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Special Issue Reprint

Emerging Trends in Energy Economics

Edited by
Periklis Gogas and Theophilos Papadimitriou

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About the Editors

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Periklis Gogas is a Professor of Economics at Democritus University of Thrace. He was recently a Visiting Scholar at the Ross School of Business at the University of Michigan. He received his Ph.D. degree from the University of Calgary, his Master's degree from the University of Saskatchewan and his B.A. from the University of Macedonia. His research interests include macroeconomics, financial economics, chaotic and non-linear dynamics, complex networks, machine learning and artificial intelligence applied to macro and finance. He regularly publishes in journals such as, the Journal of Money Credit and Banking, Journal of Banking and Finance, International Finance, Journal of Forecasting, International Journal of Forecasting, Physica A, Computational Economics, Economic Modelling, Open Economies Review, etc. He teaches graduate and undergraduate courses in Macroeconomics, Finance, Banking and Entrepreneurship at the Greek Open University, the Neapolis University of Pafos, the International Hellenic University and the Aristotle University of Thessaloniki. In the past he also taught at Plovdiv University, and the vocational center of the Athens Stock Exchange. He served for seven years as the Financial Director of a large Greek multinational corporation.

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Preface to ”Emerging Trends in Energy Economics”

In the intersection between Economics and Engineering, Energy Economics has been an active research topic for more than 150 years. From the 19nth century, the problem of creating, processing, storing and transporting Energy based on exhaustible resources (coal initially, oil, natural gas and electricity later) was well defined. It was during the major international oil crisis of 1973, however, that the national and international sociopolitical factors integrated with energy were identified, revealed, studied extensively and were finally incorporated in the scientific debate on Energy Economics. The increased interest in this multidisciplinary topic manifested in the publication of specialized scientific journals that focus and deal with this significant and complex issue. Energy Economics is a significant and broad segment of this line of research. Energy economics deals with the production, supply and demand of all forms of energy, the efficiency and optimization in the use of the relevant technology and know-how that pertains on the production, distribution and storage (when possible). It affects all aspects of real economic activity, both the supply side and the consumption. Moreover, Energy Economics include the study, analysis and forecasting of all forms of energy as a financial commodity. Investment, hedging and speculation are significant areas of research interest as with all commodities. Energy as a financial commodity that is traded in organized exchanges and over-the-counter in private contracts is an interesting, rigorous and very dynamic strain of research. The reason for this attention, is of course the significant changes that are materializing especially in industrialized countries i.e the European Union, the US, etc. These countries have started distancing themselves and limiting their use of fossil fuels – especially coal and oil. There is a transition to less dependence from those types of energy and towards renewable forms of energy that are environmentally neutral. As a result, the research interest on energy is keen and the research work on this area is also facilitated for the scholars by the availability of large sets of energy data in very high frequencies. Thus, it provides a fertile ground for the application of both traditional and emerging methodologies.

When we proposed the topic of this Special Issue for Energies, we were targeting for the innovation and the novelty in the area of Energy Economics with a special focus on production, distribution, storing, forecasting, financing, risk, taxation, trading, exchanges, networks, etc., in both spot and derivatives markets. We are very proud of the attention that our call for papers attracted from researchers in the field and of the resulting quality of the special issue that we composed from their innovative approaches.

In [4], Flouros e.a. compile a panel of 171 economies and use it to study the effect of geopolitical risk on the transition to a “green” economy. Ioannidis e.a. in [7] examine the recently introduced Target Model, its application in the wholesale electricity market of Greece and its impact on electricity prices. Chen and Rehman in [2] identify the critical periods in the trading of energy-related commodities employing an unsupervised Machine Learning framework. Balashova and Serletis in [1] uncover hidden linkages between the oil price uncertainty, the total factor productivity (TFP) growth, and the critical indicators of knowledge production and associated spillovers. Christopoulos e.a. in [3] investigated the effect that the Covid-19 pandemic and the stock market volatility have on oil price volatility. Three papers apply various forecasting techniques in forecasting energy: Gupta and Pierdzioch in [5] are forecasting the volatility of crude oil using the LASSO estimator, Hu e.a. in [6] forecast the Short-Term Load using the Ensemble Empirical Mode Decomposition coupled with the Salp Swarm Algorithm, and Mouchtaris e.a. in [9] forecast the Natural Gas Spot Prices using an arsenal of Machine Learning Methodologies. The Special Issue is concluded by two review papers: Menegaki in [8] summarizes and compares results of different studies in the energy-sustainable growth nexus for various groups of countries and Oliveira and Moutinho in [10] perform a bibliographic analysis on the topics of renewable energy, economic growth and the economic development nexus.

We express our gratitude to all the researchers that trusted their valuable research papers for our Special Issue. We must also thank all the editorial people from MDPI and the Energies journal that supported us along this effort and made the editorship a peasant and productive experience for us.

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Periklis Gogas and Theophilos Papadimitriou
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Editorial

Emerging Trends in Energy Economics

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In the intersection between economics and engineering, energy economics has been an active research topic for more than 150 years. From the 19th century, the problem of creating, processing, storing and transporting energy based on exhaustible resources (coal initially, oil, natural gas and electricity later) was well defined. It was during the major international oil crisis of 1973, however, that the national and international sociopolitical factors integrated with energy were identified, revealed, studied extensively and were finally incorporated into the scientific debate on energy economics. The increased interest in this multidisciplinary topic manifested in the publication of specialized scientific journals that focus and deal with this significant and complex issue. Energy economics is a significant and broad segment of this line of research. Energy economics deals with the production, supply and demand of all forms of energy, the efficiency and optimization in the use of the relevant technology and know-how that pertains to the production, distribution and storage (when possible). It affects all aspects of real economic activity, both the supply side and the consumption. Moreover, energy economics include the study, analysis and forecasting of all forms of energy as a financial commodity. Investment, hedging and speculation are significant areas of research interest, as with all commodities. Energy as a financial commodity that is traded in organized exchanges and over-the-counter in private contracts is an interesting, rigorous and very dynamic strain of research. The reason for this attention is of course the significant changes that are materializing especially in industrialized countries, i.e., the European Union, the US, etc. These countries have started distancing themselves from and limiting their use of fossil fuels—especially coal and oil. There is a transition to less dependence on those types of energy and towards renewable forms of energy that are environmentally neutral. As a result, the research interest on energy is keen and the research work on this area is also facilitated for the scholars by the availability of large sets of energy data in very high frequencies. Thus, it provides a fertile ground for the application of both traditional and emerging methodologies.

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Gupta and Pierdzioch in [6] are forecasting the volatility of crude oil using the LASSO estimator, Hu et al. in [7] forecast the Short-Term Load using the Ensemble Empirical Mode Decomposition coupled with the Salp Swarm Algorithm, and Mouchtaris et al. in [8] forecast the Natural Gas Spot Prices using an arsenal of Machine Learning Methodologies. The Special Issue is concluded by two review papers: Menegaki in [9] summarizes and compares results of different studies in the energy-sustainable growth nexus for various groups of countries, and Oliveira and Moutinho in [10] perform a bibliographic analysis on the topics of renewable energy, economic growth and the economic development nexus.

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Article

Oil Price Uncertainty, Globalization, and Total Factor Productivity: Evidence from the European Union

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Abstract: This paper uncovers linkages between oil price uncertainty, total factor productivity (TFP) growth, and critical indicators of knowledge production and spillovers. It contributes to the literature by investigating the effects of oil price volatility on TFP growth, controlling for two different channels for TFP growth; benefits from the quality of the national innovation system and from adopting new technologies. We use an unbalanced panel for 28 European Union countries for the period from 1990 to 2018. We find that oil price uncertainty has a negative and statistically significant effect on TFP growth, even after we control for technological advancements and the effects of globalization. We also find that the scale of research and innovation and international trade are positive contributors to TFP growth.

Keywords: economic growth; innovation activity; globalization; international trade

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1. Introduction

We use recent advances in macroeconometrics and financial econometrics to investigate the macroeconomic effects of oil price shocks and oil price uncertainty. In doing so, they appeal to the real options theory (also known as investment under uncertainty), which predicts that firms are likely to delay making irreversible investment decisions in the face of uncertainty about the price of oil, particularly when the cash flow from investments is contingent on the oil price.

In particular, we investigate the effects of oil price uncertainty on total factor productivity growth, and in doing so, we control for two different channels for TFP growth—benefits from the quality of the national innovation system and from adopting new technologies. We use an unbalanced panel for 28 European Union countries over the period from 1990 to 2018. Consistent with the earlier literature, we find that oil price uncertainty has a negative and statistically significant effect on TFP growth even after we control for technological advancements and the effects of globalization.

According to the Solow growth model [1], the aggregate value added (or GDP) growth can be decomposed into contributions from the aggregate capital input, K, aggregate labour input, L, and aggregate total factor productivity, TFP, as follows:

$$\Delta ln\text{GDP} = \nu_K \Delta ln K + \nu_L \Delta ln L + \Delta ln\text{TFP} \quad (1)$$

where ν_K is the output elasticity of capital and ν_L is the output elasticity of labour. Under the assumption of constant return to scale $\nu_K + \nu_L = 1$, TFP driven by factors, such as technological progress, that are not tied to explicit input usage. In theory, TFP growth captures technical change and overall efficiency.

We consider two separate channels of technological change: benefits from the National Innovation System and benefits from adopting new technologies. Even within the European Union (EU), there are countries with full-cycle national innovation systems and countries who mainly adopt rather than invent modern technologies. The former countries are referred to as "innovation leaders" and the latter as "innovation followers", using (here) the Innovation Union Scoreboard terminology in a slightly different manner. Thus, we consider different sets of key indicators to assess technological progress in different groups.

However, not only technological progress affects TFP growth. Globalization and openness of the modern economies suggest that there is an impact of the global business cycle on productivity. The linkage between the stock market volatility and business cycle was investigated in the literature (see, for example [2] and literature review in [3]). In addition, Elder and Serletis [4] and Serletis and Xu [5], among others, argue that volatility in oil prices has had a negative and statistically significant effect on several investment measures, durables consumption, and aggregate output.

Thus, we investigate the effects of oil price volatility on TFP growth, controlling for variables measuring technological progress and openness of the economy. Our study examines two central research questions. Firstly, we propose a regression model for TFP growth, combining different indicators depending on different innovation strategy types. Secondly, we assess uncertainty in commodity markets.

The rest of the paper is organized as follows. Sections 2 and 3 present the methodology used in the empirical investigation. Section 4 presents the data and the empirical results. Section 5 provides a discussion of the results and addresses the policy implications. The final section concludes the paper.

2. Research Model

We use the Conference Board Total Economy Database (TED) as a source of data for TFP growth (The Conference Board, 2019. The Conference Board Total Economy Database™, April 2019, http://www.conference-board.org/data/economydatabase/ accessed on: 10 March 2020). The database contains time series data for more than 120 countries, covering the period since 1990.

According to Jorgenson and co-authors [6,7], capital services and labour input are measured as translog aggregates of heterogeneous capital and labour types. Under the assumptions of competitive markets, full input utilization, and constant returns to scale, the contribution of each input to output equals the share of input cost to total cost—see Measuring Productivity [8].

TED capital is decomposed into Information and Communication Technology (ICT) capital and non-ICT-capital. Labour is decomposed into pure employment quantity and labour quality. One can find a detailed description of the sources and methods used to construct all TED variables in materials provided on the official website.

According to endogenous growth theory, TFP can be modelled as a function of a country's innovation capacity (see, for example, [9,10]). Innovation capacity depends upon the size and quality of the national innovation system, openness to international trade, the degree of technological specialization, and the ability to adopt and commercialize new-to-the-world technology.

We specify the TFP growth equation to reflect the role of the national innovation system as a source of productivity growth, the impact of technology spillovers, the role of international trade and FDI, and "the health" of the global economy as follows:

$$\Delta ln\mathrm{TFP}_{it} = \sum_{j} \beta^{j} X^{j}{}_{it} + \alpha_0 + \alpha_i + \delta Z_t + \varepsilon_{it} \tag{2}$$

where ε_{it} is an error term, i denotes a country, t denotes time, α_i captures country fixed effects, and Z_t accounts for the "health" of the global economy at time t.

As TFP growth is measured from the supply side, period effects in TFP growth models can capture global demand changes. We use oil price volatility to capture the 'health' of the economy and changes in demand instead of period fixed effect.

There are several channels through which oil prices may affect productivity. Firstly, at the end of 2019, before the pandemic, the global economy consumed around 100 million barrels of crude oil per day, compared to about 40 million barrels at the end of the 1970s (https://www.iea.org/reports/world-energy-outlook-2019. accessed on: 1 December 2020). In the case of stable oil prices, firms can more accurately plan their expenses and investments. Rising oil prices reduce the availability of inputs and lead to output decreases (see Hamilton [11]). The impact of oil price movements on GDP and several macroeconomic and financial variables for the United States economy has been widely investigated in the literature (see, for example, Barsky and Kilian [12], Kilian and Vigfusson [13], and Azad and Serletis [14], among others). In fact, Azad and Serletis [14] find the linkage between oil price uncertainty and macroeconomic indicators of emerging economies to be significant.

Secondly, financial and commodity markets are good indicators of the state of the global economy. The correlation between commodity (notably, crude oil) prices and equity prices after the global crisis has been established in the literature (see Lombardi and Ravazzolo [15]).

High volatility of financial and commodity markets causes fear among portfolio investors, and may increase risk aversion. In turn, it may reduce investments in risky innovation projects and slow down technological progress.

For EU countries, uncertainty in commodity markets is even more important, as these countries are pure importers of fossil fuels and other raw materials. According to Eurostat, (https://ec.europa.eu/eurostat/cache/infographs/energy/bloc-2c.html accessed on: 3 March 2021) the dependency rate (the share of net imports in gross inland energy consumption) was equal to 58% in 2018. The dependency rate on energy imports has increased since 2000, when it was just 56%, despite the increasing efforts to achieve the renewable energy directive target by 2020. Several barriers that were found for the United States and Russia (see [16]) are also relevant for EU countries (see, for example, [17]).

The vector X^j in Equation (2) captures a country's technological advancement and the effect of globalization.

R&D is one of the leading indicators of a national innovation system and potential readiness for technological advances. As R&D expenditure comprises all expenditure on research and development in business enterprises, the government sector, higher education and non-profit firms, it captures all national efforts on product and process innovations quite well. It is therefore suited as a proxy for technological innovation. In the EU, it is one of the main indicators of achieving the strategic goal to grow through innovations. We examine the impact of the growth rate of R&D expenditure on TFP growth to reduce heteroscedasticity in our model.

Globalization is one of the main trends of the last three decades, considered in this study. Public policy, which was changing in the 1990s and 2000s towards a free-market economic system, and communications technology innovations have been identified as the two primary driving factors of globalization. Nowadays, there is growing uncertainty in industrialized countries regarding whether globalization means more opportunity or more risk. Trump, Brexit and increasing populism are named direct consequences of this development (see [18]). However, we can't deny the impact of globalization on economic growth in general, and TFP growth in particular. One of our objectives in this study is to investigate the linkage between globalization and TFP growth.

There are several ways to measure globalization. For example, the KOF Globalization Index measures the economic, social, and political dimensions of globalization. (https://www.kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-globalisation-index.html. accessed on: 03 March 2021) We use factors included in the KOF Globalisation Index from an economic perspective, such as trade openness and free capital movement. Note that European countries are among the leaders in the globalization ranking.

Participation in international trade may be regarded as a driver of productivity increases (see [19]). Firstly, only efficient and highly productive firms can be successful in world markets. So, the increase in exports can be regarded as a sign of increasing productivity. On the other hand, EU firms mainly import raw materials and intermediate products to produce higher value-added products. So, the value of imports is also associated with productivity, at least in highly industrialized countries.

Secondly, for trading on the world market, the developed infrastructure is essential. To compete on global markets, firms need to be efficient in logistics, inventive in business processes, and successful in adopting advanced technologies. Thus, we consider the growth rate of both exports and imports to be a good candidate in explaining productivity dynamics for EU countries.

As the impact of FDI on TFP growth has been supported by many researchers, we examine FDI inflows and outflows. FDI inflows can bring technological, marketing and organizational innovations, at least in theory, affecting TFP growth. However, for the EU countries, the role of FDI outflows as a source of technology spillovers seems to also be important, as a sizable proportion of the EU outward flows typically are destined for the United States and other European countries (for example, Switzerland and Iceland) (https://ec.europa.eu/eurostat/web/products-datasets/-/bop_fdi6_geo accessed on: 3 March 2021). Moreover, transnational corporations (TNCs) benefit from investing in emerging countries [20], which can indirectly affect the TFP of the home country of the transnational corporations. Globalization is also characterized by an ongoing fragmentation of production [21]. More efficient production chains, achieved by lowering transaction costs while investing in countries with lower factor costs, are assumed to increase productivity.

The technological spillovers can also be captured through flows of payments for the use of intellectual property. We use charges for the benefit of intellectual property rights paid and received by a country to reflect the scale of new technology commercialization on the one hand and the scale of new technology adoption on the other hand.

3. Oil Price Volatility

To measure oil price volatility, we follow the procedure used in [22]. Our first step is to detrend the Brent oil price series and obtain the cyclical component, denoted as $Brent^{cycl}$. The volatility of oil price is then measured by the conditional variance of the forecast of the cyclical component of the oil price as follows:

$$Brent^{cycl}{}_t = \gamma_0 + \gamma_0\sigma_t + \varepsilon_t\sigma^2{}_t = \omega + \alpha\varepsilon^2{}_{t-1} + \beta\sigma^2{}_{t-1} \quad (3)$$

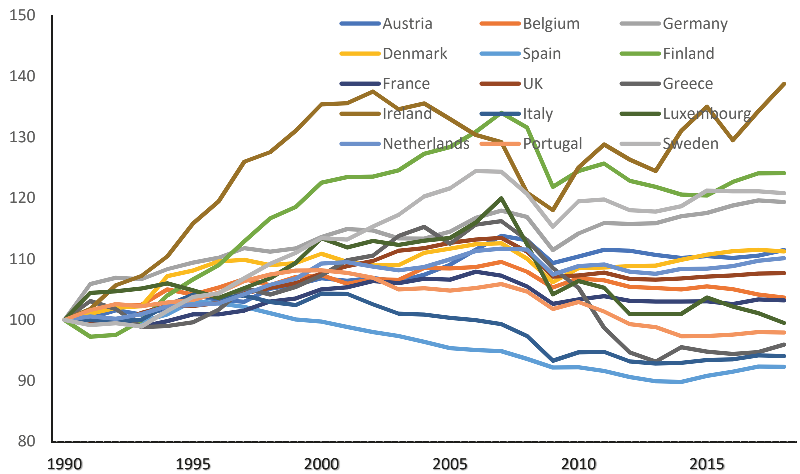
where $\sigma^2{}_t$ is the one-period ahead forecast variance based on past information (conditional variance), ε_t is a conditionally normal innovation. Thus, we use the GARCH-M(1,1) model, as in for example, [4,23,24], to measure oil price volatility. The GARCH-based measure of volatility is common in the empirical literature (see for example [25,26]).

4. Empirical Evidence

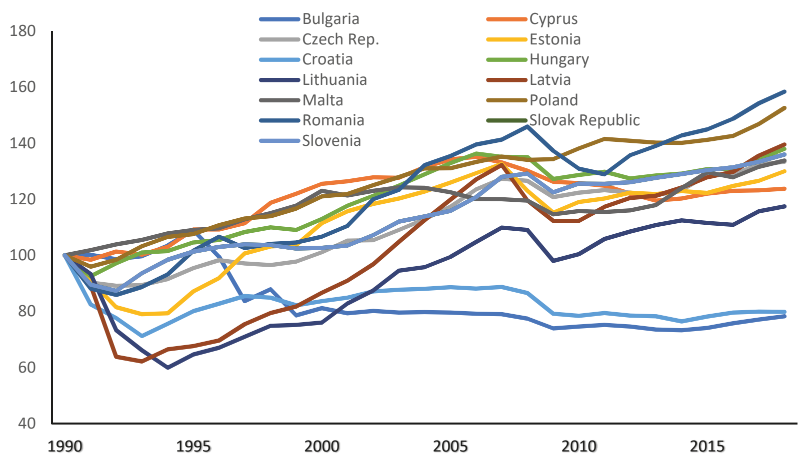
4.1. Data Description and Analysis

We retrieve data from TED, Eurostat, the OECD database, and the World Bank database. We use an unbalanced panel of 28 EU countries (including all EU members as of the end of 2019) for the period 1990–2018. Data on R&D expenditures, international trade and royalties are converted to constant PPP dollars. The growth rate is measured in log changes multiplied by 100.

To visualize the dynamics of TFP at a country level, we compute a country-specific TFP index. We create the index setting the year 1990 TFP level equal to 100 for each country. We show the TFP dynamics in panel (a) of Figure 1 for the EU15 countries and in panel (b) of Figure 1 for the EU13 countries, using data from the TED database.



(**a**)



(**b**)

Figure 1. (**a**) TFP dynamics by country, EU15 countries, 1990–2018. (**b**) TFP dynamics by country, EU13 countries, 1990–2018.

The dynamics of productivity vary significantly among the 'old' members of the EU. Ireland has the highest productivity gains, followed by Finland, Sweden and Germany (see panel (a) of Figure 1). The stagnating productivity trends in Spain and Italy are evident, and Greece shows a sharp decline in productivity in the 2010s.

The majority of the former communist states have shown an upward productivity trend since the early 2000s. For example, Romania is one of the most fast-growing EU countries in terms of TFP (see panel (b) of Figure 1). However, the TFP indexes for Bulgaria and Croatia are far below 100 in 2018, meaning that TFP in these countries was lower in 2018 compared to 1990. (It is to be noted that the TFP series for Croatia is based on TED estimates using data for Yugoslavia. http://www.conference-board.org/data/economydatabase/ accessed on: 10 March 2020) Notably, all countries display a noticeable decrease in productivity in 2009; however, the recovery rates are different.

To measure the uncertainty in commodity markets, we estimate the unknown parameters of the GARCH-M(1,1) model (3), using monthly observations of the Brent oil prices (see Figure 2).

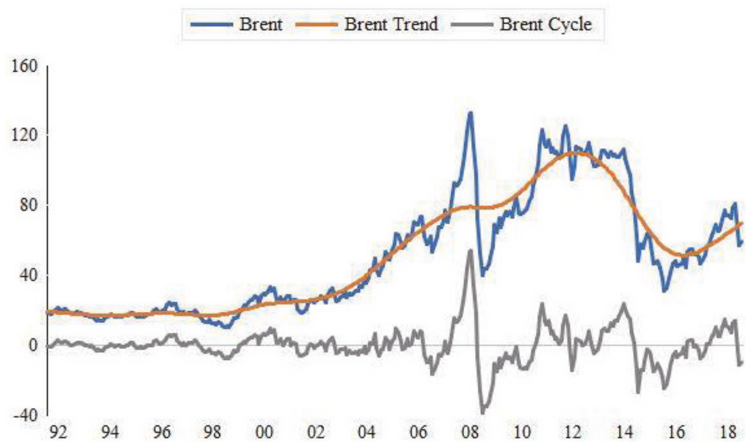


Figure 2. Trend and cyclical components of the Brent spot oil price. (FOB, dollars per barrel).

We obtain a one-period ahead forecast of monthly volatility from the GARCH-M model (3). The volatility Vol_T of the year T is measured as the monthly average of the one-year window:

$$Vot_T = \frac{1}{12}\sum_{j=1}^{12} \hat{\sigma}^2_{T,j}$$

where $\hat{\sigma}^2_{T,j}$ is an estimate of the GARH component of Equation (3) for year T at month j. We plot the obtained data in Figure 3. The sharp peak corresponds to the most significant uncertainty in oil and financial markets during the global financial crisis. This peak is closely associated with the consecutive steep decline in TFP growth of EU countries (see Figure 1).

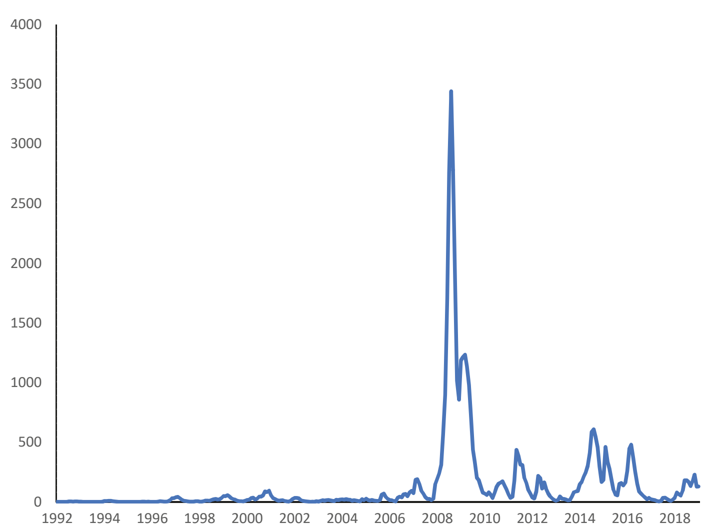


Figure 3. Oil price uncertainty from the GARCH-in-Mean model.

The model key variables' description and summary statistics are reported in Table 1.

Table 1. Variable's description and descriptive statistics.

Variable	Description	Source of Raw Data	MEAN	Std Dev	Obs
$\Delta ln\mathrm{TFP}_{it}$	Total factor productivity growth, log change, %	The Conference Board Total Economy Database™	0.49	3.35	808
Vol_Oil_t	Oil prices volatility	Europe Brent Spot Price FOB (Dollars per Barrel) from EIA	1.36	2.7	28
$\Delta ln(RD_{it})$	R&D expenditures growth, log change, %	Main Science and Technology Indicators (OECD), World Development Indicators	3.86	9.4	675
$\Delta ln(Trade_{it})$	International trade growth, log change, %	World Development Indicators	4.28	8.92	787
$\Delta ln(Royalty_{it})$	The growth rate of charges for the use of the intellectual property (receipts plus payments), log change, %	World Development Indicators	9.68	25.6	531
$\Delta(\mathrm{FDI\_}Inflow_{it})$	Change in FDI net inflow as % of GDP	World Development Indicators	0.15	23.9	765
$\Delta(\mathrm{FDI\_}outflow_{it})$	Change in FDI net outflow as % of GDP	World Development Indicators	−0.02	22.26	766

Note: Oil price volatility is defined for each of the 28 years and is a common factor for any country. The estimated values from the GARCH-M model are divided by 100.

Before running the regression model, we proceed with unit root tests for panel data. We use the the Levin, Lin, and Chu [27] test, assuming a common unit root proccess, and the Im, Pesaran, and Shin [28] ADF test, assuming individual unit root process in the considered time-series. Results are reported in Table 2.

Table 2. Unit root test.

Variable	Null: Unit Root (Assume Common Unit Root Process) LLC Test Statistic Probability	Null: Unit Root (Assume Individual Unit Root Process) Im, Pesaran and Shin Test Statistic Probability	Null: Unit Root (Assume Individual Unit Root Process) ADF Test Statistic Probability
$\Delta ln\mathrm{TFP}_{it}$	−15.5 0.000	−15.57 0.000	323.8 0.000
Vol_Oil_t	−15.8 0.000	−11.0 0.000	215.5 0.000
$\Delta ln(RD_{it})$	−11.0 0.000	−11.1 0.000	212.7 0.000
$\Delta ln(Trade_{it})$	−20.5 0.000	−18.8 0.000	365.4 0.000
$\Delta ln(Royalty_{it})$	−18.3 0.000	−15.85 0.000	302.1 0.000
$\Delta(\mathrm{FDI\_}Inflow_{it})$	−30.0 0.000	−28.8 0.000	548.3 0.000
$\Delta(\mathrm{FDI\_}outflow_{it})$	−25.7 0.000	−26.0 0.000	501.1 0.000

4.2. Estimation Results

The empirical analysis is conducted for 28 EU countries. Firstly, we estimate our model (2) with a single variable in vector X, namely the growth rate of real R&D expenditures, and oil price volatility, assuming the cross-section fixed effect. The Haussman test has shown that the random effects do not over-perform the fixed effects specification. The fixed effects specification suits better our analysis as we are interested in the country-specific part of the growth rate of TFP (parameter α_i in Equation (2)).

Then, we check whether the growth rate of international trade and changes in FDI inflows and outflows could improve the model specification. To reflect the impact of knowledge spillovers on total factor productivity growth, we include the royalty variable. It is calculated as the sum of receipts and payments for the use of intellectual property rights.

Table 3 summarizes the estimated impact of R&D expenditures, international trade and royalties, changes in FDI flows and oil price volatility on TFP growth.

Table 3. The estimated effect of global and domestic factors on TFP growth for EU28 (refers to EU members as of the end of 2019).

	Dependent Variable = ΔlnTFP$_{it}$		
	Basic Model	**Openness**	**Technology Spillover**
	(1)	**(2)**	**(3)**
Vol_Oil_t	−0.34 *** (0.03)	−0.25 *** (0.04)	−0.24 *** (0.03)
$\Delta ln(RD)_{it}$	0.06 *** (0.01)	0.03 *** (0.01)	0.02 ** (0.01)
$\Delta ln(Trade)_{it}$	——	0.12 *** (0.03)	0.13 *** (0.01)
$\Delta(\mathrm{FDI}\_inflow)_{it}$	——	−0.01 *** (0.003)	−0.007 (0.006)
$\Delta(\mathrm{FDI}\_outflow)_{it}$	——	0.01 *** (0.002)	0.012 * (0.006)
$\Delta ln(Royalty)_{it}$	——	——	0.0069 ** (0.0030)
Constant	1.0 *** (0.1)	0.43 * (0.2)	0.41 *** (0.1)
Cross section fixed effect	significant	significant	significant
Adjusted R^2	0.32	0.45	0.52
Observations	661	654	489

Notes: White cross-section standard errors in parentheses, *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10.

In order to analyze whether the effects of technological innovations, openness and knowledge spillovers differ between countries with different historical and economic development, the countries are divided into two groups: "old" and "new" EU members, which is relatively common in empirical analyses.

To test for equality of means of TFP growth rates between the EU15 and EU13 countries for the 1990–2018 period, we run the Satterthwaite–Welch t-test, which allows for unequal variances. We cannot reject the null hypothesis that the mean growth rate is equal for these two groups at the 5% significance level (the test statistic is equal to 1.9 with a p-value of 0.056). However, we assume that the impact of different factors on total factor productivity differs between countries with mature and developing markets.

4.3. Discussion

All "old" EU countries (except Finland) have negative country-specific "fixed" growth rates of TFP, although, in the case of Austria and Germany, the coefficients are very close to zero. All "new" EU countries have positive country-specific 'fixed' growth rates of TFP, with Latvia and Lithuania having the highest values. The effect is partly due to a "low base" TFP in the former Soviet countries.

R&D expenditure growth has an impact on productivity in all EU countries. The openness of the economy also helps to boost productivity growth in all EU countries. This is in line with the findings of the "Globalization Report 2018: Who Benefits Most from Globalization?" It was shown that "for the third time in a row, as in 2014 and 2016, when measured in terms of real gross domestic product (GDP) per capita, industrialized countries continue to be the biggest winners of increasing globalization, while developing and emerging economies lag behind".

Our findings of the positive impact of FDI outflows on productivity growth are consistent with the results obtained by Altomonte and Ottaviano [29] in their study of the role of international production sharing in EU productivity at the micro-level. Royalties are more important for the EU13 countries than for the EU15 countries. Among the EU13 countries, almost all countries except Hungary, pay a lot more for the intellectual property rights than they receive from other countries.

5. Conclusions

Total factor productivity measures the overall efficiency of labour and capital in the production process. During the examined period, from the early 1990s to the late 2010s, the EU countries showed a growth trend in the total factor productivity on average.

We assume that the total factor productivity is influenced by several groups of factors. Firstly, it is research and development carried out in a given country. For developed countries (most EU countries belong to this group), innovation is the most important driver of economic growth. We use internal R&D expenditure as a proxy variable for assessing the scale of research and innovation. We find that growth in R&D spending is associated with an increase in the TFP growth rate, all other things being equal.

The second group of factors includes indicators of the openness of the economy. These include the volume of foreign trade and inbound and outbound foreign direct investment. High competition in international markets increases the demands on companies to be more efficient and productive. Thus, it contributes to an increase in the overall productivity of the economy. We find a significant positive effect of international trade on TFP growth.

The impact of FDI inflow on productivity in developing countries is well documented in the literature. The positive effect of FDI-trade linkage lies in its contribution to integrating the host country into the world economy. The same is relevant for the former communist European countries which experienced a transition to a capitalist economic system during the 1990s. The impact of FDI outflow on the productivity of the home country is less examined in the empirical literature. Our estimates show that, controlling other variables, the impact of FDI inflow on TFP growth is not significant; however, the impact of FDI outflow is positive and significant.

However, it is not only innovation, technology and the overall efficiency of companies that drive productivity growth. Uncertainty on world commodity and financial markets plays a significant role and can have negative effects on economic growth. The volatility of the oil market, which is closely related to the volatility of other markets, inhibits the growth of total factor productivity, as shown in the study.

In this paper, we have focused on the effects of oil price shocks and oil price uncertainty on total factor productivity. Assessing the importance of oil price shocks, by simultaneously evaluating the effects monetary policy shocks, fiscal shocks, and other measures of risk and uncertainty, is an area for potentially productive research.

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Article

A Pattern New in Every Moment: The Temporal Clustering of Markets for Crude Oil, Refined Fuels, and Other Commodities

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Abstract: The identification of critical periods and business cycles contributes significantly to the analysis of financial markets and the macroeconomy. Financialization and cointegration place a premium on the accurate recognition of time-varying volatility in commodity markets, especially those for crude oil and refined fuels. This article seeks to identify critical periods in the trading of energy-related commodities as a step toward understanding the temporal dynamics of those markets. This article proposes a novel application of unsupervised machine learning. A suite of clustering methods, applied to conditional volatility forecasts by trading days and individual assets or asset classes, can identify critical periods in energy-related commodity markets. Unsupervised machine learning achieves this task without rules-based or subjective definitions of crises. Five clustering methods—affinity propagation, mean-shift, spectral, *k*-means, and hierarchical agglomerative clustering—can identify anomalous periods in commodities trading. These methods identified the financial crisis of 2008–2009 and the initial stages of the COVID-19 pandemic. Applied to four energy-related markets—Brent, West Texas intermediate, gasoil, and gasoline—the same methods identified additional periods connected to events such as the September 11 terrorist attacks and the 2003 Persian Gulf war. *t*-distributed stochastic neighbor embedding facilitates the visualization of trading regimes. Temporal clustering of conditional volatility forecasts reveals unusual financial properties that distinguish the trading of energy-related commodities during critical periods from trading during normal periods and from trade in other commodities in all periods. Whereas critical periods for all commodities appear to coincide with broader disruptions in demand for energy, critical periods unique to crude oil and refined fuels appear to arise from acute disruptions in supply. Extensions of these methods include the definition of bull and bear markets and the identification of recessions and recoveries in the real economy.

Keywords: energy commodities; financial crises; Brent; WTI; gasoline; clustering; *t*-SNE; machine learning; COVID-19 pandemic

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1. Introduction

1.1. The Motivation for this Research

Crises loom large in finance and macroeconomics. Defining transitions between bull and bear markets, or between recessions and expansions, helps identify distinctive financial or economic regimes. Commodity markets, especially those related to petroleum, undergo their own fluctuations. Indeed, abrupt and abnormal movements within these notoriously turbulent markets often signal trouble in other sectors of the broader economy. Oil price volatility, in particular, experiences structural shifts. The intense financialization of commodities, including crude oil and refined fuels, heightens the importance of identifying shifts and disruptions in volatility across time.

This article proposes a novel method for identifying critical moments in commodity markets, ranging from structural shifts to abrupt disruptions. It places special emphasis on markets for crude oil and refined fuels. Unsupervised machine learning can distinguish crises from normal conditions. It can identify anomalies within an economic time series and set those trading days apart for closer examination, as opposed to finding time time-varying effects through conventional analysis.

Recent work by the authors has demonstrated the use of clustering and manifold learning to arrange commodities into discrete markets for fuels, precious metals, base metals, and agricultural commodities by climate [1]. In an extension of that work, this article focuses more closely on the *temporal* domain of these markets. A suite of clustering can identify critical periods affecting all commodity markets, such as the 2008–2009 global financial crisis and the COVID-19 pandemic. These critical periods also affect markets specific to oil and refined fuels. Even closer examination reveals additional periods of special interest to energy-related markets. Most of those periods are shorter, acute supply disruptions through extreme weather or acts of war.

As between the clustering of commodities and trading days, temporal clustering poses the greater technical challenge and offers the greater practical reward. Discrete commodity markets number in the dozens. A comprehensive span of financial history can cover thousands of trading days. The configuration of commodities in metaphysical financial space need not observe a particular order. By contrast, cogent, temporally defined market regimes must represent contiguous or nearly contiguous blocs of trading days.

Certain branches of finance and macroeconomics seek to define cyclical peaks and troughs. Many conventional definitions of bull and bear markets or recessions and expansions within the broader economy, however, rely upon arbitrary benchmarks or even subjective judgment. If stock prices fall more than 20 percent from a recent peak, for instance, many analysts are prepared to declare the onset of a bear market. A 10 percent decline, by contrast, is labeled a "correction."

Relative to these arbitrary, categorical distinctions, a mathematically informed treatment of conditional volatility forecasts may identify contiguous or nearly contiguous clusters of trading days. Although this article does not immediately pursue the possibility, the methods that it applies may ultimately enable new ways to identify distinctive regimes in financial markets or the broader economy. Though bull-and-bear market indicators and peak-and-trough definitions of the business cycle will undoubtedly persist, data-driven alternatives or complements may arise from unsupervised machine learning and related forms of artificial intelligence.

Unsupervised machine learning also obviates disputes over the definition of local maxima and minima across potentially expansive spans of financial history. These methods serve as an extended metaphor for one of the greatest challenges in machine learning and artificial intelligence: determining whether a model has been globally optimized, or whether an optimization algorithm has converged locally.

By the same token, reliance on unsupervised machine learning presents challenges unique to this set of methods. Unlike conventional regression-based methods or their equivalents within predictive applications of supervised machine learning, unsupervised methods such as clustering and manifold learning are not typically used to validate research hypotheses. They struggle to perform either of the traditional tasks in economics. Other methods outperform unsupervised machine learning in forecasting values and in enabling causal inference. What unsupervised machine learning does excel in doing, however, is revealing patterns within data itself, without reliance on labels, values, or research hypotheses formulated by human analysts.

Mindful of the potential of unsupervised machine learning, as well as its limits, this article targets questions that routinely arise in traditional research on commodities, broader financial markets, and the real economy. This article answers those questions in the narrower, more specific context of energy-related commodities. There is intense interest in comovement and connectedness among commodities trading, financial markets, and macroeconomic phenomena. These relationships are known to vary across time. At its most intriguing, time-varying conditional volatility supports hypotheses regarding cyclicality and structural shifts in many branches of economics.

This article asks whether raw data consisting of nothing more than logarithmic returns or conditional volatility forecasts can distinguish among ordinary trading days, acute crises that bend the arc of energy commodities trading sharply but only temporarily, and more enduring turning points that can credibly be described as turning points or structural shifts. If unsupervised learning succeeds in this task on a limited slice of the economic universe, then this article may support new approaches that can complement traditional peak-to-trough methods of defining cyclicality in financial markets and the broader business cycle.

1.2. A Section-by-Section Summary

Section 2 of this article reviews the literature on comovement and volatility spillovers in commodity markets, particularly those involving energy. Section 2 also reviews the literature on rules-based definitions of bull and bear markets and economic recessions. This extended review of the relevant economic literature provides complete background on volatility in crude oil and refined fuel markets. Section 2 ultimately explains why connections between commodities trading, financial markets, and the broader economy motivate efforts to describe cyclicality and other manifestations of variability in the volatility of energy-related markets over time.

Section 3 presents data sources and describes the unsupervised machine-learning methods underlying this article. Conditional volatility forecasts based on a GJR-GARCH(1, 1, 1) process for 22 commodity markets from 2000 through 2020 constitute the primary data source. The subarray containing volatility forecasts for four oil and fuel markets provides the central focus. Logarithmic returns, for all commodities and the energy-specific subset, constitute an additional source of data.

Section 4 aggregates results from five clustering methods—affinity propagation, mean-shift, spectral, *k*-means, and hierarchical agglomerative clustering—as applied to a comprehensive market basket of 22 commodities and to a more focused basket of four energy-related commodities: Brent, West Texas intermediate, gasoil, and gasoline. *t*-distributed stochastic neighbor embedding, or *t*-SNE, helps visualize all clustering results.

Meaningful temporal clusters for broader commodity markets delineate the global financial crisis and the COVID-19 pandemic. Focused clustering in energy-related markets identifies several additional critical periods for crude oil and refined fuel markets. Section 5 presents and distinguishes those two sets of results.

Section 6 discusses the implications of this article's findings for managers, investors, and policymakers. Critical periods in energy-related markets demand a different approach to hedging and risk management, not merely for commodity investors, but also for investors using commodities to neutralize other sources of risk. The role of energy-related crises in macroeconomic policymaking also warrants careful consideration.

The identification of temporal regimes in commodity markets through clustering suggests the generalizability of unsupervised machine learning to other markets and to macroeconomic data. The second half of Section 6 describes these and other possible paths for future research.

2. Literature Review

The economic literature germane to this article spans four distinct subjects:

1. Price volatility in oil and refined fuel markets;
2. Comovement and volatility spillovers between these energy-related commodities and other commodity markets;
3. Similar connections between energy-related commodity markets, other financial markets, and the real economy;
4. Methods for identifying cyclicality and other time-varying effects in commodity markets, stock markets, and the real economy.

This section addresses each body of literature in turn. A review of the relevant literature on unsupervised machine learning is deferred until Section 3′s presentation of materials and methods.

2.1. Price Volatility in Crude Oil and Refined Fuels

2.1.1. Oil Price Volatility

Commodity markets figure prominently in developmental economics and international trade. Representing a quarter of global trade in goods, commodities provide the most important source of income for some of the world's poorest countries [2,3]. Because advanced economies rely so heavily on petroleum-based fuels for transportation and many industrial processes, the wealth of developed nations also hinges on oil-based commodities [4].

The pervasive financialization of commodities raises the premium on proper understanding of the price and volatility dynamics in these markets [5]. This is particularly true of crude oil and fuels refined from it [6–9]. Producers and industrial customers have the greatest stake, since oil price volatility directly affects investments in oil inventories, production and transportation facilities, and physical capital based on oil consumption [10]. These sunk investments demonstrate why "costly reversibility" is a prime mover in the economics of market structure and industrial organization [11–14].

Because of their intrinsic volatility and their dependence on global supply chains, energy markets are especially sensitive to external shocks. The diverse factors affecting oil prices include sociopolitical disturbances, shifts in the global supply and demand, and technological and regulatory changes promoting demand for renewable energy [15]. Discrete events, "such as wars, the release of OPEC production quota decisions, oil stock fluctuations and extreme weather," also affect oil prices [16] (p. 256).

Chronic or acute, these factors are never stable. Structural breaks punctuate the time-varying conditional heteroskedasticity of oil price volatility [17]. Although conventional tools for forecasting oil prices and volatility abound [18,19], models that ignore structural breaks and other sources of temporal variability in volatility "will have very low power" [17] (p. 555). This is yet another instance in which accurate forecasting relies upon the more realistic assumption that volatility does not remain constant [20].

2.1.2. Refined Fuels: Gasoline and Gasoil (Diesel)

Because gasoline and gasoil are refined petroleum products, their price and volatility dynamics depend heavily upon the economics of oil. These markets are nevertheless subject to forces befitting their proximity to retail consumers. Gasoline and gasoil are affected by time-varying consumer income [21] and the price elasticity of demand for petroleum-based fuels among other retail-level energy sources [22]. Demand for gasoline may be less elastic than typically assumed, especially in the short run [23].

Perhaps the most distinctive trait of the price behavior of refined fuels, particularly gasoline, is its asymmetry [24–27]. The "rockets and feathers" hypothesis posits that increases in crude oil prices are transmitted much more quickly to gasoline than decreases [28–30]. Data across the United States showed that retail gasoline prices increased 0.52 percent within the first week of an anticipated 1 percent increase in oil prices, but fell 0.24 percent within the first week of a 1 percent decrease [31].

Other sources describe asymmetry in gasoline pricing according to Edgeworth price cycles, characterized by sawtooth-shaped time series consisting of many price decreases punctuated by occasional upward jumps [32,33]. Straightforward measurements of gasoline demand have shown that elasticity decreases as volatility rises [34,35]. Both the "rockets and feathers" hypothesis and Edgeworth price cycles are consistent with this account of volatility.

Other sources contest the presence of asymmetry in the relationship between oil and refined fuel markets [36]. Asymmetry, if present for gasoline and gasoil in Europe, is fleeting and appears over very short time horizons [37]. Asymmetry appears in Spain and

Italy, but not in Greece, the United Kingdom, or the United States [38]. Time-varying effects such as volatility clustering and structural breaks affect the degree of asymmetry in the transmission of volatility from oil to gasoline [39]. Findings of asymmetry may depend on the frequency at which volatility data is sampled [40].

