which play important roles?

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Abstract

Purpose – Clean energy stocks have recently received significant attention from both investors and researchers, reflecting their growing importance in financial markets. This paper forecasts clean energy stock (CES) returns using many predictors, including technical, macroeconomic, climate risk and financial predictors. The goal is to reveal how different predictor groups work and their time-varying patterns.

Design/methodology/approach – This study establishes a robust forecasting framework using monthly data from the WilderHill Clean Energy Index, spanning January 2009 to December 2023, and integrates 56 predictors across four categories. To address multicollinearity and identify key drivers, the framework applies advanced shrinkage methods, regularization, quantile regression and model combination. This offers a dynamic solution for forecasting CES returns.

Findings – The study identifies macroeconomic predictors as the most stable and powerful drivers of CES returns; the Chicago Fed National Activity Index (CFNAI) is a particularly important indicator. Climate predictors show temporal variability, while technical and financial predictors are more important during market volatility. A group-level analysis highlights macroeconomic variables as key to forecasting accuracy. Climate predictors play critical roles in specific periods. Medium-term dynamics (2–4 months) associated with macroeconomic predictors have the strongest impact on performance.

Originality/value – This paper introduces a novel approach to forecasting CES returns by integrating 56 diverse predictors. This addresses research gaps, given the previous focus on traditional predictors or single-model

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frameworks. The study further examines the roles of predictor grouping, component selection, rolling windows and forecasting horizons in increasing prediction accuracy and in describing the dynamic interactions driving CES returns.

Keywords Clean energy stock, Returns forecasting, Predictor selection, Shrinkage methods, Quantile penalty methods

Paper type Research paper

1. Introduction

The global transition to renewable energy is a significant economic transformation for the 21st century. The clean energy sector has experienced unprecedented investment inflows, driven by mounting concerns over climate change and the environmental degradation associated with traditional energy sources. Over the past five years, annual investments in clean energy have consistently surpassed $300 billion, highlighting the sector's rapid expansion and growing importance within global financial markets (International Energy Agency [IEA], 2023). This surge in investment reflects the sector's growth potential and the increasing recognition of renewable energy as a cornerstone of the global economy.

As clean energy stocks (CES) gain prominence as an asset class, understanding the factors driving CES returns is critical for investors, asset managers, and policymakers. Accurately forecasting CES returns is particularly essential because these stocks are influenced by a complex interplay of factors, including evolving climate policies, technological advancements, and shifting macroeconomic conditions. Recognizing these dynamics not only provides insights into market trends but also enables more effective resource allocation, enhances market stability by reducing volatility, and supports policymakers in designing targeted strategies for the energy transition.

Despite the rapid growth of the clean energy sector, forecasting CES returns is challenging. CES volatility is driven by a complex set of factors, including macroeconomic conditions, technical market indicators, climate policies, and global commodity prices. The heightened volatility and uncertainty inherent in CES make it even more important for market participants and decision-makers to identify and understand the drivers of CES returns. Significant research on asset return forecasting has examined the forecasting of returns in traditional financial markets, such as equities, bonds, and commodities (Baumeister *et al.*, 2022; Ghosh and Jana, 2024; Hamilton, 1983; Liang *et al.*, 2020; Luo and Zhang, 2024); however, few studies have specifically focused on the unique drivers of CES returns.

This study is designed to fill this research gap. The clean energy sector operates fundamentally differently than traditional markets. Exogenous predictors play a central role in influencing CES returns; these include climate policy uncertainty, environmental regulations, and renewable energy subsidies. However, existing forecasting models do not yet adequately explore these predictors. This study addresses this gap by focusing on the unique predictors of CES returns that are not captured by traditional asset classes.

Forecasting with a large number of predictors increases the risk of overfitting. To mitigate this, the study uses different econometric techniques such as LASSO, Group LASSO, and Quantile Regression. These methods effectively manage high-dimensional datasets, as demonstrated in forecasting studies on oil prices (Zhang *et al.*, 2019) and cryptocurrency volatility (Wang *et al.*, 2023). Applying these robust methodologies improves forecasting accuracy while minimizing model complexity.

Another study driver lies in the underexplored role of technical indicators in forecasting CES returns. Traditional financial variables have been extensively studied; however, technical indicators have not been adequately incorporated into CES forecasting models; these include moving averages, momentum indicators, and volume-based strategies. Given the volatile and dynamic nature of the clean energy market, technical indicators may provide valuable insights into changes in short-term CES returns. This study explores the utility of these indicators in improving CES return predictions.

Climate-related predictors significantly influence clean energy markets; these include climate policy uncertainty, energy consumption trends, and environmental regulations

(Ren *et al.*, 2022). These predictors have not yet been sufficiently integrated into asset return forecasting models. This study incorporates both financial and non-financial predictors, providing a more comprehensive approach to forecasting CES returns and capturing the unique dynamics of the clean energy sector.

In summary, this paper fills an existing research gap by systematically identifying and analyzing the factors that most effectively predict CES returns. Specifically, the study addresses several key questions. Which factors have the greatest predictive power for CES returns? How does the relevance of these factors evolve over time? Can grouping different factors improve forecasting accuracy? Additionally, the study explores the impact of both short-term and long-term forecasting horizons on predictor effectiveness.

This paper makes a significant contribution by addressing the growing need for accurate CES return forecasting through a novel approach that integrates both traditional and climate-related predictors. Existing research has largely focused on traditional financial markets and overlooked the unique drivers of CES returns. This study expands on previous work by incorporating these critical climate-related factors into forecasting models, while also employing techniques like LASSO and Group LASSO to enhance prediction accuracy and reduce overfitting. Specifically, the paper makes two key contributions to the field. In one aspect, it constructs a comprehensive forecasting framework that integrates 56 predictors, extending beyond traditional financial variables to include macroeconomic, climate risk, technical, and financial predictors, thereby capturing the diverse influences on CES returns. In another aspect, it systematically examines how these predictor relationships evolve over time across different forecasting horizons, offering deeper insights into their varying significance and improving prediction accuracy.

First, the study introduces a novel approach to forecasting CES returns, addressing research gaps. Previous research has predominantly focused on traditional financial predictors or has used single-model frameworks; however, these approaches do not consider the integrative role of multiple predictors and their temporal variability. In contrast, this study constructs a comprehensive forecasting model by incorporating 56 distinct predictors, spanning macroeconomics, climate risk, technical, and financial predictors. Understanding the contribution of each predictor group is essential for investors, policymakers, and researchers in navigating the complexities of CES market fluctuations. Existing literature has explored the predictive power of certain individual factors, such as climate risk measures (Herrera *et al.*, 2022), and technical indicators (Neely *et al.*, 2014), but comprehensive studies that integrate these dimensions remain scarce. The analysis investigates the predictive power of these diverse predictors across different forecasting horizons, thereby enhancing descriptions of CES return dynamics.

Second, the study explores the role of different predictor groupings, predictor components, rolling windows, and forecasting horizons in improving prediction accuracy. Prior research has often considered these factors in isolation, without assessing their collective impact on CES return forecasting. By analyzing how predictor importance evolves over time and under varying market conditions, we provide empirical insights into the dynamic interactions between CES returns and key predictive factors. Moreover, by leveraging regularization techniques, our study effectively addresses the challenges of overfitting and high-dimensional predictor spaces, ensuring robust and reliable forecasts. These insights contribute to the development of a more adaptive and resilient forecasting framework for CES returns.

The rest of this paper is organized as follows. Section 2 reviews the relationship between CES and other variables. Section 3 describes the data. Section 4 introduces the methodology. Section 5 presents the empirical analysis, and Section 6 concludes the paper.

2. CES and its potential predictors

2.1 CES and macroeconomic predictors

Macroeconomic factors are key to understanding the dynamics of renewable energy markets. Global economic indicators play a crucial role in shaping investment flows into renewable energy sectors; these include gross domestic product (GDP) growth, inflation, and interest rates (Baumeister *et al.*, 2022; Hamilton, 1983). Wang *et al.* (2022) showed that global economic activity and uncertainty indices, such as the Chicago Fed National Activity Index (CFNAI) and Consumer Price Index (CPI), effectively predict the volatility of clean energy and natural gas markets. This underscores the interconnectedness between macroeconomic stability and clean energy investments.

Arouri *et al.* (2016) found that increased U.S. economic policy uncertainty dampens stock returns; this effect is more pronounced during periods of extreme volatility. This highlights the need to incorporate macroeconomic uncertainty measures when forecasting CES returns, as these factors can directly impact investor confidence and market dynamics. Baumeister *et al.* (2022) also demonstrated the significant predictive value of global economic activity indicators for energy prices. This further emphasizes the role of macroeconomic factors in shaping market outcomes.

2.2 CES and climate risk predictors

With global climate change and increased attention on green investments, academics have explored the influence of climate change on renewable energy markets (Fahmy, 2022). Since the Paris Agreement in 2015, the global energy landscape has significantly transformed, generating new opportunities for developing renewable energy. Many studies have examined the impact of climate change on CES, focusing on both physical and transition risks (Chen *et al.*, 2021; Ding *et al.*, 2022; Herrera *et al.*, 2022).

Climate change affects renewable energy markets through two primary risk areas: physical and transition. Physical risks involve direct effects, such as extreme weather events, which can disrupt energy production and consumption; these risks heighten CES volatility (Dong *et al.*, 2024). These risks are particularly relevant in understanding market stability, as disruptions in energy supply or demand can significantly alter investment decisions and economic stability (Zhou and Lin, 2025). Chen *et al.* (2021) found that increased investments in clean energy create a positive feedback loop; concerns about climate change drive further investment in clean energy technologies, making these assets crucial for risk mitigation.

Transition risks arise from policy changes, regulatory shifts, and evolving investor sentiment toward green investments. Climate risk awareness surged following the Paris Agreement, driving increased investment in clean energy sectors (Fahmy, 2022). Herrera *et al.* (2022) highlighted how investor sentiment, driven by climate policy announcements, influences CES volatility. Ghosh and Jana (2024) found that market sentiment and fear indices are strong predictors of clean energy investments, as investor preferences shift towards sustainable assets during periods of economic uncertainty. This sentiment provides valuable predictive power beyond traditional financial variables. Similarly, Khalfaoui *et al.* (2022) emphasized the importance of climate policy uncertainty (CPU) in transmitting market risk; sectors linked to clean energy and green innovation are particularly sensitive to these uncertainties.

Several studies have highlighted the long-term effects of CPU on renewable energy investments. Husain *et al.* (2022) found that CPU has strong long-term memory effects: its impact on market reactions can persist over time. He and Zhang (2022) further demonstrated that CPU is a strong predictor for energy sector stock returns; it often outperforms other uncertainty measures and macroeconomic variables in predictive accuracy. These findings collectively underscore CPU's central role in shaping the renewable energy market landscape, especially during periods of increased policy uncertainty.

