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Financing sustainable energy transition with algorithmic energy tokens

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ABSTRACT

Financing energy firms and catalyzing the energy transition are pivotal for achieving a sustainable future. In this era of increasing environmental consciousness, banks are incorporating environmental considerations into their credit rating methodologies, like the Partnership for Carbon Accounting Financial Guidelines. In the meantime, the advent of digital tokens offers new avenues for energy token creation. This study establishes a factor model as the fundamental framework for algorithmic energy tokens and employs gradient-boosting tree regression to examine energy price drivers in Italy and Austria. The results underscore the heightened motivation to invest in energy transition and security during periods of elevated energy prices. Conversely, the drive to invest in clean energy sources diminishes when operational profits are low or energy security must be maintained. This research elucidates on an innovative financing solution that handles these dynamics, produces momentum, and focuses special emphasis on its potential for implementing environmental policies by developing an algorithmic energy token mechanism based on environmental regulations and considerations.

1. Introduction

Historically, Gross Domestic Product (GDP) has been recognized as a significant factor influencing global energy prices (see Asghar (2008) and Soytas and Sari (2003)). However, it is essential to recognize that mathematically there is a mutual effect between GDP and energy prices, rather than a one-way dependency (as stated in Asghar (2008) and Stern (2018)). Therefore, to maintain the economic affordability of energy prices and promote faster development, authorities should consider the physical availability and accessibility of energy supply sources, as well as the long-term environmental and social sustainability. A term that encapsulates all these parameters is "energy security" (see Axon and Darton (2021)). Nevertheless, the literature features a substantial discussion on the definition of energy security, with a noticeable lack of methodological development in frameworks for selecting indicators and metrics (see Cherp and Jewell (2014)). Moreover, a methodological gap in financing planned economic growth alongside energy objectives, particularly within the European Union, exists and is addressed in the following discussion.

Balancing economic ambitions with environmental targets requires innovative financial mechanisms and strategic planning. Addressing this methodological gap becomes imperative for the European Union to successfully navigate the transition to a sustainable and secure energy future. As a matter of fact the ongoing discussions in the literature and the identified methodological gaps highlight the evolving nature of energy security as a critical aspect of global development.

Japan serves as a compelling example among the world's largest economies, having grappled with numerous energy insecurities, including oil embargoes in the 1970s and the Fukushima nuclear accident in March 2011. Subsequently, a plethora of articles have been published addressing the crucial issue of energy security. To date, 34 conceptual models and 104 quantitative and qualitative methods have been deliberated upon in scholarly discourse, reaching this cumulative understanding by the year 2021 (see Esfahani et al. (2021)).

Moreover, in the past decade, the discourse on renewable and low-carbon energy has introduced a new dimension to the conversation. A 2022 article by Yousaf et al. (2022) sheds light on the asymmetry and heterogeneity in the return connection between renewable energy digital tokens and the fossil fuel market. This discovery implies a heightened probability of contagion during periods of falling or rising returns, thereby influencing risk management strategies for investors in digital clean energy. Studies concentrating on specific national economies, such as China (Ren et al., 2023), Morocco (Ainou et al., 2023), and Turkey (Ertuğrul et al., 2022), further indicate a more pronounced impact on government-owned carbon-intensive industries. The introduction of secure renewable digital tokens into energy portfolios emerges as a potential strategy to bolster green financing in these contexts.

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Furthermore, additional research (Zeqiraj et al., 2020) underscores the imperative of coupling stock market development with government policies that champion innovation for energy efficiency, especially in the dynamic landscape of rapidly advancing renewable energy technologies like solar and wind. This becomes particularly crucial when constructing portfolios in extreme market conditions.

This study endeavors to bridge the existing gap by developing an integrated energy digital token. It entails a thorough examination of energy production, finance, and market economy aspects related to energy security, categorized into internal and external factors. The primary objective is to formulate a theoretical framework that seamlessly integrates all these components of energy security.

Traditionally, energy security models were employed by large, government-owned fossil fuel enterprises, concentrating on achieving supply and demand equilibrium at an affordable price within centralized supply systems (Proskuryakova, 2018). However, in recent decades, the global economy, once heavily reliant on affordable energy derived from hydrocarbons, is now shifting towards decentralized (see Lei et al. (2022)) and more diversified energy security due to escalating costs associated with climate change and geopolitical risks (Ahmad and Zhang, 2020). To ensure integrated energy firms are held accountable for climate and social risks, various approaches have emerged in the past decade. Alongside carbon allowance certificates, a noteworthy best practice that has garnered significant attention among financial organizations, especially following the Paris Climate Agreement, is the Partnership for Carbon Accounting Financials (PCAF) (PCAF, 2023) for Green House Gas (GHG) accounting and reporting (website: PCAF). This initiative aims to enhance transparency and accountability in tracking and reporting carbon emissions, reflecting the growing importance of environmental considerations in the financial sector.

In a new study conducted in 2021 by Ramsebner et al. (2021), challenges related to the security of energy supply and economic feasibility were thoroughly examined. Apart from the obstacles posed by hybrid grid technology, the primary challenge identified was a crucial factor termed as a "supportive market framework". In this context, as all sources contribute to the production and transfer of energy commodities, a need for a new economic framework arises to define values based on the underlying resource or technology (see Duvignau et al. (2021)).

Furthermore, a fundamental aspect of asset management involves realizing the value of any asset by balancing financial, environmental, and social costs and associated risks (55001, 2014). Despite the subjective nature of value, an economic perspective on the value of energy commodities can be established by considering the life cycle cost (LCC) of energy production assets, encompassing powerhouses of various types such as solar, gas, nuclear, etc., as internal factors. Additionally, macro-factors, assessed through a PESTEL (Political, Economic, Social, Technological, Environmental, and Legal) analysis, play a significant role as external factors (55002, 2021-2). Some scholars also advocate for a more advanced version known as Life Cycle Investment (LCI) (see Torres Farinha et al. (2020)). This approach provides a comprehensive view that considers the entire life cycle of energy production assets and the broader macro-environmental factors influencing their value.

In assessing external factors in the energy market, various indices have been considered, including the S&P 500, representative of the overall market, Geopolitical Risk Indices, Rotary rigs in operation as indicators of demand, and the volume of natural gas stored underground in the U.S., among others (Drachal, 2021; Herrera et al., 2019; Panella et al., 2012; Yuhanis and Zuriani, 2015). Conversely, some studies focused on the economic fundamentals of 33 countries, collectively constituting 80% of the global economy. These economic factors include output, inflation, interest rates, equity market performance, and exchange rates (see Ferrari et al. (2021), Asghar (2008) and Halkos and Tsirivis (2019)). Despite these diverse approaches, all prediction models unanimously acknowledge that forecasting natural gas prices consistently yields the lowest Mean Squared Error (MSE) values compared to other energy commodities. One plausible explanation for this phenomenon could be the inefficiency and limited regulatory control over the natural gas supply (Fries, 2019). This highlights the unique challenges and dynamics associated with predicting natural gas prices in comparison to other energy commodities.

When examining internal factors affecting electricity prices, the technology used in its production plays a crucial role. For instance, a study conducted in 2022 in the Indian market utilized a non-linear autoregressive distributed lag modeling framework. This investigation revealed that while the impact of hydraulic technology production shocks was deemed insignificant, renewable energy sources exhibited an asymmetric effect on price dynamics. Specifically, weakened electricity generation shocks (negative) had a more substantial and prolonged impact on wholesale electricity prices than oversupply (Nibedita and Irfan, 2022). Similarly, in 2022, Moutinho et al. (2022a) conducted a comparable study on the Iberian electricity market, utilizing an Autoregressive Distributed Lag (ARDL-ECM) method. They analyzed data series representing the quantity of electricity offered by hydraulic, renewable (wind/solar), and thermal (coal/oil/gas/nuclear) technologies against the wholesale electricity price series. Their findings demonstrated stationary properties between these variables, affirming that both technology and resources influence prices in both the short term and the long run. Significance levels at 1% indicated that different technologies may have either positive or negative effects on prices, contingent upon legislation and the geological characteristics of the states. Nevertheless, in the long run, renewable energy source technologies had a negative impact on energy prices. Likewise, another report, analyzing the Iberian Electricity market using Markov-Switching Dynamic or Autoregressive Regression, disclosed that even carbon prices significantly affect the probability of price transition (Moutinho et al., 2022b). This underscores the intricate interplay between various factors, including technology choices, resource availability, and regulatory frameworks, in shaping electricity prices.