One study reaches an intriguing conclusion: The "rockets and feathers" hypothesis tells the dominant story of oil–gasoline asymmetry, but not the exclusive story [28]. When oil prices are falling, on average, gasoline prices follow a contrary "boulders and balloons" dynamic by which gasoline more swiftly tracks oil price declines than increases. The reversal in the polarity of oil–gasoline asymmetry strongly suggests that volatility transmission between crude oil and refined fuels varies over time. Indeed, the presence of opposite tendencies, based on the timing of the broader business cycle, suggests that asymmetry, persistence, and cyclicality in volatility must be understood in the context of other capital markets and the macroeconomy [41,42].

Though literature on the price dynamics of gasoil is relatively sparse and inconclusive, national fuel mix policies appear to account for some of this fuel's differences relative to gasoline [43]. The European Union [44] and the United Kingdom [45] both nudge their transportation sectors to favor gasoil over gasoline. With mixed success, the United States has maintained a heating oil reserve to stabilize prices for this variant of gasoil, widely used to heat homes in the northeastern region of that country [46]. Home heating can be expected to be one of the least elastic sources of demand for gasoil, at least over short time horizons, for households that depend on this fuel.

2.2. Comovement and Volatility Spillovers within Commodity Markets

2.2.1. The Financialization of Commodities and Hedging Strategies

As a prime outgrowth of the coordination of commodity markets with other aspects of global finance [5], comovement and volatility spillovers among commodities warrant careful evaluation [47]. Commodity futures have become popular tools for diversification [48,49]. Tools for managing financial risk in other capital markets apply directly to energy-related commodity markets [50]. Commodities as safe havens can offset turbulence from other asset classes, from equities to currencies [51]. The "universe of financial assets," spanning diverse "investment strategies," heightens the importance of "risk transfer between oil" and markets for other "global, large and liquid" assets [52] (p. 56).

Unstable energy prices often induce investors to hold other assets alongside energy commodities. Hedging strategies and portfolio rebalancing enable investors to manage comovement [53]. At a minimum, oil price shocks affect non-energy commodities [54–57]. A study of volatility in oil and refined fuel should therefore consider comovement and volatility spillovers linking energy with other commodity classes, especially metals and agricultural products.

2.2.2. Precious Metals

The traditional role of precious metals as hedges against inflation and economic turbulence [58] casts those commodities in sharp relief against crude oil and refined fuels [59–61]. Markets for oil are more volatile than markets for gold and silver [62]. Precious metals exhibit hedging and safe haven properties *vis-à-vis* energy [49,59,63,64]. Connections between gold and oil extend to other financial instruments [60,65].

Financial risk may not run equally between two markets. Among instances of volatility spillover in commodity markets [66–68], the propensity of oil to transmit volatility to precious metals poses the greatest challenge to investors in energy-related commodities [69–72]. As the global financial crisis of 2008–2009 demonstrated, precious metal returns may be more sensitive to disaggregated structural oil shocks [72].

2.2.3. Base Metals

Because oil prices heavily affect input costs for industrial processes using base metals, connections between energy markets and metals extend beyond gold, silver, platinum, and palladium [73,74]. Although one study identified platinum, gold, and silver as net transmitters of volatility to oil [60], such spillover may not persist across all periods and market states. Indeed, traditional distinctions between precious and base metals may not hold across all financial conditions. Tin, gold, nickel, lead, and aluminum transmit return and volatility to oil markets. Copper, zinc, and platinum are net receivers—but only "at certain specific moments" [75] (p. 12). Time-varying fluctuations became especially pronounced during the global financial crisis [60] and the COVID-19 pandemic [75].

2.2.4. Agricultural Commodities

Energy markets also transmit volatility to agricultural commodities [3,71,76–79]. The dependence of agricultural commodity markets on energy prices varies over time [80]. A structural break appears to have shifted the relationship between oil and agricultural commodities after 2006 [81]. Sources differ in attributing the disruption to a change in biofuels policy [76] or to a broader crisis in food crops [78].

The relationship may vary more subtly over time [80]. During periods such as the financial crisis of 2008–2009, oil and agricultural commodity markets crash simultaneously. Connectedness likewise strengthened during the COVID-19 pandemic [82]. Under normal economic conditions, however, these markets move in opposite directions. This pattern implies that hedging will fail in the very conditions when hedges would prove most valuable. The counterbalancing effect also denies investors the opportunity to realize excess profits in both markets.

These conclusions are neither universal nor inevitable. A different study focusing on common crisis periods such as the global financial crisis and the pandemic rejects two key conclusions of other studies [83]. Oil and crops have a bidirectional relationship in which each class of commodities transmits volatility to the other with roughly equal probability over long time horizons. As a surprising consequence, oil and agricultural prices remained relatively stable throughout the pandemic.

Certain crops (particularly corn and soybeans) either compete directly against crude oil as a renewable substitute or serve as a complementary product [84]. A third crop, sugarcane, affects these markets because of its substitutability for corn [85]. Conventional wisdom holds that high oil prices invite competition from corn-based ethanol and soybean-based biodiesel [86].

This relationship, like many others, appears to depend on the state of the market: Spillovers from oil to agricultural and biofuel markets are stronger when oil prices are higher [87]. Conversely, concerns over the diversion of common-pool resources used in agriculture from food to fuel production reach their peak during economic crises [88].

Closer scrutiny of the impact of biofuel policies on oil and gasoline price variability [89] has not found conclusive evidence that energy markets spur volatility in corn [90] or that policy-stimulated demand for biofuels has elevated prices or volatility in agricultural markets [91]. The answer to the conundrum may lie in the limited economic impact of biofuel policies. If such policies were abolished around the world, biofuel demand would implode without materially affecting overall demand for agricultural commodities [92].

2.2.5. The Geopolitics of Energy-Related and Agricultural Commodities

The prominence of oil and export crops in many developing economies heightens the economic, political, and diplomatic sensitivity of volatility spillovers involving those markets [3]. Connectedness between these commodities bridge distant geographic markets, such as Chinese crops and crude oil, whether around the world [93] or specifically in the United States [94]. As a rule, however, research on the impact of oil price volatility on developing countries that import rather than export petroleum remains limited [95].

A global study spanning 157 countries at different stages of development attributed 40 percent of income volatility to oil price fluctuation [96]. Though "the adverse effects of [price] instability" are often "much more severe" in developing countries, those governments can rarely afford "the extensive support programs that typify the agricultural sectors of the developed world" [97] (p. 1729). Dependence on natural resource extraction is so often associated with stunted economic development that this paradox is known as the "resource curse" [98–101].

Geopolitical tension from oil divides importing and exporting countries [102,103]. Importing countries must rely on insecure foreign sources of an economic lifeblood [104], while global trade and politics drive fiscal policy and economic cycles in exporting countries [105]. The rapid emergence of China portends the revival of a Great Game among global superpowers in central Asia and other oil-rich regions [106].

Again, however, the economic effects are asymmetrical. Economic reactions to energy price shocks in exporting countries are greater and more persistent than in importing countries [107]. In the long run, both oil-importing and -exporting countries stand to lose. At least among OECD countries, oil price volatility stunts economic growth in net importers, while oil price uncertainty hurts net exporters [108]. Furthermore, to the extent that oil price volatility suppresses international trade and globalization, the ensuing reduction of global welfare harms all countries [109].

2.3. Broader Financial and Macroeconomic Effects of Oil and Fuel Price Volatility

2.3.1. Financial Markets beyond Commodities

Oil markets transmit volatility to other capital markets, including equity markets [110,111]. Although one study concludes that the American stock market is neither a net transmitter nor a net receiver of volatility relative to oil or precious metals [60], others have found spillover effects in smaller economies such as Iran [112] and South Korea [113].

Stock returns and stock market volatility in oil-exporting countries such as Qatar, Saudi Arabia, and Venezuela are assuredly affected by oil prices [114]. These effects follow a regime-switching framework based on the cyclical state of these countries' equity markets—specifically, whether stocks in oil-producing countries are in a bull or bear market [114]. Some sources advise investors in oil-exporting countries to increase their allocation to oil [115,116].

The relationship between oil price volatility and the equity market may depend on the cyclicality of both markets. The "relationship between oil prices and US equities could depend on both the nature of oil price shocks and how well the US stock market is performing" [117] (p. 6). Complete understanding of the mutual dependence of oil prices and broader capital markets requires not only some understanding of cyclicality in commodity and equity markets, but also a principled way of identifying critical periods within financial history.

To like effect, structural heterogeneities in foreign exchange markets coincide with geopolitical and economic impacts [118]. In conjunction with broader macroeconomic phenomena, oil markets exert dynamic influence on trade in currencies [118]. Portfolio management and other forms of risk management therefore hinge on the relationship between oil prices, exchange rates, and the business cycle.

2.3.2. Macroeconomic Effects

Oil price volatility impairs economic growth [119]. Like many other phenomena connected to oil and fuel markets, the macroeconomic effects of disruptions in energy-related markets are asymmetrical. Oil price increases stunt economic growth more deeply than corresponding decreases in price spur economic activity [120,121]. Even sharp price drops may reduce aggregate output in oil-importing countries by raising uncertainty or inducing inefficient reallocation of resources [122].

Macroeconomic uncertainty spurred by oil price volatility varies over time. Volatility typically peaks during financial crises and recessions [123]. Nonlinear measures capture the overall economic effects of oil price shocks [124]. Oil price volatility in the wake of economic, geopolitical, and natural disturbances often combines short-term perturbations with longer-term macroeconomic factors [125].

A useful trichotomy summarizes the macroeconomic component of oil price volatility [126]. First, "most commodity prices are endogenous with respect to the global business cycle" [127] (p. 313). Second, demand shocks cause slow but sustained changes in price. Third, and in stark contrast, supply shocks have immediate but small and ultimately evanescent price impacts. In oil-related markets, crises and recessions generally reduce demand over a sustained period, while geopolitical events and natural disasters tend to disrupt supplies on an acute basis.

This rigidly logical approach to evaluating the macroeconomic effects of oil and fuel price volatility does leave room for potentially exogenous factors to affect uncertainty. Oil "price uncertainty," conditioned "on macroeconomic uncertainty," might be a more complete and "suitable measure of uncertainty" than purely volatility-based measures [127] (p. 325). As a matter of broad theory, if not empirical precision, uncertainty may depend more heavily on the predictability of energy-related markets than on their volatility [127].

2.4. Identifying Cyclicality and Critical Periods in Energy Markets, Finance, and the Real Economy

Comprehensive financialization strengthens the connections linking commodities, capital markets, and the broader economy. These relationships reinforce other centrifugal tendencies throughout economics. For instance, asset pricing models should account for tangible assets and human capital as well as financial instruments [128]. The behavior of a firm is likewise influenced by that of its upstream suppliers, downstream purchasers, and competitors in geographically and technologically adjacent markets [129].

Appropriately enough, efforts to track economic cyclicality span stock markets and macroeconomic policymaking. These two domains, neither more than a single degree removed from commodity markets, have invited many efforts to define critical periods. Even though this article applies unsupervised machine language rather than conventional econometric methods, it is motivated by the same desire to trace economic cyclicality in commodity markets, particularly for crude oil and refined fuels.

Stock markets provide the narrower and methodologically simpler basis for comparison. Technical stock analysis typically defines bull and bear markets, respectively, as a market-wide price increase of at least 20 percent since the previous trough or a market-wide decrease of at least 20 percent since the previous peak [130–132]. A 10 percent decline is typically described as a "correction" [133]. Designations of bull and bear cycles within market trends can be made only in retrospect, and there is no justification for these arbitrary 10 and 20 percent thresholds beyond the conventions of technical analysis and financial journalism.

For its part, the Business Cycle Dating Committee of the National Bureau for Economic Research (NBER) tracks recessions and recoveries in the United States [134–137]. The NBER's methodology relies on a dynamic-factor, Markov-switching model that examines non-farm payroll employment, the index of industrial production, real personal income, and real manufacturing and trade sales [134,136].

Figure 1 describes the NBER's announcements regarding the arrival and departure of recessions in the United States [138,139]. It depicts smoothed recession probabilities as they rise and ebb. Notably, only two periods from 2000 through 2020 have exceeded 50 percent according to the NBER: the financial crisis of 2008–2009 and the COVID-19 pandemic. The "dot-com" crisis of 2001 approached but did not exceed a 50 percent probability of recession. As is evident in the shaded areas of Figure 1, however, the NBER did define March through November 2001 as a recession.

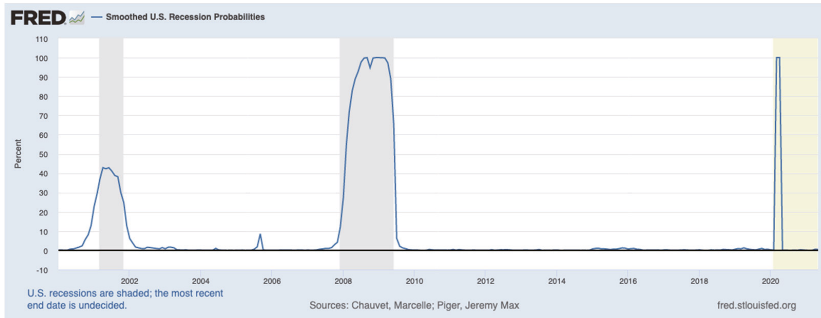


Figure 1. Smoothed U.S. recession probabilities [RECPROUSM156N], retrieved from FRED, Federal Reserve Bank of St. Louis [138].

One can also frame this problem as the mirror image of an event study [140,141]. An event study traces abnormal effects to determine the duration of a suspected market disturbance. Event studies of oil price shocks [142,143], for instance, have evaluated OPEC announcements [144,145] and storms [146]. Conversely, temporal clustering uses economic anomalies to extract events for further examination amid the flow of financial history.

The timing of recession announcements presents an economically significant issue in its own right [147]. By the NBER's own admission, its business cycle dating committee's "approach to determining the dates of turning points is retrospective" [148]. Before definitively identifying a peak, "the committee tends to wait to identify a peak until a number of months after it has actually occurred" [148]. Likewise, the committee does not immediately announce a trough. Rather, the committee "waits until it is confident that an expansion is underway" [148].

Under this methodology, announcements of recessions and recoveries are not aligned in time with actual economic activity [149]. In the three decades from 1980 to 2010, "the lag between the determined start of [a] recession" and the NBER's "peak announcement" has averaged 9 months [150] (p. 645). At a bit more than 15 months, the lag between a trough and its announcement is longer still [150].

The lag between actual macroeconomic phenomena and their announcements creates an opportunity for machine learning, artificial intelligence, and other automated methods for evaluating economic data. For instance, the United States publishes its official Consumer Price Index on a monthly basis, with a delay of several weeks between the gathering of price data by. the Bureau of Labor Statistics and the announcement of each new CPI reading [151]. By contrast, the Massachusetts Institute of Technology's Billion Prices Project reports a comparable price index on a daily basis [151].

This article develops a methodology for identifying critical periods in energy-related commodity markets. The literature on oil and fuel markets emphasizes volatility and the connectedness of oil and oil-based fuels with other commodities, other financial markets, and the macroeconomy. Instead of defining cycles akin to bull and bear markets or macroeconomic expansions and recessions, this article will try to distinguish between critical and normal periods of trading within markets for petroleum-related commodities. In seeking a crisis-based approach to understanding temporal shifts in these markets, this article aims at an intermediate level of mathematical rigor between the extremes represented by technical definitions of bull and bear markets and the NBER's recession-and-recovery methodology.

Qualitative distinctions between peaks and troughs, expansionary and recessionary cycles, and critical periods dissolve upon closer mathematical inspection. Critical points in calculus identify points within the domain of a function where the derivative or gradient is zero (assuming that the function is differentiable at those points). Peaks and troughs as maxima and minima constitute critical points in a univariate function. In a multidimensional space representing returns on more than one asset, critical points also include saddle points, where all slopes in orthogonal directions are zero, but no local extremum is attained. In this mathematically informed sense, the methods described and applied in this article cast a wider net than methods dedicated of finding peaks and troughs within a single time series.

The second derivative of logarithmic returns on a financial asset is related to volatility through the Taylor series expansion [152,153]. Points within the domain of a function where the second derivative is zero indicate inflection or undulation. Methods focusing on financial volatility may therefore find inflection and undulation points as well as critical points. These observations are not meant to suggest that this article consciously seeks to find all critical and inflection points in a strictly mathematical sense. Rather, this analogy simply offers a conceptually helpful way of understanding similarities as well as meaningful differences between traditional peak-and-trough approaches and this article's clustering methods.

As with stock markets and the broader economy, cyclicality in commodity prices has drawn scholarly attention [154]. Efforts to sharpen forecasting and the understanding of the dependence structure in oil and adjacent markets have highlighted differences between normal trading and economic turmoil [155]. The question is whether existing and novel "econometric tools" can generate reliable volatility forecasts when "periods of heightened volatility in crude oil markets are recurrent" [156] (p. 622).

Conventional econometric tools include unit root tests [157,158]. Those tests aided the discovery of structural breaks in 1990 and 2008, coinciding with the first Gulf War and the global financial crisis [17]. Technical analysis inspired by conventional methods for identifying bull and bear cycles in equity markets [159] has aided the search for cyclical effects in oil-based markets, at higher [4] as well as lower frequencies [160].

Computational tools abound amid economic "big data" [151]. Although some sources have mined linguistic [161] and Internet search data [16,162] in search of novel insights, this article uses machine learning and artificial intelligence to answer a more fundamental question: Whether financial economics can detect oil price fluctuation and its impact on the relationship between risk and return [163].

This article applies unsupervised machine learning to conditional volatility in commodity markets over two decades. An ensemble of clustering methods can identify episodes in commodity markets (especially those related to energy) warranting closer examination. Some episodes, particularly the global financial crisis and the COVID-19 pandemic, reflect a broader, more durable demand shock. Other episodes may last mere days. Such acute events should be expected more often within a confined subset of commodities, such as crude oil and refined fuels. These acute events typically involve geopolitical or natural calamities that disrupt supplies of oil and its downstream derivatives.

3. Materials and Methods

3.1. Data

3.1.1. Data Sources and Preprocessing

This article draws its raw data from sources used in [1]. Thomson Reuters' DataStream provided price data on a range of precious metals, base metals, energy commodities, and agricultural commodities. Specifically, this article relies upon daily prices from 18 September 2000 through 31 July 2020 for gold, silver, platinum, palladium (precious metals); copper, zinc, tin, lead, nickel, aluminum (base metals); Brent, West Texas intermediate crude (WTI), gasoil, gasoline (energy commodities); and palm oil, wheat, corn, soybeans, coffee, cocoa, cotton, and lumber (agricultural commodities).

The preprocessing pipeline took two further steps. Transforming daily prices into continuous logarithmic returns shortened all series by a single day: 18 September 2000. The resulting log return data (as well as the conditional volatility data derived from log returns) therefore covered the period from 19 September 2000 to 31 July 2020. Two additional days were excluded. On 20 April 2020, WTI closed at –37.63. This event rendered it mathematically impossible to calculate the log return for WTI on that day and the next, 21 April 2020. Those two trading dates were also omitted.

The second preprocessing step involved forecasts of conditional volatility from log returns. We calculated the conditional, time-variant volatility for all 22 commodities according to a GJR-GARCH(1, 1, 1) process using Student's *t* distribution [1,164]. The mathematical underpinnings of GJR-GARCH(1, 1, 1) have been thoroughly documented [165,166]. GJR-GARCH outperforms alternative time-series models in forecasting financial markets [167].

For purposes of analysis and discussion, we aggregated log return and volatility data according to a precalculated ontology of commodity markets. The vocabulary of commodities trading distinguishes between mined, nonrenewable "hard" commodities (such as metals and fossil fuels) and grown, renewable "soft" commodities [20,88,168,169]. The term "soft" is sometimes reserved for tropical crops such as cocoa, coffee, and sugar [170]. We adopt that narrower definition of "softs" and describe the temperate commodities of wheat, corn, and soybeans as "crops." Because cotton and lumber span tropical and temperate climates, these commodities can be assigned to either agricultural subcategory. Results from the clustering of log returns support the classification of cotton and lumber as tropical or semitropical softs [1].

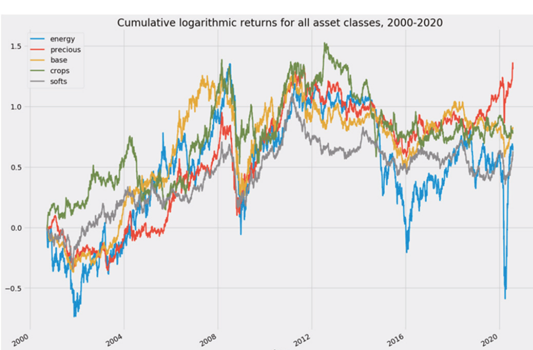
These distinctions, paired with traditional divisions among metals and fuels, can be summarized as a traditional ontology of commodities trading:

1. Energy (crude oil and refined fuels): Brent, WTI, gasoil, gasoline;
2. Precious metals: Gold, silver, platinum, palladium;
3. Base metals: Copper, zinc, tin, lead, nickel, aluminum;
4. Temperate crops: Wheat, corn, soybeans;
5. Tropical and semitropical "softs": Cocoa, palm oil, coffee, cotton, lumber.

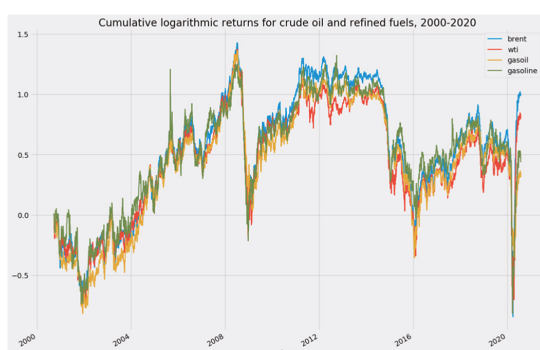
3.1.2. Visualizations of Logarithmic Return and Conditional Volatility Data

This subsection visualizes this article's core data. Although log return and conditional volatility calculations were performed on all 22 commodities, this article compares only energy-related commodities with one another on an individual basis. This article compares crude oil and refined fuels as an asset class alongside the aggregate categories for metals and agricultural commodities.

Figure 2a depicts cumulative log returns for commodities as asset classes. Relative to other classes, energy-related commodities show many sharper price movements. Figure 2b illustrates cumulative log returns for individual crude oil and fuel markets. Although comovement among individual oil and fuel markets is far tighter (as one should expect) than among broad classes of commodities, sharper upward and downward price spikes, particularly for gasoline, are evident to the naked eye.



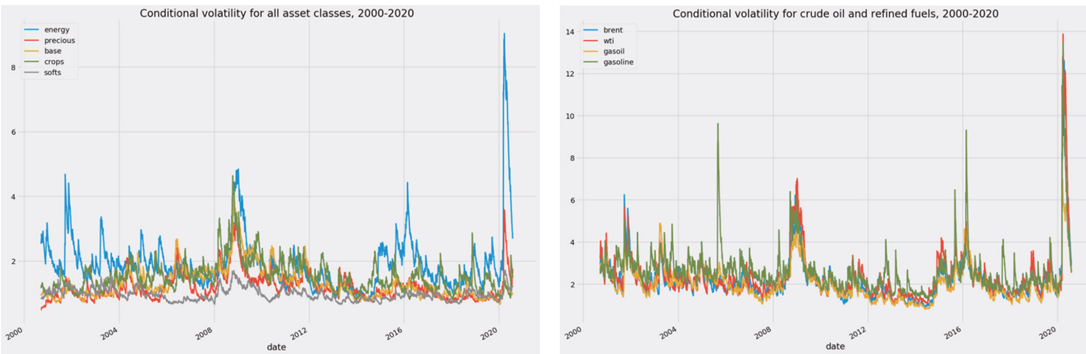
(**a**) Log returns: All commodities



(**b**) Log returns: Energy-specific commodities

Figure 2. Cumulative logarithmic returns: (**a**) All classes of commodities; (**b**) Crude oil and refined fuel markets.

Figure 3a,b depict conditional volatility. By analogy to Figure 2a,b, Figure 3a portrays the five broad classes of commodities, while Figure 3b focuses on the four individual energy-related markets. Visibly greater volatility in energy markets dominates Figure 3b. Relative to crude oil markets and even gasoil, the market for gasoline is palpably more volatile. These acute volatility spikes confirm the intuition motivating the conventional exclusion of food and fuel prices from core inflation indices used in the making of macroeconomic policy [171–174].



(**a**) Conditional volatility: All commodities (**b**) Conditional volatility: Energy-specific commodities

Figure 3. Conditional volatility forecasts: (**a**) All classes of commodities; (**b**) Crude oil and refined fuel markets.

3.2. Clustering Methods

3.2.1. General Considerations

Many applications within economics and finance exploit clustering and related forms of unsupervised machine learning [175–178]. This article applies five clustering methods: Spectral, mean-shift, affinity propagation, *k*-means, and hierarchical agglomerative clustering. Each of these methods is available in the SciKit-Learn package for Python. The implementation of hierarchical agglomerative clustering in Scipy generated visually distinctive dendrograms for that method.

Previous research had established that temporal clustering should be based on conditional volatility rather than logarithmic returns [1]. All five clustering methods were applied to volatility data arrayed in n rows of trading days and p columns corresponding to the number of distinct commodity markets. For the full volatility array covering all 22 commodities, $p = 22$. For the energy-specific subarray, $p = 4$. The two arrays, however, had the same number of trading days: $n = 5182$.

For both the full 5182×22 array and the energy-specific 5182×4 subarray, clustering results underwent a crude aggregation inspired by voting classifiers in machine learning [179]. Since clustering of the full 5182×22 array reached rough consensus on the financial crisis of 2008–2009 and the COVID-19 pandemic as the two periods of interest, that analysis relied on the union and the intersection of the five sets of clustering results. Using the union of sets is tantamount to allowing a single vote to drive a positive result. The intersection of those sets indicates unanimity. These set theory concepts therefore define the logical extremes of voting methodologies [180,181].

Greater variability in the results for the energy-specific 5182×4 subarray required a more flexible approach. For that array, this article aggregated all positive results registered by two or more of the five clustering methods. The most generous voting method, consisting of the union of all positive results, generated a wider range of dates. Though unexamined in this article, those results remain available for future research.

The balance of this subsection will describe each of the five clustering methods.

3.2.2. Spectral Clustering

Spectral clustering operates on a projection of the normalized Laplacian [182,183]. Since this article's conditional volatility arrays represent 4 or 22 commodity markets as simple functions of a common vector of trading dates, the Laplacian ($\Delta f = \nabla^2 f$) is the sum of the partial second derivatives for each of those variables.

Spectral clustering should work very well with financial data. This method exposes individual clusters within highly non-convex structures [184,185]. Since each volatility vector is plotted against the same vector of trading dates, the resulting arrays of volatility forecasts by date are tantamount to overlapping curves on a two-dimensional plane. Spectral clustering therefore excels precisely where conventional statistical measures of central tendency and variability fail to describe the shape of the data to be clustered.

These properties have made spectral clustering especially popular in computer vision and image processing [186,187]. The ability of spectral clustering to detect blobs and edges suggests potential success with economic time series. In mathematical terms, image and time-series data are quite similar. Unlike documents that have been vectorized for natural language processing, these data sources consist of perfectly dense arrays whose columns observe the same scale, or at least nearly so. Still images and simple, harmonized arrays of economic time series can be rendered in a nominally two-dimensional format.

Spectral clustering generated the fewest discrete clusters. Consequently, the spectral method may be regarded as setting the most conservative clustering baseline.

3.2.3. Mean-Shift Clustering

An extension of more traditional pattern-recognition algorithms, mean-shift clustering uses nonparametric techniques to identify deviant blobs in an otherwise smooth space [188]. Alongside k-means, mean-shift is one of two centroid-based methods in this article. The distinctive process that gives mean-shift its name relies on a recursive updating of potential centroids that would represent the mean of the points within a given region. A final postprocessing stage eliminates near-duplicates before reporting the final list of centroids. Hybridizing the mean-shift method with agglomeration can reduce the computation cost of mean-shift clustering [189].

3.2.4. Hierarchical Agglomerative Clustering

Hierarchical clustering methods decompose and arrange mathematical objects according to dendrograms, or trees expressing phylogenetic relationships [190–192]. The agglomerative method begins from the "bottom" of a dataset and combines instances into clusters until all data has been assigned to a single, overarching cluster [193].

Bottom-up agglomeration is less computationally demanding than top-down division [194,195]. Four methods for computing distances in hierarchical clustering are widely used: Ward's method and single-, average-, and complete-linkage [196–199].

In economics and finance, hierarchical clustering has evaluated stock markets [200,201], buildings and real estate [202,203], broader financial indicators [204], and the relationship between financial markets and the real economy [177]. Hierarchical clustering of cryptocurrency markets [205] intensifies the urgency of research into this asset class during market turbulence [206].

One source has used hierarchical clustering to identify correlation patterns similar enough to comprise distinct market states [207]. Aside from our own work [1] and the use of multidimensional scaling to evaluate comovement among commodities during subjectively defined crises [164], this application of hierarchical clustering represents the most extensive effort to classify periods in financial history through unsupervised machine learning.

3.2.5. Affinity Propagation

Affinity propagation identifies typical cluster members by exchanging quantitative messages between data pairs until the algorithm converges on a high-quality set of exemplars [208–210]. This property distinguishes affinity propagation from mean-shift and *k*-means clustering, which are centroid-based methods.

Under SciKit-Learn's default settings, however, affinity propagation generates far too many distinct exemplars. To the extent that other methods (specifically spectral, mean-shift, and hierarchical clustering) can better estimate the optimal number of clusters, an instance of affinity propagation can alter the element preference from its default value of the median of the array of input similarities [211]. To a limited extent, this adjustment enables affinity propagation to alter the number of clusters that it finds.

Affinity propagation spans an impressive range of applications. Affinity propagation is used to cluster microarray and gene expression data [212–214] and in sequence analysis [215]. Applications beyond bioinformatics [216] include natural language processing [217–219] and computer vision [220,221]. Especially if calibrated so that element preference yields something close to the optimal number of exemplars, this versatile clustering method should accommodate financial time series.

3.2.6. *k*-Means Clustering

One of the oldest clustering algorithms [222], *k*-means clustering remains a popular way to partition mathematical space [223]. *k*-means clustering excels in detecting fraud [224] and firms at risk of default or failure [225]. Other financial applications include the forecasting of returns and the management of investment risk [176,226–228]. Our own previous research on commodity markets relied heavily on *k*-means clustering [1].

k-means clustering does require more careful handling. More than other methods, k-means clustering depends on algorithms for determining the ideal number of clusters [229,230]. In addition to *k*, the optimal number of clusters, this centroid-based method depends entirely on randomized instantiation [231]. To ensure replicability of results, this article seeded SciKit-Learn's pseudo-random number generator with the value of 1. Finally, *k*-means clustering cannot detect objects lacking a hyper-ellipsoidal shape [232].

3.3. t-Distributed Stochastic Neighbor Embedding (t-SNE)

This article uses a single method of manifold learning: *t*-distributed stochastic neighbor embedding, or *t*-SNE [233–235]. *t*-SNE reduces distances between similar instances and maintains distances between dissimilar instances. Although this article applies *t*-SNE solely for visualization, *t*-SNE can be a valuable form of unsupervised learning on its own. Preprocessing with *t*-SNE can detect and remove outliers in preparation for the application of convolutional neural networks to computer vision [236].

4. Results, Part 1: Temporal Clustering

Clustering results differ dramatically according to the underlying array of conditional volatility forecasts. This section accordingly separates results for the full 5182×22 array of all commodities from results based on the smaller 5182×4 energy-specific array.

Differences among clustering methods are also stark. Clustering differs from classification through supervised machine learning in a crucial respect. Clustering results do not correspond to *a priori* labels assigned by a human. Analyst judgment therefore plays a subtler role. Each clustering method must be evaluated on its own terms. Moreover, each method's results must be evaluated in light of all others and against the backdrop of unavoidably subjective judgment. Each method's underlying mathematics, however, offers principled guidance on the exercise of that discretion.

4.1. Temporal Clustering of the Full Array of Conditional Volatility Forecasts

4.1.1. The Naïve Biennial Baseline

The naive clustering of all 20 years of commodities trading data provides a valuable starting point. Consider the possibility that a fixed and predetermined period of time should define each segment of financial interest. This hypothetical is far from absurd;

monthly, quarterly, or annual reporting slices financial time in precisely this way. In the interest of convenience, we select intervals of two calendar years each.

Figure 4 establishes a visual baseline for all temporal clustering. Consistent reliance on *t*-SNE to reduce all 22 dimensions produces a uniform three-dimensional projection of conditional volatility forecasts. Synthetic centroids generated by the average of all observations for each biennium supply a rough sense of those two years.

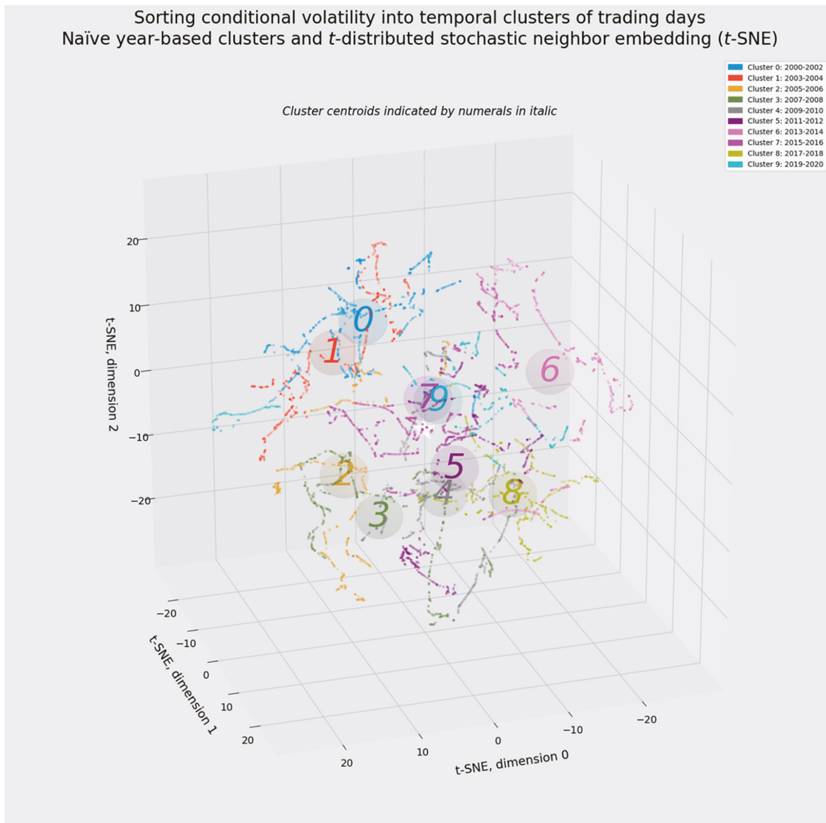


Figure 4. Naïve, biennially defined clusters of trading days in commodity markets.

Cluster 9 is particularly interesting because the 2019–2020 biennium includes the global maximum for cumulative log returns on precious metals and the global minimum in cumulative log returns on oil and fuels. That cluster's synthetic centroid falls very near the global center. Its corresponding observations, in cyan, stretch across the financial firmament, as measured by its width across the zeroth *t*-SNE dimension.

Expanding all spheres from Figures 4 and 5 reveals the futility of arbitrary biennial clusters. If spherical radii corresponding to each cluster define the mean distance of each observation from its corresponding synthetic centroid, then the size of each sphere and its overlap with other spheres suggest the extent to which each cluster is internally cogent and externally distinct. Internal cogency, if present, should reveal itself through contiguous or nearly contiguous clusters in an ordered, one-dimensional projection along a temporal axis. An ordered, horizontal representation would indeed display 10 perfectly contiguous, nonoverlapping clusters. That is an artifact of the arbitrary definition of those clusters, however, and not any mathematical property captured by *t*-SNE.

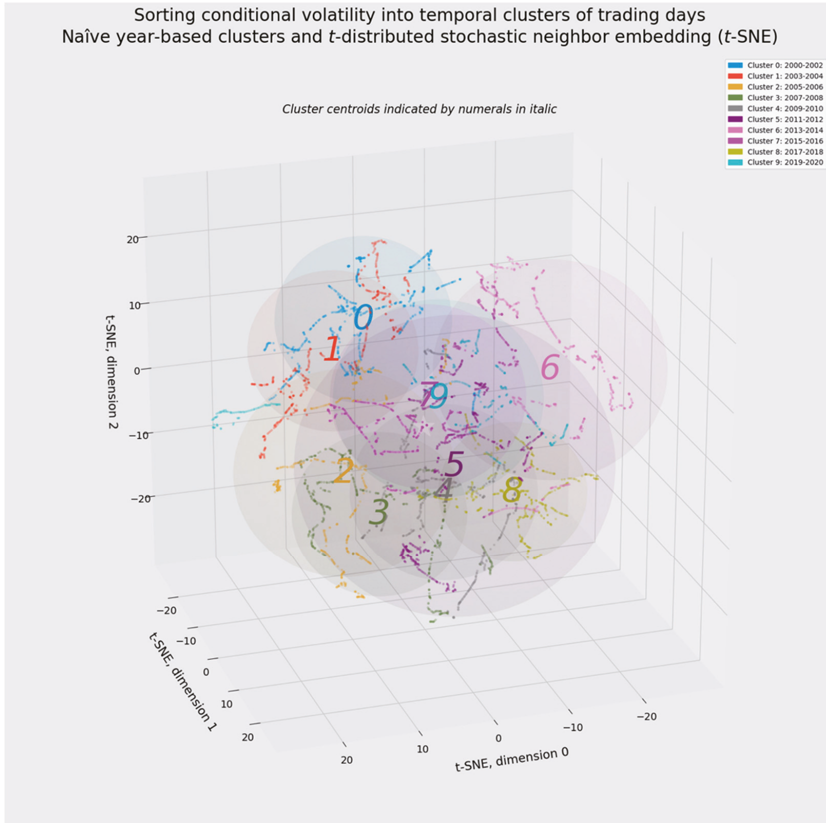


Figure 5. Naïve, biennially defined clusters in commodity markets—with spheres representing the mean distance of each cluster's observations from its synthetic centroid.

4.1.2. Spectral Clustering

Spectral clustering of all conditional volatility forecasts identifies eight clusters. Although this method does not generate centroids, finding the mean of each cluster's members in the three-dimensional *t*-SNE manifold produces synthetic centroids.

Figure 6 reveals the complete *t*-SNE manifold of spectral clusters. Clusters 1, 2, 3, and 5 appear in a tight group at upper left. Clusters 1 and 2 contain only two days each, while cluster 3 adds only nine more. The tiny size of these clusters is implied by their compactness.

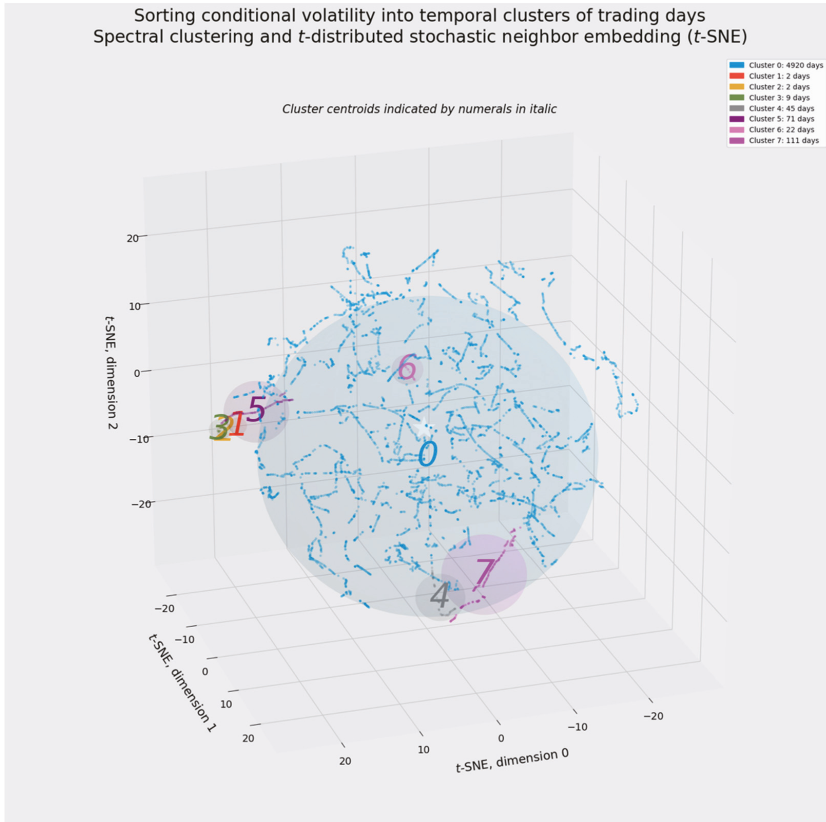


Figure 6. Spectral clustering of commodity markets—A *t*-SNE (*t*-distriubted stochastic neighbor embedding) manifold.

Two other groupings also stand out. Clusters 4 and 7 occupy the lower foreground. Cluster 6 stands alone. As with clusters 1, 2, and 3, a tight radius implies that cluster 6 consists of a small number of days. Indeed, cluster 6 contains only 22 days.

The vast majority of trading days—4920 out of 5182—belong to cluster 0. The *t*-SNE manifold suggests that cluster 0 may be the fallback cluster representing ordinary trading days, when volatility levels do not substantially deviate from their central tendency.

The most useful representation of temporal clusters, of course, is the one plotted against the ordered vector of dates. Figure 7 reveals how the eight spectral clusters almost perfectly identify two critical periods of interest from 2000 to 2020. The height of the bars communicates categorical rather than ordinal or numerical information. Because of the fortuity that spectral clustering assigned the number 0 to the default, catch-all category, all clusters numbered 1 and above identify periods of interest.

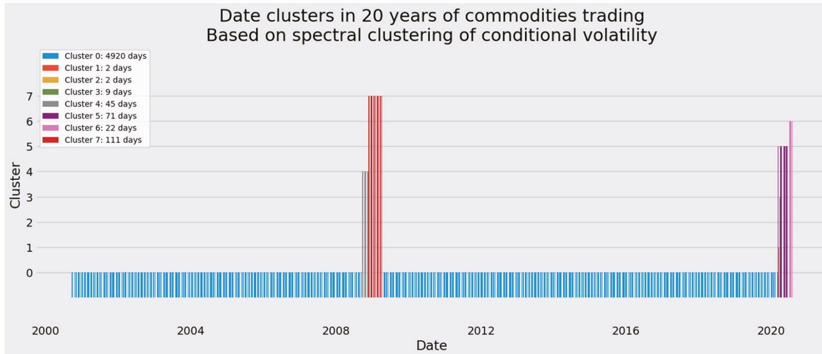


Figure 7. Spectral clustering of commodity markets—An ordered timeline.

Spectral clustering identified the financial crisis of 2008–2009 and the COVID-19 pandemic. Almost miraculously, six of the remaining seven clusters are perfectly contiguous. Instances from cluster 5, though split by clusters 1, 2, and 3, joined those other clusters to form a continuum covering the beginning of the pandemic. Cluster 6 covers the final 22 days in the dataset. Whether those days belong with the earliest phase of the pandemic or instead indicate a transition toward noncritical cluster 0 may be inferred from the location of cluster 6 in Figure 6 as well as the statistical summary of each cluster.

The resolution of Figure 7, however, is not sharp enough to reveal additional insights. Cluster 5 consists of two subclusters separated by nearly 19 years. The earliest instances in cluster 5 occur in 25–28 September 2001, exactly two weeks after the terrorist attacks of 11 September 2001. The remaining 67 days in cluster 5 started in March 2020, coinciding with the outbreak of COVID-19 in Europe and North America. This represents evidence, however faint, that an event unequivocally related to energy markets might sway the commodities market as a whole.

4.1.3. Mean-Shift Clustering

Mean-shift clustering generated results remarkably similar to spectral clustering. In certain respects, mean-shift clustering might be even more parsimonious.

Figure 8 identifies two periods of potential interest: The tight clump formed by clusters 2, 4, and 5 at left and the looser pair of clusters 1 and 3 at bottom. Because *t*-SNE manifolds are shaped by their underlying data, Figure 8 can be compared directly with other *t*-SNE manifolds. Figures 4–6 make it apparent that clusters 2, 4, and 5 correspond to COVID-19, while clusters 1 and 3 track the financial crisis of 2008–2009.

The ordered timeline in Figure 9 confirms these intuitions. Clusters 2, 4, and 5 indeed cover the COVID-19 pandemic. Notably, the final 39 trading days (9 June through 31 July 2021) fall within cluster 0. Mean-shift results suggest that the final 22 days might be better classified as "ordinary" trading days rather than part of the COVID-19 crisis.

4.1.4. Hierarchical Agglomerative Clustering

The visual signature of hierarchical clustering is the dendrogram. The dendrogram has the added benefit of offering principled guidance on the optimal number of clusters.

Figure 10 displays the dendrogram for hierarchical agglomerative clustering using Ward's method and Euclidean distances. The height of the branches offers guidance on the ideal number of clusters. In principle, the ideal number of hierarchical clusters may be as low as two. The height of the blue branches exceeds the vertical distance between any other set of splits. Splitting this dataset into two temporal clusters is tantamount to the binary classification between crises and ordinary (or non-critical) periods.