Technological advancements and growing public attention to climate issues also influence renewable energy investments. Public sentiment, as captured through media and search engine data, enhances stock market prediction accuracy (Audrino *et al.*, 2020; Gao *et al.*, 2023). Positive sentiment towards sustainable companies is linked to increased returns in clean energy stocks, whereas; negative attention adversely impacts traditional sectors (El Ouadghiri *et al.*, 2021).

2.3 CES and financial predictors

Financial and commodity markets are closely linked to CES, and many studies have emphasized their predictive importance. Oil prices, natural gas, and other commodity indices significantly influence clean energy returns. This is because fluctuations in these commodities can change the relative attractiveness of renewable versus traditional energy sources (Campbell *et al*., 2020; Filis, 2010). The relationship between fossil fuel prices and renewable energy investments is complex, and is often characterized by substitution effects. For example, rising fossil fuel prices can increase interest in renewable energy alternatives.

Financial markets also play a crucial role in CES predictions, particularly with respect to equity indices, green bonds, and volatility indices. Indices like the Morgan Stanley Capital International (MSCI) U.S. Environment, Social, Governance (ESG) Leaders Index are benchmarks for CES performance, providing insights into how broader financial market trends influence this sector. Filis (2010) also noted that financial indicators can serve as leading signals for investment shifts between traditional and renewable energy sectors, particularly during periods of economic volatility.

3. Data

3.1 Clean energy stocks

Based on Sadorsky (2012) and Khalfaoui *et al*. (2022), this study uses the WilderHill Clean Energy Index (WCEI) as a representative measure for the CES market (see Table 1, Panel A). As of 2024, 73.6% of WCEI companies are U.S.-listed, reflecting the sector's alignment with the clean energy transition. Therefore, study predictors are based on U.S. macroeconomic or market variables. This study uses monthly data spanning from January 2009 to December 2023, including the post-2008 financial recovery, the 2015 Paris Agreement, and the global shift towards renewable energy investments. This timeframe reflects significant policy changes, technological advancements, and market dynamics, offering a robust foundation for analyzing CES returns. The empirical analysis applies a rolling window length of 60 months. The in-sample period (used for model training and parameter estimation) covers January 2009 to February 2014, and the out-of-sample period (used for testing the model's predictive performance) extends from March 2014 to December 2023. To maintain consistency with the CES index data, all subsequent predictors are drawn from the January 2009 to December 2023 period.

3.2 Technical indicator predictors

Many studies have found that technical indicator predictors have statistically and economically significant predictability, both for the in-sample and out-of-sample, outperforming purely fundamental analysis benchmarks (Neely *et al*., 2014; Yin and Yang, 2016). Based on Wang *et al*. (2023) and Zhang *et al*. (2019), this study uses 14 different technical indicator predictors, including:

(1) Moving Average $\mathrm{MA}(s,l)$ predictors: MA (1, 9), MA (1, 12), MA (2, 9), MA (2, 12), MA (3, 9), and MA (3, 12). When the short-term (s-month) moving average exceeds the long-term (l-month) moving average, the $\mathrm{MA}(s,l)$ value is set as 1; otherwise, it is set as 0. $\mathrm{MA}(s,l)$ signals market momentum and trend direction characteristics.

(2) Momentum $\mathrm{MOM}(k)$ predictors: MOM (3) and MOM (9). $\mathrm{MOM}(k)$ represents the momentum over k months. It measures the rate of change in an asset's price over a specified period.

(3) On-Balance Volume $\mathrm{OBV}(s,l)$ predictors: OBV (1, 9), OBV (1, 12), OBV (2, 9), OBV (2, 12), OBV (3, 9), and OBV (3, 12). When the short-term OBV average exceeds the long-term OBV average, the $\mathrm{OBV}(s,l)$ value is set as 1; otherwise, it is set as 0. $\mathrm{OBV}(s,l)$ signals buying or selling pressure in the market [1].

Table 1. Variable description

Panel A: CES returns			
WCEI	WilderHill Clean Energy Index	FLD	Yahoo finance
Panel B: Technical indicator predictors (14)			
$\mathrm{MA}(s,l)$	MA (1, 9), MA (1, 12), MA (2, 9), MA (2, 12), MA (3, 9), and MA (3, 12)	Level	PBW, WCEI
$\mathrm{MOM}(k)$	MOM(3) and MOM(9)	Level	PBW, WCEI
$\mathrm{OBV}(s,l)$	OBV (1, 9), OBV (1, 12), OBV (2, 9), OBV (2, 12), OBV (3, 9), and OBV (3, 12)	Level	PBW, WCEI
Panel C: Macroeconomic predictors (14)			
CC	Composite Consumer Confidence	FLD	FRED
CFNAI	Chicago Fed National Activity Index	Level	FRED
CPI	Consumer Price Index	Level	FRED
GPRH	Geopolitical Risk Index	FLD	EPU Website
INDPRO	Industrial Production Index	FLD	FRED
MPU	Monetary policy uncertainty	FLD	EPU Website
PPI	Producer Price Index by Industry	FLD	FRED
USDX	Real Broad Dollar Index	FLD	FRED
T10Y3M	10-Year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity	FD	FRED
TPU	Trade policy uncertainty	FLD	EPU Website
UNRATE	Unemployment rate	FD	FRED
EPU	US energy policy uncertainty	FD	EPU Website
PMI	Project manager Index	FLD	ISM
UMCSENT	Consumer sentiment	FLD	FRED
Panel D: Climate risk predictors (14)			
CCPU	China climate policy uncertainty	FLD	CNEFN
GCPU	Global climate policy uncertainty	FLD	CNEFN
NACPU	North America climate policy uncertainty	FD	CNEFN
CPU	climate policy uncertainty	FLD	EPU Website
TRI	Transition risk index	FD	EPU Website
PRI	Physical risk index	FD	EPU Website
Ab_DRT	Abnormal drought occurrences	Level	NOAA
Ab_TND	Abnormal tornado occurrences	Level	NOAA
Ab_TEMP	Abnormal temperature variations	Level	IEA
GT1	Broad cognitive level	FLD	Google trends
GT2	Physical attention	FLD	Google trends
GT3	Opportunity attention	FLD	Google trends
GT4	Clean energy attention	FLD	Google trends
GT5	Climate commission	FLD	Google trends
Panel E: Financial predictors (14)			
NG	Henry Hub Natural Gas Spot Price	FLD	EIA
WTI	Cushing, OK WTI Spot Price FOB	FLD	EIA
Gasoline	New York Harbor Conventional Gasoline Regular Spot Price FOB	FLD	EIA
HO	New York Harbor No. 2 Heating Oil Spot Price FOB	FLD	EIA
TechIndex	NYSE Arca Tech 100 Index	FLD	FRED
OVX	CBOE oil volatility index	FLD	CBOE
VIX	CBOE implied volatility index	FLD	CBOE

(*continued*)

Table 1. Continued

SP500	SP500 index	FLD	Yahoo finance
Russell2000	Russell 2000 index	FLD	Yahoo finance
RVX	CBOE Russell 2000 Volatility Index	FLD	FRED
ESG	MSCI USA ESG leaders price index	FLD	Bloomberg
GB	S&P green bond index	FLD	Bloomberg
GSCI	S&P-GSCI Commodity Index Future	FLD	Bloomberg
WHRV	Monthly CES realized volatility calculated by WCEI daily closing price	FLD	Yahoo finance

Note(s): The computational process of Ab_DRT, Ab_TND, and Ab_TEMP is in Online Appendix B. The keywords selected in GT1, GT2, GT3, GT4 and GT5 is shown in Online Appendix A
Source(s): EPU website (http://www.policyuncertainty.com/), FRED (https://fred.stlouisfed.org/), Google trends (https://trends.google.com/trends/), CNEFN (http://www.cnefn.com/main/data_main) and NOAA (https://www.noaa.gov/)

3.3 Macroeconomic predictors

This study uses 14 macroeconomic variables as potential external predictors, including macroeconomic fundamentals, inflation, and policy uncertainty risk, as shown in Table 1, Panel C. The data sources are also listed in the table.

First, macroeconomic fundamentals provide insights into the broader economic environment that impacts CES. These predictors cover both the supply and demand sides of the economy, and include consumer confidence (CC) and unemployment rate (UNRATE). They reflect the economic cycle's expansions and contractions, which impact CES performance, as discussed in Section 2.

Second, changes in inflation levels can directly influence asset prices, corporate performance, and consumer demand, even in stable economic conditions. Key inflation indicators in this study include the CPI, Producer Price Index (PPI), and the 10-Year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity (T10Y3M).

Third, policy uncertainty risk is considered due to its critical role in shaping investor behavior, market stability, and CES resilience to external shocks. The selected predictors, including the U.S. Energy Policy Uncertainty (EPU), Geopolitical Risk Index (GPRH), Trade Policy Uncertainty (TPU), and Monetary Policy Uncertainty (MPU), are widely recognized in the literature for capturing macroeconomic and policy-driven risks (Li *et al.*, 2022; Baker *et al.*, 2016).

3.4 Climate risk predictors

As described in Section 2, CES interacts strongly with physical and transition climate risk on theoretical and empirical levels. This study analyzes 14 climate risk predictors, summarized in Table 1, Panel D. The table also includes the data sources.

Climate transition risk is generally measured using word frequency indices from news media to gauge transition risk attention (Yan *et al.*, 2020); this study uses the Climate Policy Uncertainty (CPU) index by Gavriilidis (2021). We also incorporate regional measures, including China Climate Policy Uncertainty (CCPU), Global Climate Policy Uncertainty (GCPU), and North America Climate Policy Uncertainty (NACPU) (Liang *et al.*, 2022; Ma *et al.*, 2024). Specifically, NACPU is derived from CNEFN data on U.S. and Canada CPU; it is constructed using the principal component of the original series. Further, the Transition Risk Index (TRI) provides additional information, providing a broader perspective on transition risks.

Physical risk includes impacts from extreme climate events, particularly frequent occurrences of extreme cold or heat, tornadoes, and droughts. Using Zhang *et al.* (2023), we calculate the abnormal values for these three types of extreme climate events. These variables serve as predictors of climate physical risk.

In addition to transition and physical risks, public attention to climate change also influences CES (Chen *et al.*, 2023; Lang *et al.*, 2023). This study uses Google Trends data from keyword searches to reflect public attention. Five different topic indices are constructed: broad cognitive level topic, physical risk attention topic, opportunity attention topic, clean energy attention topic, and climate commission topic. Detailed calculation methods for each attention topic index are in the Supplementary Material.

3.5 Financial predictors

Financial markets are critical in understanding CES due to their interconnectedness with broader economic and market dynamics, as discussed in Section 2. This paper summarizes these predictors and the associated data sources in Table 1, Panel E.

First, based on Sadorsky (2012) and Lu *et al.* (2021), natural gas, oil, gasoline, and heating oil are selected as CES predictors, due to their role in determining the cost structure and overall pricing dynamics within the energy sector.