Moreover, it is a fundamental reality that energy emerges as a product of an intricate engineering process. In tandem, the operation of each engineering system entails its own set of risks, quantified in financial terms as Reliability, Availability, and Maintainability (RAM) (Al-Douri et al., 2020). Notably, the risks associated with engineering (or physical assets) and financial risks have been meticulously examined over time and extensively documented (see Sutton (2010, 2015) and Cevasco et al. (2021)). However, the interconnection between these two realms has been overlooked. Thus, from a broad perspective, capital expenditures, operational costs, and RAM risks in generating clean energy can be regarded as internal factors, while market supply and demand forces influenced by environmental, social, and geopolitical concerns are deemed external factors.

In the past decade, the carbon price or allowances market has emerged as a new and influential external factor within energy commodity portfolios. Allowances, along with their option and future contracts, are actively traded on platforms such as the European Energy Exchange and International Exchange. For instance, when there is an upswing in energy demand accompanied by a decrease in coal prices, energy enterprises may find coal economically viable and opt for a long position on allowances to offset their emissions. While this illustrates the functioning of the allowance market in response to supply and demand dynamics, the complexity arising from the diverse array of energy sources and varying potentials among different companies makes predicting allowance market movements challenging. In a study conducted in 2021 (Batten et al., 2021), it is discovered that energy commodity prices, indicative of the supply/demand balance, account for only 12% of carbon price variations. Moreover, they noted that "weather variables did not affect the carbon price except for unanticipated temperature changes". This underscores the intricate and multifaceted nature of the carbon market, where numerous factors beyond traditional supply and demand dynamics contribute to its fluctuations.

However, the dynamics of sustainable energy are influenced by a complex interplay of factors. Carbon pricing, economic growth, and trade openness serve as catalysts for promoting sustainable energy, while energy demand, security concerns, and population growth act as constraints (Ibrahiem and Hanafy, 2021). In 2022, a report by Sohag et al. (2022) delved into the conditional and unconditional volatility spillover of geopolitical risks (encompassing acts, threats, narrow and broad measures) on green energy investments. Employing cross-quantilogram and Quantile and Quantile (QQ) approaches, the study revealed that these risks transmit positive shocks to bearish green energy markets, yet bullish green energy investments react negatively. Additionally, the energy market exhibits a long memory of geopolitical risks, contrasting with conventional stock markets. Similarly, Yuhui Dai et al. conducted a parallel investigation in 2022 (Wang et al., 2022), exploring the influence of the war in Ukraine on various commodity categories. Their findings indicated that elevated levels of return and volatility spillovers in the commodity market correlate with heightened geopolitical risks. Notably, energy commodities become a net transmitter of return spillover, amplifying volatility spillover on metals and agricultural commodities from 35% to 85%. FX risk, as another geopolitical-affected factor, can also impact energy commodity prices.

The impetus for renewable energy and the pursuit of net-zero carbon emissions were anticipated to gain momentum amid global disruptions in the energy markets and the war in Ukraine. Nevertheless, the challenges associated with the energy transition are becoming more pronounced as the global consensus on it solidifies (NA, 2022). One prominent hurdle, amid the variable pace of technological advancement and application, is the reemergence of energy security as a paramount requirement for nations and GDP growth. A swift abandonment of fossil fuels appears more idealistic than realistic and is poised to cause economic disruptions (see Stern (2018)).

Since the advent of Web 3.0 in 2020, numerous energy tokens have been developed and openly traded, aiming to assist energy enterprises in addressing business challenges associated with the energy transition (Wang and Su, 2020). Among these tokens, one of the most successful, although yet to demonstrate tangible results on the market, is the *Energy Web Token*.[1] Conversely, the cryptocurrency industry has encountered a significant obstacle in its journey toward achieving net-zero goals, due to its substantial environmental footprint resulting from the energy-intensive mining process. A pivotal moment prompting the industry to confront this challenge head-on was the Ethereum merge, an event that unfolded in September 2022. This transformative step resolved the colossal power demand associated with Ethereum mining, leading to a remarkable 99.84% reduction in electricity consumption, equivalent to the annual power needs of Austria. This achievement was realized by transitioning from the blockchain's "Proof-of-Work" (PoW) mining mechanism to an alternative approach known as "Proof-of-Stake" (PoS) (Gawusu et al., 2022). For energy tokens, which can subsequently be converted into currencies, stakeholders play a crucial role and can include commissions from legal authorities and energy enterprises. Nevertheless, firms operating on the supply side of energy liberal markets stand to benefit from the reward collection through mining, thereby contributing to financing initiatives for the energy transition (Mehdinejad et al., 2022).

In summary, alongside green bonds and investment campaigns, investors are increasingly incorporating the benefits of digital FinTech into energy security, transition, and sustainability financing (Gawusu et al., 2022). This trend has given rise to energy blockchain-based crypto price indexes like "ENCX" (see Gurrib (2019)). However, the path forward is not entirely smooth and clear, encountering challenges stemming from technological infrastructure and legal issues (as discussed in Yildizbasi (2021)). Addressing these concerns, a comprehensive report by Martin Fraenkel, the vice chairman of S&P Global Platts, was published in 2018 (Global, 2018), leading to a substantial increase in publications on blockchain technology in the energy sector as a burgeoning research area (Wang and Su, 2020).

This research, once again, seeks to provide a sample analysis of the theoretical foundation of an algorithmic energy token and its practical implementation through historical data analysis, exploring its potential to expedite sustainable energy transition. In Section 2, a linear regression factor model is introduced to explain energy prices, drawing on the discussed price drivers. This model is rooted in the engineering definition of energy production Life Cycle Analysis (LCA) and asset management standards. Building upon this foundation, the fabrication of an energy token, inversely related to energy prices, is conceptualized. Moving forward to Section 4, the practicality of this approach is discussed for Italy and Austria, based on collected data and the methodology outlined in Section 3. In essence, the conclusive section serves as a compass, guiding stakeholders, policymakers, and industry participants toward informed decisions that align with the broader goals of energy security, transition, and sustainability. Through a comprehensive examination of causality and the practical application of algorithmic energy tokens, the research strives to contribute valuable insights to the ongoing discourse on shaping a cleaner, more resilient energy future.

2. Model description and economical theory

As was pointed out in the introduction, the determination of energy prices involves considering both internal factors related to life cycle investment parameters, such as initial investment costs, operational expenses, maintenance and repair costs, and the expected lifespan of energy assets; and external factors associated with asset management parameters.

On the other hand, external factors encompass the broader asset management parameters that impact energy prices. These parameters can include market dynamics, government policies and regulations, as well as environmental considerations. Therefore, by defining P_{EC} as price of energy commodity, we can express the relationship as follows:

$$P_{EC} = \underbrace{\left[\beta_1 \cdot \sum_t^T (CAPex + OPex) + \beta_2 \cdot \sum_t^T RAMex\right]}_{\text{Intrinsic factors}} + \underbrace{\left[\beta_3 \cdot \sum_t^T RISex\right]}_{\text{Extrinsic factors}} \tag{1}$$

The equation states the associated expenses to a batch of energy generated during a time period from t to T, where $CAPex$ and $OPex$ are the firm's capital investments and operating expenditures, respectively. $RAMex$ is a hybrid spending of capital and operational categories to improve production reliability and product availability. $RISex$ comprises the external risks associated with energy production, i.e. environmental and geopolitical risks. Since the costs of these risks are imposed through legislation such as carbon allowance or political sanctions, they may also be called legal risks. Eq. (1) can be regarded as a fundamental factor model for energy prices, and in order to achieve a balanced equation, it is necessary to identify all the influencing factors (indexes) and their corresponding lagged time series. Yet, as pointed out in the introduction, developing an accurate and precise model is a challenge for financial researchers and commodity traders. Certainly, by focusing on the energy price trend and allowing for an acceptable marginal error, it is possible to derive a negatively correlated energy token from Eq. (1).