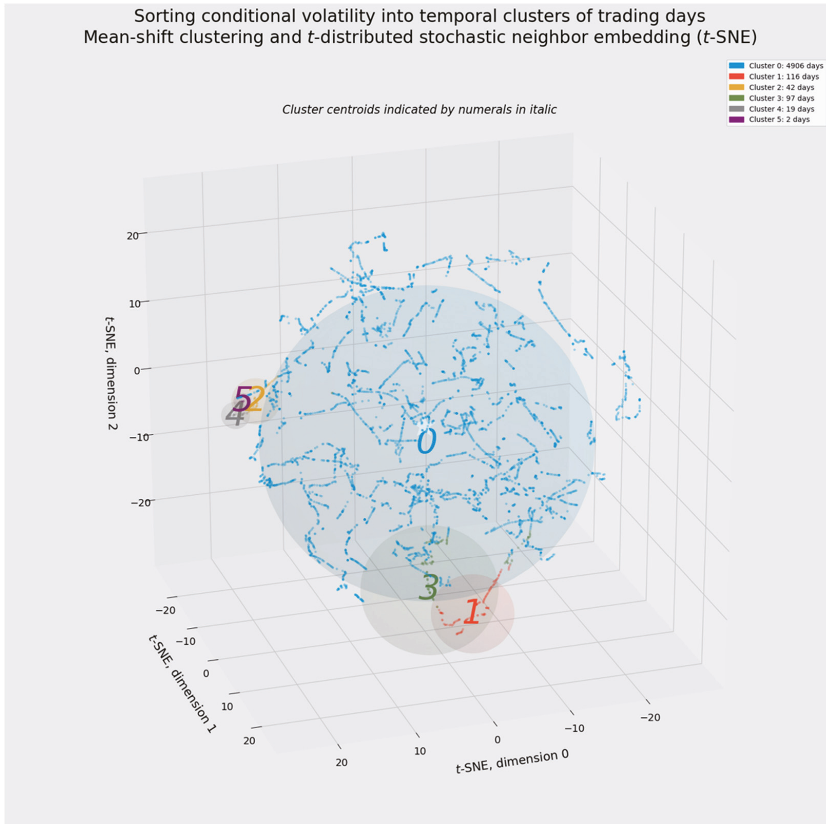


Figure 8. Mean-shift clustering of commodity markets—A *t*-SNE manifold.

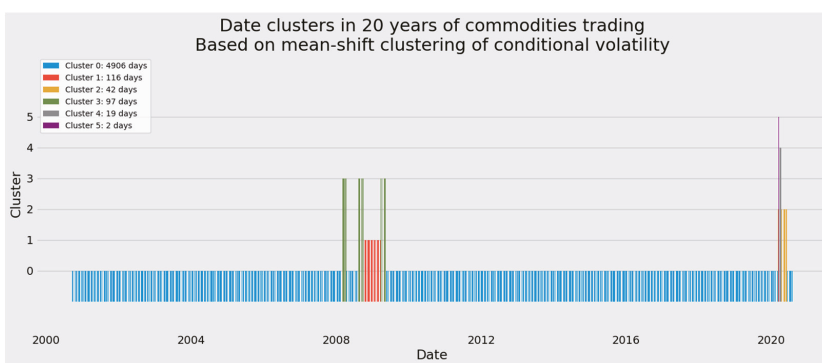


Figure 9. Mean-shift clustering of commodity markets—An ordered timeline.

The dotted horizontal line in Figure 10 intersects five vertical branches. The comfortable vertical distance on either side of 75 implies that 5 is a near-optimal number, if we are unwilling to abandon multiclass in favor of binary clustering. In any event, the logic of agglomeration makes it easy to rearrange the five clusters as two.

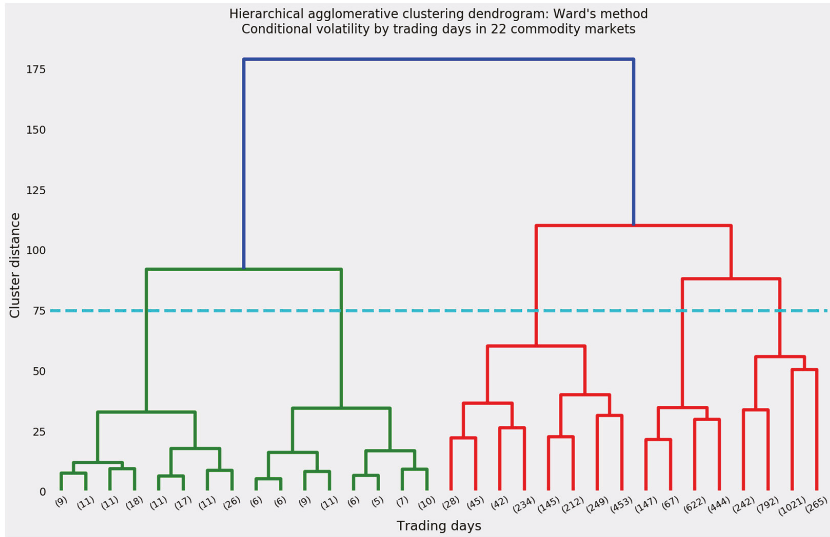


Figure 10. Hierarchical agglomerative clustering of commodity markets—A dendrogram truncated after four levels with a horizonal cut indicating five clusters.

Hierarchical agglomerative clustering in Python can designate an arbitrary number of clusters, $k \in [1, n]$. Having determined $k = 5$, we can project the t-SNE manifold in three dimensions as well as the ordered timeline.

The three-dimensional t-SNE manifold of hierarchical clustering results differs in striking ways from its spectral and mean-shift counterparts. Figure 11 divides noncritical trading days more evenly among three clusters: 0, 1, and 2. Clusters 3 and 4 are the outliers. Cluster 3 surely represents the financial crisis, while cluster 4 captures COVID-19.

The ordered timeline in Figure 12 confirms the intuitive interpretation of the t-SNE manifold. Again, departures from ordinary trading are designated by higher-numbered clusters. The spike for cluster 3 coincides with the financial crisis, while cluster 4 rises during the COVID-19 pandemic.

4.1.5. Affinity Propagation

The final two clustering methods, affinity propagation and k-means clustering, require more computation and discretionary judgment. These difficulties arise from a simple difference: Default settings for affinity propagation and k-means clustering generate a larger number of smaller clusters. Worse, many of those clusters cover non-consecutive days, despite their relatively small size.

Adjusting the element preference matrix enables affinity propagation to generate a desired number of exemplars. This trait of affinity propagation is not infinitely elastic. Nevertheless, a simple matrix of element preferences generated five clusters, the same value of k in hierarchical agglomerative clustering. Those element preferences consisted of the median (not mean) of each vector of volatility forecasts, uniformly scaled by -3000.

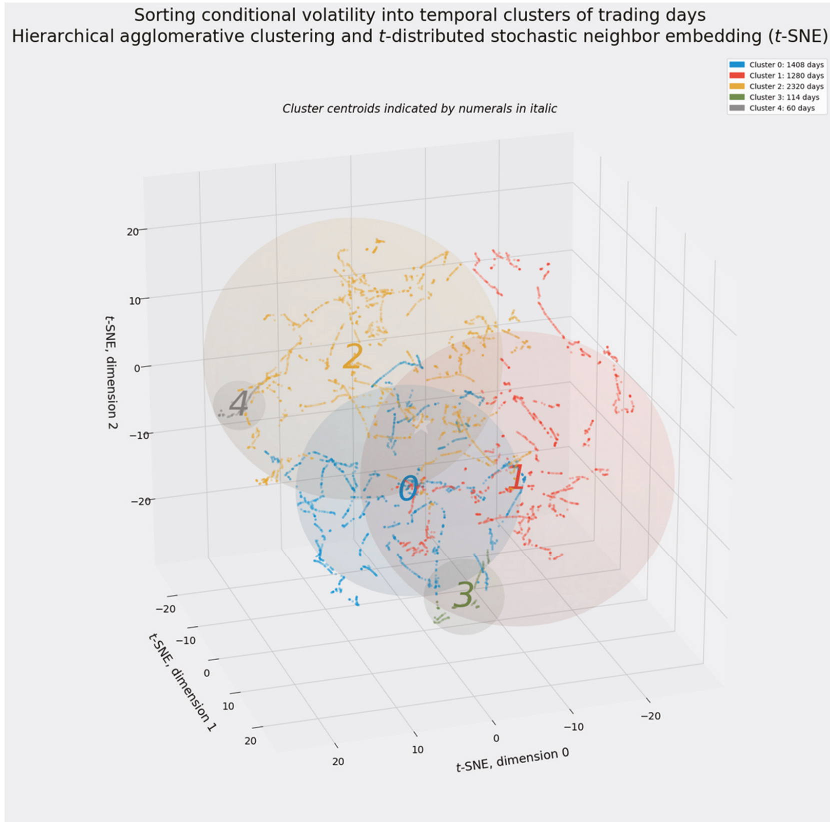


Figure 11. Hierarchical agglomerative clustering of commodity markets—A *t*-SNE manifold.

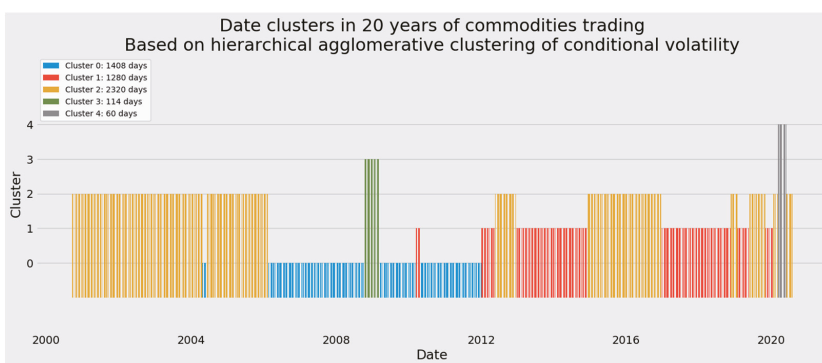


Figure 12. Hierarchical agglomerative clustering of commodity markets—An ordered timeline.

Figure 13 shows how closely affinity propagation, once nudged toward five clusters, resembles hierarchical agglomerative clustering. Critical days appear in clusters 2 and 4, which respectively define the financial crisis and the pandemic.

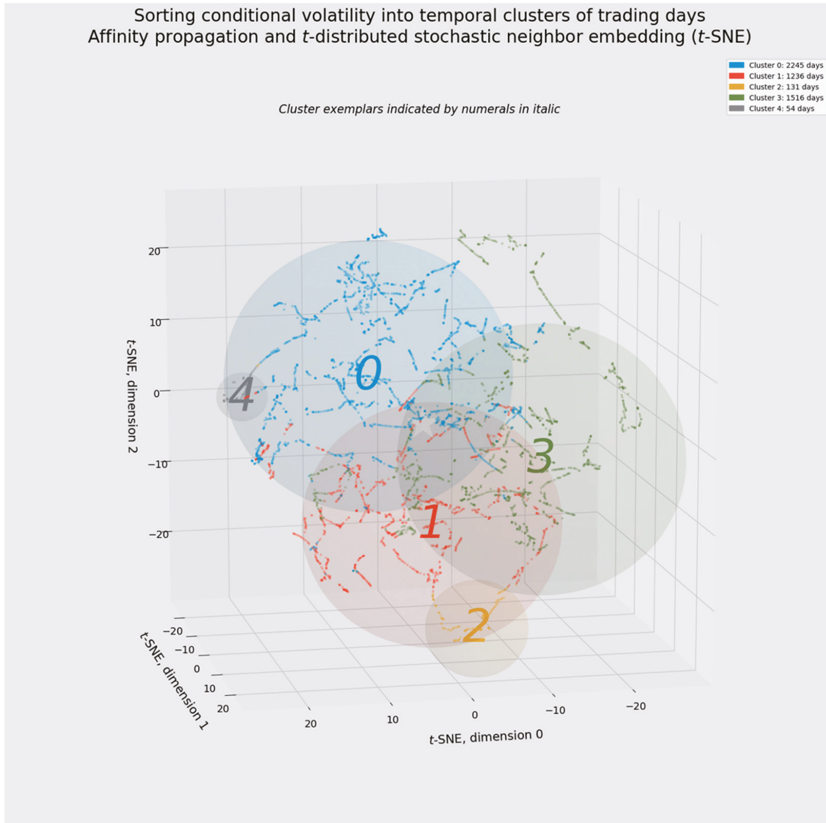


Figure 13. Affinity propagation of commodity markets—A t-SNE manifold.

Figure 14 places these clusters within an ordered timeline. Cluster 2, however, covers not only the financial crisis of 2008–2009 but also the three days immediately following cluster 4′s definition of the pandemic. Consistent with other clustering results, this minor deviation from perfect contiguity suggests that volatility during the COVID-19 crisis drifted toward conditions characterizing the longer-lasting "great recession."

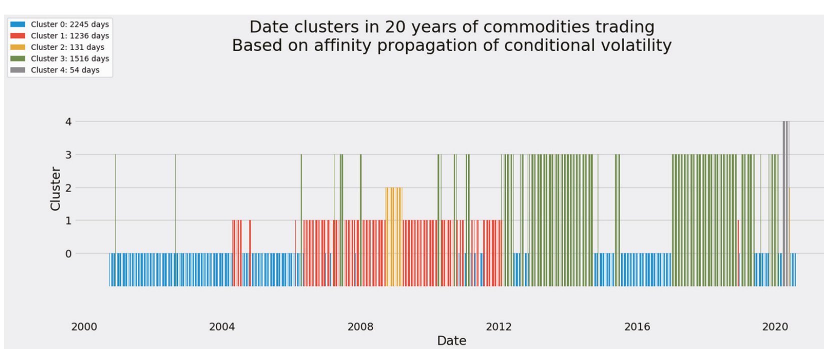


Figure 14. Affinity propagation of commodity markets—An ordered timeline.

4.1.6. *k*-Means Clustering

This article's exercise in *k*-means clustering on all conditional volatility forecasts duplicates the temporal clustering in [1], with a salient difference: The value of *k*, now fixed at six, is the average number of clusters found by other methods (Figure 15). Conventional methods for optimizing *k* did not prove particularly satisfying. It remains possible to determine *k* through other clustering methods.

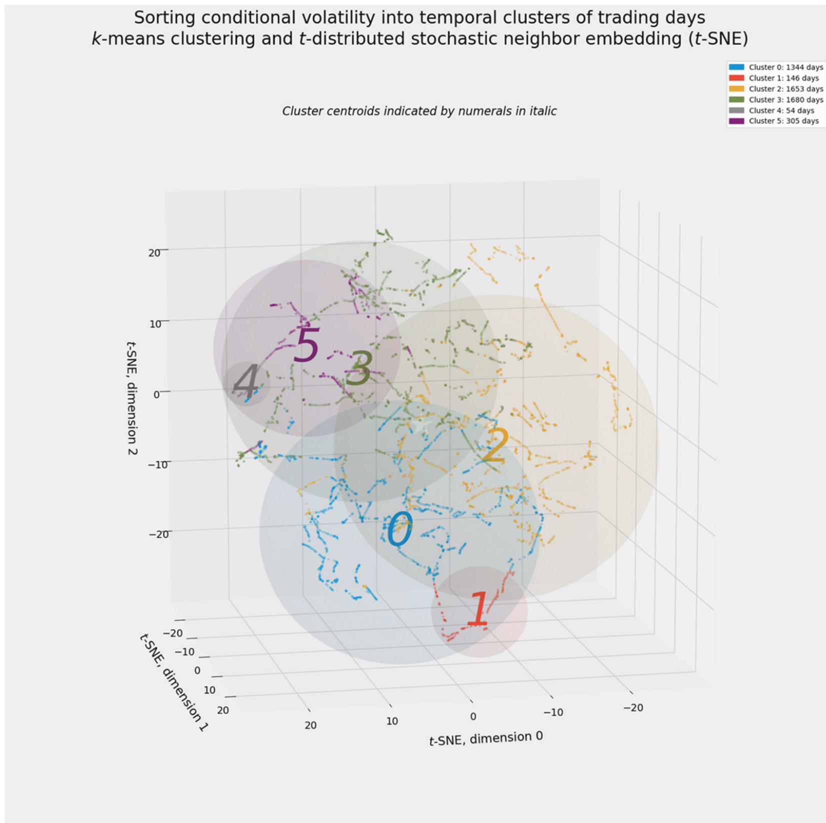


Figure 15. *k*-means clustering of commodity markets—A *t*-SNE manifold.

Like mean-shift clustering, *k*-means clustering relies on the stochastic instantiation of centroids. *k*-means clustering, however, generates the least contiguous and the least visibly cogent set of clusters. Figure 16 reveals only two wholly contiguous clusters (1 and 4), which coincide with the financial crisis and the pandemic.

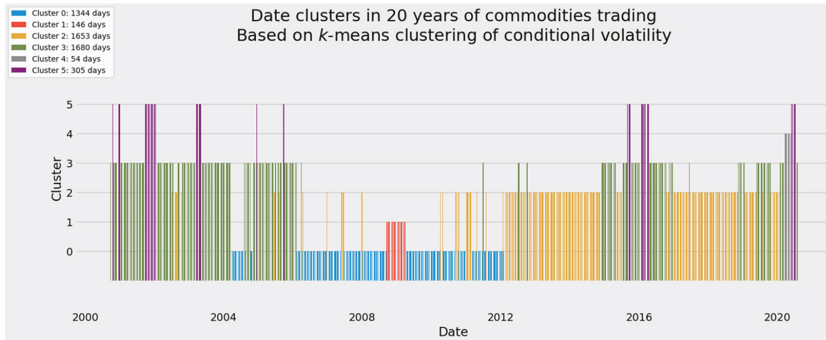


Figure 16. *k*-means clustering of commodity markets—An ordered timeline.

4.1.7. The Union and Intersection of Clustering Results for the Full Volatility Array

Though similar, these five clustering methods differ subtly, just enough to require human intervention. Some methods confine all results for the financial crisis or the pandemic to a single cluster. Others divide results among as many as four clusters. Affinity propagation associated three days after its COVID cluster with the earlier financial crisis.

Prior intuitions about any particular clustering method are just that: prior intuitions. The "no-free-lunch" theorem of machine learning posits that no single method can be expected to outperform others in every task [237]. Moreover, machine-learning ensembles typically outperform any individual model [238]. Some method of aggregating results from different clustering models seems advisable.

Elementary set theory provides a simple solution. The *union* of all clustering results identifies a critical period as long as *any* method assigns a date to a critical period. The *intersection* of those results demands agreement among *all* methods. Given the simplicity of finding agreement over exactly two periods—the financial crisis and the pandemic—these opposite extremes of any plausible voting algorithm define the range of answers.

Figure 17 depicts this simple voting algorithm's parsimonious results. The union of all results defines the financial crisis as 16 September 2008 to 24 April 2009. The intersection of those results narrows the timeframe so that it runs from 16 October 2008 to 17 March 2009.

The definition of the COVID-19 pandemic is likewise perfectly contiguous by either criterion. The union of results defines the COVID crisis as 10 March to 1 July 2020. The narrower intersection of those sets also begins on 10 March but ends on 26 May 2020.

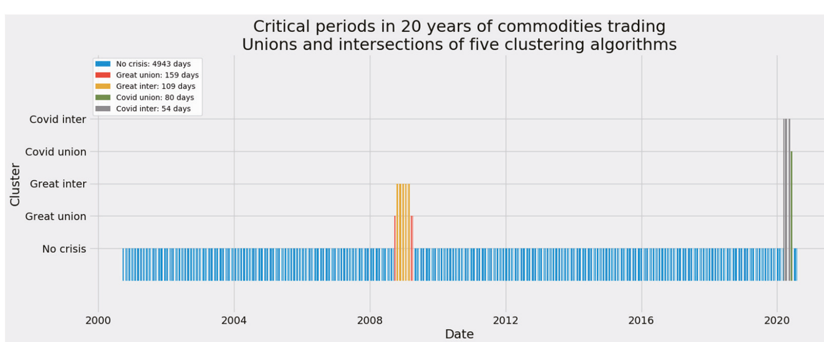


Figure 17. Set theory aggregations of temporal clusters—An ordered timeline.

4.2. Temporal Clustering of the Energy-Specific Array of Conditional Volatility Forecasts

We now apply all five clustering methods to the energy-specific 5182 $\times$ 4 subarray of conditional volatility forecasts. The smaller size of this array nudges all methods toward finding more clusters. That property makes some clustering models more difficult to manage. On the other hand, the relative stability of clustering on the grand array of 22 commodities suggests that this suite of unsupervised machine-learning methods can be successfully extended to larger financial markets (including equity markets with hundreds or thousands of stocks) and to arrays of macroeconomic indicators.

Dispensing with the naïve clustering of observations by arbitrary two-year periods, we begin with spectral clustering and progress through all other methods.

4.2.1. Spectral Clustering

Figure 18 reports spectral clustering results for the time periods within the subarray of energy-specific conditional volatility.

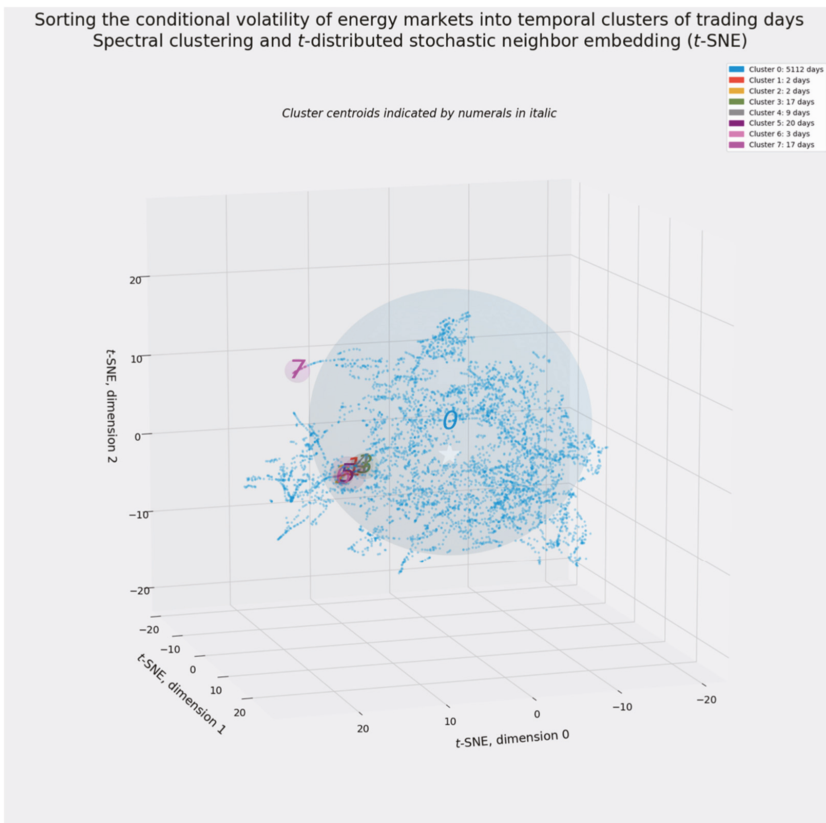


Figure 18. Spectral clustering of energy-related markets—A *t*-SNE manifold.

On the energy-specific subarray, as with the full array, spectral clustering is a very conservative method. It finds fewer and smaller clusters apart from a single large cluster of ordinary observations. In Figure 18, clusters 1 through 6 adhere together during the COVID-19 pandemic. Cluster 7 stands apart in time and contains 17 consecutive trading days. Cluster 0 accounts for nearly 99 percent of the full 5182 days.

Figure 19's ordered timeline reveals that cluster 7 does not overlap any period associated with the financial crisis of 2008–2009. Rather, cluster 7 consists of 17 days in August and September 2005. This is the first energy-specific event not identified by the broader array of all commodities. As will become apparent, these days coincided with Hurricane Katrina, which profoundly affected oil production and gasoline refining in and near the Gulf of Mexico [239,240]. Indeed, an enduring structural break between crude oil and spot gasoline prices is attributed to this event [241].

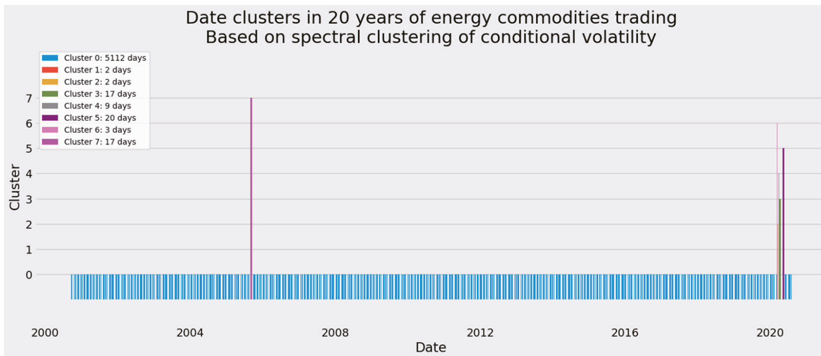


Figure 19. Spectral clustering of commodity markets—An ordered timeline.

4.2.2. Mean-Shift Clustering

Relative to spectral clustering, the mean-shift method finds nearly twice as many clusters. More intriguingly, mean-shift clusters deviating from the central tendency of energy-specific volatility gather on a single side of the three-dimensional *t*-SNE manifold.

Figure 20 shows how mean-shift clustering is based on centroids. The centroids indicated by numerals are visibly distinct from the apparent center of gravity for each cluster within the *t*-SNE manifold's stylized three-dimensional space. Clusters 0 and 1, the two largest, exhibit the greatest apparent dislocation between centroids and individual instances. All other clusters, except perhaps clusters 2 and 7, are more likely to identify brief, compact events in the trading in crude oil and refined fuels. Such events likely arise from supply disruptions, as opposed to longer-lasting shifts in demand associated with broader crises affecting all commodities.

Figure 21 renders mean-shift results on an ordered timeline. Mean-shift clustering is manifestly more sensitive than spectral clustering. Cluster 0 plays its usual role as the fallback category. All clusters numbered higher than 1 are much smaller, containing (in two instances) as few as two days. Pronounced spikes are associated with the global financial crisis and the pandemic, as well as a previously undetected 2016 event.

Clusters 1 and 2, as the second- and third-largest clusters among the 15, fall between the extremes represented by cluster 0 and collectively by clusters 3 through 14. In addition to indicating several periods in the early 2000s, Cluster 1 brackets better known, already identified volatility events. It may be reasonably surmised that this cluster indicates the beginning or the end of distinctive events. Its appearance at the end of the peak of the pandemic reinforces what all-commodity clustering has already suggested: The pandemic arrived suddenly and began to relax almost as quickly.

Cluster 2 recurs on multiple occasions in the first half of this 20-year period and again in 2015. Those 60 trading days should share characteristics that distinguish them from the financial crisis, the 2016 event, and the pandemic.

Recombining mean-shift clusters from 15 into four—0, 1, 2, and all clusters numbered 3 or higher—provides a clearer picture. Figure 22 reports this summarized timeline.

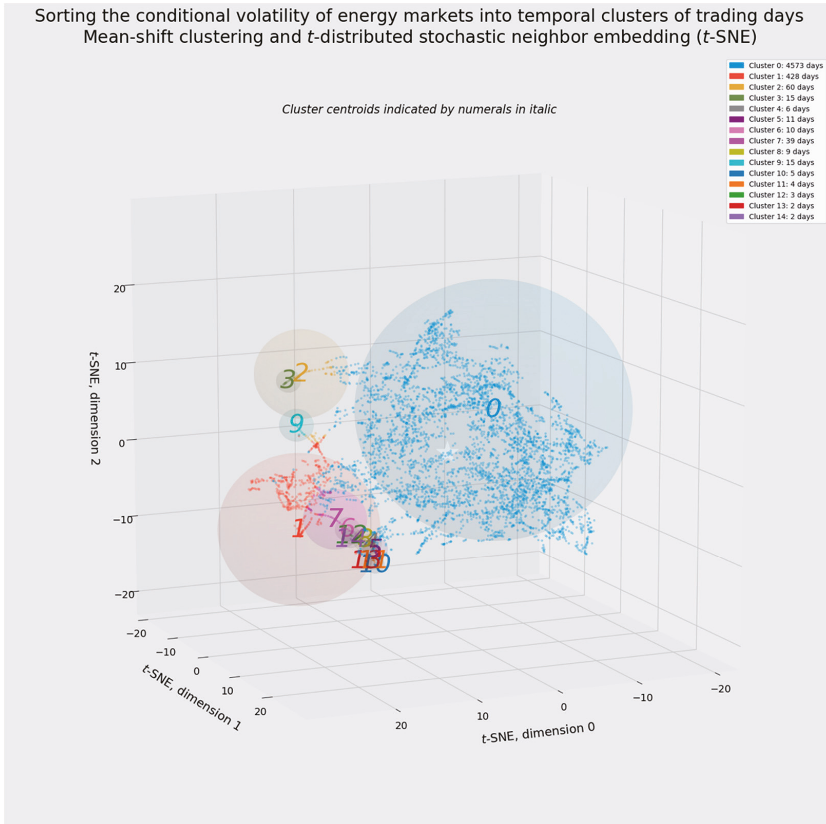


Figure 20. Mean-shift clustering of energy-related markets—A *t*-SNE manifold.

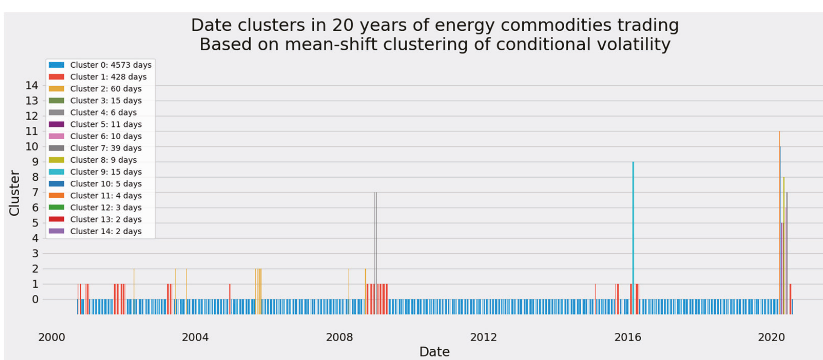


Figure 21. Mean-shift clustering of energy-related markets—An ordered timeline.

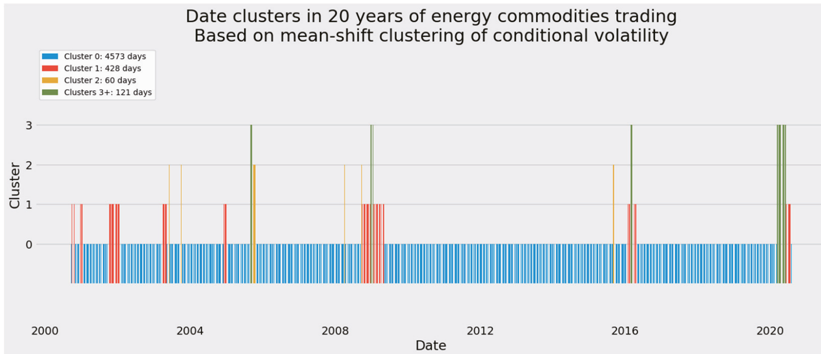


Figure 22. Mean-shift clustering of energy-related markets—A simplified timeline compressing 15 clusters into four.

4.2.3. Hierarchical Agglomerative Clustering

As a matter of visual interpretability as well as mathematical logic, hierarchical clustering begins with a dendrogram. Figure 23 suggests that the ideal number of clusters may be as low as three: A concentrated cluster of 51 trading days (not necessarily consecutive) in the middle in red, a moderately large supercluster of 848 days at right in cyan, and a very large supercluster of the remaining 4283 days at left in green. Deviating from cluster distance as a guide to the optimal value of k yields the 12 clusters along the bottom.

Distances within these 12 clusters average less than 30, as opposed to the distance of 60 separating a three-cluster configuration from its five-cluster alternative. Even so, many of these clusters will exhibit so little contiguity that it will take considerably more analyst judgment to cogently interpret hierarchical clustering.

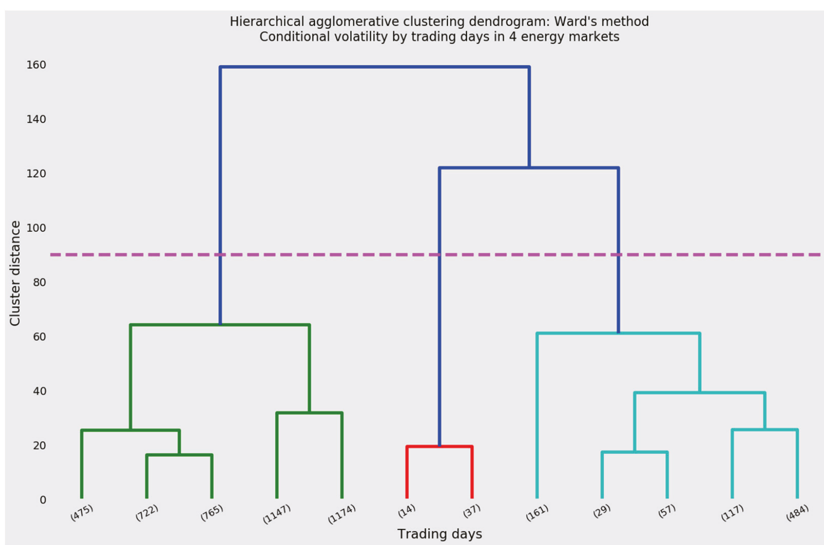


Figure 23. Hierarchical agglomerative clustering of energy-related markets—A dendrogram truncated at 12 clusters, with a horizonal cut indicating three clusters.

The t-SNE manifold of hierarchical clustering in Figure 24 looks decidedly unlike the manifolds for spectral and mean-shift clustering. The affinity propagation and k-means manifolds will exhibit a shape similar to the hierarchical results. The greatest difference lies in the relative sizes and overlapping locations of the spheres representing the clusters. Aside from clusters 9, 2, 10, and perhaps 5, these clusters have large radii and overlap their neighbors. The centroids are synthetic, as in spectral clustering, and not stochastically instantiated, as in *k*-means. Overlapping spheres suggest that the adjoining clusters will not be perfectly contiguous, or even close to being so.

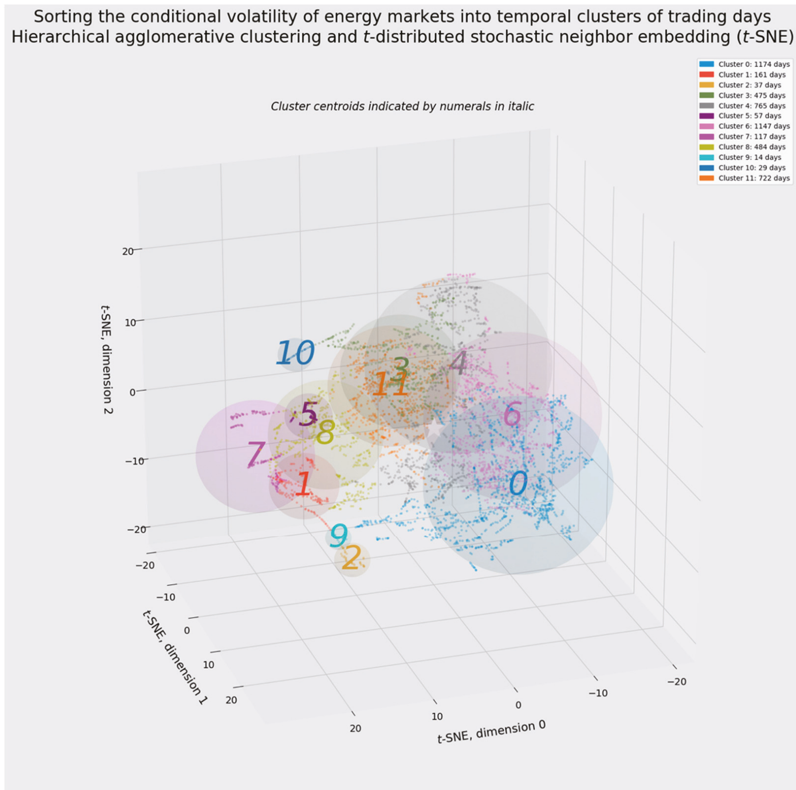


Figure 24. Hierarchical agglomerative clustering of energy-related markets—A *t*-SNE manifold.

The ordered timeline in Figure 25 confirms these fears. Cluster 0, the closest representation of normal trading, has shorter stretches of uninterrupted, contiguous cogency than the default, background trading clusters under the spectral or mean-shift methods. Cluster 1, which appears during the financial crisis and the pandemic, also appears in 2001. Reducing the total number of clusters below the 15 clusters generated by mean-shift did not bring visible order to the timeline. Additional analyst judgment seems advisable.

Figure 26, the revised manifold, highlights the six smallest hierarchical clusters. A principled case can be made to include cluster 8, the seventh smallest among 12, because of its proximity to cluster 5 in the *t*-SNE manifold and in Figure 23′s dendrogram. On the other hand, cluster 8 adds 484 days to the 415 total days in clusters 1, 2, 5, 7, 9, and 10. At 415 total days, those clusters comprise almost exactly 8 percent of the 5182 trading days. Adding 484 days from cluster 8 would raise the share of critical trading days to more than 17 percent. For the sake of comparison, mean-shift clustering identified 609 trading days of interest, while spectral clustering found only 70.

Whether critical periods in energy commodity trading comprise 8 or 17 percent of an entire timeframe requires delicate analyst judgment. An incidental benefit of forecasting conditional volatility through GARCH is the ability to estimate the degrees of freedom for the t-distribution that best fits each series of returns. Figure 27 shows that the estimated degrees of freedom for energy-related commodities ranged between 3.03 (WTI) and 3.71 (gasoil). For an equally weighted market basket of oils and refined fuels, $\nu \approx 3.51$.

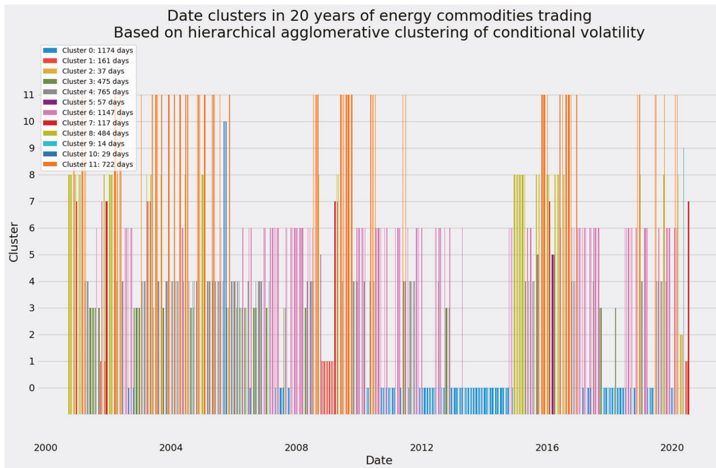


Figure 25. Hierarchical agglomerative clustering of energy-related markets—An ordered timeline.

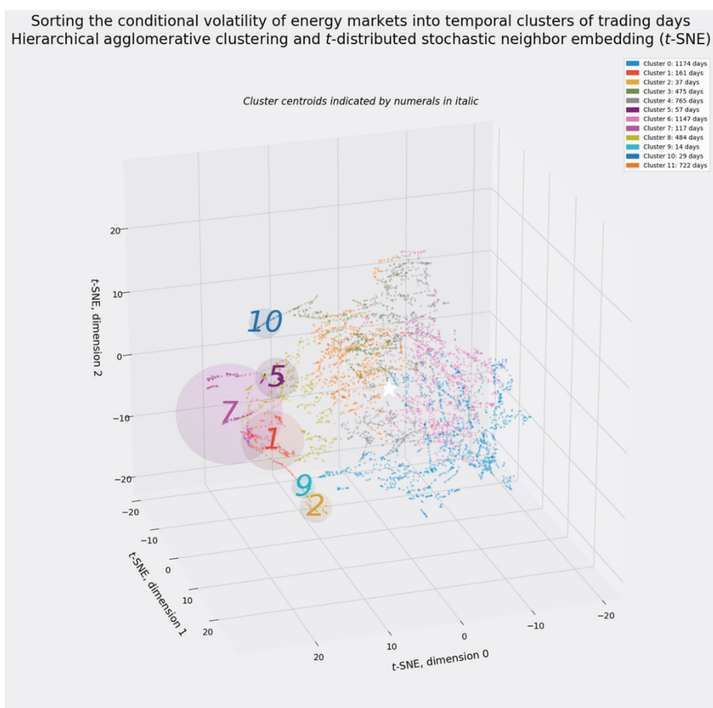


Figure 26. Hierarchical agglomerative clustering of energy-related markets—the t-SNE manifold revisited, with clusters of interest indicated by their centroids.

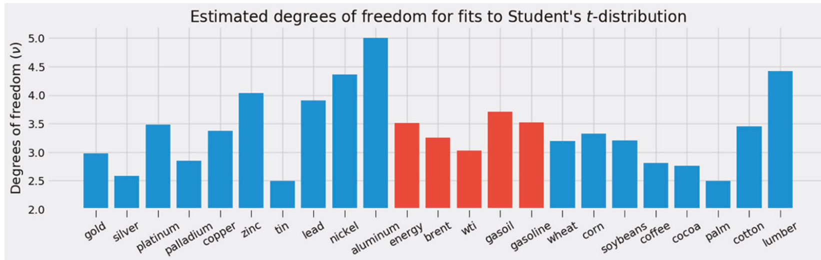


Figure 27. Estimated degrees of freedom (ν) for Student's *t*-distribution for each series of log returns. Energy-related commodities, including an equally weighted market basket, appear in red.

The degrees of freedom estimate enables the cumulative distribution function for Student's *t*-distribution with location = 0 and scale = 1 to describe the size of the tails at a given value of ν. At this dataset's estimates for ν, the two-tailed estimate for $F(x \mid |x| > 2)$ ranges from 0.121634 for gasoil to 0.138395 for WTI. The estimate is 0.125950 for the equally weighted market basket. The one-tailed estimate would be exactly half of those values. The one-tailed estimate for $F(x \mid x > 2)$ might be justified on the reasoning that volatility is invariably non-negative and that outliers found through clustering are likely to exhibit extremely high rather than extremely low volatility. That rationale, to say nothing of methodological conservatism, supports a smaller number of clusters.

By either measure, the six or seven smallest clusters occupy a distinct edge within Figure 26. All of the candidate clusters lie a palpable distance from the *t*-SNE manifold's center of gravity. This is intriguing (if not altogether conclusive) visual evidence that a size-based criterion can successfully isolate outliers among trading days.

Figure 28 simplifies the ordered timeline in Figure 25 by reducing the more conservative six-cluster interpretation of hierarchical clustering into binary classification. Those six clusters have been aggregated into a single "critical" supercluster, while all other days are classified as a normal, noncritical background. In addition to the financial crisis and the pandemic, simplified hierarchical clustering identifies periods of interest in 2000, 2001, 2003, 2005, 2015, and 2016.

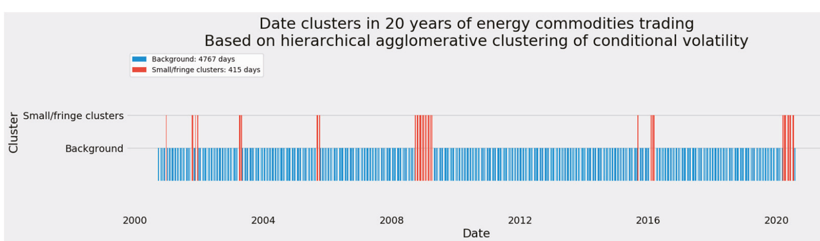


Figure 28. Hierarchical agglomerative clustering of energy-related markets—A simplified timeline aggregating the smallest six among 12 clusters.

4.2.4. Affinity Propagation

The smaller size of the energy-specific subarray created immense difficulty with affinity propagation. Scaling the element preference matrix according to the median values for each series cannot reduce the number of clusters close to the range of eight to 15, the number of clusters found by the spectral and mean-shift methods. More aggressive efforts prevented the algorithm from converging. The smallest number of viable clusters in affinity propagation appears to be 32.

Affinity propagation generates a beautiful but deadly *t*-SNE manifold (Figure 29). The large number of overlapping clusters, many enveloped in spheres with moderate to large radii, suggests that this method yields highly atomized, noncontiguous clusters.

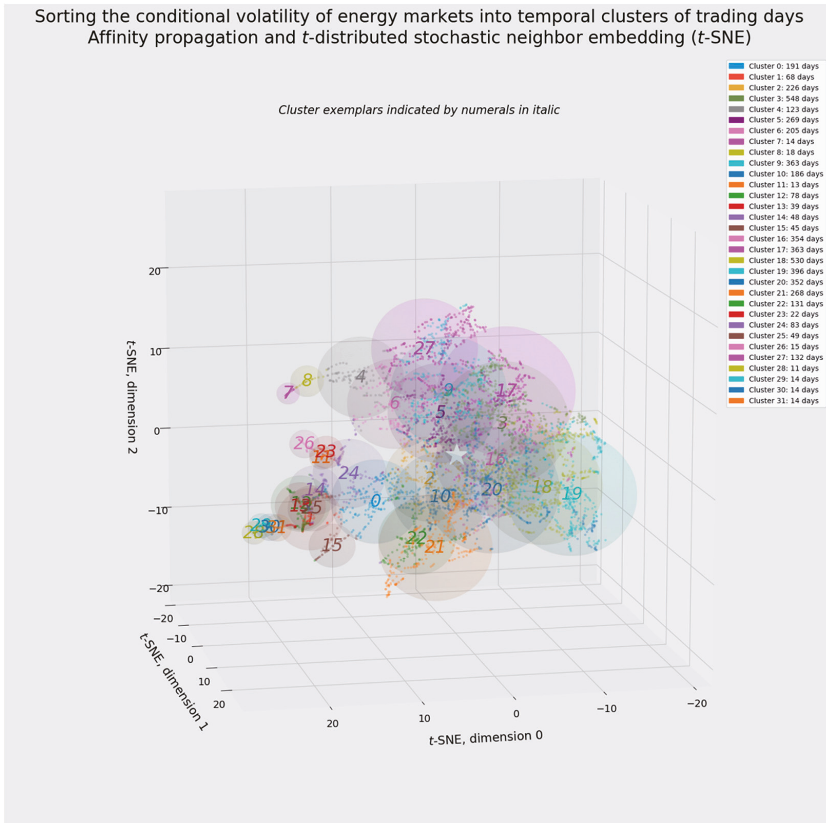


Figure 29. Affinity propagation of energy-related markets—A *t*-SNE manifold.