Second, the broader stock market also affects CES. The dynamics of major stock indices can influence investor sentiment and capital allocation toward the clean energy sector. Indices like the S&P 500 Index (SP500) and others provide a benchmark for evaluating the relative performance and risk-return profile of clean energy investments.

Third, market sentiment and fear indices also play a significant role in CES performance. Indices such as the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) reflect overall commodity price movements and green project financing dynamics, and help measure risk sentiment in financial markets. This directly affects the required risk premiums for investing in CES.

The selection of predictors in this study is based on their theoretical and empirical relevance to CES returns. Technical indicators predictors, such as MA and OBV, are widely used in asset pricing models to capture short-term price trends and trading volume dynamics, which can signal investor sentiment and momentum effects (Neely *et al.*, 2014). Macroeconomic predictors, including CFNAI and TPU, reflect broader economic trends and policy-related risks (Ghosh and Jana, 2024), which are crucial for understanding capital flows into clean energy investments. Climate risk predictors such as TRI capture transition and physical risks that influence CES valuations through regulatory uncertainty and environmental impacts (Herrera *et al.*, 2022). Financial predictors, including volatility indices (VIX, OVX) provide insights into market conditions and investor sentiment (Khalfaoui *et al.*, 2022), complementing the understanding of CES returns. Together, these predictors offer a comprehensive framework for understanding CES returns.

4. Methodology

Regularization techniques are crucial in high-dimensional forecasting as they mitigate multicollinearity and overfitting. Traditional models like OLS become unstable with numerous predictors, leading to unreliable estimates (Tibshirani, 1996), whereas penalized regression methods such as LASSO and Elastic Net impose constraints on coefficients, reducing variance and improving robustness (Zou and Hastie, 2005). Empirical studies confirm their effectiveness, with Wang *et al.* (2022) demonstrating that LASSO enhances return predictability in clean energy markets by selecting relevant predictors and addressing multicollinearity, while Zhang *et al.* (2019) show that shrinkage techniques improve out-of-sample forecasting by eliminating redundant variables and capturing key features. These findings support the necessity of penalization techniques in our approach.

4.1 Basic shrinkage models

Basic shrinkage models, such as PLS and PCR, are foundational tools for reducing dimensionality and addressing multicollinearity in high-dimensional datasets. They simplify predictor variables into principal components or latent factors, providing interpretable structures while preserving key information.

Based on the data described in Section 3, the basic prediction procedure to determine CES returns r_{t+1} at $t+1$ is:

$$r_{t+1} = \sum_{i=1}^{14} \beta_i^{\mathrm{Tech}} f_{i,t}^{\mathrm{Tech}} + \sum_{i=1}^{14} \beta_i^{\mathrm{Macro}} f_{i,t}^{\mathrm{Macro}} + \sum_{i=1}^{14} \beta_i^{\mathrm{Climate}} f_{i,t}^{\mathrm{Climate}} + \sum_{i=1}^{14} \beta_i^{\mathrm{Fin}} f_{i,t}^{\mathrm{Fin}} + u_t, \quad (1)$$

where the $\beta_i^{\mathrm{Tech}}, \beta_i^{\mathrm{Macro}}, \beta_i^{\mathrm{Climate}}$ and β_i^{Fin} represent the 56 coefficients. The $f_{i,t}^{\mathrm{Tech}}, f_{i,t}^{\mathrm{Macro}}, f_{i,t}^{\mathrm{Climate}}$ and $f_{i,t}^{\mathrm{Fin}}$ are the 56 predictors. Due to problems such as multicollinearity, the coefficient estimates in Equation (1) are not able to identify key predictors over time. As such, this study applies different dimension reduction methods to identify which predictors are most important for predicting CES.

(1) Model 1: Partial Least Squares (PLS) model

The PLS model is used to identify K principal components $f_{k,t}^{\mathrm{PLS}}$, $k = 1, 2, \ldots, K$ between r_{t+1} and the 56 predictors. This reduces the dimensionality of predictors. Subsequently, the PLS model regresses r_{t+1} on $f_{k,t}^{\mathrm{PLS}}$, as follows:

$$r_{t+1} = \sum_{k=1}^{K} \beta_k^{\mathrm{PLS}} f_{k,t}^{\mathrm{PLS}} + u_t, \quad (2)$$

where $f_{k,t}^{\mathrm{PLS}}$, $k = 1, 2, \ldots, K$ incorporate the correlation information among $r_{t+1}, f_{i,t}^{\mathrm{Tech}}, f_{i,t}^{\mathrm{Macro}}$, $f_{i,t}^{\mathrm{Climate}}$ and $f_{i,t}^{\mathrm{Fin}}$. The canonical components $f_{k,t}^{\mathrm{PLS}}$, $k = 1, 2, \ldots, K$ are mutually orthogonal. We set $K = 5$ for this study.

(2) Model 2: Principal Component Regression (PCR) model

The PCR model is used to estimate and shrink the coefficients of predictors in Equation (1). It is expressed as:

$$r_{t+1} = \sum_{k=1}^{K} \beta_k^{\mathrm{PCA}} f_{k,t}^{\mathrm{PCA}} + u_t, \quad (3)$$

where $f_{k,t}^{\mathrm{PCA}}$, $k = 1, 2, \ldots, K$ denotes the principal component, and K represents the first K principal components with the highest cumulative explained variance. This variable is set to $K = 5$.

4.2 Regularization model

This study considers three popular regularization models: the LASSO model (Zhang *et al.*, 2019), the adaptive LASSO of Zou (2006), and the elastic net (EN) of Zou and Hastie (2005). Each model modifies the baseline regression model of Equation (1) by adding penalties to manage sparsity and correlated predictors.

(3) Model 3: LASSO model

The LASSO model relies on the $l_1 -$ penalties functions to estimate and shrink the parameters β in Equation (1). The LASSO estimator $\widehat{\boldsymbol{\beta}}_{\lambda}^{\mathrm{LASSO}}$ is then defined as:

$$\widehat{\boldsymbol{\beta}}_{\lambda}^{\text{LASSO}} = \underset{\beta \in \mathbb{R}^{56}}{\operatorname{argmin}} \left(\frac{1}{T} \sum_{t=1}^{T} \left(r_{t+1} - \sum_{i=1}^{56} \beta_i f_{i,t} \right)^2 + \lambda \sum_{i=1}^{56} |\beta_i| \right), \tag{4}$$

where T denotes the sample size of observations, and $\lambda \in \mathbb{R}$ the regularization parameter that controls the level of penalty applied to predictor coefficients. By adjusting λ, the LASSO model shrinks some coefficient estimates to zero. This effectively reveals a subset of relevant key predictors.

(4) Model 4: Adaptive LASSO model

The adaptive LASSO model extends the standard LASSO by incorporating adaptive weights for each predictor in the $l_1 -$ penalty term. This allows different coefficients to experience different degrees of penalization. This mitigates the over-penalization problem in LASSO and improves variable selection accuracy. In this study's forecasting model, the parameter estimates for adaptive LASSO are calculated as:

$$\widehat{\boldsymbol{\beta}}_{\lambda}^{\text{Adap}} = \underset{\beta \in \mathbb{R}^{56}}{\operatorname{argmin}} \left(\frac{1}{T} \sum_{t=1}^{T} \left(r_{t+1} - \sum_{i=1}^{56} \beta_i f_{i,t} \right)^2 + \lambda \sum_{i=1}^{56} w_i |\beta_i| \right), \tag{5}$$

where $w_i = 1/\left|\widehat{\beta}_i^{\text{Ridge}}\right|, i = 1, 2, \ldots, 56$ is an initial estimate weight, obtained using the Ridge estimation in Equation (1).

(5) Model 5: Elastic Net model

The Elastic Net (EN) is a regularization method that linearly combines both $l_1 -$ and $l_2 -$ penalties. This approach improves forecasting performance, particularly when addressing highly correlated predictors (Zou and Hastie, 2005). The parameter estimates for Enet are calculated as:

$$\widehat{\boldsymbol{\beta}}_{\lambda}^{\text{EN}} = \underset{\beta \in \mathbb{R}^{56}}{\operatorname{argmin}} \left(\frac{1}{T} \sum_{t=1}^{T} \left(r_{t+1} - \sum_{i=1}^{56} \beta_i f_{i,t} \right)^2 + \lambda \left(2\mu \sum_{i=1}^{56} |\beta_i| + (1-\mu) \sum_{i=1}^{56} \beta_i^{\,2} \right) \right), \tag{6}$$

where μ is the tuning parameter that balances the contribution of the $l_1 -$ and $l_2 -$ penalties. This study sets $\mu = 0.5$, enabling the model to effectively handle correlated predictors.

4.3 Quantile regularization model

This study applies several widely used predictor selection methods, in conjunction with quantile regression techniques (Ren *et al.*, 2022). These include Quantile LASSO, Quantile Adaptive LASSO, and Quantile Elastic Net. Generally, the median of r_{t+1}, $r_{t+1}^{(50\%)}$ is used to estimate r_{t+1}. Equation (1) is rewritten as follows:

$$r_{t+1}^{(50\%)} = \sum_{i=1}^{14} \beta_i^{\text{tech}} f_{i,t}^{\text{tech}} + \sum_{i=1}^{14} \beta_i^{\text{macro}} f_{i,t}^{\text{macro}} + \sum_{i=1}^{14} \beta_i^{\text{Climate}} f_{i,t}^{\text{Climate}} + \sum_{i=1}^{14} \beta_i^{\text{Fin}} f_{i,t}^{\text{Fin}} + u_t, \tag{7}$$

(6) Model 6: Quantile LASSO

First, we consider the Quantile LASSO (QLASSO) model, which extends the LASSO model to the quantile regression framework. This model uses $\widehat{\boldsymbol{\beta}}_{\lambda}^{(50\%)} \in \mathbb{R}^{56}$ to estimate $\boldsymbol{\beta}$ in Equation (1). Equation (4) is then rewritten as follows:

$$\widehat{\boldsymbol{\beta}}_{\lambda}^{\text{QLASSO}} = \underset{\beta\in\mathbb{R}^{56}}{\operatorname{argmin}}\left(\frac{1}{T}\sum_{t=1}^{T}\left|r_{t+1}-\sum_{i=1}^{56}\beta_i f_{i,t}\right| + \lambda\sum_{i=1}^{56}|\beta_i|\right). \tag{8}$$

(7) Model 7: Quantile Adaptive LASSO

We also apply the quantile adaptive LASSO (Q-ALASSO), which applies adaptive weights to the $l_1 -$ penalty in quantile regression. This allows different penalties for different predictors to improve accuracy, as follows:

$$\widehat{\boldsymbol{\beta}}_{\lambda}^{\text{QALASSO}} = \underset{\beta\in\mathbb{R}^{56}}{\operatorname{argmin}}\left(\frac{1}{T}\sum_{t=1}^{T}\left|r_{t+1}-\sum_{i=1}^{56}\beta_i f_{i,t}\right| + \lambda\sum_{i=1}^{56}w_i|\beta_i|\right). \tag{9}$$

where we set w_i the same as in Equation (5).