Moreover, when considering end-user energy prices, Eq. (1) is most effective for electricity. In this context, the distribution price, assuming an existing distribution grid and solely network maintenance, is

[1] https://www.energyweb.org/.

added as a percentage of the power transmitted (network services). Conversely, for physical energy commodities such as oil and gas, the pricing becomes more intricate, encompassing cost of carry (CoC) items, namely Storage, Carry, Lease or opportunity cost, and Convenience yield. However, all the βs in Eq. (1), will have positive attributes as the higher the expenses the higher production costs and hence final price. RAMex also shows a positive relationship, as expenditures here represent the risk. The higher the risk and costs of maintainability (like wind turbines) lower availability times and reliability of continuous production. Although the OPex and RAMex may show similar expenses and correlation, the former often covers the periodical costs of consumable parts maintenance, whereas latter is a cost–benefit analysis of reactive to preventive maintenance (Govil, 1984).

The energy transition to clean sources, requires capital investments in solar and wind farms, as is with carbon capturing technologies. Also reducing the GHG emission, oil spills, and incident frequencies resulting to environmental damage needs preventive and reliability centered maintenance in the form of RAMex. As a result, in current circumstances, integrated oil and gas firms seek to raise their product pricing in order to meet specific demands of climate protection frameworks, gain the budget they need, or improve their credit scores for loans and bonds as their profit margins and future cash flows inflate. Whereas in a digital economy environment, a new energy token can be a safe financing mechanism to lessen the energy prices. In this framework, considering an inverse relationship, when energy product prices increase, digital token (credit) value diminishes, and vice versa. Considering V_{ET} as value of energy token, to develop a negative correlated energy token based on a linear regression factor model, we may set up the following dependencies:

$$V_{ET} \propto \frac{1}{P_{EC}}$$

$$r_P = \ln\left(\frac{P_{EC}(t+1)}{P_{EC}(t)}\right)$$

$$r_V = \ln\left(\frac{V_{ET}(t+1)}{V_{ET}(t)}\right)$$

where r_P is the continuous return of energy commodity price movements and r_V is the continuous return of energy token price action, that are a logarithmic difference of P_{EC} as the energy commodity price and V_{ET} as the value of energy token at times $(t+1)$ and (t). Ultimately, we observe that a negative return correlation holds, i.e.

$$if \quad P_{EC}(t+1) > P_{EC}(t) \quad \Rightarrow \quad V_{ET}(t+1) < V_{ET}(t) \quad \Rightarrow \quad r_P = -r_V$$

Returns are normally stationary factors and are employed here just to demonstrate the negative economic correlation by inverting the features. Thus, in order to ensure consistency, the model takes into account only prices and continuous non-stationary factors by utilizing comparable factors from the energy commodity price P_{EC} in Eq. (1) and transforming it into an energy token V_{ET} with different coefficients, i.e.

$$V_{ET} = \Big[\zeta_1 \cdot (CAPex + RAMex) \; + \; \zeta_2 \cdot (Profit - OPex)\Big] + \Big[\, \zeta_3 \cdot ESR \; + \; \zeta_4 \cdot GPR \Big] \tag{2}$$

The above equation emphases again that the value of a digital token V_{ET} in a specific market will depend on intrinsic (first square bracket) and extrinsic (second square bracket) factors. The intrinsics are a companies' investment and energy production costs ($CAPex$ and $OPex$), reliability and availability of continuous and demand-wise production ($RAMex$), and profit gains; while the extrinsics are Environmental, social (ESR) and geopolitical risks (GPR). The impact of commodity prices being the selling power of a firm is considered within operating expenditures as profit. It is worth noting that Eq. (2) is a straightforward linear equation that can be complicated by nonlinear interactions, such as polynomial or logarithmic trends of the features. However, in order to assess the precise non-linearity trend, the presence of a liquid, well-established, and government-backed energy token is necessary. In any case, the decision tree model will capture any non-linearity between dependent and explanatory factors in this study, but the precise link cannot be shown.

The coefficients, which represent the sensitivities of the token's value to the aforementioned characteristics, may be calibrated using market data. Nonetheless, the sign of the coefficients for the first and two last terms represented by ζ_1, ζ_3, and ζ_4 respectively, should be positive. The first term can be called capitalization for energy security, and the ESR and GRP factors can be considered the premiums for sustainable energy production. Cost increases in either case should provide firms with a return through inflated value of energy tokens and mining authority, to obtain required finance. On the other hand, ζ_2 should be negative to keep the energy affordable according to energy security definition.

In a nutshell, the logic is that when a company capitalizes on its growth and transitions to cleaner sources, or when it performs costly preventive maintenance to reduce the possibility of oil spills or flaring due to unplanned turnarounds by increasing production reliability, it should be financed and gain greater stakes in mining token. When the profit from high energy commodity prices surpasses the operational expenses, the income capital becomes self-sufficient for supporting energy portfolio expansion. When operating expenses exceed earnings, resulting in a loss, the negative total scaled by negative ζ_2 will have a positive relationship with the token price.

In a comparable manner if external influences such as geopolitical embargoes or environmental restrictions are imposed, the corporation should be able to accumulate sufficient funds to budget for production diversification, thus positive ζ_3 and ζ_4. However, this can be controversial because, when external effects increase the production risk, the supply line shifts to higher prices for the same demand quantity, resulting in company gains as illustrated in Fig. 1. Therefore, ζ_4 may be negative in some occasions.

Nonetheless, according to micro-economic principles, when the variable production costs like tax, environmental fines, emission certificates, or energy source prices (e.g. gas after the war in Ukraine) increase, the market price also increases (energy security index decreases), and the resulted ΔP_1 brings more money for the energy supplier, even more than the costs.[2] Thus, in these situations, the profits are still sufficient for self-financing (plow-back ratio) and diminishing token value lessens the energy security. So better to keep ζ_4 positive to bring energy token profit as the financing source rather than product price.

In contrast, when the economy is on the rise with growing GDP figures, obviously more energy is required to produce more domestic goods, so there would be more demand, but also more competition and qualifications on the supply prices; then, considering the current international atmosphere (climate change debates), companies face financing challenges to increase production by investing in green energy sources and get back to supply–demand equality (Q_{eq}, P_{eq}) in Fig. 1. This gap ΔP_2 can be covered by energy token returns and mining rewards as a financing source.

3. Empirical analysis: a case study in Italy and Austria

3.1. Computational methodology

Embarking on the exploration of practical implications, we delve into the introduction and justification of the theoretical formulation outlined in Eq. (2). This step is essential to assess how the discussed

[2] According to historical figures like the last quarter of 2022 after energy sanctions on Russia and unprecedented revenue figures by energy enterprises, in such situations due to market agitation, the price spikes are in favor of suppliers, implying higher profits.

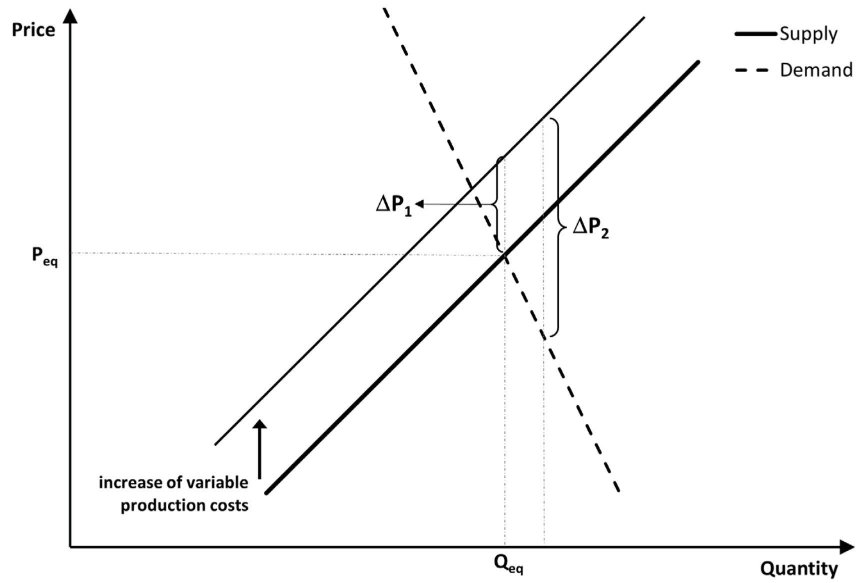

Fig. 1. Micro-economic supply and demand plot for energy commodities.

theory manifests in real-world scenarios, particularly within a specific country and its energy firms. However, employing the empirical regression factor model proposed in Eq. (2) posed challenges attributed to data constraints, incompatibility issues, and temporal variations. In response to these limitations, we pivoted towards the utilization of a gradient boosting tree model. This alternative model, integrating both national and international drivers, provides a robust framework for scrutinizing energy basket prices in Italy and Austria.