Figure 30 displays an ordered timeline whose clusters are extremely hard to interpret. Affinity propagation is even more chaotic than hierarchical clustering (Figure 25). The larger the number of clusters, the likelier that individual clusters will splinter internally. Identifying financially meaningful groups of trading days requires extensive work.

Experience with more tractable clustering methods suggests a way forward. Critical and ordinary trading days are not uniformly distributed. The very process used to forecast volatility—GJR(1, 1, 1)-GARCH—presumes heteroskedasticity in the sequence of logarithmic returns. All else being equal, clusters identifying extreme levels of volatility are likely to be smaller than clusters describing lower background levels.

A viable filter therefore consists of tagging affinity propagation clusters for further evaluation until the cumulative number of trading days reaches a certain threshold. The 415 out of 5182 days selected by hierarchical clustering provide a workable benchmark. Isolating the 14 smallest among 32 clusters yields 384 trading days, roughly 7.4 percent of the total. Adding a 15th cluster would add the 78 days from cluster 12 and raise the number of potentially critical days to 459, or nearly 8.9 percent. Because cluster 12 is so close to the 14 even smaller clusters, we included it. Fortuitously, that choice ultimately made no difference in aggregation through voting.

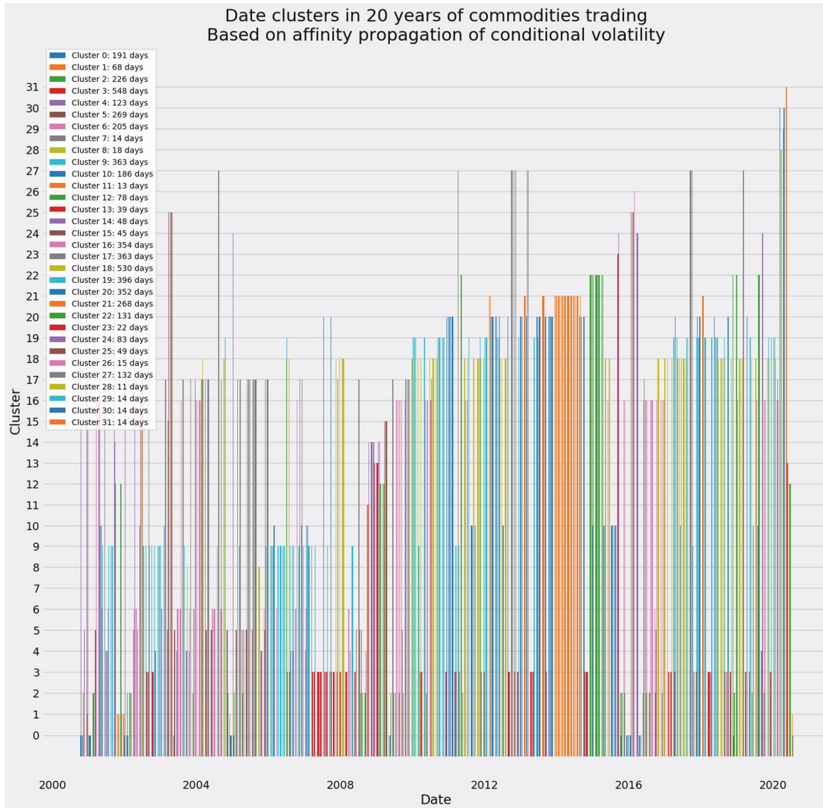


Figure 30. Affinity propagation of energy-related markets—An ordered timeline.

Figure 31 isolates the 15 smallest affinity propagation clusters. As expected, these clusters occupy the left edge of the *t*-SNE manifold and resemble the critical clusters chosen by hierarchical clustering (Figure 26). Four subgroups are evident: Two appear closer to the top: Clusters 7 and 8 in one supercluster and clusters 11, 23, and 26 in another beneath it. Clusters 28 through 31 occupy the far upper left. Finally, clusters 1, 12 through 15, and 25 comprise a more diffuse but still distinct supercluster at lower left.

Figure 32 isolates these four superclusters. The first three superclusters cover contiguous or nearly contiguous periods corresponding to energy-trading events in 2005, 2016, and 2020. The last of these plainly covers the COVID-19 pandemic—specifically, its frantic first weeks. Clusters in 2005 and 2016, wholly distinct from the financial crisis and the pandemic, imply the occurrence of events quantitatively distinct from the fourth supercluster. Those clusters unite several events in the early 2000s and the back half of the pandemic with the financial crisis.

Analyst judgment, aided by the heuristic tool of choosing the *k* smallest clusters until some fraction of all trading days is attained, rescued an initially frustrating set of results from affinity propagation. We will apply a similar approach to *k*-means clustering.

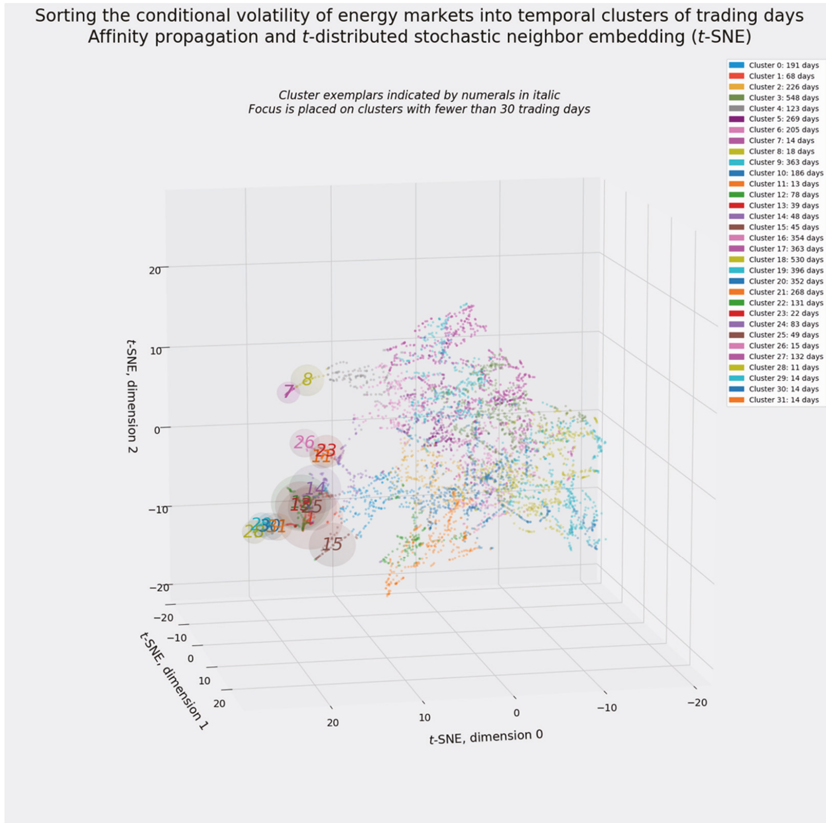


Figure 31. Affinity propagation of energy-related markets—A *t*-SNE manifold, with clusters of interest indicated by their synthetic centroids.

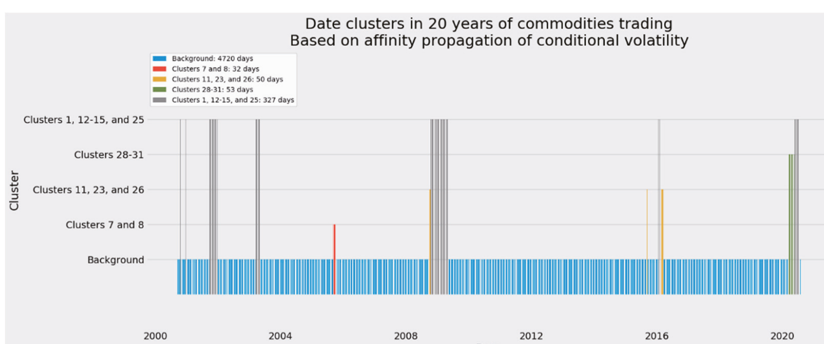


Figure 32. Affinity propagation of energy-related markets—A simplified timeline showing the 15 smallest clusters, further subdivided into four groups of interest.

4.2.5. *k*-Means Clustering

Finding the optimal number of clusters is as difficult as it is pivotal for *k*-means clustering [229,230]. Other methods have yielded as few as eight and as many as 32 clusters.

Without reliable guidance from other tests, we proceed with $k = 12$, as suggested by hierarchical clustering and roughly halfway between spectral and mean-shift clustering.

Figure 33 shows another treacherously beautiful, highly overlapping set of clusters. Although k-means clustering proceeded on a value of k akin to the number of clusters found by mean-shift and hierarchical clustering, it attains less clarity. The failure to deliver cogent clusters vexed affinity propagation and ultimately required considerable human intervention. Finally, the radial sizes of the spheres within the t-SNE manifold, aside from clusters 2, 6, 10, and maybe 11, suggest that few if any clusters will be close to contiguous.

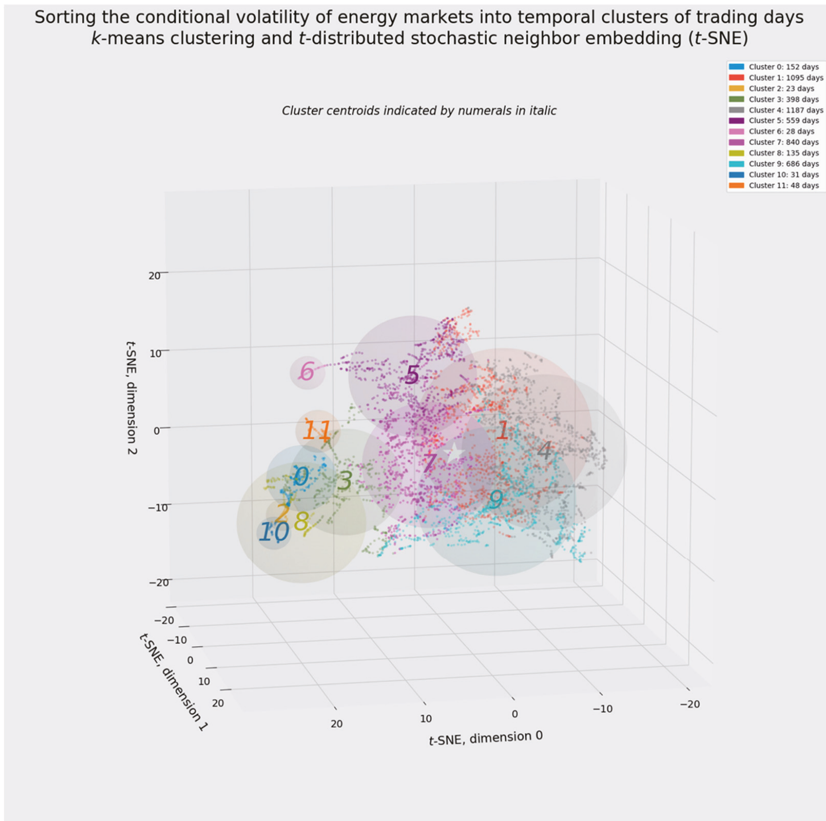


Figure 33. k-means clustering of energy-related markets—A t-SNE manifold.

As expected, Figure 34 shows a deeply fractured k-means timeline. Only clusters 6 and 10 approached perfect contiguity. Cluster 10 is more readily associated with the COVID-19 pandemic. Cluster 6 identifies the September 2005 Katrina event, which eluded detection by temporal clustering of all commodities.

The previously deployed size-based filtering technique converts the superficial chaos of k-means clustering into a credible division of energy-trading history. Figure 35 isolates the six smallest clusters (2, 6, 10, 11, 8, and 0) at the familiar left edge of the t-SNE manifold.

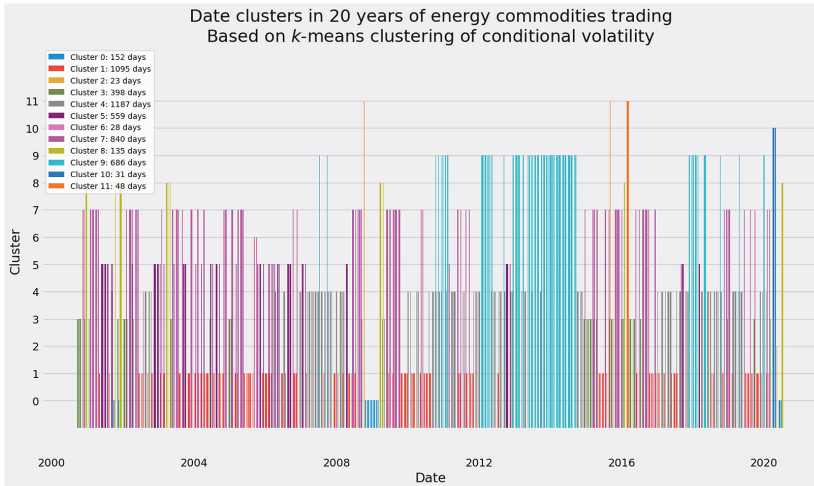


Figure 34. *k*-means clustering of energy-related markets—An ordered timeline.

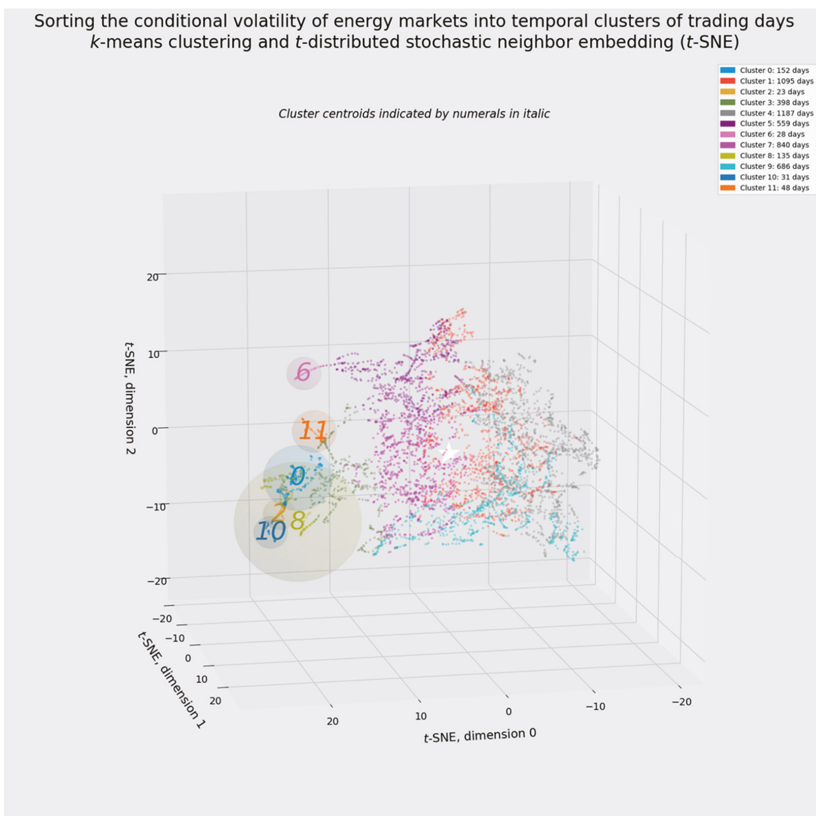


Figure 35. *k*-means clustering of energy-related markets—A *t*-SNE manifold, with clusters of interest indicated by their synthetic centroids.

Figure 36 reduces the apparent chaos in k-means clustering (Figure 34) into a binary indicator of critical events. Familiar episodes have emerged: In addition to the financial crisis and the pandemic, k-means clustering isolates events in the early 2000s (including August/September 2005) as well as events in 2015 and 2016.

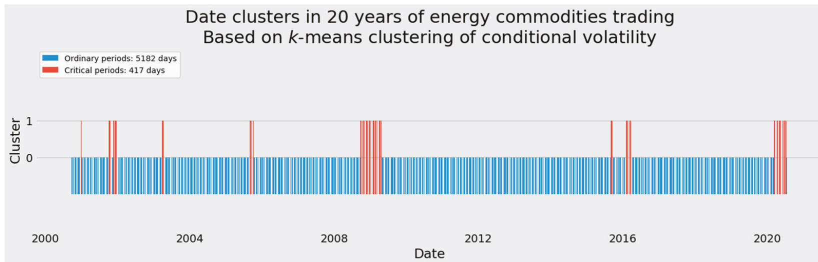


Figure 36. k-means clustering of energy-related markets—A simplified timeline showing the six smallest clusters, aggregated as indicators of critical events.

4.2.6. Aggregating Clustering Results through Voting

All that remains is the aggregation of clustering results through voting. The much smaller number of energy-related commodities makes clustering more sensitive and more likely to find a larger number of critical events. In addition, spectral clustering is much more conservative than other methods. Consequently, some gradations in addition to the extreme outcomes of set theory might be warranted.

The union of all sets of clustering results is tantamount to a one-vote regime. The intersection of those sets effectively imposes a unanimous hard voting regime. Tabulating positive results from each clustering method as a single, equally weighted vote facilitates as many gradations as there are models. In this instance, five distinct models can generate votes ranging from 0 to 5. Any positive result is an element of the union of all five sets. The more votes required, the more stringent the voting regime becomes, until the intersection of all sets reaches the extreme of unanimity.

Figure 37 displays voting results. The only trading days receiving a single vote were those identified by mean-shift clustering but by no other method. Aggregation through voting becomes most interesting at the threshold of two votes. Moreover, the 70 days receiving unanimous support are coextensive with the days found by spectral clustering. Of the other 400 days, 333 received unanimous support from the four remaining methods.

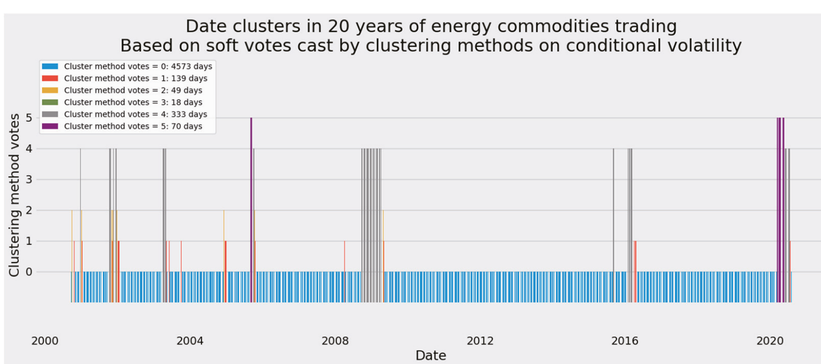


Figure 37. A voting-based aggregation of temporal clusters and critical periods in energy-related commodities trading—An ordered timeline.

5. Results, Part 2: Evaluating Critical Periods in Energy-Related Markets

5.1. Identifying and Classifying Critical Periods Located through Temporal Clustering

If all periods receiving two or more votes in Figure 37 are treated as critical, or at least as candidates for such a classification, the following events emerge from the temporal clustering of energy-related markets between 2000 and 2020:

1. Five noncontiguous days in 2000: 26, 27, and 29 September, plus 18 and 19 October;
2. The December 2000 event: 15 December 2000 through 2 January 2001;
3. The immediate aftermath of the 11 September 2001 terrorist attacks: 25 September 2001 through 7 November 2001;
4. The American invasion of Afghanistan: 13 November 2001 through 27 December 2001;
5. The second Gulf War: 19 March 2003 through 5 May 2003;
6. The single day of 30 September 2013;
7. Five noncontiguous days in 3, 6, 7, 8 December 2004 and 16 December 2004;
8. The aftermath of Hurricane Katrina: 31 August 2005 through 12 October 2005;
9. The global financial crisis: 19 September 2008 through 30 April 2009;
10. The September 2015 event: 2 September 2015 through 22 September 2015;
11. The winter 2016 event: 18 January 2016 through 25 March 2016;
12. The COVID-19 pandemic: 9 March 2020 through 17 July 2020.

Three of these 12 events may be too brief or incoherent for proper examination. The noncontiguous days in fall 2000 and December 2004, as well as 30 September 2003, comprise a total of 11 trading days. The shortest span among the nine other events is the 13 days of the December 2000 event. Even if those three events are excluded from in-depth analysis, however, the 11 days they collectively span may be worth including in a broader definition of critical (as distinct from ordinary, noncritical) trading days.

A more generous definition of critical days remains available. Several clustering methods could have been expanded to include closer to 800 rather than 400 days. Days that are noncontiguous under this aggregation of clustering results may cohere once more days of possible interest are investigated.

Among the nine surviving events, it makes sense to distinguish between (a) events uncovered by temporal clustering of all commodities and (b) events unique to the energy-specific subarray. There are three possible and nonmutually exclusive justifications for separate treatment. First, the financial crisis of 2008–2009 and the COVID-19 pandemic may have affected *all* commodity asset classes in ways that meaningfully departed from the ordinary course of trading. Second, crises affecting all commodities are likelier to be deeper recessions affecting the broader economy across a wider geographic swath. In other words, events affecting other commodities in addition to oil and refined fuels arise from comprehensive declines in demand. By contrast, crises unique to energy markets are likelier to arise from disruptions in supply, attributable to acts of war, natural disasters, or even OPEC production decisions. Finally, the impact of the financial crisis or the pandemic on energy may have been so profound as to sway the overall commodities market.

5.2. Visualizing and Evaluating Critical Periods Uncovered by Temporal Clustering

5.2.1. Condiitonal Volatility Forecasts

In principle, temporal clustering precedes and enables more extensive analysis. Identifying events such as the global financial crisis, the COVID-19 pandemic, and energy-market disruptions associated with American military engagements offers even greater value when those events' financial characteristics are distinguished from those of calmer, ordinary conditions. This section visualizes conditional volatility and cumulative logarithmic returns during critical events.

Since temporal clustering operated on arrays of conditional volatility, it makes sense to depict conditional volatility during critical events. Cumulative log returns describe the experience of commodity traders during those events. They, too, are worth illustrating.

Figure 38 shows the volatility conditions during the nine critical periods identified through temporal clustering. Throughout 20 years, an equally weighted market basket of Brent, WTI, gasoil, and gasoline exhibited an average GJR(1, 1, 1)-GARCH conditional volatility forecast of 1.918575. Collectively, all critical events exhibited average conditional volatility of 4.009828, while noncritical periods averaged 1.709983. Many but not all of the periods in Figure 38 exhibited peak volatility exceeding 4.00.

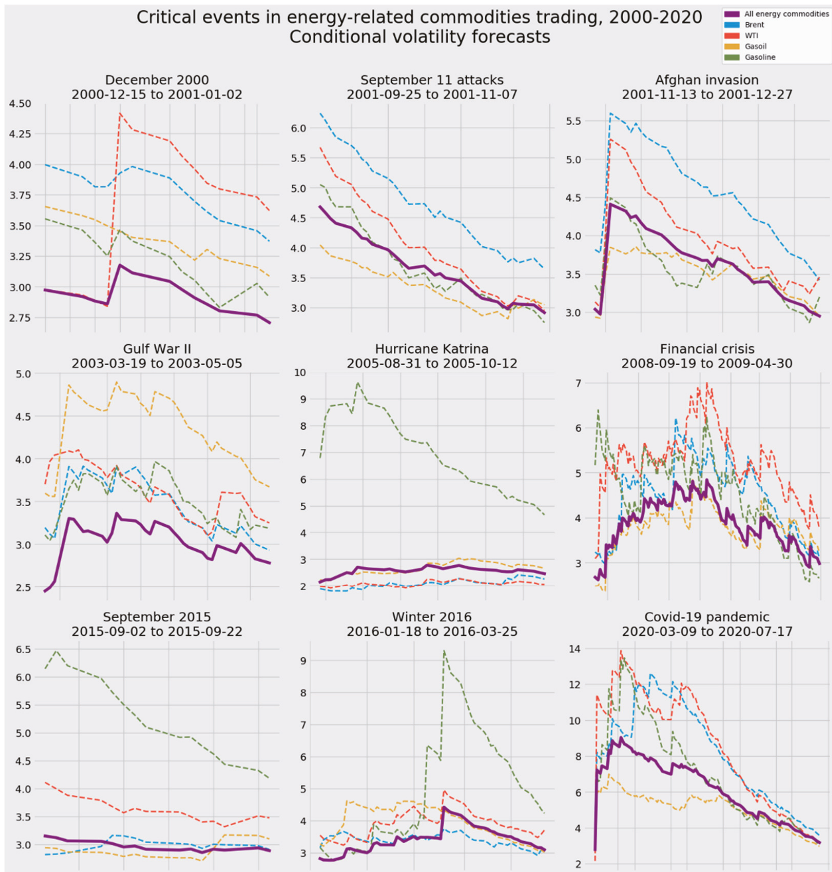


Figure 38. Conditional volatility forecasts during critical periods for an equally weighted market basket of four oil and fuel commodities, with details for each of the constituent markets.

The real question is why some periods showed elevated volatility for energy-related commodities, but others did not. Notably, both the financial crisis and the COVID-19 pandemic showed sustained volatility above 4.00. By contrast, a majority of the energy-specific critical events managed to stay below 4.00. Conditions of active warfare do not explain the difference. The Second Gulf War in 2003 remained below 4.00, while the event of 2016, comparable in duration and overall volatility, did crest above 4.00.

Every energy-related crisis does exhibit an upward volatility spike in at least one of four oil and fuel markets. The two episodes associated with the September 11 terrorist attacks and the American military response, the global financial crisis, and the COVID-19 pandemic all show the four individual markets spiking together and early. To a limited degree, the same can be said for Gulf War II in 2003.

The five other energy-specific events appear to be driven by a volatility spike in a single constituent market. Only the December 2000 event involved a spike in a crude oil market, as volatility in WTI rocketed in the middle of that month. Gulf War II occasioned a sudden rise in gasoil volatility, which remained high until markets eased seven weeks later. All other events—Hurricane Katrina in 2005 and the temporally proximate events of September 2015 and late winter 2016—involved spikes in gasoline.

At least to some degree, all nine critical periods identified by temporal clustering of volatility exhibit the imbalanced triangular shape associated with the rockets-and-feathers account of oil pricing and the Edgeworth price cycles in refined fuel markets. At or near the beginning of each event, volatility in at least one constituent market spikes. Volatility then eases slowly. Whether to describe the relaxation of volatility by analogy to feathers or gradations on a sawtooth blade appears to be a strictly esthetic question. Volatility during these critical events exhibits the triangular signature associated with either account of pricing dynamics in energy-related markets.

On the other hand, critical periods identified through temporal clustering do not invariably exhibit the peak-to-trough shape that characterizes traditional definitions of recessions and bull and bear markets. Though several episodes open with peak volatility for at least one of the four energy-related commodities, others do not. Given the mathematical basis of clustering, critical periods do not end because volatility reaches a local trough. Rather, they end because volatility has relaxed and returned to background levels.

Differences in the volatility profile of these events provide a reminder that temporal clustering by any one method reflects subtleties that can be erased during aggregation by voting. To be workable, the voting process must treat each method as though it were a binary classifier. Either a period is critical, or it is not.

Each of the individual methods nevertheless achieved subtleties by finding more than two clusters. For instance, the very conservative spectral clustering method isolated the 17 days it associated with Hurricane Katrina from six wholly separate clusters that collectively identified 53 days during the pandemic. Differences among those six periods become unrecoverable once they are aggregated as a "pandemic" supercluster.

Other methods reflect a similar subtlety. Mean-shift clustering suggested that a single cluster characterized much of the financial crisis as well as the geopolitically fraught energy crises of the early 2000s, but Katrina stood entirely apart. Hierarchical agglomerative clustering could have been interpreted as recommending three superclusters: one for 51 days during the crisis, another 848 days worthy of attention for abnormal volatility readings, and a third supercluster comprising all other trading days across two decades.

Analyst judgment looms large again. There may be no quantitatively consistent rule for striking the desired balance between the ease of isolating outliers on a binary basis and the nuance of discerning differences *among* outlier, critical periods.

5.2.2. Logarithmic Returns

These periods' log returns do provide another tool. Visualizing log returns also depicts markets as investors understand them: by the ebb and flow of profit and loss.

Volatility events are associated, perhaps stereotypically and simplistically, with harrowing declines in asset prices. This perception is reinforced by the popular depiction of VIX as the "fear index." The log returns in Figure 39 suggest far greater diversity and subtlety in the temporal clustering of energy-related markets. For the steep, sustained decline in demand associated with the financial crisis, the stereotype does apply.

Other events tell a subtly different story. The suspension of air travel in the United States after 11 September 2001 inflicted losses on all oil and fuel markets. That episode may represent a rare instance of an energy-specific crisis arising from an acute disruption in demand as well as supply, or instead of it. After a steep decline at the beginning of the ensuing invasion of Afghanistan, prices stabilized and rose. Though they were separated by less than a week, these were distinct events.

Although the rockets-and-feathers hypothesis and Edgeworth pricing cycles are associated with prices rather than volatility, the triangular charts associated with those accounts of energy markets do not appear in Figure 39. Temporal clustering of the volatility array did not isolate periods where prices rose rapidly and eased slowly. If anything, some critical periods exhibit the opposite "boulders and balloons" pattern, by which gasoline prices steeply decline in response to oil price decreases, and then recover slowly [28].

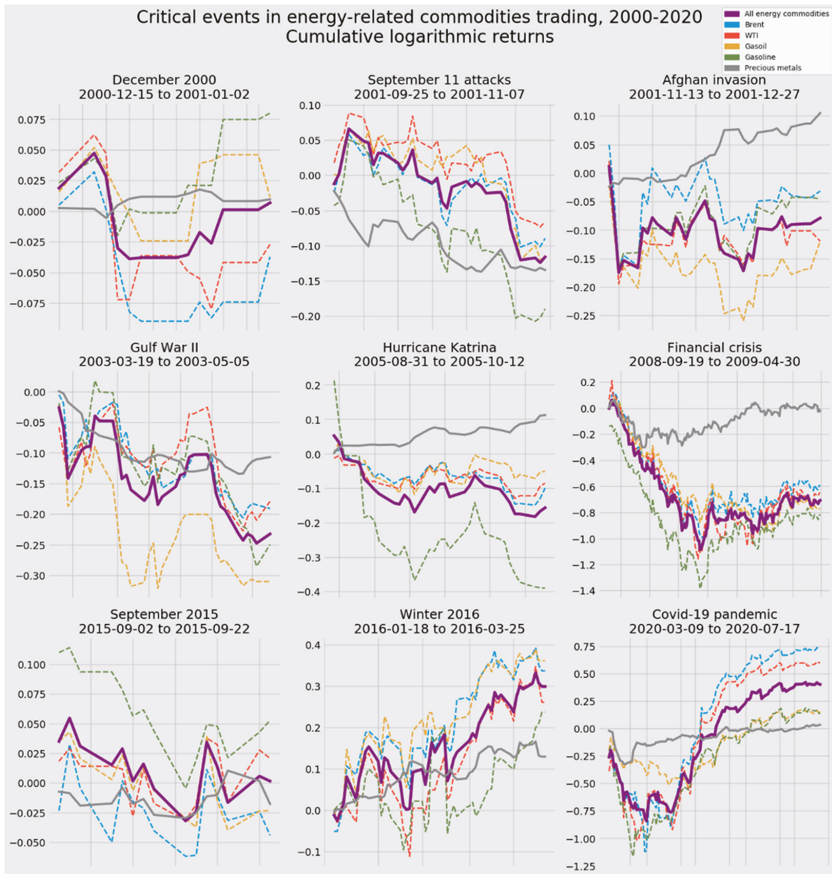


Figure 39. Cumulative logarithmic returns during critical periods for an equally weighted market basket of four oil and fuel commodities, with details for each of the constituent markets. Cumulative log returns on precious metals are shown for purposes of comparison.

On the other hand, to the extent that these signature descriptions of price- or return-based time series apply to energy markets under normal conditions, we might find that energy markets follow differently shaped arcs during critical periods. Indeed, it is entirely plausible that sawtooth-shaped or rockets-and-feathers patterns characterize volatility but not return during critical periods, while the opposite relationship governs ordinary, background trading. It is also possible that the iconic shapes associated with Edgeworth pricing cycles or rockets-and-feathers behavior do appear throughout these time series, but over time horizons longer than those of acute events isolated by temporal clustering. The behavior of energy markets during temporal clusters associated with ordinary, background trading invites further research.

The movement of precious metal prices also highlights the difference between the terrorist attacks and the Afghan invasion. Precious metals are considered hedges against inflation and geopolitical turbulence. The latter property is probably the dominant driver of precious metal prices during military activities affecting petroleum-exporting regions. Precious metal prices fell after 11 September 2001 but recouped their losses during the Afghan invasion. Precious metal prices fell again during Gulf War II, when they accompanied even steeper declines in oil and fuel prices.

At least two events proved to be net winners for energy investors and companies. Despite a few downward spikes, winter 2016 eventually rallied these energy markets.

Even more dramatically, the onset of the COVID-19 pandemic inflicted catastrophic losses on oil and fuel markets, only to spark a ferocious rally. The price of gasoil, a fuel associated with industrial uses and long-haul transport, remained more stable throughout both phases. (Despite gasoil's superior fuel efficiency and lower levels of pollution [242], and despite the popularity of diesel-powered cars in Europe, gasoline engines in passenger vehicles outnumber diesel engines four to one [243].) It is little wonder that this historically unprecedented episode generated such diverse clustering results. At the same time, aggregating all methods enables the evaluation of four months of prices, returns, and volatility that know no equal in financial history.

5.3. Comparing Energy-Market Impacts with Other Commodity Asset Classes

Energy-specific crises may be best understood through a comparison with other commodity classes. Subjectively defined crisis periods offer a good starting point. In addition to six critical periods in broader commodity markets between 2000 and 2019 [164], we propose a seventh—the COVID-19 pandemic—as defined by temporal clustering of energy-specific volatility. The critical periods are as follows:

1. The gas shock, March 2001 through December 2001;
2. The Iraq invasion, November 2002 through July 2003;
3. Oil price increases, June 2007 through August 2008;
4. Global oil and food crises, July 2008 through January 2009;
5. The coffee shock, June 2010 through March 2011;
6. Chinese deceleration, June 2015 through February 2016;
7. The COVID-19 pandemic, 10 March 2020 through 17 July 2020.

Figure 40 overlays these periods on conditional volatility for all commodity asset classes. A majority of these seven human-designated crises accompany visible spikes in volatility in energy-related markets, even though many such crises are either defined neutrally (for example, Chinese deceleration) or wholly by reference to other commodity markets (the coffee shock). Indeed, deceleration of the Chinese economy would explain the energy markets' September 2015 and winter 2016 events.

Aggregate statistics on energy-specific crises show elevated volatility for these markets (Figure 41). Energy-specific markets are more volatile on the whole, but the gap between volatility in these commodities and in all other asset classes grows considerably during volatility outliers in energy-related markets.

Unsurprisingly, defining crises according to a single asset class has the effect of highlighting volatility events unique to that class. An even more striking implication of Figure 41 is the reduction of volatility in almost every other asset class, even relative to noncritical periods generally. Only tropical and semitropical softs experienced increased volatility during energy-related events. Akin to the way VIX options and other volatility-based strategies can hedge equity portfolios, stakeholders in the fossil fuel sector might consider broader holdings as a way to offset energy-specific turbulence.

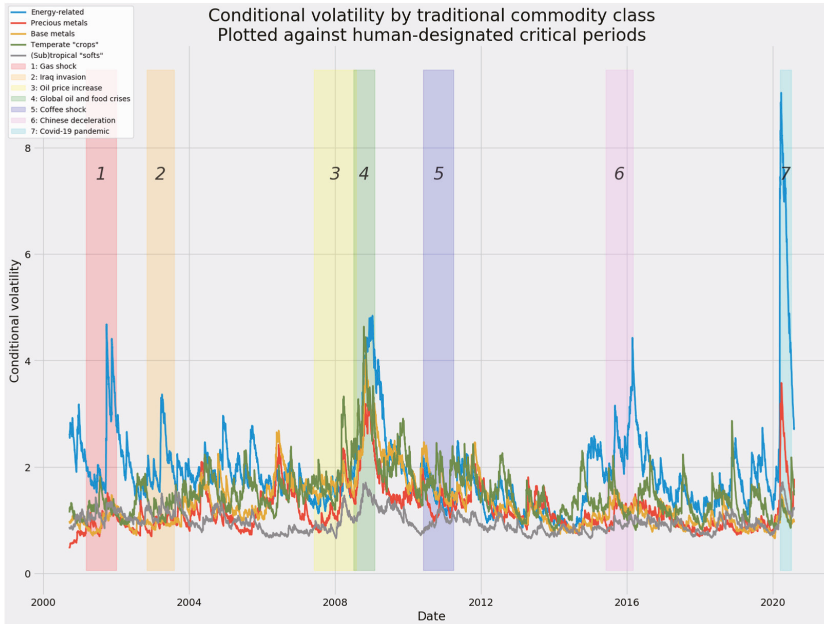


Figure 40. Six human-defined commodity crises, 2000–2020, plus the COVID-19 pandemic.

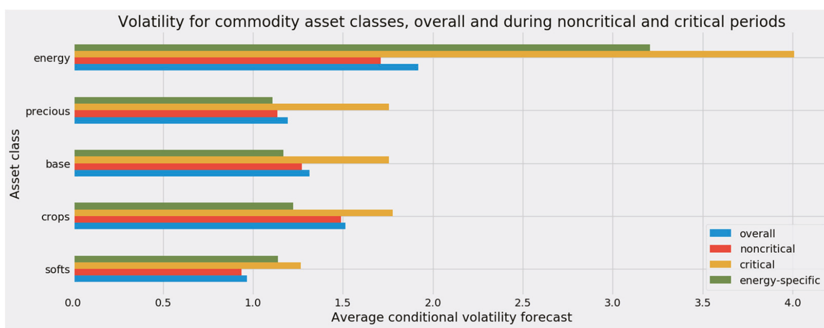


Figure 41. Volatility for commodity asset classes, overall and during noncritical and critical periods.

The opposite directions of annualized log returns on all commodity classes, as shown in Figure 42, reinforce the intuition that other commodities move separately during events affecting solely energy-related markets. This exercise vindicates the wisdom of clustering all commodity markets before focusing on energy-specific events. There have been exactly two crises affecting all commodity markets since 2000: the global financial crisis of 2008–2009 and the COVID-19 pandemic. Aside from assets related to energy, no asset class lost ground during energy-specific events. Base metals did suffer steep price declines overall and lost ground relative to baseline rates of return during energy-specific events. Even that class did not decline in the aggregate, however, during the American military interventions of the early 2000s and the energy-market disturbances of 2015 and 2016.

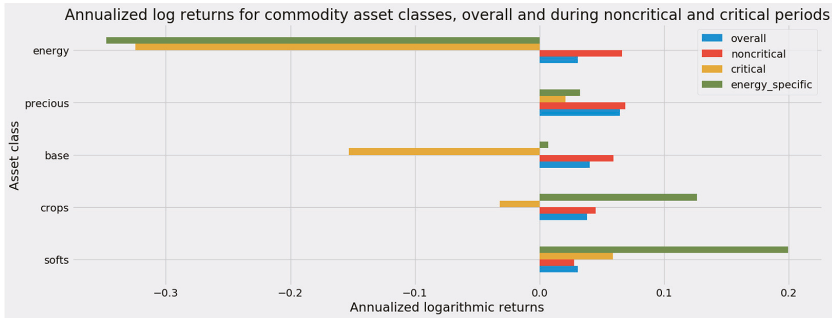


Figure 42. Annualized logarithmic returns for commodity asset classes, overall and during noncritical and critical periods.

Figures 43 and 44 highlight the effects of the financial crisis and the pandemic. Though these broad events affected all commodities, they made a far deeper impression on energy-related markets. Collapses in demand had a far greater impact on energy-related commodities and (to a lesser extent) base metals during the financial crisis. COVID-19, on the other hand, benefited the energy sector overall after historically unprecedented gyrations in both directions.

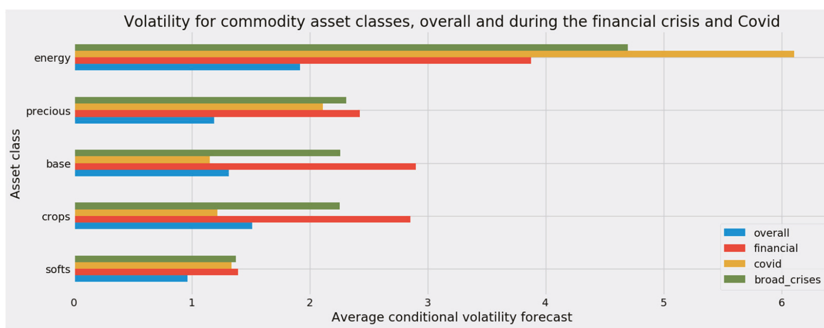


Figure 43. Volatility for commodity asset classes, overall and during the financial crisis of 2008–2009 and the COVID-19 pandemic.

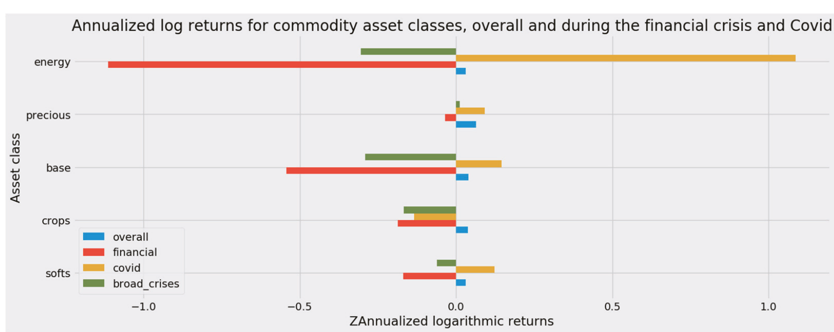


Figure 44. Annualized logarithmic returns for commodity asset classes, overall and during the financial crisis of 2008–2009 and the COVID-19 pandemic.

5.4. Comparing Crude Oil with Refined Fuels

The examination of volatility and log return for energy-related markets in Section 5.2 suggested dramatic differences among individual markets. Internal differences among these markets may be more economically meaningful than differences separating oil and refined fuels from other commodities.

Volatility for Brent, WTI, gasoil, and gasoline is elevated during all energy-related events. Figures 45 and 46 should come as no surprise at all. Differences in scaling may obscure the fact that the across-the-board, the crises of 2008–2009 and COVID-19 in Figure 46 were more volatile than the energy-specific events in Figure 45.

There is a noticeable difference between refined fuels. The palpably lower levels of volatility for gasoil in all conditions suggests that this fuel enjoys a floor of demand that undergirds prices and returns throughout varying economic conditions. The flip side of gasoil's relative stability is greater susceptibility for gasoline. Faster and less consistent changes in demand for gasoline generate greater turbulence.

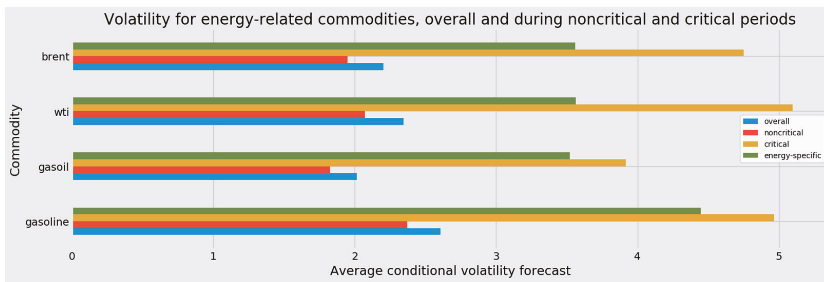


Figure 45. Volatility for energy-related commodities, overall and during noncritical and critical periods.

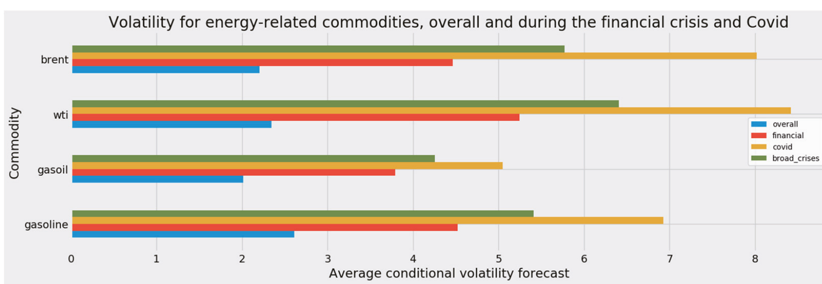


Figure 46. Volatility for energy-related commodities, overall and during the financial crisis and the pandemic.