(8) Model 8: Quantile Elastic Net

We estimate the quantile elastic net (Q-EN) model to obtain $\widehat{\boldsymbol{\beta}}_{\lambda}^{\text{QEN}} \in \mathbb{R}^{56}$ to estimate $\boldsymbol{\beta}$ in Equation (1):

$$\widehat{\boldsymbol{\beta}}_{\lambda}^{\text{QEN}} = \underset{\beta\in\mathbb{R}^{56}}{\operatorname{argmin}}\left(\frac{1}{T}\sum_{t=1}^{T}\left|r_{t+1}-\sum_{i=1}^{56}\beta_i f_{i,t}\right| + \lambda\left(2\mu\sum_{i=1}^{56}|\beta_i| + (1-\mu)\sum_{i=1}^{56}\beta_i^{\,2}\right)\right), \tag{10}$$

where $\mu = 0.5$, similar to Equation (6).

The distinction and adoption of quantile-based regularization models arise from their ability to address limitations of classical regularization methods. Classical regularization models focus on average effects and perform well in stable markets. However, they may overlook important predictor influences under extreme conditions. Quantile-based models analyze conditional quantiles capturing predictor impacts across the entire distribution of returns. This makes them particularly effective in handling heteroscedasticity and tail dynamics, which are crucial for understanding the volatility and risks inherent in CES markets.

4.4 Model combination

Single forecasting methods often have difficulty maintaining high predictive performance over the long term in dynamic markets. In contrast, combination methods improve predictive accuracy. The combined forecast at time t is expressed using the weighted average of the N individual forecasts, shown as follows:

$$\widehat{r}_{t+1}^{c} = \sum_{i=1}^{M}\omega_{i,t+1}\widehat{r}_{i,t+1}, \tag{11}$$

where $\widehat{r}_t^{c}$ is the combination forecast at month $t+1$ and $\widehat{r}_{i,t+1}$ is the individual forecast for the i-th model at month $t+1$. The term $\omega_{i,t+1}$ denotes the weight assigned to the i-th forecast at time $t+1$. Based on Rapach *et al*. (2010) and Zhang *et al*. (2019), three combination methods are used: **Model 9: Mean combination**, **Model 10: Median combination**, and **Model 11: Trimmed mean (T-Mean) combination**.

5. Empirical results

5.1 Out-of-sample forecasting performance

This subsection examines which prediction model in Section 4, achieves the most accurate prediction under a one-step-ahead forecasting scenario using a large set of predictors. This analysis also helps identify the most effective model for extracting the functional characteristics of the predictors. Tables 2-4 present the out-of-sample R^2 predictive performance of different models with rolling window lengths of 60, 72, and 84 months. The table notes explain the metrics; further clarifications are in Ren *et al.* (2022) and Campbell and Thompson (2008).

Across all three window lengths, the Q-EN model (a quantile regularization model) consistently delivers the best forecast performance compared to other models, achieving a positive R^2 and higher scores relative to both AR(1) and RW benchmarks. Specifically, under the 60-month AR(1) benchmark, Q-EN yields an R^2 of 0.632 for $\mathrm{OOR}^2_{\mathrm{MSPE}}$ and 1.909 for $\mathrm{OOR}^2_{\mathrm{MAPE}}$. These significantly outperform other models for both metrics. Similarly, under the 72-month window, Q-EN achieves an R^2 of 1.832 for $\mathrm{OOR}^2_{\mathrm{MSPE}}$ and 2.161 for $\mathrm{OOR}^2_{\mathrm{MAPE}}$. This further demonstrates the model's superior predictive accuracy. At the 84-month window, the model continues to show robust performance, with an R^2 of 1.773 for $\mathrm{OOR}^2_{\mathrm{MSPE}}$ and 2.320 for $\mathrm{OOR}^2_{\mathrm{MAPE}}$; this reflects an ongoing advantage over other competing models. These results indicate that Q-EN effectively captures out-of-sample predictability, and reduces forecast errors when considering both mean-squared prediction error and mean absolute error.

When comparing other forecasting models, basic shrinkage models (PLS and PCR) have the lowest predictive performance, with negative values across all metrics and benchmarks. This indicates they are less effective prediction models. The regularization models are also limited in their predictive effectiveness, though EN performs slightly better than the others. The EN's score is closer to zero than other models in this group; however, it falls short of achieving significant predictive accuracy compared to the benchmark.

In contrast, quantile regularization models generally demonstrate stronger predictive performance. As noted above, Q-EN consistently outperforms the other quantile models, yielding positive and higher R^2 values across all benchmarks and time windows. Of the model

Table 2. One-step ahead forecasting under 60-months window length

	Benchmark: AR(1) $\mathrm{OOR}^2_{\mathrm{MSPE}}$ (%)	$\mathrm{OOR}^2_{\mathrm{MAPE}}$ (%)	Benchmark: random walk $\mathrm{OOR}^2_{\mathrm{MSPE}}$ (%)	$\mathrm{OOR}^2_{\mathrm{MAPE}}$ (%)
PLS	−23.083	−9.489	34.295	15.830
PCR	−8.564	−5.421	41.863	18.754
LASSO	−135.428	−17.180	−26.580	9.647
ALASSO	−185.453	−16.606	−53.581	10.094
EN	−4.445	−3.168	44.118	20.558
Q-LASSO	−1.080	1.333	45.905	24.036
Q-ALASSO	−555.960	−28.447	−253.590	0.847
Q-EN	*0.632*	*1.909*	*46.829*	*24.485*
Mean	−31.435	−6.309	29.559	18.120
Median	0.536	0.574	46.791	23.458
T-Mean	−13.744	−3.904	39.084	19.971

Note(s): The out-of-sample $\mathrm{OOR}^2_{\mathrm{MSPE}}$ is calculated as $\mathrm{OOR}^2_{\mathrm{MSPE}} = 1 - (\mathrm{MSPE}_M/\mathrm{MSPE}_B)$. The MSPE_M denotes mean-squared prediction error of each forecasting model in Section 4. $\mathrm{MSPE}_M = (1/T)\sum_{t=1}^{T}(r_t - \hat{r}_t^M)^2$, where r_t is the real CES returns and $\hat{r}_t$ is the model's prediction. The $\mathrm{MSPE}_B = (1/T)\sum_{t=1}^{T}(r_t - \hat{r}_t^B)^2$, where $\hat{r}_t^B$ is the prediction result of the benchmark model. This study uses AR (1) and RW as the benchmark model. The out-of-sample $\mathrm{OOR}^2_{\mathrm{MAPE}}$ is calculated as $\mathrm{OOR}^2_{\mathrm{MAPE}} = 1 - (\mathrm{MSPE}_M/\mathrm{MSPE}_B)$. The MAPE_M denotes mean-absolute prediction error, where $\mathrm{MAPE}_M = (1/T)\sum_{t=1}^{T}\left|r_t - \hat{r}_t^M\right|$. Higher values of $\mathrm{OOR}^2_{\mathrm{MSPE}}$ and $\mathrm{OOR}^2_{\mathrm{MAPE}}$ indicate better predictive performance of the model compared to the benchmark model. The best-performing predictive model in each column is highlighted in italic
Source(s): Authors' own work

Table 3. One-step ahead forecasting with 72-months window length

	Benchmark: AR(1) OOR^2_{MSPE} (%)	OOR^2_{MAPE} (%)	Benchmark: random walk OOR^2_{MSPE} (%)	OOR^2_{MAPE} (%)
PLS	−21.967	−10.274	34.809	14.418
PCR	−4.592	−2.633	43.814	20.131
LASSO	−67.483	−9.341	9.466	14.710
ALASSO	−114.085	−12.139	−15.875	12.502
EN	−56.803	−8.085	17.450	15.702
Q-LASSO	−31.255	−4.747	29.388	18.561
Q-ALASSO	−233.970	−16.899	−81.063	8.750
Q-EN	*1.832*	*2.161*	*47.165*	*23.792*
Mean	−29.365	−5.113	30.304	18.142
Median	−37.050	−4.999	26.021	18.141
T-Mean	−22.449	−4.057	34.016	18.934

Note(s): See Table 2
Source(s): Authors' own work

Table 4. One-step ahead forecasting with 84-months window length

	Benchmark: AR(1) OOR^2_{MSPE} (%)	OOR^2_{MAPE} (%)	Benchmark: random walk OOR^2_{MSPE} (%)	OOR^2_{MAPE} (%)
PLS	−22.974	−10.787	33.741	13.774
PCR	−4.050	−1.456	43.563	20.344
LASSO	−14.081	−1.571	38.104	20.160
ALASSO	−118.084	−11.665	−18.330	12.216
EN	−27.984	−5.176	30.560	17.322
Q-LASSO	1.723	1.716	46.682	22.766
Q-ALASSO	−173.785	−15.314	−48.556	9.359
Q-EN	*1.773*	*2.320*	*46.709*	*23.242*
Mean	−12.608	−2.530	38.926	19.533
Median	0.066	1.206	45.783	22.365
T-Mean	−7.030	−1.166	41.933	20.505

Note(s): See Table 2
Source(s): Authors' own work

combination models, the median forecast model occasionally reaches positive R^2 values; this indicates that it outperforms the baseline in these instances. However, Q-Lasso and Q-ALasso generally show negative R^2 values, indicating they do not provide better predictions than individual benchmarks.

In summary, in contrast with other models showing generally lower predictive ability, the quantile-based methods, particularly Q-EN, effectively increase forecasting accuracy, especially when leveraging median robustness and adaptive elastic net regularization.

Figures 1 and 2 show the cumulative out-of-sample OOR^2_{MSPE} for different forecasting models over a 60-month rolling window, comparing the models to the AR(1) and RW benchmarks.