Italy and Austria were selected due to their distinctive energy landscapes and portfolios, encompassing a diverse range of energy sources, infrastructure, and energy policies. An exploration of energy security in these nations promises valuable insights into the challenges and opportunities they face in ensuring a secure and reliable energy supply. Moreover, these countries represent varied European regions, each characterized by unique energy dynamics and objectives, facilitating a comprehensive understanding of energy security challenges at both national and regional levels. Furthermore, their active engagement in promoting renewable energy and striving to attain energy transition goals adds an additional layer of significance to this study.

In terms of production costs, ENI and OMV, the integrated energy corporations with the greatest market capitalizations in Italy and Austria, respectively, were chosen. The firms' idiosyncratic data is best provided quarterly, which has lower entropy (variance) than daily commodity prices and GPR/ESG indices, resulting in poorer predictive power for the regression technique. Still, quarterly or annualized data can be used by decision tree models, but it lacks the granularity required for a liquid daily token.

Furthermore, the model works well with missing (NaN) data and captures nonlinear relationships. Hence, a gradient boosting tree by means of `HistGradientBoostingRegressor` function from `sklearn.ensemble` package in **python** were employed. The objective was to determine the optimal threshold values for binary separation of explanatory variables.

The reciprocal of energy basket prices (HICP[3]) normalized by its base (100) in aforementioned countries and multiplied by 100, was used as the supervised true value to train the model on a hypothetical energy token value. The collection of explanatory variables are listed in the next section. Then, using the python module `train--test-split` from `sklearn.model-selection` package, 30% of data along the time-line were chosen at random as test sample. The Mean Square Error (MSE) function was employed to train the model, while the Mean Absolute Percentage Error (MAPE) was used to assess performance. Finally, the model parameters were optimized for both models in Italy and Austria utilizing the gradient search function `GridSearchCV` from `sklearn.model-selection`, resulted in a learning rate of 0.001, a maximum depth of 2, a maximum number of iterations of 5, a maximum number of leaf nodes of 2, and a minimum number of permissible samples for each leaf of 20.

3.2. Data and preliminary analysis

Bloomberg Terminal, Refinitiv Workspace, and companies investor relations reports were the sources of the data collected. Table 1 lists economical, political and ESG indexes picked from the World Bank database and Bloomberg.

Bloomberg country scores were used for the geopolitical risk indexes, and the last six rows of Table 1 are from the Caldara and Iacoviello GPR indexes,[4] which are obtained by an automated text search through the electronic archives of ten newspapers and tallying the number of articles for each geopolitical event. The *ACT* subindex counts terms linked to the categories of war beginning or escalation and terror actions, whereas the *THREAT* subindex counts the words connected to the categories of threats and military buildups. For the eccentric energy production expenditures, the capital expenditures, and operational income comprising operational costs and relevant profit are extracted from ENI and OMV's financial statements. Also, other parameters such as ESG company score from Thomson Reuters, GHG company emission from Bloomberg Terminal, and incident rate, oil spill, and reserved product from the company Key Performance Indicator (KPI) statements were added as explanatory features during model training. Since the RAM indexes such as "percentage losses index" or "availability rank index" are inherited technical measures within the company and are not published publicly, they were not introduced into the model.

Energy prices as commodities, renewable generation, carbon allowances and future certificates, and consumer energy basket were also gathered from the Bloomberg and Eurostat terminals. Fig. 2 portrays

[3] Harmonized Index of Consumer Prices.

[4] https://www.matteoiacoviello.com.

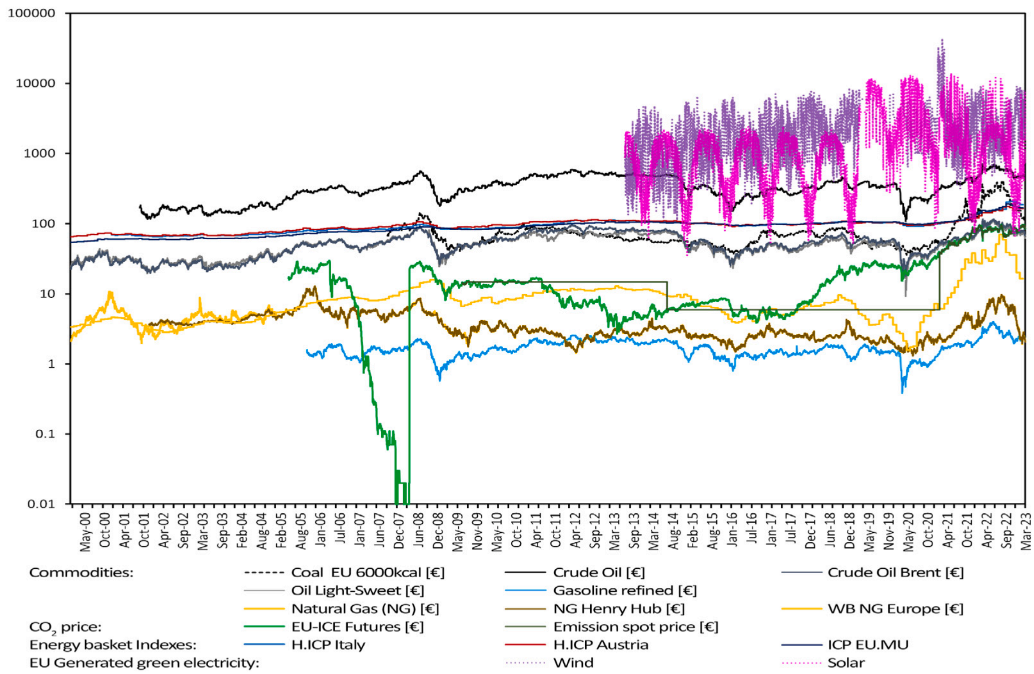

Fig. 2. Energy commodity historical prices plot.

Table 1
ESG and GPR indexes.

Index	Description
ESG100P	Euronext Eurozone 100 ESG (Dly.)
BWENVR	Bloomberg World Environmental Control Index (Dly.)
RSSCITPR	Bloomberg Country Risk Political Score for Italy (Qtly.)
RSSCITER	Bloomberg Country Risk Economic Score for Italy (Qtly.)
RSSCITFR	Bloomberg Country Risk Financial Score for Italy (Qtly.)
RSSCASPR	Bloomberg Country Risk Political Score for Austria (Qtly.)
RSSCASER	Bloomberg Country Risk Economic Score for Austria (Qtly.)
RSSCASFR	Bloomberg Country Risk Financial Score for Austria (Qtly.)
WBENRUSR	Russian Federation Adj. Savings: Annual NRD[a] (%GNI[b])
WBENMEAR	Middle East & North Africa Adj. savings: Annual NRD (%GNI)
WBENARBR	Arab World Adj. savings: Annual NRD (%GNI)
WBENEUUR	European Union Adj. savings: Annual NRD (%GNI)
AGGDEMU	World Bank GDP per Capita Growth in Annual% European Monetary Union
AGGDPIT	World Bank GDP per Capita Growth in Annual% Italy
AGGDPAS	World Bank GDP per Capita Growth in Annual% Austria
N10D	Number of daily articles about conflicts (since 1985)
GPRD	Daily GPR (Index: 1985:2019 = 100)
GPRD_ACT	Daily GPR Acts (Index: 1985:2019 = 100)
GPRD_THREAT	Daily GPR Threats (Index: 1985:2019 = 100)
GPRD_MA30	30 day moving average of Daily GPR
GPRD_MA7	7 day moving average of Daily GPR

[a] Natural Resources Depletion.
[b] Gross National Income.

historical prices over various time spans, while Fig. 3 illustrates their correlations.

Fig. 2 depicts how crude oil (solid black line) and coal (dashed black line) prices were in sync until the war in Ukraine, when coal prices skyrocketed far beyond those of oil. Sweet oil, or Brent, followed the crude oil trend, albeit on a smaller scale. As an oil derivative, gasoline has followed the trend of oil prices. Natural gas (NG) is a different story, as the universal commodity price, or Henry Hub, was typically lower than the NG commodity price in the European market. However, with the Nord-Stream pipelines, prices were expected to become more aligned, with the NG commodity price in Europe reaching parity with the international market in May 2020. Nonetheless, the war in Ukraine caused the price of natural gas in Europe to skyrocket, reaching its highest level since 2000 in late 2022 (EU.MU in Fig. 2 stands for "Europe Monetary Union" based on the European central bank monthly reports).