Annualized logarithmic returns on Brent, WTI, gasoil, and gasoline tell a more dramatic story (Figures 47 and 48). Relative to crude oil, refined fuels absorb far more punishing losses in critical periods. Such losses—though by no means universal, as demonstrated by the winter 2016 event and the COVID-19 pandemic—are far steeper for gasoil and especially gasoline. WTI essentially broke even during the two greatest economic crises of the past two decades. Brent pulled affirmatively ahead of the breakeven point.

By contrast, gasoil and gasoline staggered during the financial crisis. They cratered during the onset of the COVID-19 pandemic, only to regain their footing and actually advance as pandemic conditions retreated during the summer of 2020.

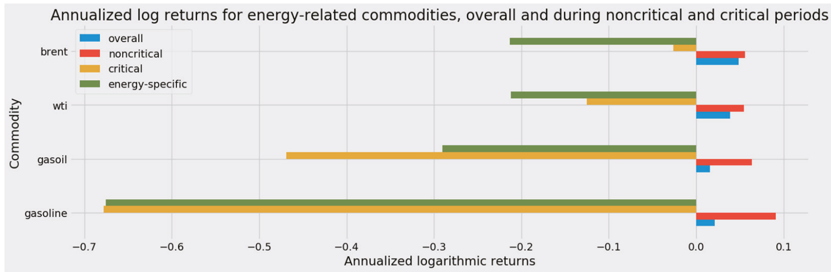


Figure 47. Annualized logarithmic returns on energy-related commodities, overall and during noncritical and critical periods.

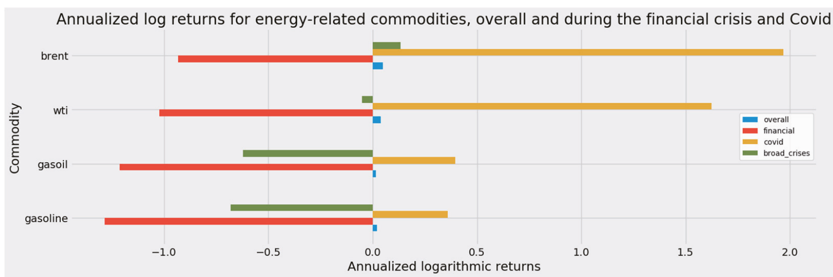


Figure 48. Annualized logarithmic returns on energy-related commodities, overall and during the financial crisis and the pandemic.

6. Discussion

6.1. Implications for Firms, Investors, and Governments

"The interconnected nature of oil, metal, and agro-commodity price movements through the transmission of price shocks have serious implications for policymakers and investors" [57] (p. 1). Oil price volatility also affects strategic investment decisions by individual firms [244,245]. All stakeholders in energy markets should pay close heed to the identification of critical periods through temporal clustering.

As expected, the temporal clustering of the limited market basket of four energy-specific commodities generated a larger number of discrete critical events. The parallel exercise of clustering the broader basket of 22 commodities proves valuable in distinguishing between supply-related and demand-related events. Disruptions in demand affect multiple commodity classes. They tend to be associated with recessions, depressions, and other events of global scale. By contrast, supply disruptions tend to arise from acute crises associated with military operations and extreme weather. At least since 2000, supply-related crises have been unique to energy-related markets and tend to be shorter in duration.

These patterns confirm the value of the trichotomy identified in [126,127]. Though commodity prices are generally endogenous with respect to the global business cycle, they respond to demand shocks slowly but steadily. They respond to supply shocks with sharp but small and momentary movements. Though these effects may not be unique to energy-related markets, this article's focus on oil, gasoline, and gasoil certainly isolated all three effects.

The different duration associated with each of the two types of critical events affects managerial, investment, and policy prescriptions. Different stakeholders in energy markets and adjacent areas of the economy have different time horizons. At one extreme, the brevity of supply-related disruptions suggests that crises identified through the temporal clustering of the energy-specific subarray of volatility forecasts carries the greatest weight for short-term hedging and managerial decisions.

Longer-term investors and strategic managerial decisions (as distinct from tactical hedging decisions) depend more heavily on demand-related crises. These tend to be crises that emerge from temporal clustering of the all-commodities array as well as clustering of the narrower, energy-specific subarray. Changes in comovement and connectedness during these periods tend to be slower but also more enduring. Structural shifts in economic dynamics are likelier to occur during these overlapping crises, as opposed to acute events arising from disruptions in the supply of oil or its distillates.

The difference between long-term structural shifts due to changes in demand and episodic disruptions in supply carries profound macroeconomic implications. Conventional measures of core inflation exclude putatively volatile food and fuel commodities [171–174]. Consumer demand, at least for fuel, turns out to be quite inelastic in the short term. Temporal clustering uncovered rapid and extreme movements in fuel prices, only a few of which coincided with broader drops in demand detected by temporal clustering of all commodities.

Generalizations of the methods demonstrated in this article promise powerful insights, microscopic as well as telescopic. Extensions of this research can and should be both introspective and teleological. Opportunities for further research lurk within the data gathered for this article. In addition to the array of log returns for all commodities, as well as those related to energy, temporal clustering can use different variations on the theme of volatility. Historical volatility or additional conditional volatility forecasts at higher frequencies may yield different results, as would implied volatility derived from options trading.

The temporal clusters also invite closer examination. Hierarchical clustering could easily have been expanded to treat 17 percent rather than 8 percent of all trading days as potentially critical. The threshold for votes among clustering methods could be reduced from two to one. A softer definition of periods to be identified by temporal clustering may uncover, as hypothesized at the beginning of this article, inflection points as well as local minima and maxima within the history of commodities trading.

Obvious extensions beyond crude oil and refined fuels involve other asset classes among commodities, such as precious metals or the surprisingly placid market for tropical and subtropical softs. Although this article did gather data for as many as four additional asset classes among commodities—precious metals, base metals, temperate crops, and semitropical and tropical "softs"—the thoroughness needed to evaluate even one of those commodity classes would have required a considerable effort.

The value of examining temperate crops alongside oil, gasoline, and gasoil could be considerable. At a bare minimum, temporal clustering would enhance the understanding of connectedness between markets for fossil fuel commodities and food crops [78–80]. Corn as a feed stock for ethanol and soybeans as a feed stock for biodiesel directly affect oil markets [84]. Sugarcane, a crop not included in this article's data sources, is an obvious candidate for inclusion in such a comparison [85].

Financialization of commodities raises the premium on hedging. First-order opportunities for diversification and hedging lie within commodity markets. Precious metals experienced relatively less volatility and retained more of their value throughout all crises. During energy-specific events, if not in broader crises, agricultural commodities as a superclass proved resilient. This was particularly true of tropical and semitropical softs. Returns on those commodities mitigated many of the losses incurred by crude oil and refined fuels during energy-specific events. They even fared reasonably well during the financial crisis.

The relationship between energy-specific and agricultural commodities should provide especially useful guidance in emerging markets. The decoupling of energy commodities from softs may reveal hedging and diversification opportunities among investment opportunities in emerging markets. Petrostates tend not to depend on agricultural exports, and coffee and cocoa producers are not coextensive with OPEC. Extensions of this work can critical moments identified through unsupervised machine learning with event studies. In addition to OPEC announcements [144,145], the public disclosure of decisions affecting major agricultural markets and the resolution of global trade disputes over agriculture can serve as bases for comparative analysis.

All capital markets invite temporal clustering. Deeper research should examine equities and sovereign debt as well as commodities. Although many sources addressing diversification opportunities affecting oil and refined fuels have specifically addressed other commodities (including but not limited to precious metals) [55,57], equity holdings can also contribute to diversification [50,114–116].

In addition to markets for equity and sovereign debt, the entire fixed-income marketplace presents an enticing target for temporal clustering. The market for debt includes Islamic sukuk [246]. Clustering by market movements should operate at two levels: Initially in financial space, as different instruments respond to interest-rate, default, and prepayment risk, and again in time as crises overtake and release different segments of the bond market.

6.2. Additional Directions for Research: Temporal Clustering and Machine Learninng

This article has demonstrated the feasibility of using unsupervised machine learning to isolate and interpret critical periods in financial and economic history. In terms of mathematical complexity, the methods demonstrated in this article lie somewhere between the most familiar benchmarks in the literature on the identification of regime shifts throughout economics. The clustering of all commodity markets, followed by a narrower focus on four energy-related markets—Brent, WTI, gasoil, and gasoline—encompasses subtleties that elude methodologies based on arbitrary 10 or 20 percent changes from short-term minima and maxima in stock market prices. By the same token, temporal clustering does not purport to capture all of the nuances of the dynamic-factor, Markov-switching model that the NBER uses to identify recessions in the United States.

The amount of subjective judgment used in this application of unsupervised machine learning likewise occupies middle ground. Since conventional definitions of bull and bear markets are based on fixed changes in stock prices, those exercises rely exclusively on the definition of peaks and valleys in recent financial history. Conversely, the selection of commodity markets and the admittedly crude taxonomy distinguishing oil and refined fuels from precious and base metals, temperate crops, and tropical and semitropical softs does not approach the depth of the research supporting the NBER's focus on non-farm employment, industrial production, real personal income, and real manufacturing and trade sales as broad macroeconomic indicators.

Much of the mathematical elaboration in temporal clustering arises from unsupervised machine learning itself. The categorical ontology of commodity markets is an artifact of the clustering of daily logarithmic returns for each commodity [1]. The clustering of trading days according to volatility forecasts generates far more diverse results. The vast difference in scale between two dozen commodities, give or take, and thousands of trading days makes temporal clustering that much more challenging.

Fixing the optimal number of clusters continues to pose a formidable barrier. One possible solution lies in using more deterministic methods, such as spectral or mean-shift clustering, to guide more malleable methods. Leading use cases include the calibration of element preferences in affinity propagation or the stipulation of k in k-means clustering.

By its nature, clustering as a branch of unsupervised machine learning divides large quantities of data into more tractable classes. The concurrent application of multiple clustering methods with wholly disparate algorithms highlights the applicability of an ensemble technique from supervised machine learning: the voting classifier. This article used voting methods to aggregate clustering results.

This article also exploited an intuition arising from clustering as a method for outlier detection. Especially for methods predisposed to generate a large number of clusters (affinity propagation) or to select noncontiguous clusters (k-means), one method for imposing order on temporal clustering consists of selecting clusters until some threshold fraction of all trading days has been reached.

This method does inflict costs of its own. Any reduction in the number of clusters pushes clustering closer to binary classification and away from the nuances attained by multiclass clustering. Even the conservative spectral clustering method distinguished between the pandemic and the energy-specific event associated with Hurricane Katrina.

The extreme turbulence associated with COVID-19 provides a unique lesson. The four months after the pandemic's outbreak in March 2020 revealed radical shifts that had no precedent in this 20-year survey. Indeed, there may be no other period like it in modern economic history. The sudden shock to demand, to say nothing of uncertainty over the progression of the greatest threat to human health apart from war, destroyed normal channels for conveying economic information [247].

Utmost care in the volatility-based clustering of critical periods is advised, especially if clustering is treated as an exercise in binary classification. The nine discernible events highlighted in this article are quite diverse, even as they were treated as outliers in the ordinary fabric of financial spacetime. Cataclysms such as the financial crisis of 2008–09 and the COVID-19 pandemic swamp all commodities, though by no means equally. Other events exhibit unusual volatility in a single energy market, often (but not always) gasoline.

Even the direction of the impact on prices and returns is not uniform. Two events, notably, the winter 2016 event and the pandemic, witnessed sharp increases in energy prices. More precisely, these events represented superclusters of temporally contiguous but economically distinct periods. Temporal clustering can steer analysts toward intriguing moments.

On the other hand, clustering cannot dictate the course of economic history. Nor can clustering define the inferences to be drawn from economic analysis. As the poet T.S. Eliot wrote [248] (p. 26):

> "The knowledge imposes a pattern, and falsifies, /For the pattern is new in every moment/And every moment is a new and shocking/Valuation of all we have been."

The comparison of temporal clustering across all commodities with the energy-specific subarray carries broad and important implications. The inescapably narrow focus on any fraction of the universe of valuable assets necessarily undermines efforts to model the entire economy according to that limited sample [128].

The reduction of complexity may ultimately prove more of a virtue than a vice. As economics advances by devising ever more elaborate models, from the decision-making level to that of the broader macroeconomy, simplification often holds the key to success [151]. The deeper the data, so it seems, the more vital it becomes to reduce complex relationships to their bare essence [151].

Unsupervised machine learning's greatest contribution may lie in its ability to reveal those moments where other analytical methods are most likely to fail. Such failures include the shortcomings of other branches of artificial intelligence. Failures in otherwise accurate deep learning models for forecasting economic time series may reveal macroeconomic regime shifts in an unintended and unsupervised fashion [249].

Temporal clustering may reveal the mirror image of this phenomenon. The application of unsupervised machine learning to economic time series can identify such shifts, or at least smaller breaks or departures, from otherwise prevalent financial or macroeconomic regimes. Such recognition, one can only hope, should happen *ex ante*, before policymakers adopt predictive models as elaborate and consequential as they are flawed.

Disruptions in financial or economic spacetime represent deviations from the "normal science" of economic exchange. Even if temporal crises do not shift economic paradigms, they raise departures from prior factual suppositions that warrant analytical calibration [250]. Posterior probabilities in Bayesian statistics and the concept of backpropagation in deep learning through neural networks embody this wisdom.

At the very least, critical periods identified through temporal clustering should not be expected to behave according to the usual rules of financial or economic engagement. *Ceteris* *paribus*, temporal outliers identify wrinkles in economic time when conventional wisdom and entrenched forecasting methods are most likely to fail. As necessity is the mother of invention, crisis is the font of philosophical foment and the father of discovery [250].

7. Conclusions

Crude oil and refined fuels are crucial elements of global trade. Through their financialization, these energy commodities sway capital markets and economic development around the world. Geopolitical struggles over oil and its distillates divide importing from exporting countries. Public policies responding to these economic and diplomatic conditions seek to nudge oil-importing countries from fossil fuels and toward a fuel mix with renewable sources and a lower carbon footprint.

Mainstream economics has exhaustively evaluated the volatility dynamics and connectedness of energy-related commodities. These effects vary considerably across time. Disruptions in supply and especially in demand punctuate distinct regimes in the relationship of oil and fuel markets to financial instruments and markets for other commodities. The rockets-and-feathers behavior of Edgeworth price cycles in gasoline markets may even reverse and follow the opposing boulders-and-balloons pattern, depending on the relationship of fuel markets to oil prices, capital markets, and broader business cycles.

At the same time, mainstream economics has traditionally relied on peak-to-trough methods to define these cycles and their temporal boundaries. Given the centrality of the time domain to fuller understanding of volatility and connectedness in energy markets, this article has used a new set of computational tools to define critical periods in the trading of energy commodities. Unsupervised machine learning and related fields of artificial intelligence promise deeper mastery of time and its economic meaning.

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COVID-19 and the Energy Price Volatility

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Abstract: The challenges of the world economy and their societies, after the outbreak of the COVID-19 pandemic have led policy-makers to seek for effective solutions. This paper examines the oil price volatility response to the COVID-19 pandemic and stock market volatility using daily data. A general econometric panel model is applied to investigate the relationship between COVID-19 infection and death announcements with oil price volatility. The paper uses data from six geographical zones, Europe, Africa, Asia, North America, South America, and Oceania for the period 21 January 2020 until 13 May 2021 and the empirical findings show that COVID-19 deaths affected oil volatility significantly. This conclusion is confirmed by a second stage analysis applied separately for each geographical area. The only geographical area where the existence of correlation is not confirmed between the rate of increase in deaths and the volatility of the price of crude oil is Asia. The conclusions of this study clearly suggest that COVID-19 is a new risk component on top of economic and market uncertainty that affects oil prices and volatility. Overall, our results are useful for policy-makers, especially in the case of a new wave of infection and deaths in the future.

Keywords: COVID-19; pandemic; energy market volatility; announcements; uncertainty; deaths; infections

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1. Introduction

It is expected for someone to think that there is no connection between a pandemic and the energy industry. But when it becomes clear that the pandemic is responsible for uncertainty, the relationship between these two magnitudes acquires a logical basis. Two years after the COVID pandemic appeared in the city of Wuhan in China in 2019 and spread rapidly in Europe and in the USA, it was obvious that consequences were going to be severe for the world economy. The main feature of this pandemic was its rapid and unprecedented negative impact on economic activity and in particular the spread of great uncertainty worldwide. It was then expected for this uncertainty to combine with financial turmoil pushing companies and individuals in taking precautionary measures. Their first measure was to decrease their spending to be able to face impending difficulties if necessary.

The environment created by the financial hardship but mostly by the daily announcements of deaths and infections naturally had a negative effect on the consumers' psychology. In such an insecure environment, it was rather normal to observe a reduction in demand for oil and therefore a reduction in its price. Speaking with numbers, during the first two years of the pandemic, global electricity demand was decreased by an average of 15% [1] resulted in a downward movement of the prices for crude oil and natural gas.

It should be noted that the COVID-19 pandemic period did not have the same characteristics as other periods of uncertainty which were due to a slowing or overheating of the economy, and thus measures to deal with COVID-19 should be different too. In any case, the focus of these measures was on the restriction of free movement and transportation. In fact, travel bans not only applied between different countries but were mainly imposed within countries themselves. So, it was natural for these restrictions on the movement of people and the transport of goods to cause a significant reduction in the demand for fuel, damaging further the energy sector.

At this point it is useful to mention that global organizations and states acted instantly, adopting measures to limit the effects of the pandemic in the global economy. The experience of the past and the tools that technological transformation provides to the policy-makers make decision framework more effective and also more complex. The main objective is to avoid a new universal quarantine of the population in their homes or even partial lockdowns of economic activities.

The main purpose of this paper is to examine the dramatical impact of the COVID-19 on the energy sector during the pandemic period, providing useful results for policy-makers, especially in case of a new wave of infections and deaths in the future.

The rest of this paper is organized as follows. Section 2 discusses the existing literature, emphasizing on the effects of COVID-19 on the energy sector while Section 3 presents the data and hypotheses. Section 4 presents the methodology applied to show the relationship between COVID-19 infections and death announcements with oil price volatility. Section 5 explains the empirical results and Section 6 presents the conclusions and a short discussion for future works.

2. Literature Review

In the recent literature we found studies that investigated the effects of COVID-19 on specific sectors or economic zones or even the global economy. Most of these studies focus on financial markets and the energy sector, while in several cases, macroeconomic factors are also examined. Most of these studies provide useful conclusions, and the effects of the pandemic are expected to remain at the top of academic interest for the next period. The purpose of these studies is to acquire the necessary knowledge to deal with similar cases in the future, in order to limit the negative effects and to reset the real economy and social life on track as soon as possible.

Ref. [2] examines the linkage of the global oil market with the USA energy stock market using their implied volatility indexes. The main conclusion of this study is the existence of a long-run relationship between oil and stock market implied volatility indexes. In a similar way, ref. [3] studied the dynamic correlation between spot oil price fluctuations and the stock uncertainty index for the USA, Japan, China, and Hong Kong in order to find out whether crude oil can be used as a hedging instrument. According to the applied wavelet coherence analysis, crude oil cannot support hedging on a long run period but it can be a hedging instrument in a state of panic, like the pandemic period.

Ref. [4] applied a heterogeneous autoregressive realized volatility model to examine the predictive power for oil-market volatility using an uncertainty index based on the daily newspaper news for the pandemic period. They found that by incorporating such information in their model, forecast accuracy improves significantly.

Ref. [5] applied a nonlinearity autoregressive distribute lag model to examine the crude oil price fluctuation while they also use an event study model to compare how different types of events affect crude oil price fluctuations. In their effort to combine crude oil price fluctuation with what causes it, a state-space model was applied and evidence of strong correlation between event shocks and event types was found.

Ref. [6] attempted to estimate the out-of-sample predictive power of crude oil price volatility in relation to financial ratios and macroeconomic variables which are commonly used in the literature. Her findings suggested that considerable economic profit is possible based on this model while useful implications are also provided for portfolio optimization and asset allocation. On the other hand, ref. [7] examined for the USA the relation between COVID-19 and oil price volatility, the stock market and the geopolitical risk among others.

By applying wavelet approaches they found that COVID-19 effect on geopolitical risk is higher than economic uncertainty in the USA.

Ref. [8] provided a way for increasing energy efficiency and energy saving. They examined the challenges of COVID-19 for the energy sector. In particular, they investigated new practices enforced by the pandemic and the way they affected energy demand and consumption. They found that demand has declined but intensity showed apparent changes as the extra energy used to fight COVID-19 was not negligible for the recovery of the demand for energy, while differences in recovery can also be found between different regions.

Ref. [9] examined the implications of COVID-19 for the sustainable energy transitions. The adopted measures by the states, firms, and individuals have motivated many changes that may influence the sustainable transition of energy. They identified the main impact of lockdown on energy and investigated how economic stimulus packages can shape energy transitions and found that the politics of sustainable energy transitions are at a critical stage.

Ref. [10] examined the risk transmission from the COVID-19 to metals and energy markets and found significant negative volatility transmission from the COVID-19 to gold, palladium, and brent oil markets. According to these results, COVID-19 risk is not transmitted to the industrial metal market but COVID-19 leads to an increase in oil market volatility.

Ref. [11] estimated the price volatility of crude oil and natural gas for the listed firms in the MCX exchange of India. Their results are interesting for policy-makers to assess the appropriate strategy in facing the effects of the pandemic as they find leverage effect of COVID-19 on the price volatility of crude oil but not on the price volatility of natural gas.

Ref. [12] examined the hourly oil price volatility and found a significant increase of volatility in the pandemic period. To achieve that, they built a dataset with hourly oil prices combined with global cases of COVID-19 and deaths and applied an OLS regression model with volatility being one of the proxies of oil price volatility. In addition, ref. [13] attempted to estimate predictors of oil prices and for that he examined the interconnection of oil prices with COVID-19 infections and oil price news. He found that effect on oil prices is more significant when infections exceed the threshold of 84,479, whereas the effect of oil price news conditioned on COVID-19 cases is limited.

Ref. [14] estimated the historical volatility of energy markets during the COVID-19 pandemic period by using infection ratio, economic policy uncertainty index and infectious diseases market volatility. His findings can explain the investors' position in implementing options to protect from risk in the energy market and their willingness to pay excess premium for that.

Ref. [15] investigated the relation between the COVID-19, the crude oil market, and the stock market by observing return and volatility spillover with both a time-domain approach and a frequency dynamics approach. Their analysis showed that spillover return mainly exist in the short term while volatility spillover mainly exists in the long term. They also applied a moving window analysis to conclude that COVID-19 created more risk for investors which resulted in high losses in the short term. It is also interesting that COVID-19 impacts on the volatility of the oil, and stock market was even higher than volatility caused in 2008 by the global financial crisis.

Ref. [16] examined the role of gold as a hedging instrument against crude oil price risks. They applied an asymmetric VARMA-GARCH model to assess the impact of COVID-19 and they found that gold can work as a hedge instrument against oil risks as their results during pandemic show negative coefficient of returns spillovers from gold to oil price returns, meaning that an increase in gold in this period will lead to a less decline in oil price returns. Moreover, volatility spillovers between the gold and oil price returns suggest that significant volatility effects are present.

Ref. [17] examined the predictive power of oil supply, demand, and risk shocks in relation to the realized volatility of the daily oil returns. They applied a heterogeneous autoregressively realized volatility approach and showed that especially financial market-driven risk shocks can improve the forecasting performance for in and out-of-sample. Their conclusions offer to investors a valuable way to use traded assets at high frequency in order to monitor oil market volatility.

Ref. [18] emphasized on vaccines by examining the storage conditions based on their thermal load to cool and found that the cold storage of Oxford–AstraZeneca, Janssen COVID-19, and CoronaVac vaccines in Brazil generates 35-times less environmental impact than Pfizer. They also developed an energy index showing that Oxford–AstraZeneca, Janssen COVID-19, and CoronaVac vaccines have 9.34-times higher energy efficiency than Pfizer.

Ref. [19] considered that COVID-19 led to an economic crisis which has changed the social behavior and reduced the industrial activity and the demand for power worldwide. To examine the impact of COVID-19 on power demand, they quantified the country load reduction of COVID-19, based on the active cases and the lockdown period as proxies. They found that in Germany and Great Britain the power demand was reduced while in France the demand was increased for the period outside the lockdown. During the lockdown, France had a much higher reduction than in Germany and Great Britain. However, the effect of COVID-19 on carbon emissions in the power sector was small.

Other studies focused on the impact of COVID-19 pandemic on stock market returns and stock market volatility.

Ref. [20] examined the response of stock market returns from 64 countries to confirmed deaths from COVID-19. His research covers the period January to April 2020 and shows a negative response of stock markets returns to confirmed deaths. Ashraf's research also suggested that negative response was stronger and faster in the first days of confirmed deaths indicating that market response depends on the period of the outbreak.

Ref. [21] investigated the effect of official pandemic announcements on financial markets volatility as expressed by S&P 500 and found that COVID-19 is a significant source of price volatility in the USA financial markets which thereafter affects the global financial cycle.

The existing literature highlights reasonable questions about the impact of COVID-19 on oil price volatility and in this paper we try providing some answers to this issue.

3. Data and Hypotheses

One question that has caught the interest of the academic community in recent years is the relationship between the pandemic and the oil price volatility. Until 2019 the literature showed that oil prices fluctuate due to the forces of supply and demand. Indeed, several research showed that during normal periods, the demand for oil is shaped by global economic activity, while on the supply side, factors related to technological innovations that improve the oil production process are incorporated.

However, in the last two years, we have observed increasing volatility in the price of oil without any economic event justifying it during the same period. As a result, the academic community has turned its attention to investigating the causes that led to this phenomenon. As it turned out, the intense uncertainty created by the pandemic, first for health reasons and then for the possible effects on the world economy, significantly affected the demand for oil. This demand shock is different from the traditional aggregate demand shock because the decline in consumer confidence is inextricably linked to the fear caused by the virus.

Consequently, one of the main questions raised by the literature is how COVID-19 death announcements and the speed of COVID-19 deaths and infections affect oil price volatility.

In this context, our paper provides answers on three theoretical questions contributing with its findings in the existing literature as follows:

Hypotheses 1. *How the announcements of new cases affect the volatility of the oil price?*

Hypotheses 2. *How the rate of change of cases affect the volatility of the oil price?*

Hypotheses 3. *Do the above influences differ between different geographical areas worldwide?*

The three hypotheses are tested with a general econometric panel model similar to the one proposed by ref. [21] who examined the response of financial market volatility on COVID-19 new cases of infection and the fatality ratio. Yet, this article (ref. [21]) does not examine the volatility of oil prices in relation to the pandemic which is the main scope of our study.

In the empirical analysis we collect daily data for COVID-19 infection announcements and deaths from the World Health Organization. Our daily data also include three crude oil volatility indices, the CBOE 30-day crude oil implied volatility index, the 3-month crude oil implied volatility index, and the Brent 3-month implied volatility index. Further, daily data involve also four market uncertainty indices, namely VIX Volatility Index, VSTOXX Volatility Index, NIKKEI Volatility Index, and CBOE China ETF Volatility Index. Last but not least, daily data concern the Economic Uncertainty index, the Baker, Bloom and Davis index of economic policy uncertainty for Europe which is based on the frequency of newspaper references to policy uncertainty.

In the first stage of analysis, our sample is divided into six main geographical areas, so that the empirical analysis leads to useful conclusions for each area separately and in the second stage of analysis the population of the six geographical areas is an aggregate sample.

4. Methodology

The current study investigates the relationship between COVID-19 infection and death announcements with oil price volatility. Our analysis considers existing economic uncertainty and stock market uncertainty in this relationship to disentangle the effects of these uncertainties from that of COVID-19 deaths and infection announcements.

$$VOL(oil) = \alpha + \beta1\ COV(f) + \beta2\ COV(s) + \beta3\ EU + \beta4\ MU + \beta5\ K + \varepsilon \tag{1}$$

where:

VOL(oil) refers to three different measures of oil price volatility,

1. *COV(f)* and *COV(s)* refer to COVID-19-related deaths and COVID-19-related speed of death and infection growth.
2. *EU* stands for economic uncertainty index.
3. *MU* is the market uncertainty index, as reflected by volatility indices in the three largest economic zones, namely in the US (VIX) Europe and Asia (China and Japan) and
4. *K* is a dummy variable representing the day of the week effect, with value one for Monday and zero otherwise.

The reason that our models apply more timeseries regarding the MU variable is due to the fact that the geographical areas are examined individually and each of them is combined with the corresponding stock index.

More details for the variables in our models can be found in the Appendix A.

Our models investigate how COVID-19 death or infection increase (speed) and actual deaths (fatal) affect oil volatility by using the following seven models

$$VOL(oil) = \alpha + \beta1\ COV(f) + \varepsilon \tag{2}$$

$$VOL(oil) = \alpha + \beta2\ COV(s) + \varepsilon \tag{3}$$

$$VOL(oil) = \alpha + \beta1\ COV(f) + \beta2\ COV(s) + \varepsilon \tag{4}$$

$$VOL(oil) = \alpha + \beta1\ COV(f) + \beta2\ COV(s) + \beta3\ MU + \varepsilon \tag{5}$$

$$VOL(oil) = \alpha + \beta1\ COV(f) + \beta2\ COV(s) + \beta3\ EU + \varepsilon \tag{6}$$

$$VOL(oil) = \alpha + \beta1\ COV(f) + \beta2\ COV(s) + \beta3\ MU + \beta4\ EU + \varepsilon \tag{7}$$

$$VOL(oil) = \alpha + \beta1\ COV(f) + \beta2\ COV(s) + \beta3\ MU + \beta4\ EU + \beta5\ K + \varepsilon \tag{8}$$

In our analysis, we run fixed-effect panel models, and we interpret the fitness of estimated model and significance of coefficients as expressed by adjusted R^2, t-statistics, and significance of t-statistics. Variance inflation factors (VIFs) of our models are between 1.6 and 1.85, significantly lower than 6. Then we investigate whether our models are robust in particular economic zones and under different model assumptions.

5. Empirical Results

In Table 1 we present the descriptive statistics from where we can observe two main results. First, there is an intensive oil price volatility, economic uncertainty, and market uncertainty and second, there is an accelerated growth rate of infections and deaths for the investigated period. The sharp increase in deaths and infection rates as a result of the pandemic COVID-19 and the consequent fear of an escalating crisis raised legitimate questions about the degree of impact of the pandemic in the price of crude oil in international markets as well as the volatility of its price.

Table 1. Descriptive statistics.

	N	Mean	Var	StDev	Min	Max
VOL(oil) [1]	2052	58.86	1627.2	40.33	30.7	325.15
VOL(oil) [2]	2052	45.80	351.9	18.76	26.692	128.891
VOL(oil) [3]	2052	43.06	213.8	14.62	10.5338	103.318
MU [1]	2052	27.68	121.4	11.02	12.91	82.69
MU [2]	2052	27.29	132.0	11.49	12.2389	85.6206
MU [3]	2052	25.75	75.82	8.70	14.26	60.67
MU [4]	2052	28.46	49.27	7.01	19.76	69.28
EU	2052	259.4	20,151	141.9	22.25	807.66
Week	2052	0.1988	0.1593	0.3992	0	1
COV(f)	1912	−3.591	0.2230	0.4722	−5.77	−2.30
COV(s) [1]	1923	−4.306	4.107	2.026	−8.99	3.93
COV(s) [2]	1701	−4.476	2.336	1.528	−7.04	1.60
COV(s) [3]	1678	−4.350	3.166	1.779	−7.03	3.82
COV(s) [4]	1650	−4.262	3.794	1.948	−7.02	5.48

Note: VOL(oil) [1, 2] and [3] are respectively the CBOE 30 day crude oil implied volatility index, Crude oil 3 month implied volatility index, and Brent 3 month implied volatility index. Estimates of 3-month implied volatility. COV(s) [1,2,3] and [4] are respectively the logarithm of (new daily COVID-19 infection case announcements divided by seven days lagged total COVID deaths), the logarithm of (new daily COVID-19-related deaths divided by 7 days lagged total COVID deaths), the logarithm of (new daily COVID-19-related deaths divided by 14 days lagged total COVID deaths), and the logarithm of (new daily COVID-19-related deaths divided by 21 days lagged total COVID deaths). MU[1,2,3] and [4] are respectively the VIX index, VSTOXX Index-EURO STOXX 50 Volatility, the NIKKEI Volatility Index, and the Cboe China ETF Volatility index.

Table 2 shows the results of the individual models presented above for the examined geographical areas of our study.

Our results in Table 2 are based on world panel data, and they indicate that COVID-19 deaths (COV(f)) and speed of death increase (COV(s)) can explain as stand-alone variables 11% and 39% of the oil-volatility (Columns 2 and 3 on Table 1 respectively).

Table 2. COVID-19 death announcements and oil price volatility, panel world data.

Model	1	2	3	4	5	6	7	8
COV(f)	341.2 ***	851.6 ***		943.2 ***	647.4 ***	418.0 ***	145.7 ***	139.8 ***
	(7.52)	(16.14)		(18.84)	(14.81)	(8.20)	(8.21)	(11.63)
COV(s)	4.192 ***		17.58 ***	16.79 ***	6.400 ***	10.72 ***	1.426 ***	1.240 ***
	(7.66)		(33.56)	(35.10)	(11.32)	(20.88)	(6.66)	(8.55)
MU	1.771 ***				2.188 ***		0.954 ***	0.754 ***
	(21.46)				(26.24)		(29.55)	(34.51)
EU	0.0905 ***					0.131 ***	0.0429 ***	0.0324 ***
	(15.57)					(21.15)	(18.86)	(21.03)
C	−6.108	34.33 ***	139.4 ***	106.0 ***	7.200	59.41 ***	9.998 ***	14.89 ***
	(−1.43)	(19.77)	(56.26)	(36.97)	(1.61)	(17.63)	(5.98)	(13.16)
R^2 adj	0.690	0.110	0.397	0.501	0.645	0.605	0.773	0.825
N	1701	2052	1701	1701	1701	1701	1701	1701

Note: The table includes panel data of six geographical areas, namely North America, South America, Europe, Africa, Asia and Oceania. The number in parentheses represent t-statistics. *** asterisks indicate 1% level of significance. COV(f) is the logarithm of total deaths, COV(s) is the logarithm of (new daily COVID deaths divided by 7 day lagged total COVID deaths), MU is the US vix index, EU is the economic uncertainty index. R^2 adj is the R-square adjusted. The dependent variable in Model 1–6 is CBOE 30 day crude oil implied volatility index, the dependent variable in Model 7 is Crude oil 3 month implied volatility index, and the dependent variable in Model 8 is Brent 3 month implied volatility index.

When market uncertainty (Column 5, Table 2) or economic uncertainty (Column 6, Table 2) is taken into account, the significance of the overall model (adjusted R-square) increases to 64% and 60% respectively. If both Market Uncertainty (MU, expressed by the American VIX index) and Economic Uncertainty (EU) alongside with COV(f) and COV(s) are considered in the model (Column1, Table 2) the adjusted R-square of the model increases to 69% if the dependent variable is the CBOE 30 day crude oil implied volatility index. In the models presented in that Table, COV(f) is the logarithm of total deaths, and COV(s) is the logarithm of new daily COVID-19 deaths divided by seven days lagged total COVID-19 deaths. The model illustrated in Column 7 uses as dependent variable the Crude oil three months implied volatility index, and the model presented in Column 8 uses as the dependent variable in Brent 3 month implied volatility index. The latter models report an even higher (77% and 82%) adjusted R-square. All the dependent variables in all these models are positive and significant at a 1% level, providing robust evidence of significance for world data.

The above observations lead to comparable conclusions with other studies of the same period, which examine the effect of the pandemic on stock values or energy prices or on other products (Refs. [2,7,14]).

From the above we conclude that the pandemic affected the volatility of the price of crude oil globally. This influence is confirmed both by the new cases of infections and by the rate of infections.

Robustness Tests

To test the robustness of our models first we focus on the three major economic areas, Asia, Europe, and North America to find out if our conclusions are in line with global conclusions presented in Table 2. The findings of these analysis are presented in Tables 3–7.

Table 3. COVID-19 death announcements and oil price volatility, European data.

	1	2	3	4	5	6	7	8
COV(f)	349.2 ***	775.4 ***		877.2 ***	458.5 ***	621.2 ***	135.4 ***	130.1 ***
	(4.99)	(11.96)		(16.33)	(6.35)	(10.63)	(4.78)	(6.76)
COV(s)	5.880 ***		12.31 ***	13.18 ***	10.67 ***	6.398 ***	1.610 ***	1.196 ***
	(5.56)		(11.33)	(16.43)	(13.34)	(5.73)	(3.77)	(4.12)
MU	1.249 ***					1.586 ***	0.800 ***	0.664 ***
	(6.45)					(8.04)	(10.22)	(12.48)
EU	0.0887 ***				0.114 ***		0.0427 ***	0.0299 ***
	(6.29)				(7.91)		(7.49)	(7.73)
C	11.87	24.64 ***	118.1 ***	81.05 ***	58.07 ***	15.95 *	13.54 ***	16.28 ***
	(1.37)	(7.25)	(21.65)	(17.56)	(11.33)	(1.75)	(3.88)	(6.86)
R^2 adj	0.713	0.294	0.287	0.613	0.676	0.678	0.780	0.831
N	318	342	318	318	318	318	318	318

Note: The table includes daily aggregated data of European countries. The number in parentheses represent t-statistics. * and *** indicate 10%, and 1% level of significance, respectively. COV(f) is the logarithm of total deaths, COV(s) is the logarithm of (new daily COVID deaths divided by 7 days lagged total COVID deaths), MU is the US vix index, EU is the economic uncertainty index. R^2 adj is the R-square adjusted. The dependent variable in Model 1-6 is CBOE 30 days crude oil implied volatility index, the dependent variable in Model 7 is Crude oil 3 months implied volatility index and the dependent variable in Model 8 is Brent 3 months implied volatility index.

Table 3 presents the model's predictive ability in European data, while Table 4 presents the North American data under the specifications of the models presented in Table 2. They illustrate solid predictive power in terms of coefficients and adjusted R-square. In particular adjusted R-square ranges between 70% (Column 1, Tables 3 and 4) and 84% (Column 8, on both Tables 3 and 4).

Table 4. COVID-19 death announcements and oil price volatility, North American data.

	1	2	3	4	5	6	7	8
COV(f)	272.5 **	843.5 ***		553.1 ***	237.5 **	578.0 ***	166.1 ***	181.1 ***
	(2.48)	(7.05)		(5.55)	(2.10)	(5.98)	(3.83)	(6.22)
COV(s)	8.762 ***		20.61 ***	19.57 ***	15.55 ***	12.31 ***	2.520 ***	1.885 ***
	(4.73)		(22.61)	(21.98)	(13.54)	(6.86)	(3.44)	(3.83)
MU	1.148 ***					1.202 ***	0.809 ***	0.685 ***
	(4.59)					(4.61)	(8.18)	(10.31)
EU	0.0772 ***				0.0801 ***		0.0361 ***	0.0250 ***
	(5.21)				(5.24)		(6.17)	(6.36)
C	37.94 **	31.46 ***	156.1 ***	132.0 ***	102.3 ***	63.41 ***	19.96 ***	20.11 ***
	(2.36)	(7.17)	(35.00)	(21.68)	(12.59)	(3.97)	(3.14)	(4.70)
R^2 adj	0.704	0.125	0.624	0.657	0.684	0.678	0.782	0.837
N	309	342	309	309	309	309	309	309

Note: The table includes daily aggregated data of North American countries. The number in parentheses represent t-statistics. ** and *** indicate 5% and 1% level of significance, respectively. COV(f) is the logarithm of total deaths, COV(s) is the logarithm of (new daily COVID deaths divided by 7 days lagged total COVID deaths), MU is the US vix index, EU is the economic uncertainty index. R^2 adj is the R-square adjusted. The dependent variable in Model 1–6 is CBOE 30 days crude oil implied volatility index. The dependent variable in Model 7 is Crude oil 3 months implied volatility index. The dependent variable in Model 8 is Brent 3 months implied volatility index.

On Table 5 we investigate whether by using the VSTOXX Index-EURO STOXX 50 Volatility index as a measure of Market Uncertainty for European data we can have significantly different results. In this case, the results we find are comparable.

Table 5. COVID-19 death announcements, European volatility, and oil price volatility, European data.

	1	2	3	4	5	6	7	8
COV(f)	314.4 ***	775.4 ***		877.2 ***	458.5 ***	603.0 ***	109.4 ***	106.0 ***
	(4.35)	(11.96)		(16.33)	(6.35)	(9.73)	(3.75)	(5.42)
COV(s)	6.155 ***		12.31 ***	13.18 ***	10.67 ***	6.946 ***	1.670 ***	1.165 ***
	(5.81)		(11.33)	(16.43)	(13.34)	(6.18)	(3.91)	(4.07)
MU	1.148 ***					1.444 ***	0.765 ***	0.655 ***
	(6.09)					(7.39)	(10.07)	(12.88)
EU	0.0937 ***				0.114 ***		0.0454 ***	0.0318 ***
	(6.68)				(7.91)		(8.02)	(8.39)
C	16.71 **	24.64 ***	118.1 ***	81.05 ***	58.07 ***	23.92 ***	15.58 ***	17.23 ***
	(2.00)	(7.25)	(21.65)	(17.56)	(11.33)	(2.71)	(4.63)	(7.64)
R^2 adj	0.709	0.294	0.287	0.613	0.676	0.669	0.778	0.835
N	318	342	318	318	318	318	318	318

Note: The table includes daily aggregated data of European countries. The number in parentheses represent t-statistics. ** and *** indicate 5%, and 1% level of significance, respectively. COV(f) is the logarithm of total deaths, COV(s) is the logarithm of (new daily COVID deaths divided by 7 days lagged total COVID deaths), MU is the VSTOXX Index-EURO STOXX 50 Volatility index, EU is the economic uncertainty index. R^2 adj is the R-square adjusted. The dependent variable in Model 1–6 is CBOE 30 days crude oil implied volatility index, the dependent variable in Model 7 is Crude oil 3 months implied volatility index and the dependent variable in Model 8 is Brent 3 months implied volatility index.

We examine Asian data in Tables 6 and 7, using the Japanese stock market volatility (Table 6) and Chinese stock market volatility (Table 7) index to express market uncertainty.

Table 6. COVID-19 death announcements, Japanese volatility, and oil price volatility, Asian data.

	1	2	3	4	5	6	7	8
COV(f)	1533.7 ***	4018.7 ***		4686.9 ***	3534.3 ***	2359.5 ***	442.6 ***	298.9 ***
	(4.32)	(23.35)		(22.34)	(13.62)	(6.71)	(3.05)	(2.97)
COV(s)	−0.777		13.10 ***	−6.604 ***	−4.588 ***	−2.193	0.232	0.481
	(−0.57)		(7.46)	(−4.65)	(−3.36)	(−1.55)	(0.42)	(1.25)
MU	1.932 ***					2.110 ***	1.076 ***	0.884 ***
	(7.64)					(7.92)	(10.40)	(12.32)
EU	0.0721 ***				0.0812 ***		0.0401 ***	0.0324 ***
	(6.51)				(6.82)		(8.86)	(10.32)
C	−47.27 ***	−30.76 ***	117.9 ***	−74.52 ***	−61.19 ***	−57.67 ***	−1.149	7.374 ***
	(−5.21)	(−7.56)	(14.50)	(−7.42)	(−6.36)	(−6.09)	(−0.31)	(2.87)
R^2 adj	0.740	0.615	0.140	0.654	0.696	0.708	0.798	0.840
N	337	342	337	337	337	337	337	337

Note: The table includes daily aggregated data of Asian countries. The number in parentheses represent t-statistics. *** indicate level of significance. COV(f) is the logarithm of total deaths, COV(s) is the logarithm of (new daily COVID deaths divided by 7 days lagged total COVID deaths), MU is the Nikkei Volatility index, EU is the economic uncertainty index. R^2 adj is the R-square adjusted. The dependent variable in Model 1–6 is CBOE 30 days crude oil implied volatility index, the dependent variable in Model 7 is Crude oil 3 months implied volatility index, and the dependent variable in Model 8 is Brent 3 months implied volatility index.

Tables 6 and 7 show the robustness of the significance data (COV(f)) but they do not confirm consistency for the significance of COVID-19 growth data (COV(s), columns 1, 6–8 of Table 6 and columns 7 and 8 of Table 7). This may be due to the slow growth of these indices in Asian markets, which probably does not reflect the importance of demand for oil consumption worldwide, as the main markets are the European and the North American markets.

Table 7. COVID-19 death announcements, Chinese volatility, and oil price volatility, Asian data.