The plots show that Q-EN consistently shows stable and better forecasting performance compared to the benchmarks. In both the AR(1) and RW comparisons, Q-EN maintains the highest cumulative OOR^2_{MSPE} for most of the forecasting period. This demonstrates its consistently better predictive performance compared to other models. The Q-EN curve has a

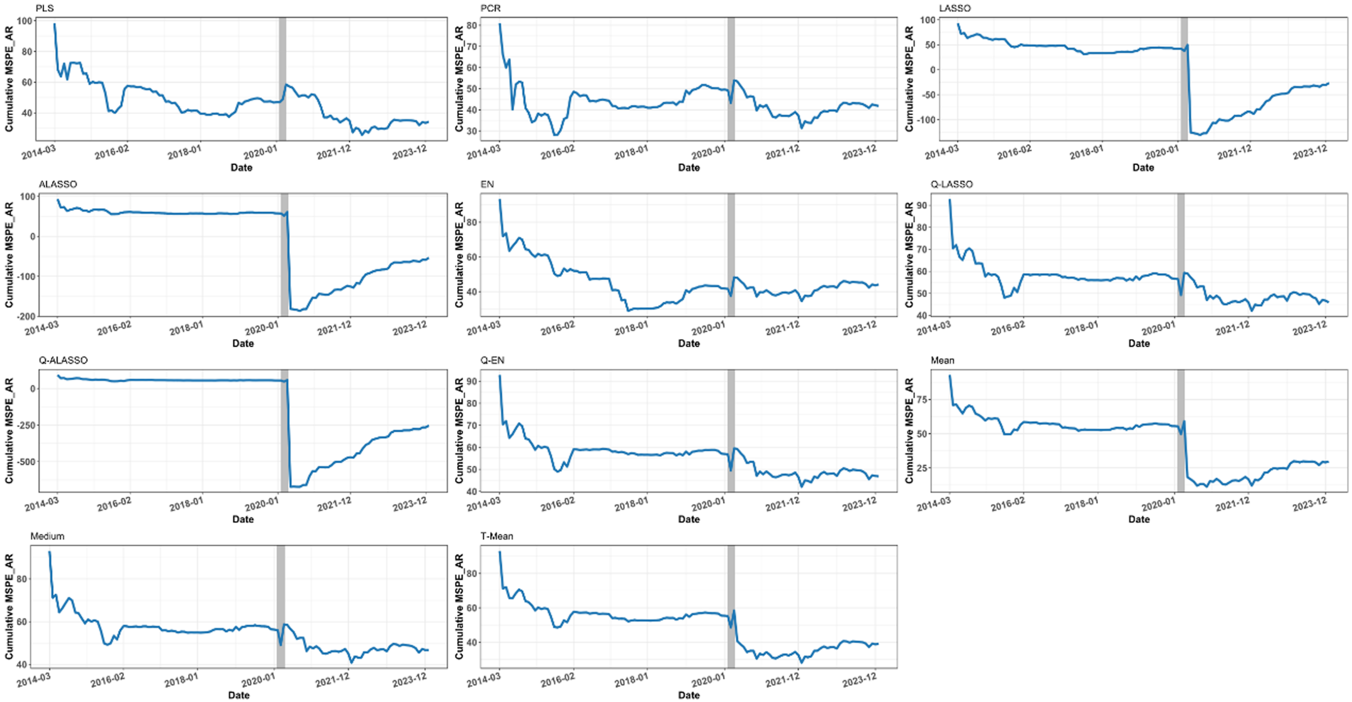

Figure 1. Cumulative $\mathrm{OOR}^2_{\mathrm{MSPE}}$ (AR(1)) for each model under 60-months rolling window. **Note(s):** The cumulative out-of-sample $\mathrm{OOR}^2_{\mathrm{MSPE}}$ at time t is calculated as $\mathrm{Cum\,OOR}^2_{\mathrm{MSPE}}(t) = \sum_{i=1}^{t} \mathrm{OOR}^2_{\mathrm{MSPE},i}$, where $\mathrm{OOR}^2_{\mathrm{MSPE},i}$ is the value for the i-th period. Specifically, a positive curve slope at time t indicates that the forecasting model outperforms the benchmark model. The NBER recession periods are highlighted with gray lines. Source(s): Authors' own work

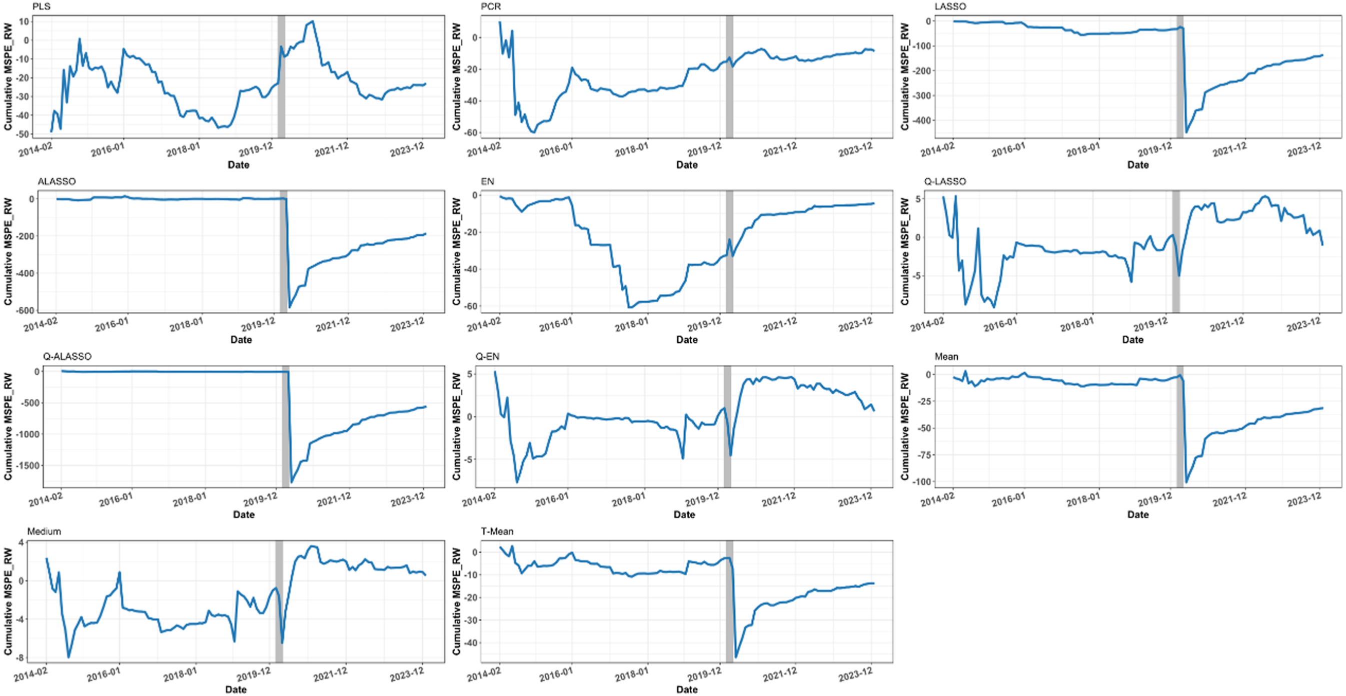

Figure 2. Cumulative OOR^2_{MSPE} (RW) of each model under 60-months rolling window. **Note(s):** See Figure 1. Source(s): Authors' own work

relatively flat slope after the initial adjustment phase, indicating sustained predictive accuracy over time.

Additionally, all models fluctuate in their cumulative OOR^2_{MSPE} compared to the benchmark models around early 2020, a period with significant volatility. This period, highlighted by vertical bars in the figure, corresponds to the outbreak of the COVID-19 pandemic. This caused abnormal shifts in CES returns and reduced predictability. This is also when the National Bureau of Economic Research (NBER) officially declared the onset of a recession.

5.2 The individual-level predictors pick-up feature

The previous section evaluated the predictive accuracy and performance of different models under out-of-sample conditions. It identified the Q-EN model as being most accurate across different forecasting windows. This section further examines the importance of the 56 predictors, to understand their contributions in forecasting CES returns. The discussion focuses on overall and time-varying pick-up rates (degree of importance in predicting CES) to provide insights into their forecasting roles.

5.2.1 Overall pick-up rate. The predictability of CES returns stems from macroeconomic mechanisms, such as CFNAI and TPU, which reflect economic trends and uncertainty, and climate risk predictors like TRI, capturing policy impacts and extreme events. Indicator predictors, such as OBV, are effective for short-term trends driven by market activity. These drivers collectively explain CES predictability under varying conditions. Figure 3 shows that macroeconomic predictors dominate the pick-up rate, with UNRATE ranking the highest at 25.64%, followed by GPRH at 20.86%, and TPU at 20.80%. These predictors capture key aspects of labor market dynamics, geopolitical risks, and trade policy uncertainty. This aligns with Baumeister *et al*. (2022), who demonstrated that macroeconomic indicators, such as unemployment rates and economic activity indices, are robust predictors of energy-related market performance.Among the technical indicator predictors, OBV(3,12) has the highest pick-up rate, at 16.93%. This reflects the influence of market volatility. TRI leads the climate predictors at 14.56%. This highlights the importance of climate transition factors. The SP500 is the top-ranked predictor in the financial assets group at 15.92%; this highlights the role of broader market movement.

When comparing predictor groups, macroeconomic predictors have the highest average pick-up rates, reaffirming their critically influential role in forecasting CES returns. Financial predictors rank second. These are followed by climate risk predictors, which show increasing relevance, particularly those related to the energy transition. Technical indicator predictors have lower pick-up rates.

5.2.2 Time-varying pick-up rate. Figure 4 provides a detailed view of the time-varying pick-up rate of predictors throughout the out-of-sample period, showing distinct patterns across groups. The macroeconomic predictors UNRATE, USDX, and TPU maintain consistently high pick-up rates. During periods of increased uncertainty, predictors like GPRH and EPU become more important. This reflects their ability to capture external shocks and sentiment.

Climate risk predictors, including TRI and Ab_TEMP, show significant variability, with higher pick-up rates during climate policy shifts or extreme weather events. For example, TRI increases as green energy policy changes, while Ab_DRT aligns with severe energy production disruptions due to weather.

In the technical indicator predictors group, $\mathrm{OBV}(s,l)$ and $\mathrm{MOM}(k)$ are consistently relevant during periods of high market volatility, indicating their role in capturing short-term market dynamics. However, their intermittent importance reflects their sensitivity to specific market conditions, rather than broader economic trends. Financial predictors, such as SP500 and WTI, also vary across time, often becoming significant during periods of financial turbulence. The low, but growing, pick-up rate of ESG signals the increasing integration of sustainability metrics into clean energy investment decisions.