Since the inception of European Emission certificates (EU-ICE), the market experienced a failure during the credit crunch crisis in late 2007, but since then it has become a more liquid asset. In recent years, these certificates have gained more attention due to multiple climate-protection conferences around the world, and their prices now exceed those of Brent crude oil. Two dotted cyclic clouds in Fig. 2 represent electricity produced by wind and solar energy in Europe. Although the production of wind and solar energy is highly volatile, these two methods are complementary to each other. When solar energy is at its peak, wind energy is at its lowest, and vice versa. However, since their introduction in 2014, the amount of electricity produced by these renewable methods has not increased as expected. While the amount generated has increased by a factor of ten at some points, the volatility range has also increased by the same factor.

Fig. 3 portrays the correlation between the prices of various energy commodities. Kendall tau is the method used since it can handle non-linearity and price ties in some commodities. As the heatmap shows, most commodities have a positive correlation with each other, with the exception of generated wind and solar energy and emission certificates, which are slightly negatively correlated with fossil fuels. Thus carbon allowances show a positive correlation around 0.4 with solar and wind generated energy. On top of that, natural gas (NG) commodities have a near-zero correlation to oil commodities. The energy customer price index correlation to global natural gas prices is negative for Italy, Austria, and Europe in general, but positive for European NG prices.

Furthermore, the causality test was carried out in Python using the `grangercausalitytests` function from the `statsmodels.tsa.stattools` package. The F-test is used in the context of this function to test the significance of the lagged values of the explanatory variables predicting the dependent variable. The null hypothesis H_0 states that the potential causal variable adds no explanatory power. As a result, if the F-test p-value was less than 5%, H_0 was rejected in favor of the conclusion that there is statistically sufficient evidence that a time series can be used to predict an energy price index. The primary issue to consider was determining the appropriate amount of lags, and the

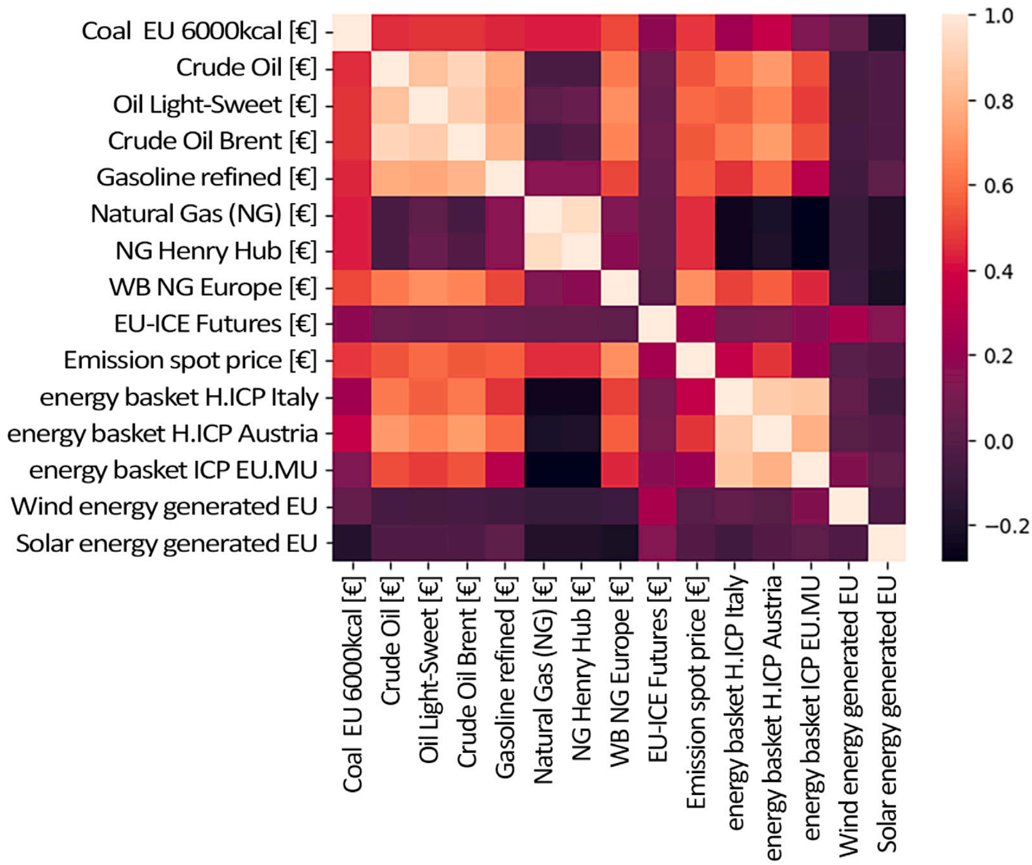

Fig. 3. Kendall tau correlation matrix on energy commodity prices.

best results came after several trials with varying delays. The relevant results are listed in brevity in table 3, appendix E.

Regarding the geopolitical risk, the GPRD with 5 days lag for lightweight sweet oil and Brent Oil yielded p-values of 3.3% and 0.01%, respectively. It also had an influence on the Gasoline commodity price with a one-and-a-half month lag, with a p-value of 0.01 percent on the null hypothesis. Natural Gas (NG) was a completely different story. The Granger-effect from GPRD to Henry Hub prices in a 5 day lag resulted in a p-value of 3.6%, whereas natural gas prices within Europe or global NG commodities result in p-values below the significance level of 5% in much longer lag periods of 3 months and one year, respectively; the latter can be considered useless as news on changing prices does not seem logical after a year. However, because NG prices in Europe are synchronized quarterly, the three-month lag may be effective. There was no statistically detectable Granger-cause relationship between geopolitical risk and renewable energy generation. The emission certificates and geopolitical risk demonstrated mutual Granger-cause only on future contracts on short lag times ranging from 5 to 15 days, with p-values as low as 0.07 percent.

The Bloomberg World Environmental Control Index demonstrated a Granger effect on oil commodity prices and natural gas commodities in Europe or globally, with lag durations ranging from 15 to 45 days. Natural resource depletion in Russia, the Middle East and North Africa, the Arab world, and Europe had a statistically proven causal effect on global natural gas commodity prices, but not in Europe. Except for Russia, natural resource depletion has shown statistical causality for crude oil over a two-month lag period. The significance and entropy of idiosyncratic corporate data were not satisfactory to the computation assumptions in the Granger-causality test given that accessible public data cover a short time span and are published annually or at most quarterly.

4. Results and discussion

4.1. Trained model as algorithm

Delving into the intricacies of our analysis, Figs. 4 and 5 serve as visual representations of the forecasted values derived from the decision tree models. These models, meticulously trained with similar parameters, hone in on significant features intricately linked to the energy price drivers within the contexts of both Italy and Austria. As we scrutinize these figures, not only are we presented with the projected values, but we also gain valuable insights through the accompanying mean absolute percentage error. This metric provides a quantitative measure of the accuracy and reliability of the models in predicting energy prices in the selected countries. The specificity of our approach in tailoring these models to the unique energy landscapes of Italy and Austria ensures a focused examination of pertinent factors influencing energy prices. By doing so, we aim to capture the nuanced dynamics of each country's energy market, contributing to a more comprehensive understanding of the projected values. Thus, Figs. 4 and 5 stand as instrumental visual aids, showcasing the effectiveness of our trained models as algorithms that adeptly capture and project energy price trends in the distinct environments of Italy and Austria.

The mean absolute percentage error for both the train and test data is negligible, indicating a high level of accuracy in the predicted values. The dependent variables, represented by Y_{pred} and Y_{true}, which correspond to the fictional energy token values in our study, align closely along the diagonal dashed line, indicating a perfect fit.