	1	2	3	4	5	6	7	8
COV(f)	2717.6 ***	4018.7 ***		4686.9 ***	3534.3 ***	3720.2 ***	937.1 ***	710.8 ***
	(9.14)	(23.35)		(22.34)	(13.62)	(13.65)	(7.91)	(8.56)
COV(s)	−2.981 **		13.10 ***	−6.604 ***	−4.588 ***	−4.716 ***	−0.671	−0.272
	(-2.20)		(7.46)	(−4.65)	(−3.36)	(-3.34)	(−1.24)	(−0.72)
MU	1.198 ***					1.316 ***	0.909 ***	0.738 ***
	(5.09)					(5.28)	(9.69)	(11.24)
EU	0.0768 ***				0.0812 ***		0.042 ***	0.034 ***
	(6.66)				(6.82)		(9.12)	(10.52)
C	−68.85 ***	−30.76 ***	117.9 ***	-74.52 ***	−61.19 ***	−82.14 ***	-14.71 ***	−3.714
	(−7.33)	(−7.56)	(14.50)	(−7.42)	(−6.36)	(−8.41)	(−3.93)	(−1.42)
R^2 adj	0.717	0.615	0.140	0.654	0.696	0.680	0.791	0.831
N	337	342	337	337	337	337	337	337

Note: The table includes daily aggregated data of Asian countries. The number in parentheses represent t-statistics. ** and *** indicate 5%, and 1% level of significance, respectively. COV(f) is the logarithm of total deaths, COV(s) is the logarithm of (new daily COVID deaths divided by 7 days lagged total COVID deaths), MU is the Cboe China ETF Volatility index, EU is the economic uncertainty index. R^2 adj is the R-square adjusted. The dependent variable in Model 1–6 is CBOE 30 days crude oil implied volatility index, the dependent variable in Model 7 is Crude oil 3 months implied volatility index, and the dependent variable in Model 8 is Brent 3 months implied volatility index.

A second evidence for robustness is also provided in Table 8 which presents the results of our models using world aggregated data and shows that coefficients are positive and significant irrespectively of which model is applied while adjusted R-square is also sufficient.

Table 8. COVID-19 death announcements and oil price volatility, world aggregated data.

	1	2	3	4	5	6	7	8
COV(f)	657.8 ***	1758.7 ***		1391.5 ***	682.3 ***	981.5 ***	277.2 ***	256.2 ***
	(5.93)	(17.26)		(13.96)	(5.33)	(11.20)	(6.25)	(8.64)
COV(s)	5.748 ***		18.15 ***	11.41 ***	10.35 ***	5.497 ***	1.853 ***	1.267 ***
	(5.34)		(12.77)	(9.28)	(9.10)	(4.97)	(4.30)	(4.40)
MU	1.504 ***					1.746 ***	0.831 ***	0.683 ***
	(10.57)					(12.85)	(14.60)	(17.96)
EU	0.0602 ***				0.112 ***		0.032 ***	0.022 ***
	(4.56)				(7.93)		(6.03)	(6.32)
C	4.009	−1.936	139.1 ***	61.20 ***	51.72 ***	0.725	13.07 ***	15.05 ***
	(0.53)	(−0.50)	(21.35)	(8.03)	(7.29)	(0.09)	(4.28)	(7.38)
R^2 adj	0.730	0.466	0.325	0.573	0.640	0.713	0.799	0.852
N	337	342	337	337	337	337	337	337

Note: The table includes world aggregated data. The number in parentheses represent t-statistics. *** indicate 1% level of significance. COV(f) is the logarithm of total deaths, COV(s) is the logarithm of (new daily COVID deaths divided by 7 days lagged total COVID deaths), MU is the US vix index, EU is the economic uncertainty index. R^2 adj is the R-square adjusted. The dependent variable in Model 1–6 is CBOE 30 days crude oil implied volatility index, the dependent variable in Model 7 is Crude oil 3 months implied volatility index, and the dependent variable in Model 8 is Brent 3 months implied volatility index.

Third, in Tables 9–11 we test the robustness of our models by replacing one of our variables using world panel data. In Table 9 we investigate the effect of COVID-19 infection speed instead of examining COVID-19 death speed. These models are significant, but they report a slightly lower adjusted R-square, indicating that markets are more worried about death growth rates and actual deaths than COVID-19 infection growth rates. This may be because they regard that economic effect of deaths is more certain and robust than reporting cases that can be manipulated or affected by the number of tests taken.

Table 9. COVID-19 death announcements, infection speed, and oil price volatility, world panel data.

	1	2	3	4	5	6	7	8
COV(f)	211.0 ***	851.6 ***		909.5 ***	279.8 ***	548.8 ***	95.00 ***	94.45 ***
	(5.28)	(16.14)		(18.47)	(6.06)	(13.49)	(6.02)	(8.65)
COV(s)	1.890 ***		13.18 ***	13.39 ***	7.789 ***	3.182 ***	0.773 ***	0.760 ***
	(4.41)		(26.97)	(29.69)	(18.53)	(6.75)	(4.56)	(6.48)
MU	1.811 ***					2.397 ***	0.935 ***	0.747 ***
	(25.78)					(33.44)	(33.70)	(38.91)
EU	0.107 ***				0.158 ***		0.0502 ***	0.038 ***
	(21.21)				(29.43)		(25.18)	(27.83)
C	−17.8 ***	34.33 ***	119.0 ***	92.33 ***	43.83 ***	−10.1 ***	7.207 ***	12.79 ***
	(−5.33)	(19.77)	(51.16)	(35.70)	(16.18)	(−2.73)	(5.46)	(14.00)
R^2 adj	0.681	0.110	0.271	0.380	0.571	0.607	0.767	0.815
N	1943	2052	1943	1943	1943	1943	1943	1943

Note: The table includes panel data of six geographical areas, namely North America, South America, Europe, Africa, Asia, and Oceania. The number in parentheses represent t-statistics. *** indicate 1% level of significance. COV(f) is the logarithm of total deaths, COV(s) is the logarithm of (new daily COVID infection case announcements divided by 7 days lagged total COVID deaths), MU is the US vix index, EU is the economic uncertainty index. R^2 adj is the R-square adjusted. The dependent variable in Model 1–6 is CBOE 30 days crude oil implied volatility index, the dependent variable in Model 7 is Crude oil 3 months implied volatility index, and the dependent variable in Model 8 is Brent 3 months implied volatility index.

Tables 10 and 11 present the results under different assumptions (2-week and 3-week respectively, instead of 7-day speed) about the COVID-19 death speed. These models are significant and report similar coefficients but convey slightly lower significance than our 7-day basic Model presented in Table 2.

Table 10. COVID-19 death announcements, 2-week speed, and oil price volatility, world panel data.

	1	2	3	4	5	6	7	8
COV(f)	342.5 ***	851.6 ***		919.4 ***	448.8 ***	621.7 ***	151.5 ***	145.2 ***
	(7.47)	(16.14)		(18.77)	(8.89)	(14.07)	(8.48)	(12.01)
COV(s)	4.144 ***		15.41 ***	14.45 ***	9.532 ***	6.093 ***	1.313 ***	1.165 ***
	(8.54)		(35.19)	(35.98)	(21.54)	(12.32)	(6.95)	(9.11)
MU	1.751 ***					2.147 ***	0.928 ***	0.727 ***
	(19.56)					(23.72)	(26.58)	(30.80)
EU	0.0861 ***				0.121 ***		0.0418 ***	0.0315***
	(14.54)				(19.40)		(18.12)	(20.19)
C	−5.206	34.33 ***	127.2 ***	93.78 ***	54.03 ***	7.021	10.08 ***	15.16 ***
	(−1.26)	(19.77)	(61.80)	(36.32)	(17.40)	(1.64)	(6.27)	(13.93)
R^2 adj	0.683	0.110	0.424	0.524	0.611	0.644	0.763	0.817
N	1678	2052	1678	1678	1678	1678	1678	1678

Note: The table includes panel data of six geographical areas, namely North America, South America, Europe, Africa, Asia, and Oceania. The number in parentheses represent t-statistics. *** indicate 1% level of significance. COV(f) is the logarithm of total deaths, COV(s)is the logarithm of (new daily COVID deaths divided by 14 days lagged total COVID deaths), MU is the US vix index, EU is the economic uncertainty index. R^2 adj is the R-square adjusted. The dependent variable in Model 1–6 is CBOE 30 days crude oil implied volatility index, the dependent variable in Model 7 is Crude oil 3 months implied volatility index and the dependent variable in Model 8 is Brent 3 months implied volatility index.

Table 11. COVID-19 death announcements, 3-week speed, and oil price volatility, world panel data.

	1	2	3	4	5	6	7	8
COV(f)	328.2 ***	851.6 ***		850.4 ***	462.8 ***	565.6 ***	154.2 ***	144.5 ***
	(7.09)	(16.14)		(17.81)	(9.31)	(12.66)	(8.60)	(11.94)
COV(s)	4.642 ***		14.20 ***	12.85 ***	8.994 ***	6.405 ***	1.432 ***	1.257 ***
	(10.44)		(37.22)	(35.95)	(22.40)	(14.40)	(8.31)	(10.81)
MU	1.715 ***					2.057 ***	0.890 ***	0.701 ***
	(17.50)					(20.76)	(23.43)	(27.37)
EU	0.0782 ***				0.106 ***		0.0398 ***	0.0301 ***
	(13.02)				(16.88)		(17.10)	(19.15)
C	−0.0438	34.33 ***	119.6 ***	86.73 ***	53.60 ***	11.83 ***	11.87 ***	16.50 ***
	(−0.01)	(19.77)	(66.94)	(35.14)	(17.83)	(2.80)	(7.42)	(15.29)
R^2 adj	0.672	0.110	0.456	0.543	0.611	0.638	0.748	0.808
N	1650	2052	1650	1650	1650	1650	1650	1650

Note: The table includes panel data of six geographical areas, namely North America, South America, Europe, Africa, Asia, and Oceania. The number in parentheses represent t-statistics. *** indicate 1% level of significance. COV(f) is the logarithm of total deaths, COV(s)is the logarithm of (new daily COVID deaths divided by 21 days lagged total COVID deaths), EU is the US vix index, MU is the economic uncertainty index. R^2 adj is the R-square adjusted. The dependent variable in Model 1–6 is CBOE 30 days crude oil implied volatility index, the dependent variable in Model 7 is Crude oil 3 months implied volatility index and the dependent variable in Model 8 is Brent 3 months implied volatility index.

Table 12 compares the basic Model (Column 1, Table 12) with a model that takes account the weekly effect (Column 2, Table 12). The findings illustrate that there is no significant "day of the week" effect in the data examined, and the robustness of these data remains intact after we account for this factor.

Table 12. COVID-19 death announcement and oil price volatility, world panel data.

	1	2
COV(f)	341.2 ***	338.7 ***
	(7.52)	(7.45)
COV(s)	4.192 ***	4.135 ***
	(7.66)	(7.48)
MU	1.771 ***	1.771 ***
	(21.46)	(21.47)
EU	0.0905 ***	0.0912 ***
	(15.57)	(15.51)
Week		−1.112
		(−0.76)
C	−6.108	−6.260
	(−1.43)	(−1.46)
R^2 adj	0.690	0.690
N	1701	1701

Note: The table includes panel data of six geographical areas, namely North America, South America, Europe, Africa, Asia, and Oceania in columns 1–2. The number in parentheses represent *t*-statistics. *** indicate 1% level of significance. COV(f) is the logarithm of total deaths, COV(s) is the logarithm of (new daily COVID deaths divided by 7 days lagged total COVID deaths), EU is the US vix index, MU is the economic uncertainty index, and week is a dummy variable taking the value one on Mondays, zero otherwise. The dependent variable is CBOE 30 days crude oil implied volatility index. R^2 adj is the R-square adjusted.

Our findings offer a valuable contribution to the existing literature as we provide evidence that COVID-19 death growth rates and deaths affect oil volatility significantly. The pandemic affects the volatility of the price of crude oil worldwide. This result is confirmed both by the new cases of infections and by the rate of infections. These conclusions are verified separately for each geographic area and the world as a whole. The contribution of this study is not limited to the indication that COVID-19 is a new factor of risk that affects oil prices on top of economic and market uncertainty but also provides new measures of risk factor like the speed rate of death.

6. Conclusions

In this study we investigate the relationship between COVID-19 infection and death announcements with oil price volatility. We use the speed rate of deaths as a proposed measure for the COVID-19 risk and we apply panel data from six world geographical areas taking into consideration the existing economic uncertainty and stock market uncertainty in order to separate these effects from the effects resulting from the announcements of COVID-19 deaths and infection. The applied tests show that oil volatility is significantly affected by COVID-19 deaths which indicates that COVID-19 is a new factor of risk which one can argue has intensified the market risk.

The findings of our study underscore the importance of better understanding the effects of a pandemic shock on movements and the volatility of oil prices. In addition, it emphasizes the need for policy-makers and market stakeholders to explicitly consider changes in global health conditions when analyzing the causes and consequences, in order to plan an appropriate response to oil price shocks. In this regard, although lockdown policies of certain economic activities and restrictions in travelling had some positive effects in reducing the transmission of the health crisis, at the same time there were negative effects on the economy. In addition, the policies of governments around the world as well as Central Banks to support economies and individuals by offering them access to affordable financing have sent a clear message of calming the markets and addressing the crisis in many ways.

In particular, the EU has taken bold decisions by setting up a recovery fund for its Member States. Based on the results of our study, such measures are in the right direction and what is proposed at this stage is to create a framework with a permanent form. Such a framework should have two pillars, one institutional and one economic, in order to calm the markets from any concerns about similar cases in the future. The institutional framework will outline possible restrictive measures in countries with high rates of infection, but at the same time, these measures will be supplemented by financial support.

The conclusions of this study can be used as a guide for future decisions of managers, investors, and policy-makers regarding management, asset pricing, and market stability. Risk managers and asset pricing managers have already incorporated the pandemic in their short and medium-term decisions to prepare their business plans. Especially, for the energy companies that affected substantially by the restrictions in travelling and transportation, this study provides interesting considerations. Especially, oil and gas producers, it is crucial to have always a plan B to face similar phenomenon in the future while, individual investors must also take into consideration COVID-19 in their expectations.

In any way, we already know that although vaccines were available in the first semester of 2021 for the public worldwide, the Delta mutation of COVID-19 is spreading rapidly. Nonetheless, for future work, another important factor of this equation is the technological advances and especially the 5G infrastructure which provided significant solutions in business communication and education especially in the more developed countries.

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Appendix A

Table A1. Description of variables used in the study.

(VOL(oil))	CBOE 30 day crude oil implied volatility index.
	Crude oil 3 month implied volatility index. Estimates 3-month implied volatility. IVOLCRUD Index.
	Brent 3 month implied volatility index. Estimates of 3-month implied volatility. IVOLBREN Index.
COVID Deaths (COV(f))	The logarithm of cumulative COVID-19-related deaths
COVID-19 related speed of death and infection growth (COV(s))	The logarithm of (new daily COVID-19 infection case announcements divided by seven days lagged total COVID deaths)
	The logarithm of (new daily COVID-19-related deaths divided by 7 days lagged total COVID deaths)
	The logarithm of (new daily COVID-19-related deaths divided by 14 days lagged total COVID deaths)
	The logarithm of (new daily COVID-19-related deaths divided by 21 days lagged total COVID deaths)
Economic Uncertainty (EU)	The Baker, Bloom and Davis index of economic policy uncertainty for Europe is based on the frequency of newspaper references to policy uncertainty. 10 newspapers from the 5 largest European Union economies (Germany, UK, France, Italy, and Spain) are used: Handelsblatt, FAZ, the Financial Times, The Times of London, Le Monde, Le Figaro, Corriere Della Sera, La Repubblica, El Pais, and El Mundo. The index is constructed based on the number of news articles containing the terms uncertain or uncertainty, economic or economy, as well as policy-relevant terms (scaled by the smoothed number of articles containing "today"). Policy-relevant terms include: "policy", "tax", "spending", "regulation", "central bank", "budget", and "deficit".
Market Uncertainty (MU)	VIX Volatility Index.
	VSTOXX Index-EURO STOXX 50 Volatility.
	NIKKEI Volatility Index.
	Cboe China ETF Volatility index.

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Geopolitical Risk as a Determinant of Renewable Energy Investments

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Abstract: The advent of various initiatives around the globe in shaping an energy transition towards a "greener" energy production future sparked a research interest towards the determinants that will shape their success. In this paper, we depart from the relevant literature evaluating the potential effect of geopolitical tensions on renewable energy investments, building on an explicit quantitative approach that provides clear empirical evidence. In doing so, we compile a large panel of 171 economies and measure the effect of geopolitical risk on "green" investing as measured by popular geopolitical risk indices, while controlling for all major variables proposed by literature. Our flexible Autoregressive Distributed Lag model with heterogenous effects across economies suggests that geopolitical risk has a significantly measurable effect on green investments both in the short and the long run. In fact, our results suggest that proper model specification is robust across alternate risk assessments. Overall, our study has direct policy implications suggesting that renewable energy could be an important part of our energy mix only if we take into account its linkages with geopolitical tensions.

Keywords: geopolitical risk; renewable energy sources; energy production; ARDL; GDP; CO_2 emissions

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1. Introduction

Energy is considered a vital element to the development and prosperity of societies, especially in the modern age of interconnection, high technological advancement, and globalization. Despite the fact that energy as a fuel for sustainable development continues to play a vital role, the acute environmental issues of our times have sparked a conversation on the forms and types of energy that should be used to ensure a high quality of life in developed economies and a safe energy environment to underdeveloped and developing ones. Thus, the debate focuses on the right to seek energy abundance and a just energy transition towards more environmentally friendly energy sources for all societies.

Unlike other societal dilemmas, the historical evolution of energy transition cannot be used to shape a cause-and-effect framework in the near future. In particular, the initial changes in fuel from wood to coal, and even oil, may have been influenced by the need to provide better services to society. Now, the latest changes may be deliberate and can be seen as driven, for others, by concerns about greenhouse gas emissions, nuclear risks, energy prices or dependence on energy imports. The problem lies in the fact that certain types and forms of energy, such as fossil fuels, emit gases that directly affect the environment to a critical extent, a fact that has already caused potentially irreversible damage globally [1].

The aim of this study is to evaluate the potential relationship between Renewable Energy Sources (RES) and Geopolitical Risk (GPR) as a driver of energy transition, since most of the studies focus mainly on the role of stakeholders and policy-making. More specifically, the term "energy transition" refers to a more sustainable use of energy, that of renewable sources. According to the literature, "transition" concerns socio-technical system changes. In particular, according to [2], transition is based on three levels: the niche level, the regime level, as well as the landscape level, "where impactful global events take place—like wars, economic crises, environmental disasters, geopolitical events, supranational decision-making—that influence both regime stability and the emergence and development of niches". In this context, there are several studies highlighting the role of stakeholders and policy makers in energy transition. Indicatively, according to [3] "policy makers should take stakeholders' perceptions into due consideration when trying to design a well suited and balanced policy intervention", since energy transition requires socio-economic and environmental interactions, which create a complicated context in which decision-making takes place. In addition, [4] index takes into account several variables, such as governance and economic dynamics, in order to create a useful tool for policy-makers in order to evaluate energy transition, given that energy transition policy is determined mainly by stakeholders, since they affect the decision-making in several levels [5]. Therefore, the contribution of this study towards existing literature not only examines the potential effect of geopolitical tensions on renewable energy investments, but further enriches the stakeholders' arsenals in the decision-making process.

The correlation of international politics and energy is perceived under several aspects, such as environmental issues and climate change [5–8], nuclear proliferation [9–11], as well as energy security as a vital determinant of economic growth [12–14]. In a sense of competitiveness and struggle for power rather than cooperation, none of the countries are willing to jeopardize their access in energy production as it would have severe implications on economic growth and development [15–17]. As mentioned by [18], "the climate regime has been afflicted by the 'free rider' problem. If some countries join together and agree to make cuts which are costly, then others who do not can enjoy the environmental benefits of such action without paying". Especially developing countries, such as India and China, refuse to give up coal as an energy source, since their development is highly dependent on this element [19,20]. Besides, access to energy sources is a matter of national security, either in terms of demand or supply [21]. The issue of energy security and even energy autonomy through investing in renewable energy investments has become even more pressing during the latest tensions between Russia and the rest of Europe, the closure of the Maghreb-Europe Gas Pipeline between Algeria and Spain, or the tensions in the Middle East that mounted fossil fuel prices. The European Union has marked the first significant effort in mitigating its dependence to other oil and natural gas producing countries with the ambitious "Green Deal" policy initiative.

The intensive use of fossil fuels during previous eras had severe environmental impacts. Increased energy consumption associated with high CO_2 emissions due to the combustion of fossil fuels led to global warming. The current policies implemented by developed countries did not work effectively for various reasons, including weak political propensity to effectively address the problem. The most illustrative example is the decision of the Trump administration to withdraw from the Paris Climate Agreement, even though it would be possible for the country to return back and rejoin in the near future should a new administration decide to do so. It was the first nation in the world to formally withdraw from the Paris Climate Agreement.

During the recent pandemic crisis of COVID-19, the energy demand decreased due to the slowdown of economic activities and business on a global level. Two years and counting from the start of the pandemic, global energy demand seems close to reverting back to its earlier levels as the global economy is recovering to its previous state. The crisis people have been forced to manage without preparation in terms of its extent and intensity seems to be a prelude to handling future crises, which will most likely become more frequent in other areas such as energy, economics and other. At the same time, the necessary energy for producing one global GDP unit declined during the last years, while investments in energy efficiency reverted and almost started increasing from 2021. Such investments can be linked to better efficiency in terms of optimal energy use and higher yield rates that contribute to the need for less energy consumption for the same outcome.

Although economically developed countries account for about 60% of the total expenditure projected in the Sustainable Recovery Report (Figure 1), the available funds of these economies are much larger than those of emerging and developing economies, which already face a large infrastructure deficit [22]. These emerging markets and emerging economies account for one-fifth of the world's spending on clean energy, while accounting for two-thirds of the world's population [22].

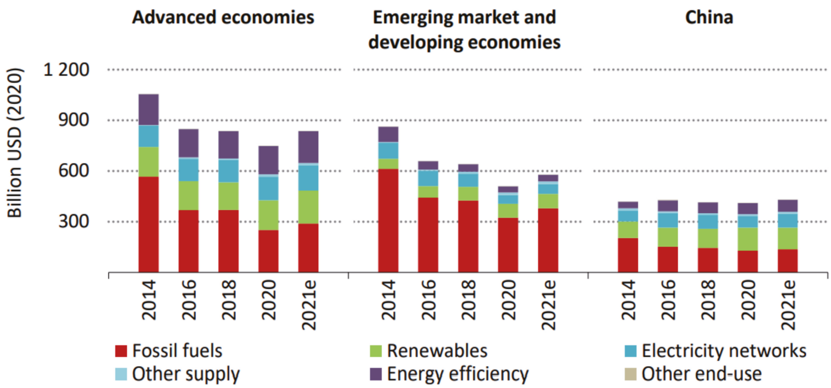


Figure 1. Energy investments by region. (Source: [22]).

The falling cost of key clean energy technologies offers a huge opportunity for all countries to chart a new, lower emissions pathway towards economic growth and prosperity. This is reflected on the revenue of listed renewable power companies' stocks outperforming fossil fuel companies and public equity market indices in recent years. However, clean energy investment still remains far short of what is required to put the energy system on a sustainable track (Figure 2). At the same time, the amount being spent on oil and natural gas is also short of what would be required to maintain current consumption trends [22]. A possible option could be to achieve higher capital investments for clean energy, which would not be an easy process due to required adjustments during the energy transition period. The possibility of increasing investments in green and renewable energy technologies is a function of their investment costs and the policy of the countries—incentives or charges. As the cost of basic green and renewable energy technologies decreases, so will a market of opportunities emerge. It is observed that investments in green and renewable energy technologies remain low and there is a distance from the point that is considered sufficient to put the energy system on a sustainable path [22].

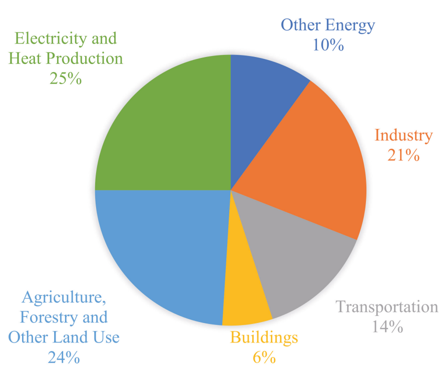


Figure 2. Energy investments by region. (Source: [22]).

Since fossil fuels are limited, the concentration on them comes from their dominant position in the global energy landscape, which accounts for almost 86% of the global energy consumption [23]. At the same time, Renewable Energy Sources (RES) can be reproduced in order to replace the consumed number of resources such as solar, wind, hydropower, geothermal, and biomass. The case of geopolitical risk in this scenario is the mix of military disputes between nation states and war threats that can have an impact on the international political system [24]. RES are known to be clean, green energy and friendly to the environment, and for that reason, RES can critically contribute to reduce CO_2 emissions and other pollutants. Renewables, including solar, wind, hydro, biofuels, biomass, and others, are at the center of the transition to a less carbon-intensive and more sustainable energy system [22]. Based on the use of the energy mix in 2015, the fuel mix used for global energy production in 2015/16 can be considered as: fossil fuels represent 85% of the total amount of energy produced worldwide, while renewable energy sources account for only 1–2%. It should be noted that crude oil (40%), coal (22%), and natural gas (23%) are considered fossil fuels, while geothermal, sunlight, wind and recycling are considered renewable energy sources. The appearance of RES balances the influence of oil and gas producers in global politics. RES is closely related to climate change issues, natural resource depletion, and energy diversification, which contribute to energy security. Since geopolitical interests in the fossil fuels market changes, it makes RES appear more important in the international economy [25].

Energy and geopolitics have been tightly related to each other. Security of supply and access to the main natural resources have critically contributed to the energy security and consequently the national security of the involved nation-states. Moreover, access to energy resources has been proved a critical parameter in determining the winners of wars in the last century. Energy has been considered as one of the available tools that could influence neighboring states and strengthen national security through properly implemented energy policies. It has been seen that nation-states use energy as a geopolitical weapon in order to protect their vital interests and contribute to their national security [26].

Nevertheless, the development of new resources is changing the geopolitical and energy landscape since the transition to more environmentally friendly solutions has already started and is undergoing on a global scale. The availability of new resources is driving the creation of new geopolitical tools and opportunities, while at the same time climate change supports the energy transition to more green choices. The Intergovernmental Panel on Climate Change (IPCC), a group convened by the United Nations, set a specific target in its 1.5 °C report that clear benchmarks are required for action, such as cutting all emissions in half by 2030. Those countries with more capacity and responsibility must lead the way and support others in their journey. Governments must align their targets and plans with 1.5 °C according to the commitment of COP26 event, held in Glasgow in 2021. Based on current policies it looks that we are only on track to a critical 2.9 °C future [27]. Numerous studies and discussions in the literature show that ongoing climate change is primarily due to the rapid increase in Green House Gas (GHG) emissions from carbon dioxide $(CO_2)_3$ as well as from methane gas and nitrous oxide [28,29]. The major source of carbon dioxide (CO_2) emissions is the burning of fossil fuels, which represented 87% of the world's energy supply in 2012 [30].

The motivation of this study stems from the understudied relationship between Geopolitical risk and energy transition towards an environmentally friendly production path. The hypothesis tested is whether GPR influences Renewable Energy Sources (RES) production and thus investments in this sector should be treated as any other investment. Although the existing literature reaches mixed results regarding the sign of this relationship, its existence is of great importance both to practitioners and policy authorities. The limited number of studies in the relevant literature treats the estimation problem based on cointegrated panel regressions or on univariate time-series, no approach evaluates a heterogenous response framework that includes contemporaneously short and long-term dynamics. Following this string of literature, we develop a panel Autoregressive Distributed Lag (ARDL) estimator with heterogeneous effects [31] to study the relationship between RES and GPR on a wide range of economies. In doing so, we evaluate the Caldara and Iacovello [24] GPR index that comes in two flavors; an aggregated one for the global economy and a disaggregated one for 18 developing economies. As a robustness test, we repeat our analysis using the World Uncertainty Index of [2]. Our empirical findings support the existence of a significant negative relationship between GPR and investments in RES. Thus, despite the significance of a just energy transition towards "green" energy, the nature of the investments in the sector does not exhibit different characteristics than any other investment and is heavily relied upon traditional investment criteria such as GPR. Our contribution could be summarized to the following items:

- Use of a heterogeneous approach on a panel dataset that is able to grasp asymmetric effects among different economies.
- A broad examination of the entire global geopolitical landscape and its relationship with the evolution of renewable energy sources.
- A definite empirical suggestion that geopolitical tensions are a crucial deterrent of investing in "green" energy.

2. Literature Review

One of the main questions posed in the relevant literature is how geopolitics interact with energy, either regarding fossil fuels or renewables sources [32–34]. Up to now, most scholars analyze the correlation between political and economic uncertainty with energy, finding mixed results. In particular, according to [35], the determinants of renewable energy are mainly determined by consumption, supply and demand while political variables represent only 23% of the overall literature, focusing on institutional quality, democracy, ideology and governance as independent variables. As the author mentions "[. . .] the strand of literature to which the reviewed papers contribute to is relatively new and fragmented". However, there are only few studies which focus on the relationship between Geopolitical Risk (GPR), as developed by [24], and RES.

The majority of empirical studies examine the impact of political and economic instability on fossil fuels. More specifically, focusing on the correlation between geopolitics and energy, as measured by geopolitical risk, most scholars examine the connection between these two variables based on fossil fuels, such as CO_2 emissions, and most find mixed results. For example, [36] argue that high geopolitical risk is associated with high CO_2 emissions, especially in the case of BRICS. Implementing a STRIRPAT model, [37] find that CO_2 emissions increased due to GPR for BRICS. Other scholars find similar results, but they measure geopolitical risk in terms of military power [38], or terrorism [39,40]. By employing ARDL and a fully modified ordinary least regression model, most of the mentioned studies argue that militarization escalates CO_2 emissions. However, according to [41], militarization mitigates CO_2 emissions as far as India and Pakistan is concerned, due to the fact that they find an asymmetric impact between these two variables.

Reference [41] argue that GPR has an asymmetric effect on CO_2 emissions. Using the non-linear autoregressive distributed lag model (NARDL), they find that any change in geopolitical risk negatively affects energy consumption and CO_2 emissions. In particular, measuring the impact of geopolitical risk on CO_2 emissions and energy consumption in BRICS, they conclude that "clean energy consumption can be a useful tool to reduce the geopolitical risks in BRICS". Reference [42] also argue that geopolitical risk is negatively correlated to CO_2 emissions, and that oil prices seem to remain unaffected on shocks from investments in RES. However, [43], focusing on energy transition behavior with an emphasis on geopolitical risk and implementing the ARDL method, suggest that there is a positive correlation between geopolitical risks and energy transition and "any increase in CO_2 emissions has negative and statistically significant impact on energy transition in Russia".

Given that a group of scholars considers the impact of geopolitical risk in a wider sense, that of political and economic instability, they measure its impact both on CO_2

emissions and renewable sources. In particular, [44] implements a Generalized Method of Moments approach using two panel data estimation techniques. He concludes that political instability increases CO_2 emissions, given that "democracy itself can also lead to environmental degradation". Moreover, [45] is one of the first studies that examines the effects of geopolitical risk, based on the [24] index, on the oil stock nexus for the years 1899–2016. By implementing an unrestricted Vector Autoregressive-GARCH model in order to model time-varying conditional variances, they conclude that oil market volatility is larger compared to that of the stock market and the former is more significantly affected by GPR than the stock market index.

Regarding the economic aspect, [46] based on the Economic Uncertainty Index developed by [47], argue that in the short run, economic uncertainty increases CO_2 emissions, and, additionally, apart from political instability, economic instability can have a positive impact on environmental degradation in the long run. However, [48] based on the World Uncertainty Index (WUI) and using an ARDL approach, find that there is a positive correlation between the WUI and CO_2 emissions in the long run. On the other hand, [49] implemented non-linear econometric approaches and found a negative correlation between WUI and RES. As they mention, "the nonparametric LLLS regression estimates exhibit a negative long-run association between renewable energy consumption and policy uncertainty i.e., higher uncertainty regarding economic policy lowers renewable energy consumptions and vice-versa". However, when renewable energy consumption is examined in relation to political factors by [50], political and institutional factors have a strong and statistically significant effect on renewable energy consumption. In particular, implementing a short and long-run panel causality approach on an Error Correction Model, they conclude that "renewable energy markets are strongly interwoven with major political decisions".

On a different path, [51] measure the impact of WUI on investments for various industrial sectors. On a panel approach, they conclude that although the economic policy uncertainty inhibits the energy enterprises of fossil fuels, such as coal and petroleum, it significantly promotes solar and renewable energy. However, [52] finds no correlation between economic policy uncertainty and renewable energy growth. Implementing the empirical model based [52], the author finds a negative but statistically insignificant effect between the two variables. In addition, more attention is given on the impact of geopolitics on investments rather than on RES investments. For instance, many scholars argue that geopolitical risk has a severe impact on investments and affects negatively other economic sectors, such as tourism, trade flows, and oil prices [53–55] but positively affects government investments [56]. Other studies show that the impact of GPR varies depending on the geopolitically-sensitive sector [48] and energy can be considered as such. Moreover, given that RES is heavily depended on in R&D products, again, GPR has a negative relationship with R&D investments, although even in this field there are mixed results [57].

Additionally, geopolitical risk seems to significantly affect the diffusion of RES and energy production [58,59] and has a positive effect on renewable energy consumption [60]. In particular, [58] examined the correlation between geopolitical risk and renewable energy deployment in the United States based on quarterly data for the period of 1973 to 2020, using cointegration analysis and the ARDL approach. The study concludes that geopolitical risk has a positive and significant impact on renewable energy diffusion, since renewable energy, in a way, diminishes the level of energy dependency, thus providing energy security. Thus, "geopolitical risk is a driver to renewable energy deployment because of the expected negative consequences of these uncertainties on the economy". Similarly, [59] finds corresponding results in a similar study focusing on 10 crude oil importer countries for the period of 1985–2017, employing a panel cointegration analysis and the ARDL approach. Similarly, [60] investigated the effect of geopolitical risk on renewable energy consumption in emerging economies over the period of 1996–2015. They employed a two-step system generalized method of moments (GMMs) approach. The results showed that geopolitical risk has a positive and significant impact on renewable energy consumption. Besides, financial development also supports renewable energy consumption in emerging economies, while the proper selection of a power plant based on renewable resources has to fulfil many criteria and incorporates high uncertainty.

The geopolitics of Renewable Energy Sources (RES), seems to have quite different characteristics compared to the cases where conventional fuels are met, such as crude oil, natural gas, lignite and coal. In the case of RES—when compared to conventional fuels—there is a greater need for Foreign Direct Investment (FDI) and allocation of necessary capital for the creation of fixed assets that will relate to the appropriate infrastructure, since most countries do not have them available at the moment. Moreover, there is a need for new distribution networks as well as creation of an appropriate network of suppliers and consumers, while RES energy production is much more decentralized and distributed in more areas within the country. The production of energy from RES creates the immediate need for design, construction, and availability of energy storage methods, which is now a necessary condition for the energy security of a country and the avoidance of unforeseen interruptions in the availability of electricity in the distribution network to consumers. Furthermore, the production of energy from RES could have a positive impact on the geopolitical relations in the world, although such a condition is not always unambiguous, since it could be considered the opposite, taking into account basic observations regarding RES. Finally, the use of RES still requires a great deal of effort to inform, build knowledge on, accept and integrate into existing networks of each country in a correct and efficient manner.

The increasing use of RES and the replacement of traditional forms of energy has already been under progress, referring to the energy transition process that takes place in the international energy scene. This transformation in the energy mix seems to be accompanied by a corresponding geopolitical risk that may drive new developments and changes in international politics [61,62]. Such a massive energy transition, although it would take time and several obstacles could delay its initial plan, can impact international relations and drive nation-states to gain more strength and power in case they succeed in gaining access to the related natural resources that are critical for the development of RES [63–65]. Current findings on the contribution of RES to normality and peace at both regional and global levels differ. One strand of literature poses that an increase of RES and their greater contribution to the energy mix contributes to the reduction of geopolitical risk and to the deepening of the cooperation between states. The need for cooperation between economies and the interconnection of energy systems for the maintenance of an adequate energy production system with smooth and efficient operation is also supported [66,67]. Moreover, energy production based solely on the "green" RES will contribute more to global energy security and thus smoothen tensions and frictions among states [68,69].

The intensification of cryptocurrency mining and the need to use environmentally friendly energy production to sustain respective investments has spurred a novel research path. [70] present an algorithm designed for the trading of energy saving certificates, implemented via a blockchain-based smart contract system, that can be used to reward "green" energy consumption and penalize all other forms in mining cryptocurrencies. [71] calculate an environmental performance index that introduces crypto mining to the energy consumption mix, suggesting that European countries have a firmer commitment in reducing the environmental impact from mining. Finally, [65] show that Bitcoin and gold respond positively to the composite geopolitical risk indicator when risk is high. This underscores that both Bitcoin and gold have the ability to act as safe havens for assets whose valuations plummet during times of violent geopolitical conflicts.

3. The Data

As we discuss in the introduction section, the scope of this study is to evaluate the potential causal relationship between RES and GPR. To account for this scope, we compiled an annual dataset of 171 countries from the period 1980–2018 from the U.S. Energy Information Administration (EIA) on the ratio of Energy production from RES. The GRP index we selected was the Caldara and Iacovello [24] from the Federal Reserve (FRB), given its broad use in relevant literature. The aforementioned index creates an index on the range of 0–100 based on a selection of newspaper articles from 10 outlets covering geopolitical tensions. In our framework, we merge the recent index that covers the period of 1985–2021 to the historical index (with only 3 newspapers) that goes back to 1990. Moreover, we control for various other effects using Real GDP growth rates to control for heterogeneities in economic development levels between economies, energy consumption per capita, and energy consumption per 2015 PPP GDP (MMBtu/$) to control for access to energy and brent oil prices from the repository of the Federal reserve of St. Louis (Fred), to account for the cost of energy production and the comparison with other energy production means. The descriptive statistics of our dataset are reported in Table 1.

Table 1. Aggregated GPR index descriptive statistics.

Variable	Abbreviation	Observations	Mean	Std. Dev.	Min	Max	Source
Ratio of Energy Production from Renewable sources (%)	ren_prod_r	5630	0.152	0.259	0.000	0.999	EIA
Energy consumption per capita (MMBtu/person)	cons_cap	6198	80.731	122.504	0.000	1139.321	EIA
Energy consumption per 2015 PPP GDP (MMBtu/$)	Energy_gdp	6198	4.182	4.831	0.000	166.913	EIA
Geopolitical risk index	gpr	39	104.057	38.970	40.662	181.954	FRB
CO_2 Emissions (metric tons per capita)	CO_2	6298	4.521	8.214	0.000	266.483	World Bank
Real GDP growth rate (%)	gdp	6084	0.035	0.066	−0.667	1.480	World Bank
Brent oil prices ($ per barrel)	brent	39	44.117	29.829	13.200	111.27	Fred
Countries		171					
Time Span	1980–2018						

As we observe, our panel dataset is unbalanced, since we miss observations for a number of variables. Nevertheless, the panel approach provides substantially more robust results than a simple Least-Squares regression with only 39 observations. Our variables have different logarithmic range, therefore we use logarithms for all variables apart from the RES ratio (ren_prod_r) and real GDP growth rate (gdp). Moreover, we observe large heterogeneities as we find countries with no RES production (South Sudan, Haiti, and Sri Lanka) and others with very large production ratios (Ireland, Austria, and Iceland). While the Caldara and Iacovello [24] index is a popular choice among researchers, it measures only global geopolitical risk without a spatial characteristic. Thus, to account for country specific results, we examine a sub-sample of 18 developing countries, for which Caldara and Iacovello produce an economy-specific index. This exercise could potentially highlight heterogeneity better than the aggregated index. The descriptive statistics of this subsample are reported in Table 2.

The sample is again heterogenous and logarithms are used to account for a different arithmetic range in variables. Finally, as a robustness test, we evaluate the World Uncertainty Index of [2] as the geopolitical risk measure. The index is produced annually for the period 1980–2018 for 130 countries. The index is country-specific and thus can be used to evaluate the results from the above approaches. We report descriptive statistics in Table 3.

Table 2. Country-specific descriptive statistics.

Variable	Abbreviation	Observations	Mean	Std. Dev.	Min	Max	Source
Ratio of Energy Production from Renewable sources	ren_prod_r	598	0.133	0.182	0	0.869	EIA
Energy consumption per capita (MMBtu/person)	cons_cap	598	4.106	0.900	1.898	5.838	EIA
Energy consumption per 2015 PPP GDP (MMBtu/$)	Energy_gdp	589	1.623	0.501	0.689	3.066	EIA
Geopolitical risk index	gpr	612	98.759	28.719	35.747	261.257	FRB
CO_2 Emissions (metric tons per capita)	CO_2	607	1.313	0.867	−0.660	3.292	World Bank
Real GDP growth rate	gdp	599	3.903	5.099	−22.900	18.300	World Bank
Brent oil prices ($ per barrel)	brent	39	44.117	29.829	13.200	111.27	Fred
Countries		18					
Time Span	1985–2018						

Table 3. World Uncertainty Index descriptive statistics.

Variable	Abbreviation	Observations	Mean	Std. Dev.	Min	Max	Source
Ratio of Energy Production from Renewable sources	ren_prod_r	4660	0.1667	0.265	0	0.999	EIA
Energy consumption per capita (MMBtu/person)	cons_cap	4830	85.274	126.346	0	1139.321	EIA
Energy consumption per 2015 PPP GDP (MMBtu/$)	Energy_gdp	4830	4.436	5.242	0	166.914	EIA
World Uncertainty Index	wui	4839	0.141	0.136	0	1.343	[2]
CO_2 Emissions (metric tons per capita)	CO_2	4866	4.426	5.804	0	58.874	World Bank
Real GDP growth rate	gdp	4720	3.454	6.248	−66.700	124.700	World Bank
Brent oil prices ($ per barrel)	brent	5070	44.117	29.829	13.200	111.27	Fred
Countries	130						
Time Span	1980–2018						

Again, we resort to logarithmic forms of the variables, while the heterogeneity is obvious.

4. Empirical Results

The relationship between GPR and RES cannot be examined using a typical regression model, applied in quite a few empirical approaches in the literature, given that infrastructure investments need a significant time horizon to be completed and create a "critical mass" for shaping consumption preferences. The typical regression approaches (even in more advanced machine learning approaches) evaluate short-term relationships between variables. To account for long-term relationships and the possible evolving stationary of variables in the short-term, we use a panel Cross-Section Augmented Autoregressive Distributed Lag (CS-ARDL) model of [27] that accounts for long-term relationships and possible cointegration between variables as in (1):

$$\Delta y_{i,t} = \beta_{0,i} + \sum_{l=1}^{p_y} \beta_{i,l} \Delta y_{i,\, t-l} + \sum_{j=0}^{p_x} \beta'_{i,l} \Delta x_{i,t-j} + \sum_{l=0}^{p_{\bar{z}}} \psi'_{i,l} \bar{z}_{t-l} + \left(\theta_{o,i} y_{i,t-1} + \sum_{j=0}^{k} \theta_{i,k} x_{i,t-k} \right) + \varepsilon_{i.t} \quad (1)$$

where $\theta_{o,i} y_{i,t-1} + \sum_{j=0}^{k} \theta_{i,k} x_{i,t-k}$ is the Error correction term (ECM) of the model, p_y the lag order of the dependent variable, p_x the lag order of the control variables, $p_{\bar{z}}$ the lag order of the added cross-sectional averages to account for endogeneity issues. The ECM part of the model captures long-term relationships between the dependent and the independent variables, while the rest of the model accounts for short-term relationships. The lag order p_y, p_x and $p_{\bar{z}}$ are determined according to the Bayesian Information Criterion (BIC), while the ARDL/Bounds Testing methodology determines long-term (cointegration) relationship.

In estimating models' coefficients we consider the Mean Group [MG] [72] estimator that allows for cross-sectional heterogenous coefficients and nonstationary (but cointegrated) data, the Common Correlated Effects Mean Group [CCEMG] [27] estimator that controls for cross-sectional dependence in addition to the characteristics of MG and the

Dynamic Common Correlated Effects Mean Group [DCCEMG] [27] that adds lagged dependent variables to CCEMG to address endogeneity issues which render the estimators biased and inconsistent. The D/CCEMG estimator treats common dynamic factors as nuisance parameters used solely for controlling cross-sectional dependence without actual interpretation ability.

4.1. Aggregated Caldara and Iacovello Index

We start our analysis on testing cross-sectional dependencies among variables to account for the use of the aforementioned estimators [73,74], using the fixed-T variance estimator from [75] in all standard error estimations. This estimator is heteroscedasticity robust and allows for panels with a fixed time dimension (balanced). Nevertheless, the differences with unbalanced panels (Table 4) are not statistically different.

Table 4. Cross-sectional dependence test results.