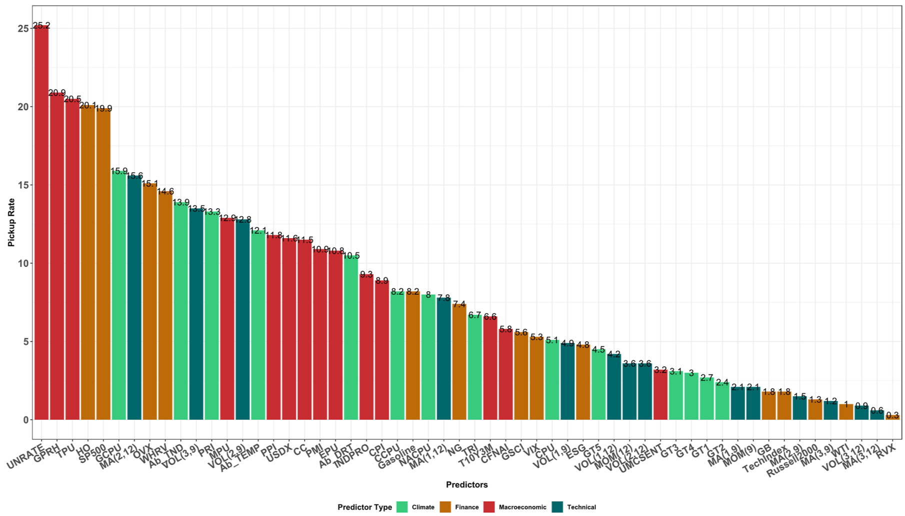

Figure 3. Pick-up rate across all the predictors. **Note(s):** Variable selection frequency of all predictors in each one-month-ahead forecasting step across the out-of-sample period. The color-coded bars represent different predictor categories. Source(s): Authors' own work

To further explore these dynamics, predictor importance is considered across distinct time periods. From 2016 to 2018, the macroeconomic predictors UNRATE and TPU are most important, driven by the global economic recovery and trade policy uncertainty during this period. Relatively stable markets limit the importance of the technical indicator predictors $\mathrm{OBV}(s,l)$ and $\mathrm{MOM}(k)$. In 2019 and 2020, escalating geopolitical risks, including U.S.-China trade disputes and the COVID-19 pandemic, increase the importance of GPRH, TPU, and UNRATE in CES predictions. Climate risk predictors such as TRI also gain importance, reflecting shifts in energy policies and rising public awareness of climate issues.

From 2021 to 2022, the global post-pandemic recovery and accelerated green energy transitions increase the influence of the climate predictors TRI and Ab_DRT. Concurrently, market volatility increases the relevance of technical indicator predictors, particularly $\mathrm{OBV}(s,l)$ and $\mathrm{MOM}(k)$. In 2023, the stabilization of the clean energy sector results in a more balanced distribution of predictor pick-up rates. Macroeconomic predictors USDX and INDPRO, and climate risk predictors TRI and Ab_TEMP, maintain their consistent level of importance. This reflects a long-term focus on economic and climate-related trends.

In summary, this time-based analysis highlights how predictors respond to global economic shifts, policy changes, and climate dynamics. Macroeconomic predictors are consistently most important, overall and in time-varying contexts, with respect to predicting CES returns, particularly during economic fluctuations. Climate risk and financial predictors play notable but secondary roles. Climate risk predictors are more important during sustainability transitions, while technical and financial predictors influence forecasts during period of market volatility. This underscores the importance of integrating diverse predictors and accounting for temporal dynamics to improve forecasting accuracy.

5.3 The group-level predictors pick-up feature

This subsection investigates the group-level performance of the 56 predictors, to assess the overall importance of each predictor group (macroeconomic, climate risk, technical, and financial predictors) in forecasting CES returns. Group regularization models are used; these apply a uniform penalty to the coefficients of predictors within the same group. This approach

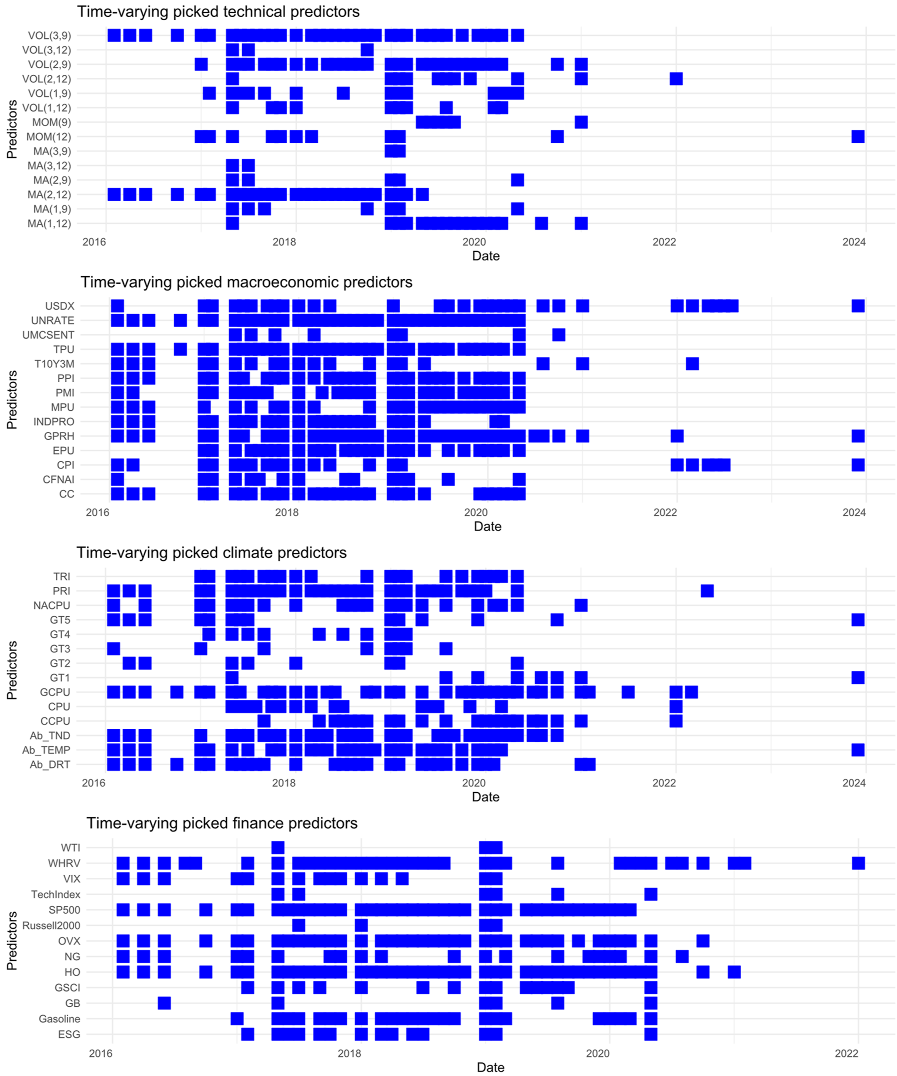

Figure 4. Time-varying pick-up rate of predictors. **Note(s):** Time-varying selection of predictors across four categories during the out-of-sample forecasting period. Blue bars represent the periods when the forecasting models identify specific predictors as significant, reflecting their relevance over time. Source(s): Authors' own work

ensures that predictors within a group influence the model consistently. This helps identify the collective importance of a group of predictors.

5.3.1 Group LASSO model. The Group LASSO (Yuan and Lin, 2006) extends the LASSO model to enable variable selection for grouped predictors. In this study, the predictors fall into four groups. The parameter vector in Equation (1) has a group structure $\{g_1, g_2, g_3, g_4\}$, subject to the following: $\bigcup_{i=1}^{4} g_i = \{1, 2, \ldots, N\}$ and g_i are disjoint. The Group LASSO estimator is formulated as:

$$\widehat{\boldsymbol{\beta}}_{\lambda}^{\text{GLASSO}} = \underset{\beta\in\mathbb{R}^{56}}{argmin}\left(\frac{1}{T}\sum_{t=1}^{T}\left(r_{t+1}-\sum_{i=1}^{56}\beta_i f_{i,t}\right)^2+\lambda\sum_{j=1}^{4}m_j\left\|\boldsymbol{\beta}_{g_j}\right\|_2\right), \tag{12}$$

where $\boldsymbol{\beta}_{g_j}$ are the parameters in the g_j-th group. The multiplier m_j is used to balance cases where the groups have very different sizes (different number of variables). We set $m_j = \sqrt{T_j}$, where T_j is the number of parameters in the j-th group.

5.3.2 Group smoothly clipped absolute deviation (SCAD). This study also considers the group SCAD model. The parametric estimator in the penalized regression with the group SCAD is:

$$\widehat{\boldsymbol{\beta}}_{\lambda}^{\text{GLASSO}} = \underset{\beta\in\mathbb{R}^{56}}{argmin}\left(\frac{1}{T}\sum_{t=1}^{T}\left(r_{t+1}-\sum_{i=1}^{56}\beta_i f_{i,t}\right)^2+\lambda\sum_{j=1}^{4}P_\lambda\left\|\boldsymbol{\beta}_{g_j}\right\|_2\right), \tag{13}$$

where P_λ is the group SCAD penalty, defined as:

$$P_\lambda(|x|) = \begin{cases} \lambda|x|, & |x|\le\lambda; \\ -\dfrac{|x|^2-2a\lambda|x|+\lambda^2}{2(a-1)}, & \lambda<|x|<a\lambda; \\ \dfrac{(a+1)\lambda^2}{2}, & |x|>a\lambda. \end{cases} \tag{14}$$

5.3.3 Quantile group LASSO. The Quantile Group LASSO (Group-QLASSO) model addresses situations where predictors are naturally grouped together. The estimator is defined as:

$$\widehat{\boldsymbol{\beta}}_{\lambda}^{\text{QGLASSO}} = \underset{\beta\in\mathbb{R}^{56}}{argmin}\left(\frac{1}{T}\sum_{t=1}^{T}\left(r_{t+1}-\sum_{i=1}^{56}\beta_i f_{i,t}\right)^2+\lambda\sum_{j=1}^{4}m_j\left\|\boldsymbol{\beta}_{g_j}\right\|_2\right). \tag{15}$$

5.3.4 Group regularization model forecasting performance. Table 5 presents the predictive performance of the group-based models in terms of $\text{OOR}^2_{\text{MSPE}}$ and $\text{OOR}^2_{\text{MAPE}}$ percentages across different forecast horizons and rolling window lengths. We also report the predictor group pick-up rates across multiple forecast horizons, highlighting the relative contribution of each group when predicting CES returns.

In the 60-month rolling window, the Group-QLasso model excels in the 1-step ahead forecast; this model achieves the highest $\text{OOR}^2_{\text{MSPE}}$ (46.038) and $\text{OOR}^2_{\text{MAPE}}$ (23.308) values. This highlights its strength in capturing short-term dynamics. For 2-step ahead predictions, the Group-Lasso model achieves the highest $\text{OOR}^2_{\text{MSPE}}$ (49.258) and $\text{OOR}^2_{\text{MAPE}}$ (26.006) values, followed closely by Group-SCAD. In the 3-step ahead forecast, the Group-Lasso model remains the top forecasting performer, further demonstrating its robustness in medium-term forecasting.

In the 72-month rolling window, the Group-QLasso model performs best again in the 1-step horizon. For 2-step and 3-step forecasts, the Group-SCAD is better in its predictions compared to Group-Lasso and Group-QLasso. It particularly excels in the 3-step horizon, with the highest $\text{OOR}^2_{\text{MSPE}}$ (50.321) and $\text{OOR}^2_{\text{MAPE}}$ (26.094) values. The Group-Lasso model is also strong; it ranks second in these longer horizons, but maintains consistent prediction performance. In the 84-month rolling window, the Group-QLasso model remains the best in the 1-step horizon. The Group-Lasso model shows strength in the 2-step horizon (48.176 $\text{OOR}^2_{\text{MSPE}}$, 24.778 $\text{OOR}^2_{\text{MAPE}}$) and remains competitive in the 3-step forecast.