On the right sides of Figs. 4 and 5, the time series of energy token values is plotted for Italy and Austria, respectively. A noticeable overall downward trend can be observed in both cases, which can be attributed to the effect of inflation and interest rates from 2000 until February 2023. In this study, since the token value is mapped to energy

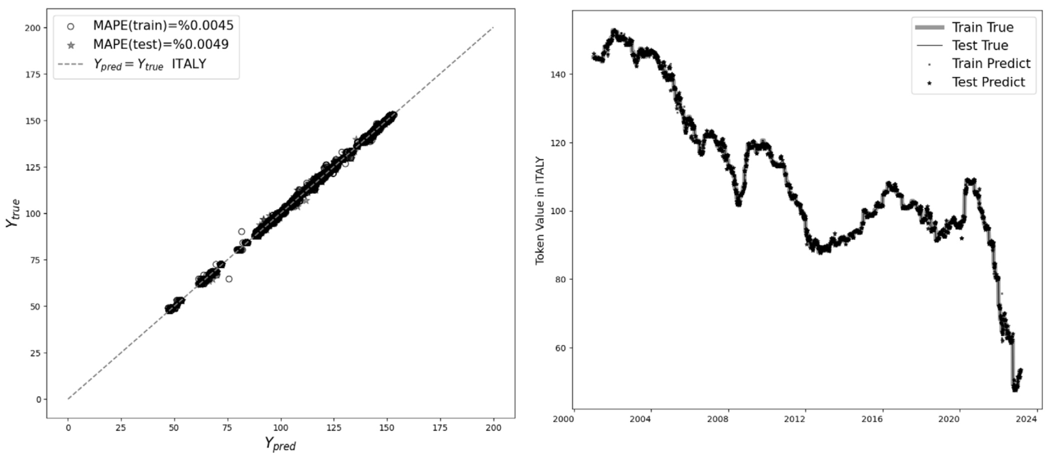

Fig. 4. GBoost regression results on Italy historical energy data.

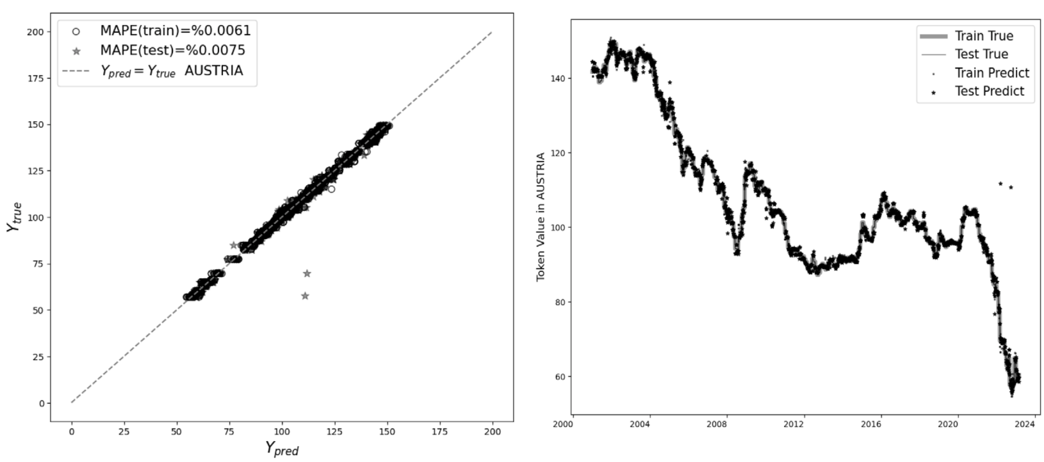

Fig. 5. GBoost regression results on Austria historical energy data.

basket prices, the general downward trend or negative drift is primarily influenced by the impact of interest rates and inflation on the energy Index of Consumer Prices ICP. However, in practice, this trend can be addressed by removing the inflation impact, adjusting the valuation to standard figures, and subsequently observing a positive trend influenced by inflation, similar to other financial assets. Nevertheless, the model used in this study effectively responds to the factors as explained by the aforementioned theoretical principles.

The cyclic movements of the token value, which are driven by the explanatory factors, are visualized using SHAP (Shapley Additive exPlanations) in this study, disregarding the overall trend. SHAP provides insights into the contribution of each explanatory factor in shaping the fluctuations of the token value over time. By analyzing the SHAP values, we can understand the relative importance and impact of different factors on the fluctuations observed in the token value.

To this end, the `SHAP` library in Python was employed to explain the complex model created by gradient boosting trees. SHAP stands for SHapely Additive exPlanations, and it prioritizes the relevance of feature values in the model's prediction capacity using game theory mathematics and loses each feature step by step to measure its impact on the dependent variable, as illustrated in Figs. 6 and 7.

In relation to the fictitious energy token value in Italy, Fig. 6 illustrates that the coal commodity price holds the highest priority. The red dots, representing higher feature values, are positioned on the left side of the model output diagram, indicating a negative correlation. The subsequent influential factors include the natural gas price in Europe, carbon allowance prices, crude oil, and Henry Hub NG, all showing negative correlations. On the other hand, ENI's GHG emission indicator, Italy's economic and financial risk exhibit positive correlations.

On average, the diagram indicates that Italy's energy token value would be more susceptible to changes in commodity prices rather than the financial status of a single major energy company. Despite ENI's recent investments in renewable energy, the impact of renewable energy generation in this particular scenario is negligible. Geopolitical and environmental indices hold the least significance. This highlights the importance of the proposed idea to establish an energy token pegged to a well-defined algorithm based on ESG (Environmental, Social, and Governance) policies. By doing so, authorities can seize the opportunity in the cryptocurrency market, formulate regulations, and introduce a national energy token. This approach aims to elevate the average importance rank of environmental issues in energy production while maintaining the same level of international geopolitical risk.

On the other hand, in Austria, its integrated energy corporation, OMV, has a greater impact on token value. Fig. 7 illustrates that as commodity prices, particularly gasoline, increase, the value of the energy token decreases. Similarly to Italy, higher prices for emission allowances have a noticeable effect on the token value, leading to a decrease. This is because the authorities generate revenue from the sale of carbon certificates and can reinvest the funds by providing loans to companies that adhere to stringent energy transition plans. Additionally, OMV's ESG scores also play a role in influencing the token value. In Austria, lower scores in ESG rankings result in an increase in token value. This allows the firm to secure financing for necessary improvements to enhance its ESG ranking and move closer to the net-zero goal.

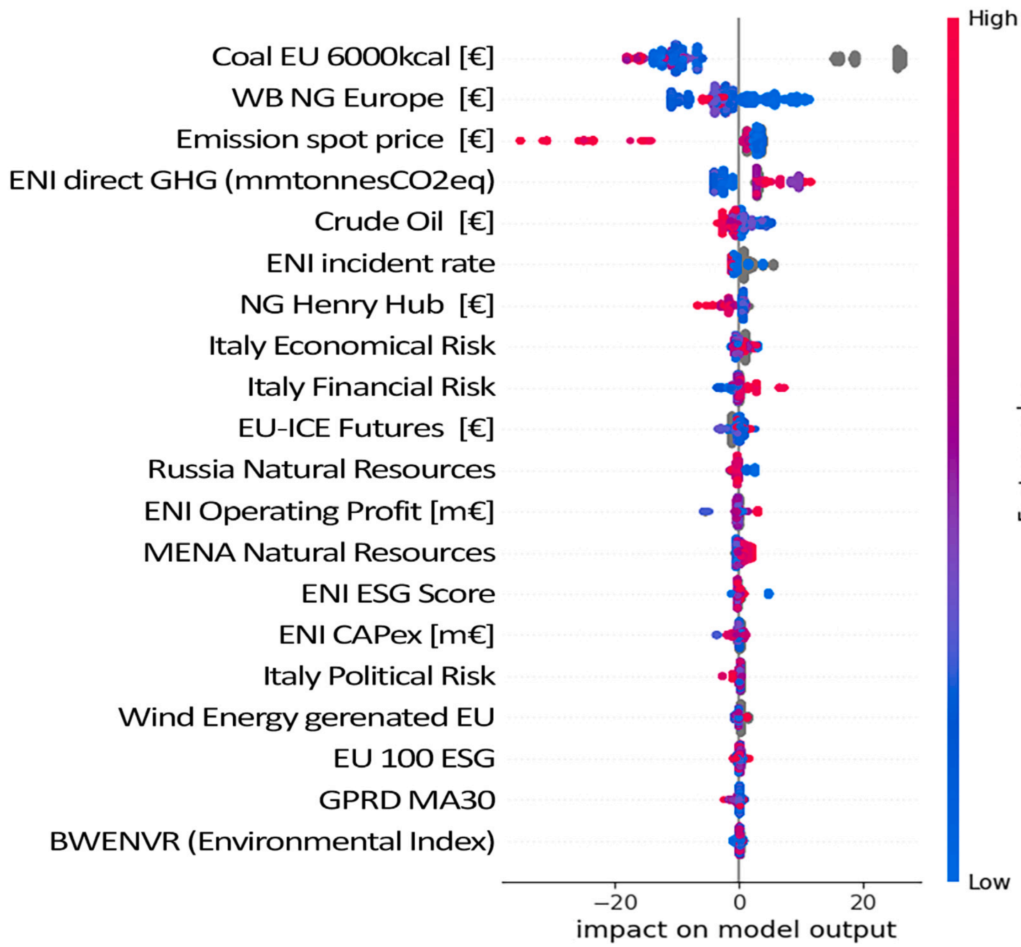

Fig. 6. Shapely additive explanation of GBoost regression on Italy energy token.