Panel A: Chudik et al. (2016) Test: 0.5 ≤ alpha < 1 Implies Strong Cross-Sectional Dependence				
Variable	**Alpha**	**Std. Err.**	**[95% Conf.**	**Interval]**
ren_prod_r	0.591	0.052	0.489	0.693
cons_cap	0.949	0.401	0.162	1.737
Energy_gdp	0.947	0.055	0.839	1.055
gpr	1.002	0.017	0.968	1.036
CO_2	0.906	0.026	0.855	0.957
gdp	0.445	0.223	0.006	0.884
brent	1.002	0.035	0.934	1.071
Panel B: Pesaran (2015) The null hypothesis is the existence of weak cross-sectional dependence				
variable	CD	*p*-value	Cross-sections	Observations
ren_prod_r	55.601	0.000	117	39
cons_cap	204.019	0.000	142	39
Energy_gdp	234.030	0.000	142	39
gpr	752.904	0.000	171	39
CO_2	0.000	1.000	141	39
gdp	59.316	0.000	129	39
brent	752.904	0.000	171	39

The cross-sectional dependence test of [76] [Panel A], suggests a strong cross-sectional dependence for most variables since alpha is very close or above 0.5. We reach similar results with the [77] test, where we reject the null hypothesis of weak cross-sectional dependence for all variables. Before estimating models' parameters, we need to test the stationarity of the variables, since for a CS-ARDL model to provide valid estimates, we should have either I(0) or I(1) variables, but not I(2). In the case that we have a variable that is second order integrated ARDL, estimates can be explosive and irrelevant. We perform a unit root test using the Augmented Dickey-Fuller (ADF) and its version using Generalized Least Squares estimators (DF-GLS) for the gpr and brent prices that are constant across panels, while we implement the Breitung and the Cross-sectional version of the Im-Pesaran-Shin (CIPS) tests for the other variables that change across panels. The latter is an augmented version of the typical IPS test including cross-sectional means to account for endogeneity issues in the regression.

All variables are stationary in first differences (Panel B, Table 5) while gdp, brent, CO_2, GPR, cons_cap and ren_prod_r are non-stationary in levels. Thus, there could be a cointegration relationship, but this cannot be detected with typical ECM models since we have a mixture of I(0) and I(1) variables. To overcome this issue, we use an "unrestricted" ECM model based on an ARDL model with heterogenous (different) coefficients among cross-sections (countries) to allow for higher flexibility [76]. The model's coefficients are reported in Table 6.

Table 5. Unit root test results.

	ADF Test	DF-GLS	Breitung	CIPS
Panel A: Levels				
Null Hypothesis	**Non Stationarity**	**Stationarity**	**Panels Contain Unit Roots**	**Homogeneous Non-Stationary Panels**
ren_prod_r			11.735	−0.689
cons_cap			4.196	−2.498 *
Energy_gdp			−1.998 **	−2.713 ***
gpr	−2.198	−2.557		
CO_2			4.285	−2.122
gdp			−27.982 ***	−4.468 ***
brent	−2.674	−2.234		
Panel B: First differences				
ren_prod_r			−19.805 ***	−3.163 ***
cons_cap			−33.999 ***	−5.640 ***
Energy_gdp			−42.123 ***	−5.501 ***
gpr	−4.682 ***	−5.178 ***		
CO_2			−35.357 ***	−5.618 ***
gdp			−46.334 ***	−6.250 ***
Brent	−5.897 ***	−5.316 ***		

Note: *, ** and *** denote rejection of the null hypothesis at 10%, 5% and 1% level of significance. Pesaran Panel Unit Root Test with cross-sectional and first difference mean included. Deterministics chosen: constant & trend. Dynamics: lags criterion decision Portmanteau (Q) test for white noise.

Table 6. Model's coefficients estimates.

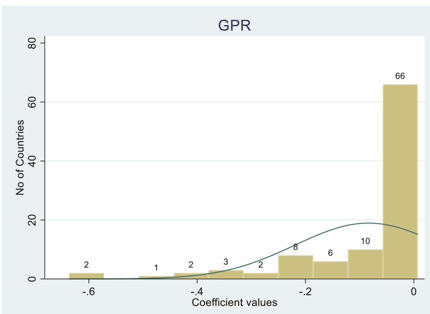
Dependent Variable $\Delta ren\_prod\_r_t$	**Mean Group ARDL Estimator (1)**	**Common Correlated Effects ARDL Estimator (2)**	**Dynamic Common Correlated Effects ARDL Estimator (3)**
Panel A: Short-run coefficients			
$\Delta ren\_prod\_r_{t-1}$	0.250	0.139	0.203
	(0.290)	(0.218)	(0.151)
$\Delta ln(cons\_cap_t)$	0.010	0.023 *	0.016
	(0.016)	(0.014)	(0.018)
$\Delta ln(energ\_gdp_t)$	−0.007	−0.010 **	−0.009 **
	(0.005)	(0.004)	(0.005)
$\Delta ln(gpd_t)$	−0.001	−0.001	−0.001
	(0.000)	(0.000)	(0.000)
$\Delta ln(gpr_t)$	−0.084 ***	−0.085 ***	−0.087 ***
	(0.013)	(0.014)	(0.014)
$\Delta ln(co2_t)$	0.003	0.002	0.004
	(0.005)	(0.004)	(0.005)
$\Delta ln(brent_t)$	−0.000488	−0.001	−0.001
	(0.001)	(0.002)	(0.001)
$\Delta(ren\_prod\_r_{t-1} \times ln(gpr_{t-1}))$	0.663 ***	0.544 ***	0.577 ***
	(0.115)	(0.115)	(0.138)
Constant	0.001 ***	0.001 ***	0.001 ***
	(0.000)	(0.000)	(0.000)

Table 6. *Cont.*

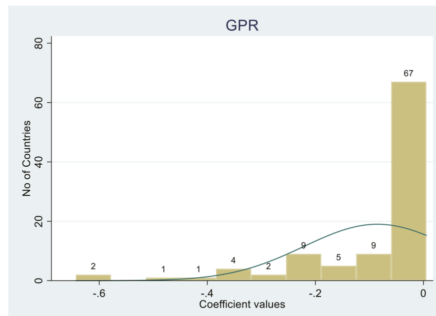
Dependent Variable $\Delta ren\_prod\_r_t$	Mean Group ARDL Estimator (1)	Common Correlated Effects ARDL Estimator (2)	Dynamic Common Correlated Effects ARDL Estimator (3)
	Panel B: Long-run coefficients		
$ln(cons\_cap_t)$	0.011	0.023 *	0.016
	(0.016)	(0.013)	(0.018)
$ln(energ\_gdp_t)$	−0.007	−0.009 **	−0.009 *
	(0.005)	(0.004)	(0.005)
$ln(co2_t)$	0.003	0.000	0.004
	(0.004)	(0.004)	(0.005)
$ln(gdp_t)$	−0.001 *	−0.001 *	−0.001 ***
	(0.000)	(0.000)	(0.000)
$ln(gpr_t)$	−0.084 ***	−0.0851 ***	−0.087 ***
	(0.014)	(0.014)	(0.010)
$ln(brent_t)$	−0.001	−0.001	−0.001
	(0.001)	(0.002)	(0.001)
$ren\_prod\_r_t \times ln(gpr_t)$	0.470 ***	0.426 ***	0.463 ***
	(0.046)	(0.070)	(0.047)
Constant	0.001 ***	0.003 ***	0.001 ***
	(0.000)	(0.000)	(0.000)
	Panel C: Adjustment Term (ECM)		
$ren\_prod\_r_t$	−0.750 ***	−0.861 ***	−0.797 ***
	(0.290)	(0.218)	(0.151)
Observations	2805	2805	2668
Number of groups	100	100	97
R-squared	0.99	0.050	0.050
Cross-sectional means lag	-	-	2
Cross-sectional Exponent on residuals	0.606	0.588	0.607
Weak cross-sectional dependence on residuals	33.390 ***	31.81 ***	33.79 ***
Long-run common F-test	7.430—I(1)	9.10—I(1)	10.73—I(1)
Long-run ECM *t*-test	6.69 ***	15.64 ***	27.94 ***
Linear trend	Cross-section	No	No
Pooled Constant	Yes	Yes	Yes

Note: Standard errors are reported in parenthesis. All standard errors are [76] fixed-T standard errors for pooled coefficients. According to [77] the I(0) and the I(1) bounds of the bounds test for the joint F-test of all long-run coefficients are 2.42 and 3.52 at the 5% level of significance. The respective *t*-test on the null hypothesis on which the adjustment term equals zero has an upper boundary of −3.65 and a lower of −5.59. The null hypothesis of the [77] test for weak cross-sectional dependence assumes that residuals are weakly cross-sectional dependent. A value of 0.5 ≤ exponent < 1 implies strong cross-sectional dependence. Note: *, ** and *** denote rejection of the null hypothesis at 10%, 5% and 1% level of significance.

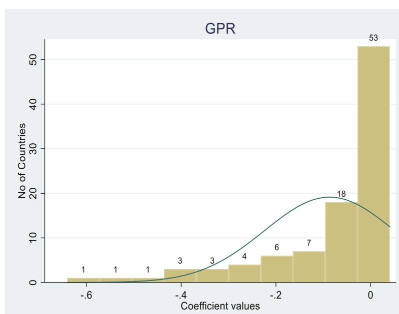
Starting from the short-run estimates (Panel A, Table 6) the GPR coefficient has a negative and significant effect on the dependent variable (ratio of RES produced energy), as well as the interaction term of GPR with the dependent variable. The latter measures the multiplier effect of GRP on RES production as we move from countries with low production to countries with higher production. Our interest in Panel B where we report the long-run effects, where GPR has a negative and significant (although very small) effect on the production ratio and a significant multiplier effect of the interaction term. The ECM coefficient is negative, significant and greater than −1 (as expected). The Cross-sectional Exponent on residuals is close to 0.5 (but above it) suggesting weak cross-sectional dependency on residuals after estimation. Moreover, we also detect cointegration of all variables based on the boundaries F-test, while all variables are above the upper boundaries of the Student-t bounds test. The long-run common F-test which evaluates the null hypothesis that all ECM terms are zero concludes that the use of the ECM test is warranted, while the same applies for the long-run ECM *t*-test (bounds test) of [77]. Thus, all models are well-identified and reach similar conclusions, suggesting that our findings are robust and independent of the selection of the estimator. The counterfactual signs of the energy consumption based on the GDP coefficient probably stem from the fact that GPR is constant across sections (countries). Thus, we need a more granular examination, with a more detailed panel dataset. In Figure 3 we depict the full distribution of the coefficients, as Table 6 reports mean estimates across coefficients. As we observe, all values are negative but are heavily skewed towards zero.



(**a**)



(**b**)



(**c**)

Figure 3. Coefficients estimates on long-term effect of GPR on the ratio of RES production based on the MG (subplot (**a**)), CCE (subplot (**b**)) and DCCE (subplot (**c**)) estimator.

4.2. Disaggregated Caldara and Iacovello Index Data

We extend our analysis focusing only on the 18 country-specific indices provided by [25]. The disaggregated data are expected to provide a further insight on the heterogeneity effects of GPR on RSE production. In Table 7 we report directly the model's estimates.

Table 7. Disaggregated index data estimates.

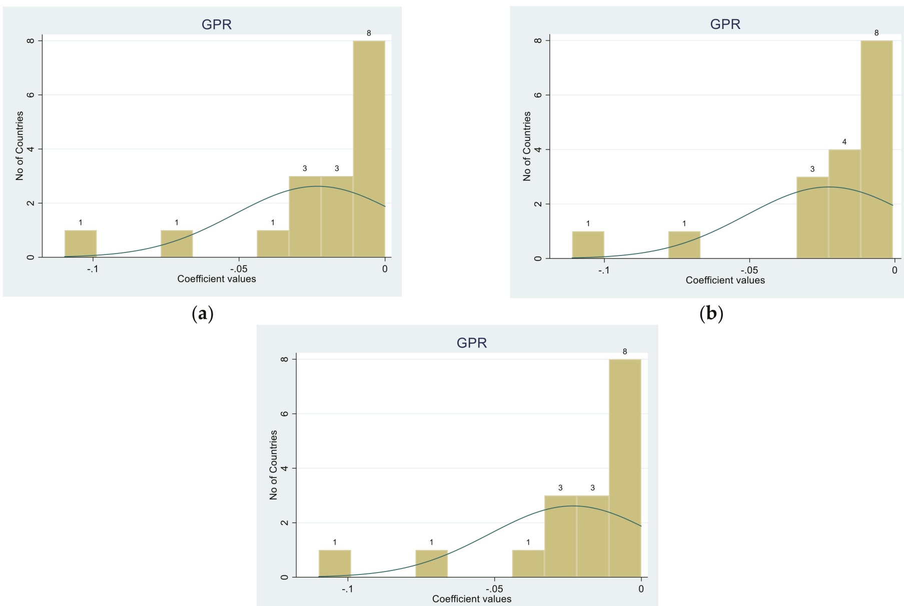
Variable	Mean Group ARDL Estimator (1)	Common Correlated Effects ARDL Estimator (2)	Dynamic Common Correlated Effects ARDL Estimator (3)
	Panel A: Short-run coefficients		
$\Delta ren\_prod\_r_{t-1}$	0.001	0.068	0.207
	(0.006)	(0.076)	(0.206)
$\Delta ln(cons\_cap_t)$	−0.048	−0.031	−0.047
	(0.040)	(0.036)	(0.045)

Table 7. *Cont.*

Variable	Mean Group ARDL Estimator (1)	Common Correlated Effects ARDL Estimator (2)	Dynamic Common Correlated Effects ARDL Estimator (3)
$\Delta ln(energ\_gdp_t)$	0.001	−0.002	−0.000
	(0.008)	(0.007)	(0.008)
$\Delta ln(gpd_t)$	0.001	0.001	0.000
	(0.001)	(0.001)	(0.000)
$\Delta ln(gpr_t)$	−0.024 ***	−0.023 ***	−0.023 ***
	(0.007)	(0.007)	(0.007)
$\Delta ln(co2_t)$	0.002	0.002	0.002
	(0.006)	(0.005)	(0.007)
$\Delta ln(brent_t)$	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
$\Delta(ren\_prod\_r_{t-1} \times ln(gpr_{t-1}))$	0.217 ***	0.181 ***	0.212 ***
	(0.003)	(0.037)	(0.007)
Constant	0.000	−0.002 **	−0.002 **
	(0.000)	(0.001)	(0.001)
Panel B: Long-run coefficients			
$ln(cons\_cap_t)$	−0.049	−0.035	−0.048
	(0.040)	(0.035)	(0.046)
$ln(energ\_gdp_t)$	0.001	−0.001	−0.000
	(0.008)	(0.001)	(0.008)
$ln(co2_t)$	0.002	0.001	0.0018
	(0.006)	(0.005)	(0.008)
$ln(gdp_t)$	0.001	0.001	0.000
	(0.000)	(0.000)	(0.000)
$ln(gpr_t)$	−0.023 ***	−0.023 ***	−0.023 ***
	(0.007)	(0.007)	(0.007)
$ln(brent_t)$	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
$ren\_prod\_r_t \times ln(gpr_t)$	0.218 ***	0.289 ***	0.203 ***
	(0.004)	(0.073)	(0.016)
Constant	0.000	−0.001 ***	−0.001 ***
	(0.000)	(0.001)	(0.000)
Panel C: Adjustment Term (ECM)			
$ren\_prod\_r_t$	−1.000 ***	−0.932 ***	−0.793 ***
	(0.001)	(0.076)	(0.206)
Observations	478	495	478
Number of groups	17	17	17
R-squared	0.996	0.004	0.005
Cross-sectional means lag	-	-	1
Cross-sectional Exponent on residuals	0.619	0.609	0.587
Weak cross-sectional dependence on residuals	−0.52	2.27 **	1.63
Long-run common F-test	569.34—I(1)	77.45—I(1)	4.89—I(1)
Long-run ECM *t*-test	215.65 ***	150.21 ***	14.84 ***
Linear trend	No	No	No
Pooled Constant	Yes	Yes	Yes

Note: Standard errors are reported in parenthesis. All standard errors are [76] fixed-T standard errors for pooled coefficients. According to [77] the I(0) and the I(1) bounds of the bounds test for the joint F-test of all long-run coefficients are 2.42 and 3.52 at the 5% level of significance. The respective *t*-test on the null hypothesis on which the adjustment term equals zero has an upper boundary of −3.65 and a lower of −5.59. The null hypothesis of the [77] test for weak cross-sectional dependence assumes that residuals are weakly cross-sectional dependent. A value of $0.5 \leq$ exponent < 1 implies strong cross-sectional dependence. Note: ** and *** denote rejection of the null hypothesis at 5% and 1% level of significance.

The disaggregated data provide a clear depiction of the heterogenous effects of GPR on the production of RSE. The GPR is negative and significant at the short-term for all models, the interaction term is significant with the correct sign and the same applies in the long run. The ECM (adjustment term) implies cointegration and is lower than unity in absolute value, has a negative sign, and is statistically significant. Apparently, all other control variables have a statistically insignificant effect, but this is not an issue as the variable of interest is GPR and control variables are used to shape the dimensional space that we minimize the cost function. In Figure 4 we depict the country specific coefficients. As we observe, all coefficients are negative and clustered towards zero, with a few countries exhibiting higher distance from zero.



(**a**) (**b**) (**c**)

Figure 4. Coefficients estimates on long-term effect of GPR on the ratio of RES production based on the MG (subplot (**a**)), CCE (subplot (**b**)) and DCCE (subplot (**c**)) estimator.

4.3. Robustness Tests

As a robustness test we change our measure of GPR and use the World Uncertainty Index from [2] that is available at the country level for 143 countries (130 after data pre-processing). In Table 8 we depict model's coefficient values for the MG, CCE and DCCE estimators.

Table 8. WUI data model.

Variable	Mean Group ARDL Estimator (1)	Common Correlated Effects ARDL Estimator (2)	Dynamic Common Correlated Effects ARDL Estimator (3)
		Panel A: Short-run coefficients	
$\Delta ren\_prod\_r_{t-1}$	0.021	0.042	−0.008
	(0.035)	(0.056)	(0.039)
$\Delta ln(cons\_cap_t)$	−0.012	−0.010	−0.058
	(0.069)	(0.069)	(0.066)

Table 8. *Cont.*

Variable	Mean Group ARDL Estimator (1)	Common Correlated Effects ARDL Estimator (2)	Dynamic Common Correlated Effects ARDL Estimator (3)
$\Delta ln(energ\_gdp_t)$	0.082	0.085	0.113
	(0.066)	(0.062)	(0.069)
$\Delta ln(gpd_t)$	0.001 **	0.001	0.001 *
	(0.000)	(0.000)	(0.000)
$\Delta ln(wui_t)$	−0.465 ***	−0.473 ***	−0.458 ***
	(0.079)	(0.079)	(0.079)
$\Delta ln(co2_t)$	−0.082 ***	−0.085 ***	−0.079 **
	(0.026)	(0.027)	(0.032)
$\Delta ln(brent_t)$	−0.002	−0.004	0.003
	(0.002)	(0.003)	(0.004)
$\Delta(ren\_prod\_r_{t-1} \times ln(wui_{t-1}))$	2.050 ***	2.027 ***	2.023 ***
	(0.226)	(0.233)	(0.218)
Constant	0.000	−0.000	0.033
	(0.000)	(0.000)	(0.023)
Panel B: Long-run coefficients			
$ln(cons\_cap_t)$	−0.011	−0.011	−0.079
	(0.071)	(0.072)	(0.076)
$ln(energ\_gdp_t)$	0.079	0.077	0.169
	(0.069)	(0.066)	(0.108)
$ln(co2_t)$	−0.086 ***	−0.084 ***	−0.121 *
	(0.028)	(0.029)	(0.067)
$ln(gdp_t)$	0.001 **	0.001 *	0.001 *
	(0.000)	(0.000)	(0.000)
$ln(wui_t)$	−0.490 ***	−0.494 ***	−0.487 ***
	(0.087)	(0.085)	(0.086)
$ln(brent_t)$	−0.002	−0.005	0.009
	(0.002)	(0.003)	(0.009)
$ren\_prod\_r_t \times ln(wui_t)$	2.063 ***	2.027 ***	2.059 ***
	(0.269)	(0.233)	(0.284)
Constant	0.000	−0.000 ***	0.080
	(0.000)	(0.000)	(0.063)
Panel C: Adjustment Term (ECM)			
$ren\_prod\_r_t$	−0.979 ***	−0.958 ***	−0.997 ***
	(0.0350)	(0.0560)	(0.039)
Observations	2934	3033	2934
Number of groups	98	98	98
R-squared	0.644	0.350	0.520
Cross-sectional means lag	-	-	2
Cross-sectional Exponent on residuals	0.500	0.508	0.519
Weak cross-sectional dependence on residuals	1.64	4.410 ***	1.670*
Long-run common F-test	169.47—I(1)	66.100—I(1)	154—I(1)
Long-run ECM *t*-test	783.57 ***	292.000 ***	669.82 ***
Linear trend	No	No	No
Pooled Constant	Yes	Yes	No

Note: Standard errors are reported in parenthesis. All standard errors are [76] fixed-T standard errors for pooled coefficients. According to [77] the I(0) and the I(1) bounds of the bounds test for the joint F-test of all long-run coefficients are 2.42 and 3.52 at the 5% level of significance. The respective *t*-test on the null hypothesis on which the adjustment term equals zero has an upper boundary of −3.65 and a lower of −5.59. The null hypothesis of the [77] test for weak cross-sectional dependence assumes that residuals are weakly cross-sectional dependent. A value of 0.5 ≤ exponent < 1 implies strong cross-sectional dependence. Note: *, ** and *** denote rejection of the null hypothesis at 10%, 5% and 1% level of significance.

Regardless of the model examined, we find a significant ECM term, negative and below unity in absolute terms, reject weak residual dependency after estimation, detect cointegration of the variables, and all residuals pass the Student-t bounds test. Strong residual dependency is not warranted. The WUI, interaction term and CO_2 emissions are significant both in the short and the long run. All coefficients have the correct sign, while GDP growth has a marginal effect. The stronger negative effect of the WUI data corroborates to our finding in previous sections and supports a negative relationship between geopolitical uncertainty and the ration of "green" produced energy. In Figure 5 we depict the country-specific coefficients for WUI.

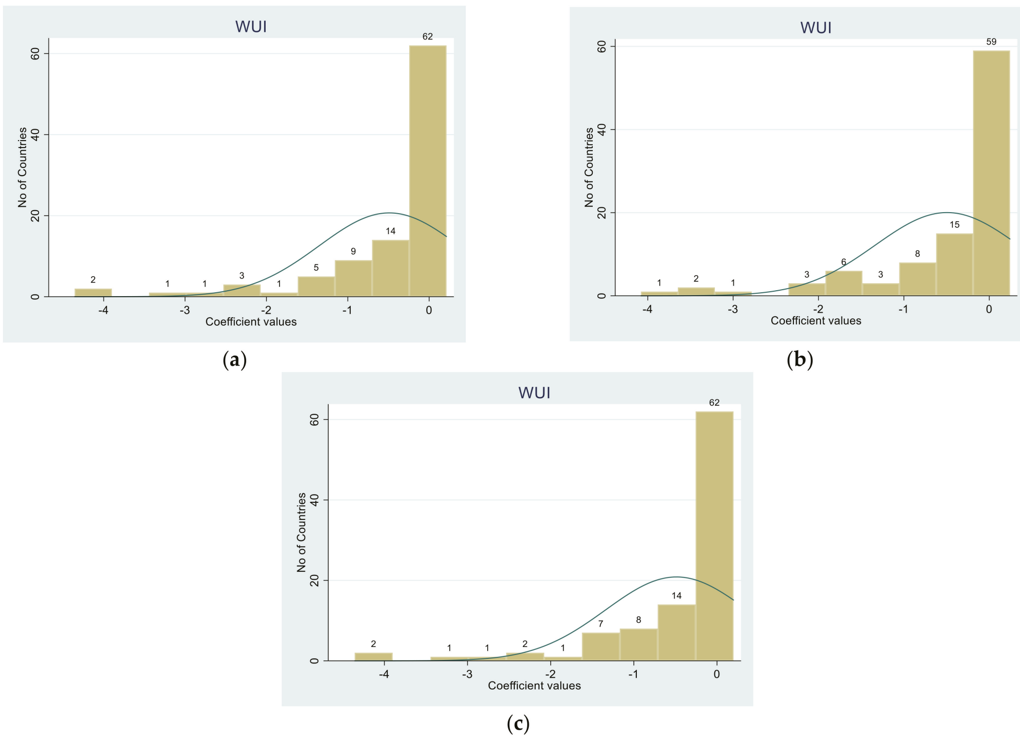


Figure 5. Coefficients estimates on long-term effect of GPR on the ratio of RES production based on the MG (subplot (**a**)), CCE (subplot (**b**)) and DCCE (subplot (**c**)) estimator.

5. Conclusions and Policy Implications

The energy transition towards greener production choices already being implemented in many developed economies seems to be dependent on geopolitical risk, which can effectively drive international politics and affect RES investments. Existing literature mostly focuses on geopolitics through examining the effect of traditional energy sources, such as crude oil and natural gas [65]. In this paper, we depart from the traditional approach and evaluate the relationship between RES and GPR on an explicit quantitative framework. Building on an aggregated GPR index on available data for 171 economies, we evaluate the effect of GPR fluctuations on energy produced by RES, controlling for the majority of variables proposed in literature. In doing so, we train a panel ARDL model where we allow for heterogenous effects between economies (largely overlooked in the relevant literature), with the flexibility of the model including both long and short-term relationships.

Our empirical findings suggest that:

i GPR has a negative effect on RES production regardless of the estimator used.
ii In parallel, this relationship between GPR and RES is obvious both in short and longer horizons.
iii The inclusion of an interaction term suggests that the effect of GPR on RES increases with the increase in the production level.
iv Our results are robust to a country-specific examination or the use of alternative GRP measures.
v Apparently, no other variable exhibits a universal (in terms of GPR specification or estimator selection) consistent effect.

All models are well-specified according to our statistical controls, and answer inclusively our research scope, complementing the relevant literature and can have direct policy implications.

The current energy transition taking place globally is massive and is expected to take time, and could eventually become a game changer and alter the power status of nations globally. Moreover, it can affect international relations and drive nation-states to gain more strength and power if they succeed to gain access to related natural resources that are critical for the development of RES. The final share of RES in the energy mix for total primary energy supply and electricity generation of a nation state's short and long-term energy security seem to be important. Diversification of energy mix is always seen as the proper strategy for a nation state to follow, in order to be sure that any change to be implemented in its national energy policy will be sustainable and effective. Since RES is not purely geographically concentrated as traditional types of energy and thus not fully managed by each country, it depends on different geopolitical risks.

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Article

Forecasting the Volatility of Crude Oil: The Role of Uncertainty and Spillovers

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Abstract: We use a dataset for the group of G7 countries and China to study the out-of-sample predictive value of uncertainty and its international spillovers for the realized variance of crude oil (West Texas Intermediate and Brent) over the sample period from 1996Q1 to 2020Q4. Using the Lasso estimator, we found evidence that uncertainty and international spillovers had predictive value for the realized variance at intermediate (two quarters) and long (one year) forecasting horizons in several of the forecasting models that we studied. This result holds also for upside (good) and downside (bad) variance, and irrespective of whether we used a recursive or a rolling estimation window. Our results have important implications for investors and policymakers.

Keywords: uncertainty; spillovers; realized variance; crude oil; forecasting

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1. Introduction

Heightened macroeconomic uncertainty, as observed over the last decade and half due to the global financial crisis (GFC), the European sovereign debt crisis, and, of course, the ongoing COVID-19 pandemic, has tended to make the path of the future aggregate demand of commodities, and, as a result, also aggregate production, less predictable. Given this, risk averse commodity producers prefer to hold physical inventory, which causes a rise in the convenience yield, which, in turn, results in increased volatility of commodity prices, as outlined in the 'Theory of Storage' [1,2]. With crude oil being undoubtedly the most actively traded commodity, quite a few recent studies have analyzed the role of uncertainty in forecasting the volatility of the oil market (see, for example, [3–7]). For earlier studies, the reader is referred to the references cited in these papers.

As far as the existing literature is concerned, Bonaccolto et al. [3], analyzed the relevance of newspaper-based measures of economic policy and equity market uncertainty of the United States (US) in predicting the conditional quantiles of crude oil returns and volatility, using a nonparametric k-th order causality-in-quantiles model. A dynamic analysis showed that these US-based uncertainty indexes are primarily relevant during periods of market distress, when the role of oil risk is the predominant interest, with heterogeneous effects over different quantile levels.

Along similar lines, Bouri et al. [4] analyzed the predictive power of a daily newspaper-based index of US uncertainty associated with infectious diseases (EMVID) for oil-market volatility. These authors documented that incorporating EMVID into a forecasting setting significantly improved the forecast accuracy of oil volatility at short-, medium-, and long-run horizons, based on a heterogenous autoregressive model of (realized) volatility. Li et al. [5], using a mixed data sampling generalized autoregressive conditional heteroscedastic (MIDAS-GARCH) model, highlighted the role of monetary policy uncertainty in addition to overall economic policy uncertainty of the US in forecasting oil market volatility.

However, Dutta et al. [7], relying on a quantiles-based approach, showed that, unlike the overall uncertainty of the US related to policy decisions, equity market volatility of the US in general, and the same due to commodity market movements and crises, carried higher forecasting power for oil market volatility. Interestingly, while Li et al. [5] did not find a metric of global uncertainty to be important in forecasting oil market volatility, Liang et al. [6] did highlight its relevance along with the importance of the overall equity market volatility indices of the US, as the existing studies above discussed , using a standard predictive regression framework, model combination, and shrinkage approaches.

As can be observed from the concise review presented in the preceding paragraph, a general tendency of the above studies is to primarily incorporate the role of the uncertainty of the US in predicting movements of the oil market volatility, barring to some extent the work of Liang et al. [6], who considered a role of a measure of global uncertainty. While this is understandable to some extent given the dominance of the US as a major player in the global oil market (and also because the GFC originated in the US), Bahloul and Gupta [8] and Dinçer et al. [9], indicated that uncertainties of other economies within the G7 (comprising of Canada, France, Germany, Italy, Japan, the United Kingdom and the US) and China, also tend to drive oil market volatility due to the importance of their position as exporters and importers in the oil market.

In light of this, and the fact that oil is a global market, we forecast the quarterly realized variance (*RV*) of oil (West Texas Intermediate, WTI, and Brent crude) price volatility and consider not only the role of uncertainties of all the G7 countries and China but also their respective spillover of uncertainty to the rest of the world, over the period from 1996Q1 to 2020Q4. Accounting for the total amount of uncertainty spillovers of these major economies onto other countries renders it possible to better model worldwide uncertainty and its influence on global oil demand in a parsimonious manner, i.e., without incorporating the information from uncertainties of multiple other (135 to be exact, based on our data source, which we shall discuss later in detail) countries in the world.

In this regard, we were motivated by the work of Liang et al. [6], who suggested the need to look at a global measure of uncertainty (based on 22 countries, unlike 143 in our case) over and above the same of the US in predicting oil-price volatility. Following Andersen and Bollerslev [10], we captured *RV* as the sum of squared returns over a quarter, which yielded an observable, unconditional, measure of volatility, which is otherwise a latent process. Conventionally, the time-varying volatility was modeled and the fit assessed using various GARCH models, under which the conditional variance is a deterministic function of the model parameters and past data. Alternatively, some recent papers considered stochastic volatility (SV) models, where the volatility is a latent variable that follows a stochastic process. Irrespective of whether one uses GARCH or SV models, the underlying estimate of volatility is not model-free (or unconditional) as in the case of *RV*.

One must realize that identifying factors that, in our case, happen to be the uncertainties of the G7 and their spillovers, that help to accurately forecast oil market volatility also has economic implications that are of key importance for both policymakers and investors. This is because, as shown by van Eyden et al. [11], movements in the second-moment of crude oil can predict slowdowns in worldwide economic growth.

Moreover, the recent financialization that has characterized developments in the oil market has led to the increased participation of hedge funds, pension funds, and insurance companies in the market, as per Bampinas and Panagiotidis [12], Degiannakis and Filis [13], and Bonato [14], which resulted in oil being viewed as an alternative investment in the portfolio decisions of financial institutions (especially post the GFC). Precise forecasts of oil-price volatility are of vital importance to oil traders, since volatility is a key input to investment decisions and portfolio choices [15].

To the best of our knowledge, this is the first paper to evaluate the out-of-sample forecasting power of uncertainties of the G7 and China and its spillovers for oil returns volatility. In order to account for the fact that market agents care about the level and nature of volatility, the latter making it important to distinguish between upside ("good") and downside ("bad") volatilities [16], we also forecast good *RV* (the sum of daily squared positive returns only over a quarter) and bad *RV* (the sum of daily squared negative returns only over a quarter), in addition to the overall *RV*.

Given that our data sample spans a 25 year period (1996–2020) of 100 quarterly observations, and we have 16 predictors, besides one lag of *RV* that captures the well-known persistence of *RV* associated with the oil market [17,18], we use, as our econometric approach, a machine-learning technique known as least absolute shrinkage and selection operator (Lasso), proposed by Tibshirani [19], which, in turn, is a regression-analysis method that performs both variable selection and regularization (i.e., the process of adding information to prevent overfitting) in order to enhance the prediction accuracy and interpretability of the resulting statistical model.

In this regard, it should be noted that the better performance of the Lasso model over forecast-combination methods in forecasting oil-market volatility has been demonstrated by Liang et al. [6] and, hence, motivates us to rely on this framework as well. Our paper, thus, adds to the already existing large literature on the forecastability of oil-returns volatility by considering the role of the uncertainties of major economies in the world and the associated spillover, where the literature can be grouped into the following broad categories, using a wide variety of models and macroeconomic, financial, behavioral, and climate pattern-related predictors (see, for example, Lux et al. [20]), Bonato et al. [21], Demirer et al. [22,23], Gkillas et al. [24], Bouri et al. [25]; Salisu et al. [26], and the references cited within these papers).

We organize the remainder of this paper as follows: In Section 2, we describe our data. In Section 3, we briefly discuss the forecasting models, along with the Lasso approach used to estimate these models. In Section 4, we present the results from our forecasting experiment. In Section 5, we conclude.

2. Data

As for crude oil prices, we used the nominal daily data derived from the US Energy Information Administration (EIA, https://www.eia.gov/dnav/pet/hist/RWTCD.htm (accessed on 1 May 2021)) for West Texas Intermediate (WTI). After computing the daily log-returns, we obtained quarterly overall, upside ("good"), and downside ("bad") realized variances by taking the sum of the daily squared returns, positive returns only, and negative returns only over a specific quarter. As a robustness check, we also analyzed the quarterly *RV* of the Brent crude oil returns, which, in turn, was also sourced from the US EIA (see https://www.eia.gov/dnav/pet/hist/RBRTED.htm (accessed on 1 May 2021)).

Figure 1 plots the *RV* (and its "good" and "bad" counterparts, as defined in Section 3) of both the WTI and Brent crude oil returns. During the GFC, sharp fluctuations in *RV*s were observed over 2020 associated with the COVID-19 outbreak, thus, highlighting the importance of our question.

Uncertainty is a latent variable and, hence, requires methods to measure it. As documented by Gupta et al. [27], there are three broad approaches to quantify uncertainty, apart from the various ones associated with financial markets (such as implied-volatility indices, like the popular VIX, realized volatility, idiosyncratic volatility of equity returns, and corporate spreads): (1) a text-based approach, with the main idea to construct indices from searches of key words or terms related to (economic and policy) uncertainty in major newspapers or country-reports; (2) using stochastic-volatility estimates from various small and large-scale structural models (related to macroeconomics and finance) to derive measures of uncertainty; and (3) using the dispersion of professional forecaster disagreements to obtain uncertainty estimates.

For our metric of uncertainty, we used the first approach outlined by Ahir et al. [28], mainly because it is not model-specific, as it does not require any complicated estimation of a large-scale model to generate it in the first place. In addition to the uncertainty data, the associated spillover of the G7 economies and China to other economies in the world, are available publicly for download (https://worlduncertaintyindex.com/data/ (accessed on 1 May 2021)).

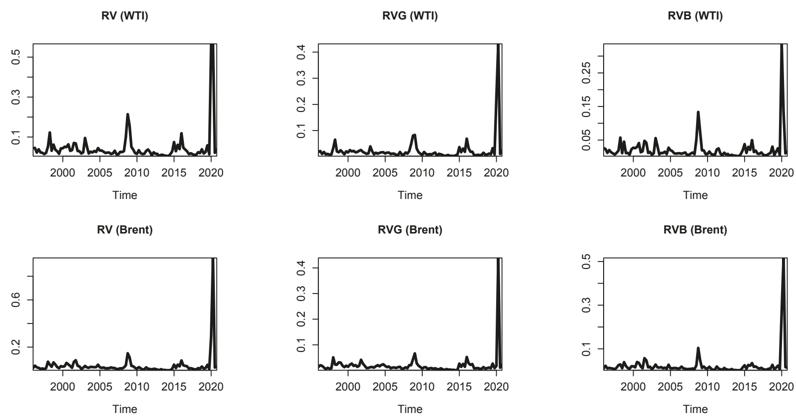

Figure 1. Realized volatility. For better readability, the vertical axes of the panels are not the same for all time series.

From frequency counts of "uncertainty" (and its variants) in the quarterly Economist Intelligence Unit (EIU) country reports from 1996 for 8 of the 143 countries, Ahir et al. [28] constructed quarterly indices of economic uncertainty for 37 countries in Africa, 22 in Asia and the Pacific, 35 in Europe, 27 in the Middle East and Central Asia, and 22 in the Western Hemisphere. The EIU reports provide an analysis and forecasts of political, policy, and economic conditions, as well as a discussion of significant political and economic developments in each country. These reports are compiled by a central EIU editorial team from work done by country-specific teams of analysts.

In order to make the uncertainty indexes comparable across countries, the raw counts were scaled by the total number of words in each report. In addition to the uncertainty indexes of each of the 143 countries, the dataset of Ahir et al. [28] also provides the uncertainty spillover metrics for the G7 and China, which, in turn, determine the choice of the countries in our paper, and the quarterly sample period of 1996Q1 to 2020Q4, which was the latest available data at the time of writing this paper. Specifically, the eight (G7 plus China) uncertainty spillover indexes of one of these particular countries to the remaining 142 countries was computed by counting the percent of word "uncertain" (or its variant) mentioned within a proximity to a word related to a particular G7 country or China in the EIU country reports.

The spillover index was then rescaled by multiplying 1,000,000 with a higher number suggesting higher uncertainty related to the specific country involving the G7 or China and vice versa. For further details regarding the words related to the G7 and China that were used, the reader is referred to Ahir et al. [28]. We used the cross-sectional sum over time to obtain the total uncertainty spillover (on to the remaining 142 economies) indexes of each of these eight countries.

Understandably, since we aimed to contribute to the oil *RV* forecasting literature by analyzing whether accounting for spillovers of uncertainty of the G7 countries and China to the rest of the world mattered over and above the uncertainty of these economies, we relied on the method of Ahir et al. [28] for a matter of consistency and similarity in how both these indexes are derived, even though alternative ways of constructing country-level uncertainty indexes, though not spillovers, are available in the public domain (see, for example, the indexes avilable at: http://policyuncertainty.com/ (accessed on 9 July 2021) based on the work of Baker et al. [29]).

Figures 2 and 3 plot the uncertainty time series and the international spillover effects. While the uncertainty series tended to fluctuate consistently over time, the spillovers had sudden massive spikes from the country(ies) of origin of the GFC, the European sovereign debt crisis, "Brexit", and the outbreak of the Coronavirus pandemic.

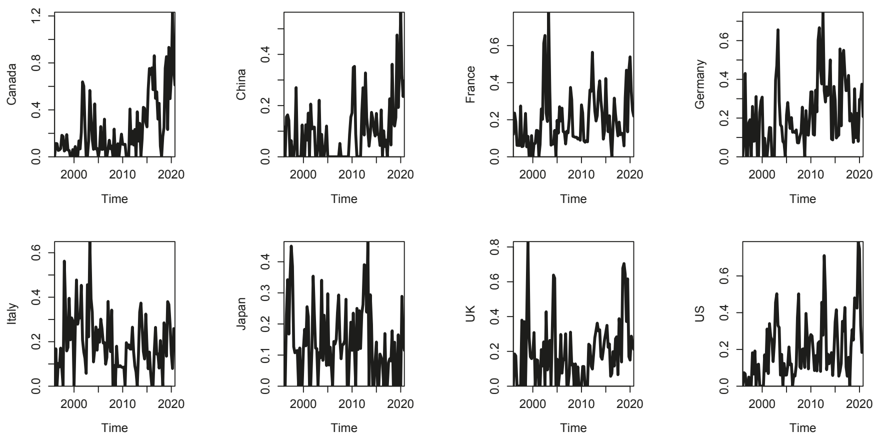

Figure 2. Time series of uncertainty. For better readability, the vertical axes of the panels are not the same for all time series.

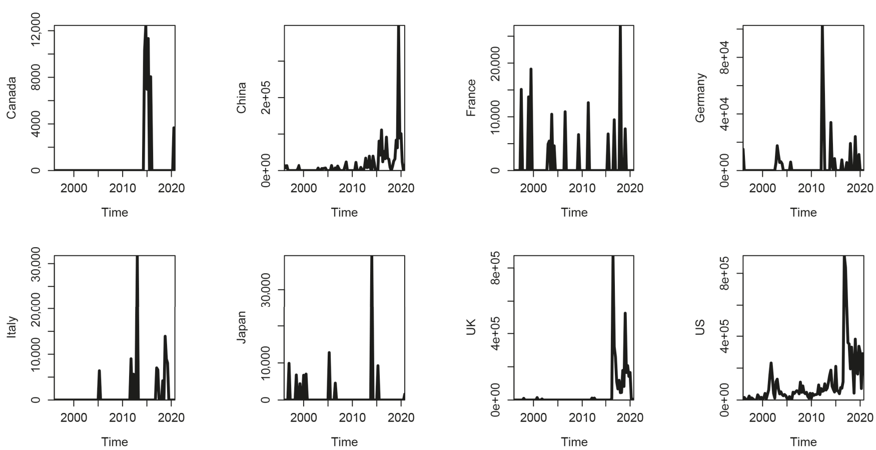

Figure 3. Time series of international spillovers. For better readability, the vertical axes of the panels are not the same for all time series.

3. Methodologies

For the forecasting analysis, we used a linear regression model. The model featured an intercept and an autoregressive term as its core components. The autocorrelation functions for the realized volatility (for the estimator that we used in our empirical research, see Equations (5)) plotted in Figure 4 showed that this simple autoregressive model should suffice to capture the main elements of the persistence of *RV* (and its "good" and "bad" counterparts).

Based on the suggestion of an anonymous referee, we also compared the in-sample performance of our benchmark autoregressive *RV* model with that of the best-fitting GARCH model, namely the Exponential GARCH (EGARCH), in predicting *RV* and found that the former produced a lower root mean square error (RMSEs) than the latter, which is not surprising given the insignificant coefficient in the volatility equation corresponding to the lagged GARCH term, highlighting the inability of the model to adequately capture volatility at a quarterly frequency. Complete details of these results are available upon request from the authors.

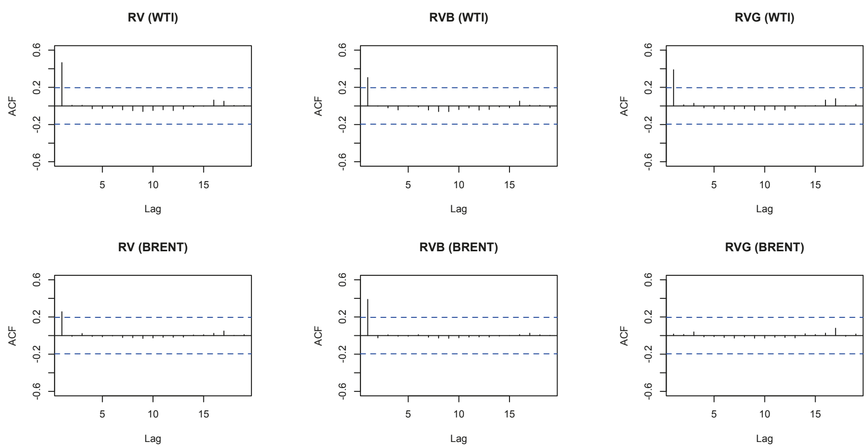

Figure 4. Autocorrelation functions of realized volatility. Dashed horizontal lines: bounds of the 95% confidence interval. RVB: Downside ("bad") RV. RVG: Upside ("good") RV.

In addition, we considered the various uncertainties, U, and international spillovers, S, as additional predictors. In our empirical application, this gave four forecasting models:

$$RV_{t+h} = \beta_0 + \beta RV_t + \epsilon_{t+h}, \tag{1}$$

$$RV_{t+h} = \beta_0 + \beta RV_t + \sum_{j=1}^{n_u} \beta_{u,j} U_{t,j} + \epsilon_{t+h}, \tag{2}$$

$$RV_{t+h} = \beta_0 + \beta RV_t + \sum_{j=1}^{n_s} \beta_{s,j} S_{t,j} + \epsilon_{t+h}, \tag{3}$$

$$RV_{t+h} = \beta_0 + \beta RV_t + \sum_{j=1}^{n_u} \beta_{u,j} U_{t,j} + \sum_{j=1}^{n_s} \beta_{s,j} S_{t,j} + \epsilon_{t+h}, \tag{4}$$

where the index h denotes the forecast horizon, and (for $h > 1$) RV_{t+h} denotes the average realized variance over the forecast horizon being studied, with $h = 1$, 2, and 4 in our context. When computing out-of-sample forecasts, we constructed the data matrix in such a way that the number of forecasts was the same for all forecast horizons. In addition, n_u and n_s denote the number of uncertainties and international spillovers being studied, and ϵ_{t+h} denotes an error term.

Figures 5 and 6 plot the autocorrelation functions for the uncertainties and international spillovers. The figures show that all uncertainty measures exhibited a certain degree of persistence, while we observed persistence in the case of the international spillovers mainly for Canada, China, the United Kingdom, and the United States only.