Table 5. Multi-forecasting horizon and window lengths results with group shrinkage models

Window lengths	1-step ahead OOR^2_{MSPE} (%)	OOR^2_{MAPE} (%)	2-steps ahead OOR^2_{MSPE} (%)	OOR^2_{MAPE} (%)	3-steps ahead OOR^2_{MSPE} (%)	OOR^2_{MAPE} (%)
Panel A: 60-months						
Group-Lasso	32.913	16.685	*49.258*	*26.006*	*48.966*	25.531
Group-SCAD	31.098	17.246	47.854	24.005	47.856	*25.873*
Group-QLasso	*46.038*	*23.308*	46.296	23.336	47.773	25.357
Panel B: 72-months						
Group-Lasso	33.390	17.517	47.578	23.488	48.06	24.716
Group-SCAD	37.288	17.860	*48.057*	24.323	*50.321*	*26.094*
Group-QLasso	*46.959*	*23.755*	47.921	*24.678*	47.899	24.680
Panel C: 84-months						
Group-Lasso	33.379	16.979	*48.176*	24.778	47.709	*25.382*
Group-SCAD	36.312	17.157	47.922	24.031	44.108	23.483
Group-QLasso	*46.799*	*23.380*	47.972	*24.813*	*47.929*	24.679

Note(s): Multi-forecasting horizon and window length results for the group shrinkage models. The panels correspond to different rolling window lengths: 60, 72, and 84 months
Source(s): Authors' own work

Overall, the analysis reveals that the three models have clear differentiated predictive strengths. The Group-QLasso model is particularly effective for short-term forecasts across all rolling windows; this makes it the preferred choice for immediate predictions. The Group-Lasso model consistently excels in multi-step horizons, particularly in medium-term forecasts. This showcases its robustness across conditions. Group-SCAD, while not preferred in shorter horizons, delivers strong performance in longer forecasting horizons and rolling windows. These results emphasize the importance of selecting the most effective model based on the forecast horizon and window length.

5.3.5 Predictor group pick-up rate. The predictor group pick-up rates in Table 6 describe the relative importance of each group in forecasting CES returns across different time horizons.

Macroeconomic predictors are consistently most important for accurate predictions, with a pick-up rate of 37.50% for 1-step ahead forecasts. This rate decreases to 15.62% by the 7-step horizon; however, macroeconomic predictors remain the most influential group overall. This finding highlights their critical role in short-term forecasts, explained by the direct and immediate impact of economic conditions on market behavior. Studies like Arouri *et al.* (2016) highlight the lasting impact of macroeconomic uncertainty on renewable energy investments, which supports the empirical findings here.

Climate risk predictors are second most important, with a 34.38% pick-up rate for 1-step ahead forecasts. Their importance gradually decreases as the forecast horizon lengthens. These

Table 6. Predictor group pick-up rates under different forecasting

Group	1-step	2-step	3-step	5-step	7-step
Technical	16.67%	6.25%	8.33%	5.21%	0.00%
Macro	*37.50%*	*16.67%*	*12.50%*	*12.50%*	*15.62%*
Climate	34.38%	12.50%	9.38%	10.42%	11.46%
Fin and Com	30.21%	5.21%	5.21%	7.29%	4.17%

Note(s): Selection frequency of four predictor groups across different forecasting horizons during the out-of-sample period. The most frequently selected predictor group for each horizon is in italic
Source(s): Authors' own work

results align with the structural and long-term nature of climate-related factors. These factors are less responsive to short-term market fluctuations but remain moderately relevant over longer horizons.

Financial predictors decline in importance as the forecast horizon increases. They contribute significantly to 1-step ahead forecasts (30.21%), but have a minimal level of importance for 7-step ahead forecasts (4.17%). This verifies that their short-term focus is driven by external shocks, such as oil price changes or financial crises.

Finally, technical indicator predictors are sporadically important, with relatively low pick-up rates across all horizons. Their contributions peak at 16.67% for 1-step ahead forecasts, but fall to 0% for 7-step forecasts. This indicates their contextual dependence, influenced primarily by short-term market momentum and volatility.

In summary, macroeconomic and climate risk predictors are key to CES forecasting: macroeconomic predictors are most important over short-term horizons and climate risk predictors decline in importance over time. Technical and financial predictors have limited, short-term relevance. As with the previous model-based analysis, these results emphasize the need to align predictor groups with forecasting horizons.

5.4 The time-based component pick-ups

This subsection focuses on analyzing the time-based trends associated with predictors, to evaluate their contributions to CES return forecasting. Decomposing predictors into short-term, medium-term, and long-term components shows how these components work and perform in predicting CES returns. This approach highlights the most impactful time-based components of predictors and provides deeper insights into how different trends influence CES forecasting.

5.4.1 Wavelet decomposition forecasting performance. This analysis focuses on macroeconomic and climate predictors, due to their higher rates of importance. Wavelet decomposition, a technique that separates a signal into components at different frequency levels, is used here to capture the multi-scale nature of predictor impacts (Dai *et al.*, 2025; Miao *et al.*, 2022; Xue *et al.*, 2024; Zhang *et al.*, 2025). Each predictor is decomposed into four components:

$$\begin{aligned} r_t &= S_{3,t} + D_{3,t} + D_{2,t} + D_{1,t} \\ &= \sum_{k=0}^{2^3-1} S_{3,k} \cdot \phi_{3,k,t} + \sum_{k=0}^{2^3-1} D_{3,k} \cdot \psi_{3,k,t} + \sum_{k=0}^{2^2-1} D_{2,k} \cdot \psi_{2,k} + \sum_{k=0}^{2^1-1} D_{1,k} \cdot \psi_{1,k,t}, \end{aligned} \tag{16}$$

where $\phi_{j,k,t}$ denotes the father wavelet function and $\psi_{j,k,t}$ denotes the mother wavelet function, expressed as:

$$\begin{aligned} \phi_{j,k,t} &= \frac{\phi\left(2^{-j}t - k\right)}{\sqrt{2^J}}, \\ \psi_{j,k,t} &= \frac{\psi\left(2^{-j}t - k\right)}{\sqrt{2^J}}, \end{aligned} \tag{17}$$

where J denotes the maximum level of decomposition; this level is set to 3. Additionally, the father and mother wavelet functions satisfy the following:

$$\begin{aligned} \int_{\mathbb{R}} \phi(x)\mathrm{d}x &= 1, \\ \int_{\mathbb{R}} \psi(x)\mathrm{d}x &= 0, \end{aligned} \tag{18}$$

Then, the coefficients of the high frequency $D_{j,k}$ and low frequency $S_{j,k}$ have the following form:

$$\begin{aligned} D_{j,k} &= \int \phi_{j,k} \cdot r_t \mathrm{d}t, \\ S_{j,k} &= \int \psi_{j,k} \cdot r_t \mathrm{d}t. \end{aligned} \tag{19}$$

This generates four decomposed components: $D_{1,t}$ (short-term cycles, 1–2 months), $D_{2,t}$ (medium-term cycles, 2–4 months), $D_{3,t}$ (long-term cycles, 4–8 months), and $S_{3,t}$ (longer-term trend components, over 8 months).

Table 7 shows the predictive performance of these macroeconomic and climate risk predictor components over three forecasting horizons: 60, 72, and 84 months. The results indicate that the D1 component contributes less to accurate predictions. The Group-QLasso model shows the most consistent performance, particularly for the 84-month horizon. In contrast, the Group-SCAD model does not work effectively with D1, overall and especially for longer horizons. This is shown by the negative $\mathrm{OOR}^2_{\mathrm{MSPE}}$ values. This indicates that Group-SCAD may be less effective in capturing short-term dynamics.

The D2 component has the most robust predictive power across all models. The Group-SCAD model performs best at the 84-month horizon, followed by the Group-Lasso model. The Group-QLasso model is effective, but is somewhat less effective for D2. This indicates it is more suitable for short-term rather than medium-term forecasting. The significant impact of D2 components likely reflects their ability to capture market transitions and investor sentiment. Macroeconomic predictors like UNRATE and TPU show medium-term effects, aligning with Baumeister *et al.* (2022) on energy markets. Climate risk predictors also peak in this period due to their relevance during policy and regulatory changes, as noted by Herrera *et al.* (2022). These findings suggest that the 2–4 months window optimally captures predictors with a balance of short-term responsiveness and longer-term trends, enhancing predictive performance across models.

For the D3 component, the Group-SCAD model again outperforms other models. The Group-Lasso model shows more volatility, including negative $\mathrm{OOR}^2_{\mathrm{MSPE}}$ values at the 60-

Table 7. Macro-climate subcomponents after wavelet decomposition

Window lengths	60-months		72-months		84-months	
Group-Lasso-D1	0.85	1.06	1.43	0.86	2.27	1.53
Group-SCAD-D1	1.84	1.43	−9.60	−2.05	2.41	1.93
Group-QLasso-D1	0.82	1.83	1.55	2.11	1.94	2.49
Group-Lasso-D2	3.60	2.31	*3.57*	2.29	3.55	3.29
Group-SCAD-D2	*3.61*	*2.33*	2.36	1.96	*4.50*	*3.58*
Group-QLasso-D2	0.87	1.96	1.56	2.15	1.94	2.49
Group-Lasso-D3	−1.62	0.60	−2.74	1.62	2.10	2.29
Group-SCAD-D3	1.35	1.20	2.68	*3.40*	3.45	3.22
Group-QLasso-D3	−0.06	1.78	1.63	2.16	2.11	2.51
Group-Lasso-S3	2.59	1.43	−2.68	−0.51	−1.26	−0.04
Group-SCAD-S3	0.63	1.08	−0.33	0.63	−0.74	−0.03
Group-QLasso-S3	0.64	1.87	1.09	1.69	1.90	2.44

Note(s): Group-Lasso-D1 represents the predictive performance based on short-term dynamics (1–2 months) captured by the Group-Lasso model following wavelet decomposition. This model leverages high-frequency components for forecasting. Other components follow a similar logic, focusing on different frequency ranges or patterns in the predictors

Source(s): Authors' own work

month horizon. Finally, the S3 component contributes the least to prediction accuracy, with both Group-Lasso and Group-SCAD models showing mixed results across horizons. The Group-QLasso model maintains relatively stable performance, especially at the 84-month horizon. However, overall, the S3 component is less useful.

5.4.2 Macroeconomic and climate risk predictors pick-up rate. Figure 5 illustrates the importance of macroeconomic and climate predictors, particularly the macroeconomic variables. Among the macroeconomic predictors, CFNAI (53.12%) and INDPRO (24.38%) have the highest relevance for forecasting, and are significantly more important than climate predictors. Several climate-related predictors have values of zero, with limited individual utility for predicting CES returns. This result aligns with findings above, emphasizing the higher stability and relevance of macroeconomic predictors in forecasting CES returns.