The fourth rank for OMV's operating income and its negative correlation highlight the fundamental financing challenge discussed in the Theory section. Following that, the influencing factors in Austria's decision tree model include energy commodity prices and the Russian resource depletion index. Interestingly, unlike Italy, environmental factors hold a higher position in Austria's model, indicating their relative importance. However, geopolitical risk is still considered to be of lesser significance compared to other factors.

4.2. Token application and trading mechanism

In addition to the exploration of the hypothetical token value model in this study, it is noteworthy that there are real-time energy tokens actively traded on the cryptocurrency market. Among these tokens, Energy Web Token[5] (EWT) holds particular relevance to the research concept under discussion. Fig. 8 illustrates the linear or rank-based correlation of the EWT price in EUR against energy commodity prices in EUR, employing Pearson, Spearman, and Kendall correlations. Remarkably, all correlation figures boast p-values well below 5%, providing statistical evidence of the existence of a negative correlation. This observation not only emphasizes the tangible application of energy tokens in the real-time cryptocurrency market but also underscores the potential influence of energy commodity prices on the value of these tokens. The negative correlation suggests that as energy commodity prices fluctuate, there is a discernible impact on the value of the EWT token, thereby establishing a dynamic relationship worth exploring further. As we navigate the evolving landscape of cryptocurrency and energy markets, the insights drawn from this correlation analysis shed light on the intricate interplay between energy token values and commodity prices. This nuanced understanding is pivotal for investors, policymakers, and industry stakeholders seeking to comprehend the broader implications of energy token dynamics in the context of real-time trading.

Table 2
Regression results of energy consumer price index on EWT.

	Italy HICP energy	Austria HICP energy	Euro area MUICP electricity gas & other fuels
EWT.EUR	−0.45261	−0.4694	−0.4766
Adj. R-Sq	20.51%	22.07%	22.75%

Furthermore, a linear regression on EWT.EUR was computed to examine the impact of new digital energy token, EWT, and their financing potential on the index of consumer prices in Italy, Austria, and Europe in general, albeit it is new and in development phase. As shown in Table 2, the coefficients for all of the equations are negative, associated with the negative correlations desired. Since both the regressor and dependent variables were standardized prior to regression, the ETW.EUR coefficients are comparable and can represent the sensitivity of energy price over EWT investment. The adjusted R-squared indicates that the EWT digital token investment can explain approximately 21% of the energy consumer prices on average. It is truly remarkable to elucidate that as of the advent of Web 3.0 in 2020, and with a mere handful of energy corporations as participants, nearly 21% of the variation in HICP prices can be attributed to a recently developed energy token.

[5] https://www.energyweb.org.

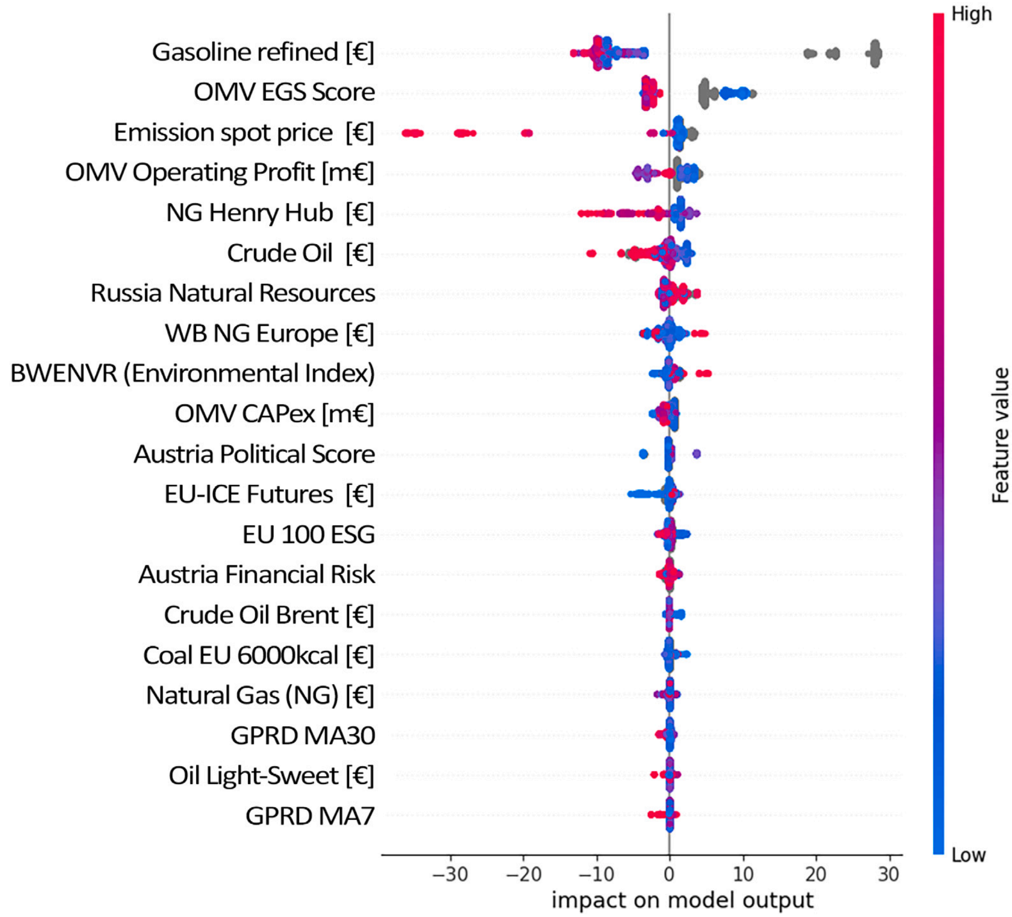

Fig. 7. Shapely additive explanation of GBoost regression on Austria energy token.

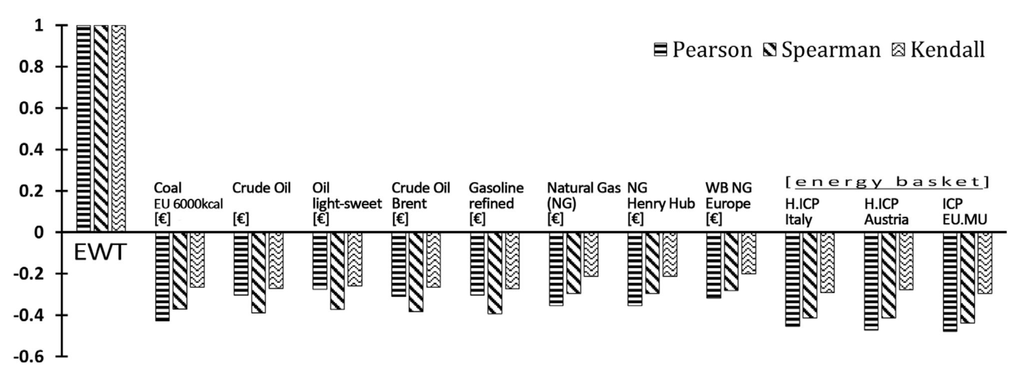

Fig. 8. Linear and Rank-based correlation between EWT and energy commodities.

In conclusion, the adoption of energy tokens as a financing mechanism emerges as a viable solution to address the challenges confronting energy suppliers, particularly those related to high debt burdens and the slow transition to green energy. Energy tokens, complemented by Proof-of-Stake mining technology, present a contemporary financing tool capable of imparting the necessary momentum to businesses in the energy sector. During periods characterized by economic growth and heightened energy consumption, energy suppliers typically find themselves as price takers. However, in instances where external factors, such as war and geopolitical issues, lead to surges in energy prices and subsequent declines in the value of energy tokens, companies can capitalize on elevated profit margins to fund their development plans. This phenomenon was notably evident in the financial statements of integrated oil and gas energy companies following the war in Ukraine in 2022. In essence, energy tokens wield the potential to facilitate the transition to green energy by furnishing energy companies with a flexible and efficient financing option. This capability is crucial in navigating the complexities of the energy market, ensuring adaptability during periods of economic fluctuations and geopolitical uncertainties.

In addition, the circular economy concept can be applied to the energy transition by leveraging energy coins. When energy prices are high and a company generates substantial profits, it can allocate a higher portion of its earnings for reinvestment (plowback). Additionally, the company can buy back energy coins from the market, increasing its stake and involvement in the mining rewards system. During periods when the company's budget is tight or there is a need for additional funds, it can either mine the energy coins it holds or sell them on the market. This flexibility provides a source of liquidity and financial resources that can be utilized to support the company's operations or investment plans. The business cycles and circularity of profits in this scenario are similar to the concept of share repurchase in the stock market.

On the flip side, a pertinent question emerges: why should investors consider purchasing energy tokens or coins? Let us consider the scenario where an individual, factory owner, or institutional investor, with inelastic exposure to energy prices, decides to invest in nationally developed energy coins. In the event that the value of an energy coin surges while energy commodity prices decline, investors stand to realize profits, and all appears favorable. However, the scenario takes a downturn when energy commodity prices experience a sharp increase. Energy coins, given their inherent negative correlation, suffer a significant loss in value, leading investors to face a challenging day as they witness the depletion of their assets while grappling with escalating energy bills.

Nevertheless, under the guidance of regulatory policies, the cycle of energy token mining, short selling, and buyback can be adjusted to market circumstances. This strategy facilitates also market access and capitalization for households engaging in a micro-grid energy supply and demand framework (Ramsebner et al., 2021).

Certainly, the concept of financing through decentralized tokens holds significant potential benefits for energy producers and investors looking to diversify their portfolios. Institutional investors, by incorporating energy coins into their portfolio, stand to gain from the potential upside of energy token appreciation during periods of low commodity prices. Simultaneously, this strategic inclusion serves as a hedge against potential losses in other energy investments when commodity prices experience an upswing. This diversification approach effectively mitigates overall risk exposure, bolstering the resilience and robustness of the portfolio.

Moreover, the availability of digital coins pegged to commodity prices provides a convenient and efficient way to access diversified energy assets without the need for physical ownership or complex trading mechanisms. It allows investors to participate in the energy market and benefit from its potential growth while maintaining a level of flexibility and liquidity.

In summary, while investing in energy coins may not be beneficial to individual investors, institutional investors with energy portfolios and energy producers may employ decentralized tokens tied to a factor model algorithm to diversify their holdings and effectively manage energy-related risks.

In addition to the imperative for regulatory frameworks in decentralized finance, there exists an opportunity to delve into more sophisticated valuation algorithms. One notable approach is the adoption of Reinforcement Learning (RL) algorithms. These algorithms have the potential to establish a nuanced connection between the value of an energy token and the aforementioned factors and market dynamics, all while aligning with national and international policies.

In RL algorithms, specifically, the valuation technique is not reliant on extensive data inputs but rather learns and adapts in response to market movements. Assuming the current value as $V(s)$, where s represents the "state" in RL, the implemented agent within the energy market factors makes decisions on the next value based on considerations of both company-specific and national interests in order to maximize rewards. The state transitions or variations in token value in this context, denoted as s to s', are limited to either increasing (↑) or decreasing (↓). Consequently, the Bellman equation in the RL algorithm can be expressed as follows:

$$V(s) = max_{\uparrow\, or \downarrow} \left(R(s,a) + \gamma V(s') \right) \tag{3}$$

where $R(s,a)$ is the reward given to the agent as an incentive to follow the policy within the algorithm, and the degree of it is based on the current state s and the actions a it takes to move to state s'. Within this equation, γ is the discount factor qualifying future token value.

In summary, within a Reinforcement Learning (RL) framework, the significance of historical data availability and granularity is diminished. Instead, token value transitions are guided by a comprehensive policy that addresses both energy security and the imperative for a green transition. This approach enables the token value to adapt and respond to changing conditions, providing flexibility in the system. Effective implementation of this algorithm and policy necessitates robust collaboration between blockchain companies and energy authorities at the national level. This collaboration is particularly crucial during the initial coin offering (ICO) stage, marking the introduction of the energy token to the market. Through concerted efforts, these stakeholders can ensure proper regulation, compliance with environmental standards, and the establishment of a robust framework for the energy transition. Such collaboration will enhance transparency, trust, and accountability in the financing and implementation of sustainable energy projects.

5. Conclusion

This research pioneers an innovative approach to financing energy transitions, steering away from conventional debt and equity methods. It proposes the development of an algorithmic national energy currency using blockchain technology, a concept explored within the unique contexts of Italy and Austria. The examination is framed by their distinctive energy consumption patterns and the challenges arising from the post-war landscape in Ukraine.

To discern the intricate dynamics influencing the proposed energy token, the research employs a gradient-boosting decision tree regression model. This analytical tool scrutinizes relevant ESG and GPR indices, commodity prices, and production KPIs. Notably, this model adeptly captures non-linear relationships and adapts to missing data, providing valuable insights into the significant features shaping token value fluctuations.

The study uncovers that the value of the fabricated energy token is adversely affected by the ascent of commodity and emission certificate prices. Governments are presented with an opportunity to leverage emissions allowance proceeds, steering corporations toward cleaner energy sources. The introduction of a national energy token not only emphasizes environmental controls but also maintains a steady level of international geopolitical risk.

Zooming into the simulated scenarios in Italy and Austria, the research elucidates a decline in the energy token's value in response to heightened commodity prices, notably for coal, crude oil, and natural gas in Italy, and gasoline in Austria. Concurrently, elevated emission certificate prices exert a substantial downward pressure on the token's value. It is noteworthy that in Austria, the influential role of the energy firm OMV in determining energy basket prices and the hypothetical energy token comes to the fore.

Delving into alternative financing avenues, the research underscores the role of cryptocurrencies, specifically those utilizing the Proof-of-Stake methodology. This provides governments and international policymakers with a lever to adjust token valuation by modifying climate-related thresholds or coefficients within the underlying algorithm. The adoption of energy tokens not only aligns with circular cryptocurrency principles but also facilitates the integration of newly developed PCAF guidelines, incorporating processes like mining and buyback.

This comprehensive approach transcends financial insights, weaving together strategic considerations and policy implications. In considering managerial implications, it is crucial for companies to remain vigilant about the impact of commodity prices and emission certificate costs on energy token values. This vigilance underscores the imperative of aligning corporate strategies with environmental goals, emphasizing the potential influence of emission allowances. This strategic alignment becomes pivotal in navigating the evolving landscape of sustainable energy financing.

Policy implications extend beyond corporate strategies to authorities, urging them to leverage emissions allowance proceeds as incentives for corporations. This approach fosters a transition to cleaner energy sources, placing governments in a pivotal role with the power to adjust token valuations through policy decisions. This underscores their regulatory influence in shaping the renewable energy landscape. Corporations, as recipients of incentives tied to emissions allowances, are strategically positioned to facilitate a smoother transition towards sustainable energy practices. This symbiotic relationship aligns with a broader global initiative for environmentally conscious practices, showcasing the interconnectedness of economic development and environmental considerations.

Finally, investors and financial analysts, as key stakeholders, are advised to factor in the influence of commodity prices and emission certificate costs when assessing the value of energy tokens. Understanding these dynamics becomes paramount in making informed investment decisions within the evolving landscape of sustainable energy financing. This holistic understanding enhances their ability to navigate the intricacies of the market and align investments with the principles of environmental sustainability.

In essence, the research transcends traditional financial insights by seamlessly integrating strategic and policy considerations. It presents a comprehensive picture of how energy tokens can reshape financial landscapes, acting as a bridge between economic development and sustainable energy practices. The interconnected nature of these considerations highlights the transformative potential of energy tokens in fostering a more sustainable and environmentally conscious future.

CRediT authorship contribution statement

Omid Razavi Zadeh: Conceptualization, Data curation, Formal analysis, Methodology, Software, Investigation, Project administration, Validation, Writing – original draft. **Silvia Romagnoli:** Conceptualization, Formal analysis, Project administration, Resources, Supervision, Validation, Visualization, Writing – review & editing.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107420.

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