Moreover, the time-based varying rates of the D2 components, as shown in Figure 6, further highlight the importance of macroeconomic predictors. Variables such as CFNAI, INDPRO, and CPI are persistently important over time, indicating their robust predictive contribution across different forecasting periods. Macroeconomic predictors consistently provide valuable information, particularly in capturing medium-term cycles. In contrast, climate predictors are less consistent in their importance, reflecting their more volatile and unstable contributions to predicting CES returns. This variation further supports the conclusion that macroeconomic predictors play a more dominant and stable role, while climate predictors have more limited and sporadic utility.

In conclusion, the wavelet decomposition method highlights the significant contribution of D2 components in forecasting CES returns, particularly for macroeconomic predictors. Components D1 and D3 also have predictive value, but their effectiveness depends on the forecasting method and the horizon. Medium-term components provide a more consistent and stable contribution, especially when considering the robust performance of the macroeconomic predictors CFNAI and INDPRO.

The consistently higher relevance and stable time-varying contributions of macroeconomic predictors emphasize their significant role in forecasting CES returns. These predictors provide valuable information across different time horizons, particularly in the medium term. Climate risk predictors play a role, but their impact on prediction is more sporadic and has less stable utility. Thus, medium-term macroeconomic predictors should be prioritized to accurately forecast CES returns.

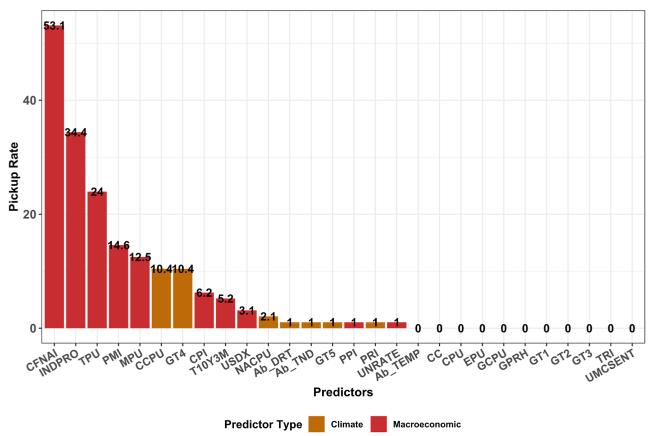

Figure 5. Pick-up rate across the macroeconomic and climate risk predictors. **Note(s):** See Figure 3. Source(s): Authors' own work

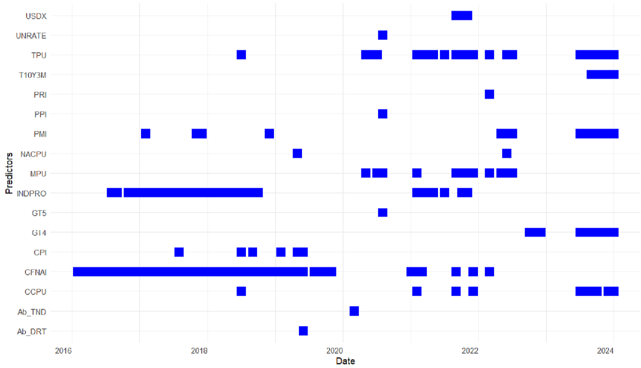

Figure 6. Time-varying pick-up rate across the macroeconomic and climate risk predictors in D2 components.
Note(s): See Figure 4. Source(s): Authors' own work

5.5 Robustness check and further analysis

Additional analyses are conducted to assess the robustness of the findings and to explore further implications. Specifically, we conduct multi-horizon forecasting and investigate the role of predictors compared to autoregressive components in improving forecast accuracy.

5.5.1 Multi-horizon forecasting. Multi-horizon forecasting examines predictive performance over different timeframes, including two-, three-, five-, and seven-step ahead forecasts. This approach describes and evaluates how our models perform when extended beyond short-term predictions. This helps further assess the model's stability and predictive capability over multiple horizons. Tables 8 and 9 present the multi-step data for each model.

Each model is compared against AR(1) and RW across the different forecast horizons. The table shows that quantile-based methods consistently have lower forecast errors across multiple horizons, particularly for longer forecasting periods such as five and seven-steps ahead. The Q-EN model has the most robust predictive performance; this indicates its effectiveness in capturing complex dynamics over extended time horizons. The traditional models PLS and PCR do not perform as well; they are limited in multi-horizon scenarios.

5.5.2 Predictors vs. autoregressive term. This subsection explores the relative contribution of this study's predictors, compared to autoregressive components in improving forecast accuracy. Specifically, we investigate the degree to which including external predictors increases predictive performance beyond the baseline AR model.

To evaluate predictor impact, we compare the forecasting results of models that incorporate external predictors (*e.g.* including macroeconomic, inflation, and policy uncertainty indicators) against models that rely only on autoregressive terms. The results show that incorporating external predictors significantly improves forecast accuracy across different models and horizons. Specifically, the quantile regularization models show the most significant improvement in predictions. This indicates that these predictors capture critical external information that autoregressive terms do not effectively account for on their own.

In particular, provide crucial information to help anticipate shifts in CES performance, especially during periods of economic instability. The comparison shows that models relying purely on autoregressive terms tend to underperform, particularly when market conditions change rapidly. This emphasizes the importance of including diverse external predictors.

The analysis highlights the value of combining traditional autoregressive terms with well-chosen external predictors for more accurate and robust forecasts. The empirical evidence shows that external predictors play a vital role in predicting CES returns, outperforming the baseline AR(1) model alone.

Table 8. Multi-forecasting horizon result rankings

	Two-step ahead forecasting				Three-step ahead forecasting			
	AR(1)		RW		AR(1)		RW	
	OOR^2_{MSPE} (%)	OOR^2_{MAPE} (%)	OOR^2_{MSPE} (%)	OOR^2_{MAPE} (%)	OOR^2_{MSPE} (%)	OOR^2_{MAPE} (%)	OOR^2_{MSPE} (%)	OOR^2_{MAPE} (%)
PLS	8	8	8	8	8	8	8	8
PCR	7	5	7	5	5	7	5	7
LASSO	5	7	5	7	7	6	7	6
ALASSO	2	2	*1*	*1*	4	3	4	3
EN	6	6	6	6	6	5	6	5
Q-LASSO	3	3	3	3	*1*	*1*	*1*	*1*
Q-ALASSO	4	4	4	4	3	4	3	4
Q-EN	*1*	*1*	2	2	2	2	2	2

Note(s): The table ranks shrinkage models (1–8) by their multi-step forecasting performance based on out-of-sample R^2
Source(s): Authors' own work

Table 9. Multi-forecasting horizon result rankings

Benchmark	Five-step ahead forecasting AR(1) OOR^2_{MSPE} (%)	OOR^2_{MAPE} (%)	RW OOR^2_{MSPE} (%)	OOR^2_{MAPE} (%)	Seven-step ahead forecasting AR(1) OOR^2_{MSPE} (%)	OOR^2_{MAPE} (%)	RW OOR^2_{MSPE} (%)	OOR^2_{MAPE} (%)
PLS	6	8	6	8	8	8	8	8
PCR	4	5	4	5	4	6	5	6
LASSO	2	3	2	3	3	5	2	4
ALASSO	7	6	7	6	7	7	7	7
EN	*1*	2	*1*	2	5	4	4	3
Q-LASSO	5	4	5	4	2	2	3	2
Q-ALASSO	8	7	8	7	6	3	6	5
Q-EN	3	*1*	3	*1*	*1*	*1*	*1*	*1*

Note(s): See Table 8
Source(s): Authors' own work

6. Conclusion

This study provides a comprehensive framework for forecasting CES returns using diverse predictors, including technical, macroeconomic, climate risk, and financial factors. Different shrinkage models are used to systematically analyze the role and effectiveness of individual predictors, group-level predictors, and their trend components in CES forecasting. This study approach addresses key research questions about their predictive power, time-varying relevance, and group-level contributions.

The findings provide clear economic insights into CES returns. Macroeconomic predictors, such as CFNAI, capture economic cycles and guide investment decisions during uncertainty. Climate predictors, like TRI, highlight sustainability's growing role in shaping market responses to policy changes. Technical and financial predictors, though short-term, help investors navigate market volatility. These results connect CES forecasting with broader financial theories and offer actionable guidance for navigating the complexities of clean energy markets. Key results are as follows.

First, at the individual level, macroeconomic predictors are the most influential for predicting CES returns; they consistently demonstrate high relevance across different forecasting models and periods. Unemployment rates and geopolitical risk indices play a critical role, particularly during periods of increased uncertainty. Climate risk predictors are temporally variable, reflecting the dynamic impacts of policy shifts and public sentiment. Technical and financial predictors are relevant primarily during volatile market conditions.

Second, at the group level, macroeconomic predictors are the main contributors to forecasting accuracy when analyzed collectively. Applying group shrinkage models shows that macroeconomic predictors consistently outperform other predictors in both short- and long-term horizons. Climate risk predictors are more important during periods of increased focus on sustainability and energy transitions. Technical and financial predictors are less stable, but provide valuable insights during periods of market disruption.

Third, analyzing trend components shows that medium-term dynamics play a key role in forecasting CES. These components, particularly among macroeconomic predictors, contribute the most to predictive accuracy. This highlights their importance in capturing the underlying trends at work with CES returns. While short-term and long-term components provide useful information, their effectiveness depends on specific market conditions and forecasting methods.

These findings are valuable for both investors and policymakers. Investors can use the time-varying relevance of predictors to make better decisions. During economic uncertainty, focusing on predictors like UNRATE and GPR can improve CES return forecasts. When sustainability or energy transitions are prioritized, climate risk predictors become more significant. Policymakers can tailor policies to align with key predictors at different times, optimizing their response to economic shifts or sustainability goals, thereby improving effectiveness in the clean energy sector.

Overall, this study addresses key questions about which predictors have the greatest power for forecasting CES returns, how their relevance evolves over time, and whether grouping and decomposing predictors improves forecasting accuracy. These findings emphasize the critical role of macroeconomic predictors, the value of group-level analysis, and the importance of medium-term trend components in improving predictions of CES returns. These insights offer valuable guidance for investors and policymakers navigating the complexities of the clean energy sector amidst rapid economic and environmental change. This study is limited by its use of monthly data and focus on the WilderHill Index, which may reduce generalizability. Future research could explore higher-frequency data or other regional markets to uncover new dynamics and further optimize forecasting methods for improved accuracy, particularly by incorporating advanced machine learning techniques to capture non-linear relationships in CES returns.

Note

1. This study uses trading volume data from the Invesco Wilder Hill Clean Energy ETF (PBW) to compute $\mathrm{MOM}(k)$ and $\mathrm{OBV}(s, l)$. PBW is highly correlated with the WCEI and effectively tracks its performance. Additionally, PBW has significant trading volume, making it a mainstream ETF for tracking the WCEI. Panel B of Table 1 summarizes the technical indicator predictors.

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Supplementary material

The supplementary material for this article can be found online.

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