As the dependent variable, we used the classical estimator of RV (Andersen and Bollerslev, 1998). In our case, we used the sum of the squared daily returns per quarter. We have

$$RV_t = \sum_{i=1}^{M} r_{t,i}^2, \tag{5}$$

where $r_{t,i}$ is the daily return, which is defined as the log-difference in prices as observed on two consecutive days, and $i = 1, \ldots, M$ is the number of quarterly observations. As a robustness check, we shall also study whether uncertainties and international spillovers help to forecast $\sqrt{RV}$, which researchers also often call "volatility" in empirical finance applications.

We also studied the predictive value of uncertainties and international spillovers for upward ("good", RVG) and downward ("bad", RVB) realized variance. Thus, we also forecast RVG and RVB with our forecasting equations. In line with Barndorff-Nielsen et al. (2010), we computed the bad and good realized volatility as described by the following two equations ($\mathbf{1}$ = indicator function):

$$RVG_t = \sum_{i=1}^{M} r_{t,i}^2 \, \mathbf{1}_{[(r_{t,i})>0]}, \tag{6}$$

$$RVB_t = \sum_{i=1}^{M} r_{t,i}^2 \, \mathbf{1}_{[(r_{t,i})<0]}. \tag{7}$$

For the estimation of our forecasting model, we used the least absolute shrinkage and selection operator (Lasso) estimator. Our choice of the Lasso as our preferred estimation technique reflects the fact that the dimension of the forecasting model became quite large (relative to the size of our sample period) when we added the various uncertainties and international spillovers to the core components of the model. The Lasso technique chose the coefficients, $\beta, \beta_{u,1}, \beta_{u,2}, \ldots, \beta_{s,1}, \beta_{u,2}, \ldots$, so as to minimize the following expression (for a detailed discussion of the Lasso, see, e.g., Hastie et al. [30]):

$$\sum_{t=1}^{N} \left(RV_{t+h} - \beta_0 - \beta RV_t - \sum_{j=1}^{n_u} \beta_{u,j} U_{t,j} - \sum_{j=1}^{n_s} \beta_{s,j} S_{t,j} \right)^2 + \lambda \left(|\beta| + \sum_{j=1}^{n_u} |\beta_{u,j}| + \sum_{j=1}^{n_s} |\beta_{s,j}| \right), \tag{8}$$

where N denotes the number of observations used for estimation of the model. Hence, the Lasso shrinking used the $L1$ norm of the coefficient vectors to shrink the dimension of the estimated model. Depending on the magnitude of the shrinkage parameter, λ, the Lasso estimator shrinked and even set to zero some of the coefficients and, thus, can be viewed as a predictor-selection technique.

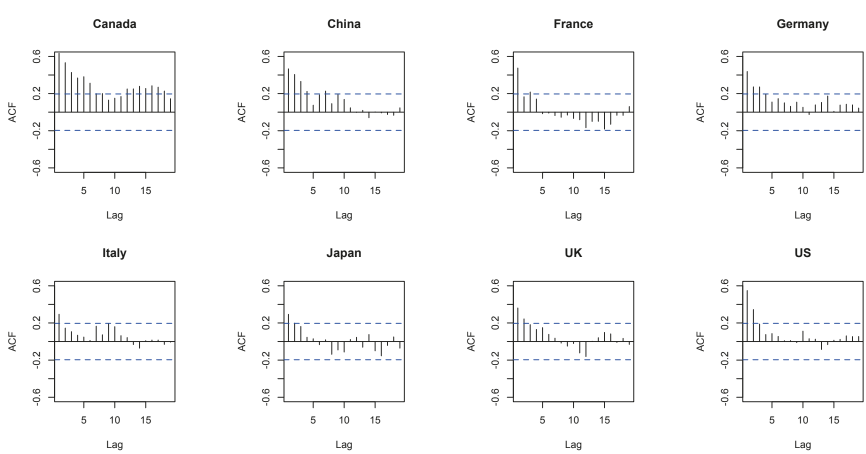

Figure 5. Autocorrelation functions of uncertainties. Dashed horizontal lines: bounds of the 95% confidence interval.

We selected the value of the shrinkage parameter, λ, to minimize the minimum mean cross-validated error when we used 10-fold cross validation. For estimation of the Lasso models, we used the R package "glmnet" [31]. For the R environment for statistical computing, see the R Core Team [32].

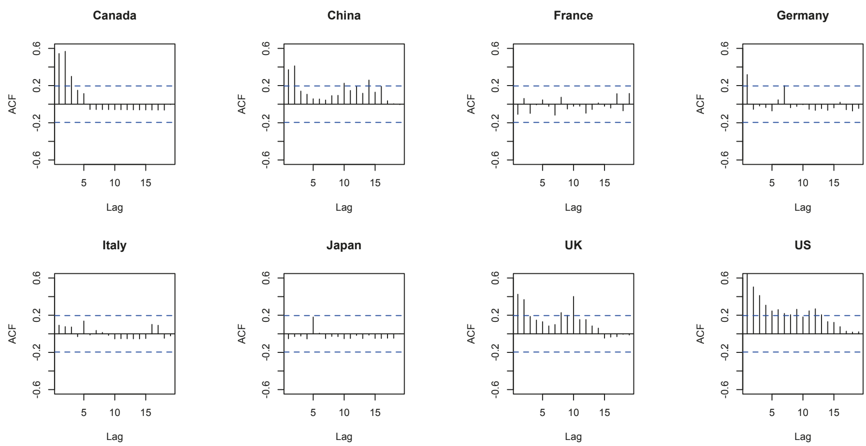

Figure 6. Autocorrelation functions of international spillovers. Dashed horizontal lines: bounds of the 95% confidence interval.

In order to compute out-of-sample forecasts, we primarily used a recursively expanding estimation window (with a training period of 10 years to initialize the estimations) and, as a robustness check, a fixed-length rolling estimation window. We, then, evaluated the forecasts by means of the Clark and West [33] test. The null hypothesis was that the models being compared had an equal out-of-sample mean-squared prediction error (MSPE).

The Clark–West test requires regressing the quantity $\hat{f}_{t+h} = (RV_{t+h} - \hat{RV}_{A,t+h})^2 - [(RV_{t+h} - \hat{RV}_{B,t+h})^2 - (\hat{RV}_{A,t+h} - \hat{RV}_{B,t+h})^2]$ on a constant, where a hat denotes the forecast of RV, and the subindices A and B denote the two models under scrutiny (B denotes the larger model). The Clark–West test is based on an adjusted difference of the MSPEs implied by Models A and B. The test rejects the null hypothesis if the t-statistic of the constant in this regression model is significantly positive (one-sided test; we used Newey–West robust standard errors to study the significance of the t-statistic).

4. Empirical Results

In Table 1, we report the baseline forecasting results for WTI and Brent. The table gives the *p*-values of the Clark–West test. The key message to take home from the results given in the table is that the Lasso model that included uncertainty and/or international spillovers outperformed in our out-of-sample forecasting exercise for the core model at the intermediate and long forecasting horizon. We obtained this key result for both WTI and Brent crude oil-price realized variances.

We used robust standard errors to compute the *p*-values because (as one would have expected) the forecast errors were autocorrelated at the longer forecast horizons due to the overlapping forecast horizons. As suggested by an anonymous reviewer, we also tested whether the forecast errors had a unit root. A standard unit root test (Kwiatowski et al. [34] showed that the forecast errors could be regarded as stationary time series. Detailed results are not reported to save journal space but are available from the authors upon request.

There was also evidence of predictive value when we further extended the forecast horizon to six and eight quarters. Further, when we studied the natural logarithm of RV, we observed improvements in the forecasting performance at the longer and, depending on the model specification, at the intermediate forecasting horizon. Detailed results are available from the authors upon request.

Table 1. Baseline forecasting results.

Panel A: WTI			
Model	**h = 1**	**h = 2**	**h = 4**
Uncertainty	0.8103	0.0019	0.1347
Spillovers	0.8665	0.0161	0.0681
Both	0.8930	0.0005	0.0013
Panel B: Brent			
Model	**h = 1**	**h = 2**	**h = 4**
Uncertainty	0.1723	0.0024	0.1191
Spillovers	0.7901	0.0706	0.0463
Both	0.2008	0.0106	0.0008

CW test: p-value (based on Newey–West robust standard errors) of the Clark–West test. Training period used to initialize the recursive-estimation scheme: 40 quarters.

In order to shed further light on the relative forecasting performance of the model, we document in Table 2, for both WTI and Brent, the forecasting gains expressed as the percentage increase (or decrease) in the ratio of the root-mean-squared-forecasting error (RMSFE) of the benchmark (that is, autoregressive) model and the alternative models. A positive forecasting gain, thus, shows that the RMSFE of the benchmark model exceeded the RFMSFE of the alternative model, implying that the alternative model yielded better forecasts under a standard quadratic loss function.

We observed positive forecasting gains mainly at the intermediate and especially at the long forecasting horizon. The forecasting gains were the largest when we combined uncertainty and international spillovers ($h = 2, 4$). The autoregressive benchmark model, in turn, tended to fare better than the alternative models at the short forecasting horizon. Taken together, the results corroborated the results of the Clark–West test. The correlation between the forecasting gains reported in Table 2 and the p-values of the Clark–West test given in Table 1 was significantly negative (coefficient of correlation = -0.48, t-statistic of -2.19, p-value = 0.04), showing that higher forecasting gains tended to be associated with lower p-values and, thus, significant test results.

Table 2. Forecasting gains.

Panel A: WTI			
Model	**h = 1**	**h = 2**	**h = 4**
Uncertainty	−2.2952	−0.0290	0.2379
Spillovers	−3.3006	3.0384	2.4165
Both	−2.6771	3.6453	4.4951
Panel B: Brent			
Model	**h = 1**	**h = 2**	**h = 4**
Uncertainty	0.3186	0.6375	0.1207
Spillovers	−7.5552	−12.9077	0.3586
Both	−0.0492	1.5670	6.7234

Note: The forecasting gains are defined as $100 \times (\mathrm{RMSFE}_0/\mathrm{RMSFE}_1 - 1)$, where the index 0 denotes the benchmark (autoregressive) model, and the index 1 denotes the alternative models (including uncertainty and/or spillovers). RMSFE: root-mean-squared-forecasting error. Training period used to initialize the recursive-estimation scheme: 40 quarters.

A major exception arose in the case of Brent and the spillovers model and $h = 2$, where the forecasting gain was negative (and large in absolute terms), while the Clark–West test (which is, as described in the methodology in Section 3, based on the adjusted difference of the out-of-sample MSPEs generated by the two models being compared) yielded a significant result.

Next, we summarize in Table 3 the results (Clark–West test) for the good and bad realized variances, again for both WTI and Brent. The results corroborated that uncertainty and/or international spillovers added to the forecasting performance of the model estimated on data for bad realized variance at the intermediate and long forecast horizon. For good realized variance, we observed insignificant test results in the case of uncertainty for WTI and significant test results for international spillovers at the intermediate and long forecast horizon. In addition, the test results for both uncertainty and international spillovers were insignificant at the short and the intermediate, but not at the long, forecast horizons for Brent.

Table 3. Forecasting results for upside and downside volatility.

Panel A: Bad Realized Variance (WTI)			
Model	**h = 1**	**h = 2**	**h = 4**
Uncertainty	0.1540	0.0447	0.0334
Spillovers	0.7545	0.0362	0.4446
Both	0.9393	0.0228	0.1652
Panel B: Bad Realized Variance (Brent)			
Model	**h = 1**	**h = 2**	**h = 4**
Uncertainty	0.4946	0.0003	0.0073
Spillovers	0.2806	0.0838	0.0472
Both	0.2907	0.0029	0.0211
Panel C: Good Realized Variance (WTI)			
Model	**h = 1**	**h = 2**	**h = 4**
Uncertainty	0.7907	0.1301	0.5917
Spillovers	0.8808	0.0202	0.0007
Both	0.8691	0.0021	0.0003
Panel D: Good Realized Variance (Brent)			
Model	**h = 1**	**h = 2**	**h = 4**
Uncertainty	0.6569	0.1818	0.0001
Spillovers	0.3599	0.8717	0.0027
Both	0.7035	0.4739	0.0010

Note: CW test: *p*-value (based on Newey–West robust standard errors) of the Clark–West test. Training period used to initialize the recursive-estimation scheme: 40 quarters.

Table 4 gives the forecasting results for $\sqrt{RV}$. We use the terms "realized volatility" and "realized variance" interchangeably in this paper, while researchers in the empirical-finance literature often use the term "volatility" to refer to $\sqrt{RV}$. The results for WTI showed that uncertainty had predictive value at the long forecast horizon, but international spillovers did not add to the forecasting performance of the model. The test results for Brent, in turn, were significant for uncertainty at the intermediate and the long forecast horizon, and for international spillovers at the long forecast horizon.

Table 5 summarizes the results for a rolling-estimation window. The test results were significant for all three forecasting horizons (at the 10% level) for uncertainty in the case of WTI. In addition, the test results for international spillovers were significant for WTI when we studied the long forecast horizon. As for Brent, the test results for uncertainty and international spillovers were significant for the long forecast horizon and, in addition, for the intermediate forecast horizon in the case of international spillovers.

Table 4. Forecasting results for the realized volatility ($\sqrt{RV}$).

Model	h = 1	h = 2	h = 4
Panel A: WTI			
Uncertainty	0.7271	0.2133	0.0255
Spillovers	0.8681	0.1204	0.1304
Both	0.8946	0.1175	0.0298
Panel B: Brent			
Model	**h = 1**	**h = 2**	**h = 4**
Uncertainty	0.1570	0.0317	0.0083
Spillovers	0.5702	0.1058	0.0557
Both	0.4063	0.0651	0.0070

Note: CW test: p-value (based on Newey–West robust standard errors) of the Clark–West test. Training period used to initialize the recursive-estimation scheme: 40 quarters.

Table 5. Forecasting results for a rolling-estimation window.

Model	h = 1	h = 2	h = 4
Panel A: WTI			
Uncertainty	0.0894	0.0916	0.0018
Spillovers	0.1562	0.2739	0.0775
Both	0.1395	0.1714	0.0006
Panel B: Brent			
Model	**h = 1**	**h = 2**	**h = 4**
Uncertainty	0.1832	0.1606	0.0734
Spillovers	0.3552	0.0105	0.0020
Both	0.4020	0.0114	0.0004

Note: CW test: p-value (based on Newey–West robust standard errors) of the Clark–West test. Length of the rolling-estimation window: 40 quarters.

In order to illustrate how the Lasso estimator works, we plot in Figure 7 the importance of the uncertainty and international spillovers over time. The results are for WTI and a recursive-estimation window. We used a simple metric of importance. Specifically, we define importance as the number of nonzero coefficients estimated for uncertainty (international spillovers) divided by n_u (n_s). Hence, zero means that the Lasso sets all coefficients, for example, of uncertainty to zero in a given forecasting period, and one means that all coefficients of uncertainty are included in the model.

The results show that uncertainty tended to be of more importance on average than international spillovers at the short and the intermediate forecast horizon, while the importance of both categories of predictors was more or less balanced at the long forecast horizon. The results also illustrate that the importance of both uncertainty and international spillovers was not stable over the out-of-sample period, lending support to our decision to use a recursive- and a rolling-estimation window to analyze the forecasting properties of uncertainty and international spillovers for the realized volatility over time.

This result is not surprising but is indicative of the fact that uncertainty and its spillovers themselves are not constant and vary across time (as shown in Figures 2 and 3) depending on events that affect the macroeconomic uncertainty in these major economies and the associated spillovers, thereafter, to the rest of the world.

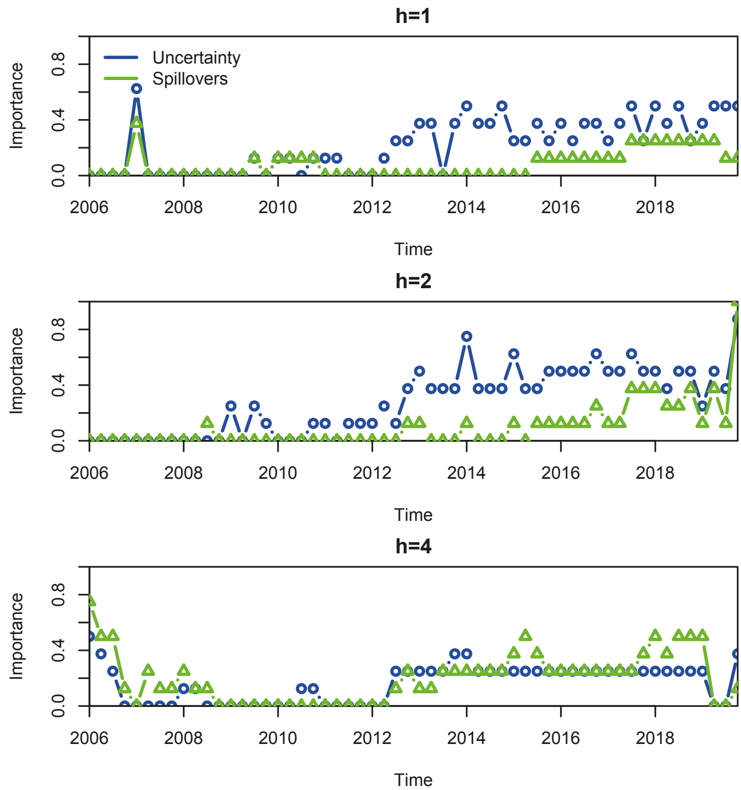

Figure 7. Importance of uncertainty and international spillovers. The results are for WTI and a recursive-estimation window. Importance is defined as the number of nonzero coefficients estimated for uncertainty divided n_u and similarly for spillovers. Hence, zero means that all coefficients of, for example, uncertainty are zero in a given forecasting period, and one means that all coefficients of uncertainty/spillovers are nonzero. The time axis refers to the period in which a forecast is being made.

Table 6 summarizes, as a further robustness check, the results for a ridge-regression approach. A ridge regression also solves the minimization problem given in Equation (8) for the Lasso with the difference being that the penalty term multiplied by the λ coefficient used the L2 norm to shrink the estimated coefficients of the forecasting model. The results show that, at the intermediate forecast horizon, only the uncertainty improved the forecasting performance, whereas, for the long forecasting horizon, both uncertainty and international spillovers (Brent) helped to improve the forecast accuracy.

Our forecasting analysis confirmed the initial premise of our paper that the uncertainties of other important economies within the G7 in addition to the US and China also tend to drive oil market volatility due to the importance of their position as exporters and importers in the oil market. Especially in the longer-run, the spillovers of uncertainty from these major economies to other countries in the world are important in capturing the accurate size of the global demand in the oil market in the wake of increased uncertainty.

The relatively stronger long-run influence of spillovers on oil market volatility is understandable, since it takes time for uncertainty originating in the G7 and China to spread to the rest of the world, via various channels namely, trade, financial markets, and exchange rates [35,36], to the extent that it leads to uncertainty convergence over time [37]. In sum, our findings are indicative of the fact that accounting for the total amount of uncertainty spillovers of the major economies, over and above their own uncertainties, allowed us to better model worldwide uncertainty and its influence on global oil demand, which, in turn, translated into more accurate forecasting of the realized variance capturing oil-market volatility.

Table 6. Forecasting results for a ridge regression.

Model	h = 1	h = 2	h = 4
Panel A: WTI			
Uncertainty	0.7883	0.0017	0.0005
Spillovers	0.8775	0.4673	0.1202
Both	0.8018	0.4647	0.0225
Panel B: Brent			
Model	**h = 1**	**h = 2**	**h = 4**
Uncertainty	0.4852	0.0013	0.0027
Spillovers	0.8576	0.1443	0.0076
Both	0.8233	0.3856	0.0053

Note: CW test: p-value (based on Newey–West robust standard errors) of the Clark–West test. Length of the recursive-estimation window: 40 quarters.

5. Conclusions

Based on a dataset for the G7 countries and China, our results showed that uncertainty and international spillovers had predictive value in an the out-of-sample forecasting exercise for the realized variance of crude oil (West Texas Intermediate and Brent), where our sample period ranged from 1996Q1 to 2020Q4. Given that, on the one hand, our sample period was relatively short and, on the other hand, our data comprised measures of uncertainty for eight countries and eight measures of international spillovers, we used the Lasso estimator to estimate our forecasting models. Taken together, our empirical results demonstrated that, depending on the model specification, uncertainty and international spillovers had predictive value for the realized variance (and its "good" and "bad" counterparts) at an intermediate (two quarters) and a long (one year) forecasting horizon.

Compared to the current literature, which has relied only on the role of US uncertainty in predicting oil market volatility, our paper extends this line of research by highlighting the importance of not only the uncertainty of the G7 countries and China but also their respective spillovers of uncertainty to the rest of the world. This being the first study of its kind, it is impossible to provide comparative quantitative assessment of our results with the existing papers in this related area; however, its academic value in terms of depicting the pertinent role of uncertainty and its spillovers beyond the US in forecasting oil-market volatility cannot be overlooked.

In addition, our results can be used by policy authorities to obtain information on the future path of the volatility of oil prices due to uncertainty of G7 countries and China, as well as the associated global spillovers of uncertainty from these economies. This knowledge, in turn, could be useful to predict economic activity, given that oil-price volatility is known to lead business cycles. Our results, therefore, may help policymakers to reach appropriate policy decisions in the wake of the movements in the uncertainties of major global economies and the spillovers. Moreover, with volatility being a key input in portfolio decisions, the forecastability of oil-price volatility due to the uncertainties of G7 and China, as well as the associated spillovers, should be of vital importance to traders in the oil market.

Having indicated the important implications of our results, it is also necessary to acknowledge one limitation of our study in terms of the low-frequency of our data. Ideally, we would have preferred to have conducted the forecasting exercise of realized variance of oil at a higher frequency, as it is of great importance for policymakers and investors to make timely policy and portfolio decisions; however, the uncertainty spillover indexes were available only at a quarterly frequency and, hence, constrained us in our ability to provide higher-frequency (say, for example, daily or monthly) results.

As a part of future research, it would be interesting to extend our analysis to other commodity markets, in particular gold, which is a well-established safe haven in the wake of heightened uncertainty [38,39].

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Short-Term Load Probabilistic Forecasting Based on Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise Reconstruction and Salp Swarm Algorithm

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Abstract: Short-term load forecasting is an important part of load forecasting, which is of great significance to the optimal power flow and power supply guarantee of the power system. In this paper, we proposed the load series reconstruction method combined improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN) with sample entropy (S_E). The load series is decomposed by ICEEMDAN and is reconstructed into a trend component, periodic component, and random component by comparing with the sample entropy of the original series. Extreme learning machine optimized by salp swarm algorithm (SSA-ELM) is used to predict respectively, and the final prediction value is obtained by superposition of the prediction results of the three components. Then, the prediction error of the training set is divided into four load intervals according to the predicted value, and the kernel probability density is estimated to obtain the error distribution of the training set. Combining the predicted value of the prediction set with the error distribution of the corresponding load interval, the prediction load interval can be obtained. The prediction method is verified by taking the hourly load data of a region in Denmark in 2019 as an example. The final experimental results show that the proposed method has a high prediction accuracy for short-term load forecasting.

Keywords: load forecasting; load series; mode decomposition; extreme learning machine; kernel density estimation

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1. Introduction

With the development of industry and the economy, the conflict between supply and demand for energy is becoming increasingly acute. Among them, electric energy is not only closely related to people's lives, but also closely related to industrial production. Therefore, the balance between the supply and demand of electric energy is of particular concern. At present, the main power generation model in the world is still coal combustion power generation, which will cause air pollution. To ensure the sustainable development of economy, countries all over the world are vigorously developing new energy [1]. With the development of electric energy conversion technology and electric energy storage technology [2,3], photovoltaic power generation, wind power generation, tidal power generation, and geothermal power generation are more and more incorporated into the power grid, which not only alleviates the energy shortage but also introduces a large number of random power flows. This poses a new severe challenge to the stability and load balance of the power grid.

In the power system incorporating a large number of new energy sources, power needs to achieve a two-way balance between supply and demand. However, due to the uncontrollability of the power generation on the supply side being affected by a variety of influencing factors, the power consumption behavior of users on the demand side also has certain randomness. The interaction between supply and demand increases more uncertain factors for the load flow of the system, and accurate short-term load forecasting is of great significance to ensure the balance of the power system [4]. On the other hand, since September 2021, China has notified many places to limit the power load, which has had a certain impact on the lives of some people and the production of enterprises. Therefore, accurate prediction of power load is a major demand for social development. Finally, with the construction of the smart grid [5], it is not only to improve the stability and energy utilization of the system, and reduce the power generation cost, but also an important goal. Accurate prediction of power demand in various regions is helpful to realize the economic operation of a power system [6].

Load forecasting can be divided into point forecasting [7,8] and probability forecasting [9,10] according to the forecasting results. At present, most load forecasting is mainly point forecasting of load, and the forecasting result is the single point expectation of load at a certain time in the future. Power load is nonlinear and time-varying, so point prediction is difficult to reflect the fluctuation range of load change. The estimation of some uncertain factors in power market by probabilistic prediction method is helpful to the control and stable operation of power grid [11].

According to whether the prediction object or the distribution type of prediction error presupposes, probability prediction can fall into parametric probability prediction [12] and nonparametric probability prediction [13,14]. Using the parametric methods for probability density estimation requires the object is estimated to conform to a specific distribution, which has limitations in the present situation where more and more new energy generation is being integrated into the grid. The a priori assumptions avoided by the non-parametric method and the absence of excessive human intervention make it easier to approach the actual distribution.

In most decomposition and integration models, the load series is decomposed into several components by decomposition method. Then, predicting each component, the number of models is large, and the training time is long. In order to solve this problem, we use improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN) combined with sample entropy to reconstruct the load series into three parts: random component, periodic component, and trend component, which reduces the number of models. In this way, the number of prediction models can be reduced to three and the training time can be shortened. For most load forecasting, point forecasting is used, which is difficult to reflect the load variation range. We use point forecasting combined with probability forecasting to predict the load interval. The error interval of the prediction set is obtained by combining the probability distribution of the error of the training set with KDE, and the final prediction interval can be obtained by combining the predicted value of the point. Finally, under the 90% confidence interval, the prediction intervals coverage probability (PICP) reached 0.919, indicating that 91.9% of the prediction set data fell within the prediction interval. On the other hand, the prediction intervals normalized averaged width (PINAW) on the cover is 0.112, which shows that we do not improve the prediction accuracy by increasing the bandwidth. In conclusion, we can draw a conclusion that the method proposed in this paper has good prediction accuracy and has a good application prospect in the field of load probabilistic forecasting.

The rest of this paper is structured as follows. The second section introduces the current research work of load forecasting. The third section introduces the relevant methods used in this paper. The fourth section mainly introduces the realisation process of the model and evaluation indicators. The fifth section is the experimental results and analysis. The sixth section is the summary of this paper.

2. Literature Review

At present, load forecasting methods are mainly divided into traditional methods and artificial intelligence methods. Artificial intelligence methods mainly include deep learning methods represented by the short-term memory network (LSTM) [15,16] and the convolutional neural network (CNN) [17,18], and machine learning methods represented by support vector regression (SVR) [19,20] and the artificial neural network (ANN) [21,22]. The deep learning method has the characteristics of a good prediction effect and high fault tolerance to input, but the model spends a lot of time in training. At present, decomposition and integration models have made preferable effects in load forecasting and other energy forecasting fields, but these models often predict all decomposed components one by one and then superimpose the results, so the training time is usually long. In addition, there is a direct relationship between the decomposition and the prediction accuracy of the integrated model and the decomposition method. The phenomenon of mode aliasing may occur in empirical mode decomposition (EMD) [23]. The amplitude and iteration number of white noise added by ensemble empirical mode decomposition (EEMD) [24] depends on the human experience setting. When the numerical setting is not set, it may be unable to overcome the phenomenon of modal aliasing. These factors may affect the prediction results.

At present, most load forecasting still takes the determined load value as the forecasting goal. Ge et al. [25] achieved good accuracy in industrial load prediction using reinforcement learning combined with least squares support vector machines for particle swarm optimisation. Zhang et al. [26] used complete ensemble empirical mode decomposition with adaptive noise combined with support vector regression with dragonfly optimization to forecast the electric load, which also had good prediction results. Rafi et al. [27] used convolutional neural networks combined with long- and short-term memory networks to construct a prediction model for short-term electricity load forecasting and achieved good prediction reliability. Wang et al. [28] used a long- and short-term memory network to forecast short-term residential loads with consideration of weather features. Phyo et al. [29] used classification and regression tree and the deep belief network for 30-min granularity load forecasting.

On the other hand, deterministic forecasting is difficult to fully reflect the load information. Therefore, using the probability forecasting method to predict the load change range is helpful to provide strong support for the production, dispatching, operation, and other links of the power grid system.

In addition, the prediction accuracy of decomposition and the integrated model is directly related to the decomposition method, and the phenomenon of mode aliasing may occur in empirical mode decomposition. On the other hand, most decomposition and integration models build prediction models for each component. Although the prediction accuracy is high, the number of models is large and the training time is long.

In this paper, we first carry out point prediction, and then analyze the training set error to obtain the distribution of prediction error in different load intervals to realize load probability prediction. The improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN) [30] effectively solves the problem of mode mixing in empirical mode decomposition (EMD) and avoids the residual noise in decomposition ensemble empirical mode decomposition (EEMD), which helps to improve the prediction accuracy of the model. Firstly, the ICEEMDAN combined with sample entropy is used to reconstruct the load series, which is decomposed into three parts—random component, periodic component, and trend component—which effectively reduces the number of prediction models and shortens the prediction time. Since the extreme learning machine (ELM) algorithm was proposed, it has achieved good results in many fields, such as fault diagnosis [31,32], coal mine safety [33], and so on. The accuracy of the prediction results can be effectively improved by using the salp swarm algorithm (SSA) to optimize the ELM. Then, the kernel density estimation method is used to analyze the training set error, obtain the probability density curve of the training set error, and then estimate the error interval of the prediction set to obtain the final interval prediction result.

3. Methods

3.1. Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN)

Improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN) is an algorithm based on empirical mode decomposition (EMD) proposed by Colominas et al. [34]. ICEEMDAN can effectively solve the mode mixing problem of EMD and the residual noise problem of EEMD. The decomposition process is as follows:

(1) Calculate the local mean of $S^{(i)} = S + \lambda_0 C_1\left(\alpha^{(i)}\right)$ by EMD to obtain the first-order residue R_1 and corresponding intrinsic mode function (IMF) IMF_1.

$$R_1 = \left(M\left(S^{(i)}\right)\right) \tag{1}$$

$$IMF_1 = S - R_1 \tag{2}$$

where $i \in \{1, 2, 3 \ldots M\}$, S is the original signal; λ is the signal-to-noise ratio; $\alpha^{(i)}$ be a realization of zero mean unit variance white noise; $C_j(\cdot)$ is the operator represents the jth order intrinsic mode function obtained by EMD; and $M(\cdot)$ is the operator represents the local mean of the resulting signal.

(2) Calculate the local mean of $R_1 + \lambda_1 C_2\left(\alpha^{(i)}\right)$ by EMD to obtain the second-order residue R_2 and corresponding intrinsic mode function IMF_2.

$$R_2 = \left(M\left(R_1 + \lambda_1 C_2\left(\alpha^{(i)}\right)\right)\right) \tag{3}$$

$$IMF_2 = R_1 - R_2 \tag{4}$$

(3) Repeat the process until the signal cannot be decomposed.

$$R_l = \left(M\left(R_{l-1}(t) + \lambda_{l-1} C_l\left(\alpha^{(i)}\right)\right)\right) \tag{5}$$

$$IMF_l = R_{l-1} - R_l \tag{6}$$

where $l = 2, 3, \ldots L$, L are the total numbers of IMF.

Finally, the original signal is decomposed into $S = \sum\limits_{j=1}^{L} IMF_j + R_L$.

3.2. Sample Entropy S_E

Sample entropy (S_E) [35] is a method to measure the complexity of unstable time series. Compared with the general method, the sample entropy method does not depend on the data length and has a better consistency. The value of sample entropy is positively correlated with the degree of sequence self-similarity. The sample entropy is calculated as follows:

(1) For the time series $x(i)$ with sample size N, the following vectors are obtained according to the order of m dimensional vectors of the time series:

$$X(i) = [x(1), x(2), \ldots, x(N - m + 1)] \tag{7}$$

where, $i = 1, 2, 3 \ldots N - m + 1$.

(2) C group optimization algorithm proposed by Mirjaln $X_m(i)$ whose distance from $X_m(j)$ is less than r in $X_m(i)$. Define this number as B_i. The ratio of B_i to the total number of vectors is denoted B_i^m.

$$d_m = [X_m(i), X_m(j)] = \max_{0 \le k \le m-1} |x(i+k) - x(j+k)| \tag{8}$$

$$B_i^m(r) = \frac{B_i}{N-m+1} \tag{9}$$

$$B^m(r) = \frac{\sum\limits_{i=1}^{N-m} B_i^m}{N-m} \tag{10}$$

(3) Increase the dimension to $m + 1$, and repeat the step to calculate the $B^{m+1}(r)$
(4) Calculate sample entropy S_E.

$$S_E = -\ln\left[\frac{B^{m+1}(r)}{B^m(r)}\right] \tag{11}$$

3.3. Salp Swarm Algorithm (SSA)

The Salp Swarm Algorithm (SSA) is a heuristic group optimization algorithm proposed by Mirjalili et al. [36] in 2017. The SSA algorithm mimics the swarm behaviour of salp on the seabed to find the optimal parameters. In the sea, the salp group is in a chain shape; the frontmost salp is responsible for guiding the whole swarm, and the following salps are responsible for searching the global situation according to the forward direction. The specific process of the SSA is as follows:

Initialize all parameters, the number of salp is M, the maximum number of iterations is I, and $[lb, ub]$ is the search range. d is the dimension of the parade target.

(1) Population initialization. SSA initializes the population by generating random numbers.

$$X_{M\times d} = lb + rand(M,d) \times (ub - lb) \tag{12}$$

(2) Calculate the fitness of each salp. Save the salp coordinates with the highest fitness.
(3) Calculate variable c_1.

$$c_1 = 2e^{-\left(\frac{4i}{I}\right)^2} \tag{13}$$

In the Equation (13), i is the current iteration number; and I is the maximum iteration number.

(4) Update the first salp's position. The first is responsible for searching for food to lead the movement direction of this salp population. The update equation the position of the first salp is:

$$x_d^1 = \begin{cases} P_d + c_1((ub_d - lb_d)c_2 + lb_d), c_3 \geq 0.5 \\ P_d - c_1((ub_d - lb_d)c_2 + lb_d), c_3 < 0.5 \end{cases} \tag{14}$$

where, x_d^1 denotes the position of the leader of the salp in d dimensional space; ub_d and lb_d are upper and lower bounds of d dimensional space, respectively. P_d is the position of food source in d dimensional space; c_2 and c_3 are random numbers uniformly generated within the range of [0, 1].

(5) Update the location of the follower, update the equation is:

$$x_d^m = \frac{1}{2}\left[x_d^m + x_d^{m-1}\right] \tag{15}$$

where, $m \geq 2$, x_d^m is the position parameter of the mth salp in the d dimensional space.

(6) Calculate the fitness of each salp. Save the salp coordinates with the highest fitness. Update iteration number $i = I + 1$.
(7) If the $i > I$, then output the coordinates of the salp with the optimal fitness. Otherwise skip to step (3).

3.4. Extreme Learning Machine (ELM)

Extreme learning machine (ELM) [37] is proposed by Huang et al. It is a supervised learning method for a single hidden layer feedforward neural network. The input weight matrix and hidden layer threshold of ELM are randomly generated, which has the advantages of fewer training parameters and a short training time.

The mathematical model of ELM is as follows:

$$y_i = \sum_{j=1}^{l} g(\omega_j \cdot x_i + b_j) \cdot \beta_j \quad (16)$$

In the Equation (19), $i = 1, 2, \ldots, N$; x_i is the input vector; y_i is the output vector; $g(x)$ is the incentive function; ω_j is the input weight matrix; b_j is the hidden layer threshold; β_j is the output weight matrix; l is the number of hidden layer nodes; and N is the number of samples.

3.5. Kernel Density Estimation (KDE)

Kernel density estimation (KDE) [38–40] is proposed by Parzen, mainly by using differentiable kernel function to estimate the probability density function.

$$\hat{f}(x) = \frac{1}{Mw} \sum_{i=1}^{M} F\left(\frac{x - x_i}{w}\right) \quad (17)$$

In the formula, M is the number of samples; $F(x)$ is a kernel function, which includes Normal kernel, Box kernel, Triangle kernel, Epanechnikov kernel; w is the window width.

4. Realisation Process and Evaluation Index

4.1. Realisation Process

Although the traditional decomposition "model and ensemble" prediction model has a good prediction effect, it also needs to establish forecasting models for all components separately, which requires a lot of training time. In this paper we reconstructed the ICEEMDAN decomposed components by combination with sample entropy and load characteristics. Specifically, the load is divided into a stochastic component, a periodic component, and a trend component. Then, the three components are predicted respectively, and the final point prediction result is obtained by superimposing the prediction results of the three components. The specific prediction process of the model is as follows:

(1) Decomposition of load data. ICEEMDAN is used to decompose the original load series to obtain some IMF. Then, calculate the sample entropy of the original series and each IMF.
(2) Reconstruction of load data. The IMF with sample entropy greater than 0.5 is reconstructed as the random component, the IMF with sample entropy less than 0.04 is reconstructed as the trend component, and the remaining IMF is reconstructed as the periodic component.
(3) Forecasting of load values. The data set contains 8760 load data. The training set and prediction set are divided according to 4:1. The first 7008 load data are used as the training set, and the remaining data are used as the prediction set. Use SSA-ELM to establish models for random component, periodic component, and trend component respectively for prediction. Take the load value two hours before the prediction time as input to obtain the prediction results of each component, and overlay the three results to get the final point prediction results. SSA searches the number of hidden layer neurons and hidden layer threshold of ELM group optimization to improve the prediction performance of ELM.
(4) Normalisation of error data. To avoid the effect of predicted value size on the error estimates, the error values were normalised using the maximum actual value of the load in the training set.
(5) Calculate the upper and lower limits of error. Several error intervals are divided according to the prediction results of the training set. The kernel density estimation is used to obtain the probability density function of each interval training set error.

Select the appropriate kernel function by fitting the probability density function image and real error data fitting. Combined with interval confidence, the upper and lower error limits are obtained.

(6) Obtain the final prediction interval by superimposing the load value of the prediction set with the corresponding upper and lower limits of error.

4.2. Evaluation Index

To evaluate the point prediction results of the proposed model, we use the mean absolute percentage error (MAPE), mean absolute error (MAE), and mean square error (MSE) to evaluate the accuracy of the prediction results. The equations are as follows:

$$\mathrm{MAPE} = \frac{1}{M}\sum_{i=1}^{M}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{18}$$

$$\mathrm{MAE} = \frac{1}{M}\sum_{i=1}^{M}|y_i - \hat{y}_i| \tag{19}$$

$$\mathrm{MSE} = \frac{1}{M}\sum_{i=1}^{M}|y_i - \hat{y}_i|^2 \tag{20}$$

In the above equations, M is the number of samples; y_i is the actual load value; and $\hat{y}_i$ is the predicted load value.

To evaluate the interval prediction results, PICP and PINAW are introduced. The equations are as follows:

$$\mathrm{PICP} = \frac{1}{M}\sum_{i=1}^{M}c_i \tag{21}$$

$$\mathrm{PINAW} = \frac{1}{MR}\sum_{i=1}^{M}|U_i - L_i| \tag{22}$$

In the formula, M represents the number of samples; when the prediction result is in the interval, $c_i = 1$; when the prediction result is not in the interval, $c_i = 0$; R is the true value range; U_i is the upper bound of prediction; and L_i is the lower bound of prediction.

5. Experiments and Analysis

5.1. Experimental Data and Conditions

To further test the prediction performance of the model, we use the hourly load data of a region in Denmark in 2019 for verification obtained from ENTSO-E. The load value is shown in Figure 1. We can see that the load value is generally stable, and the distribution shows a trend of high, medium, and low at both ends.

Experiments were conducted on 64-bit Windows 10 using MATLAB R2018a with an i7-7700hq CPU and a GTX-1050 graphics card.

From the Figure 1, we can see that the load data at 5–7 p.m. on May 1 is 0, which may be the abnormal data caused by missing data. At 8:00 a.m. and 9:00 a.m. on November 4, the load reached the highest value of the whole year, but this value is relatively isolated. This situation also shows that the change of load is affected by many factors and has some randomness. On the whole, the fluctuation of annual load data is small, and the load at the beginning and end of the year is slightly larger in the overall trend.

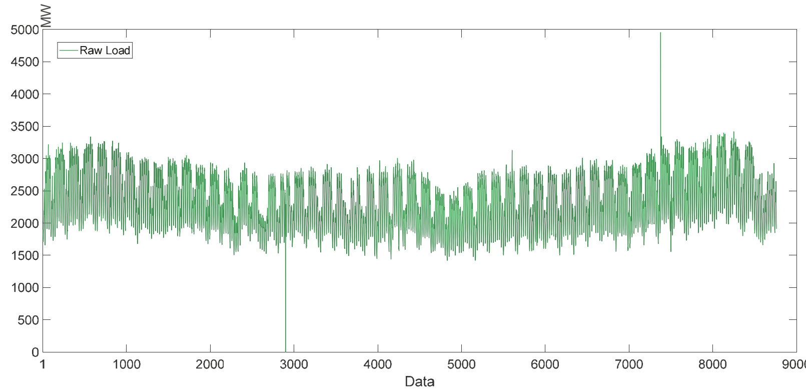


Figure 1. Load value of a region in Denmark in 2019.

5.2. Selection of Mode Decomposition Method

Firstly, empirical mode decomposition (EMD), ensemble empirical mode decomposition (EEMD) and improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN) are used to decompose the original load series. To control the experimental variables, we set the noise weight of EEMD and ICEEMDAN to 0.2 and the number of noise additions to 50. A higher entropy value of the intrinsic mode function (IMF) means a lower autocorrelation of the IMF. The results are shown in Table 1. The sample entropy of the original series is 1.462. The higher the sample entropy, the lower the autocorrelation of the IMF series and the more complex the IMF. The sample entropy of IMF 11 and IMF 12 generated by EEMD decomposition is 0, because the sample entropy of the two IMF is less than 1×10^{-5}. The series is chaotic and random. Table 1 shows the sample entropy values and correlation coefficients for each IMF.

Table 1. Sample entropy and correlation coefficient.

Method		IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8	IMF9	IMF10	IMF11	IMF12	IMF13
EMD	CC	0.087	0.352	0.672	0.203	0.280	0.244	0.104	0.155	0.217	0.324	0.033		
	S_E	0.192	0.518	0.6173	0.1767	0.329	0.155	0.247	0.041	0.084	0.341			
EEMD	CC	0.205	0.582	0.607	0.232	0.380	0.272	0.120	0.195	0.339	0.153	0.336	0.308	0.191
	S_E	0.763	1.121	0.873	0.092	0.064	0.300	2.63×10^{-3}	3.00×10^{-3}	1.42×10^{-3}	9.56×10^{-4}	0	0	2×10^{-5}
ICEEMDAN	CC	0.193	0.511	0.618	0.195	0.342	0.212	0.065	0.134	0.350	0.019			
	S_E	0.729	1.123	1.059	0.108	0.082	0.041	4.30×10^{-3}	3.30×10^{-3}	1.66×10^{-3}	1.30×10^{-3}			

We reconstruct the IMF with entropy > 0.5 into a random component. The IMF with 0.04 < entropy < 0.5 is reconstructed into a periodic component. IMF with entropy < 0.04 is reconstructed as a trend component. The composition of the three components under different modal decomposition methods is shown in Table 2.

Table 2. Division of three components by different decomposition methods.

Method	Random Component	Periodic Component	Trend Components
EMD	IMF1–IMF3	IMF4–IMF7	IMF8–IMF11
EEMD	IMF1–IMF3	IMF4–IMF6	IMF7–IMF13
ICEEMDAN	IMF1–IMF3	IMF4–IMF6	IMF7–IMF10

According to the division results in Table 2, we reconstructed the decomposed load series and then used the extreme learning machine (ELM) to predict the results as shown in the following Table 3. When the ELM algorithm is used for prediction, to ensure the optimal number of neurons in the hidden layer, we set a cycle, that is, the number of hidden neurons is from 1 to 100, and the optimal number of neurons is selected. The prediction results are shown in Table 3. It can be seen that the accuracy of load series prediction after decomposition and reconstruction using ICEEMDAN algorithm is the highest, absolute percentage error (MAPE) is 2.50, mean absolute error (MAE) is 63.84, and mean square error (MSE) is 9625.20. The prediction results based on EMD decomposition and reconstruction are worse. It is possible that a mode mixing situation has occurred. Therefore, we can judge that using ICEEMDAN to reconstruct and predict the load series has good accuracy.

Table 3. Prediction results of ELM.

Method	MAPE(%)	MAE	MSE
EMD-ELM	2.60	67.23	16,393.89
EEMD-ELM	2.66	68.20	12,555.00
ICEEMDAN-ELM	2.50	63.84	9625.20

Based on the above experimental results, we choose to use ICEEMDAN combined with sample entropy reconstruction to decompose the load data. The reconstructed load data is shown in Figure 2.

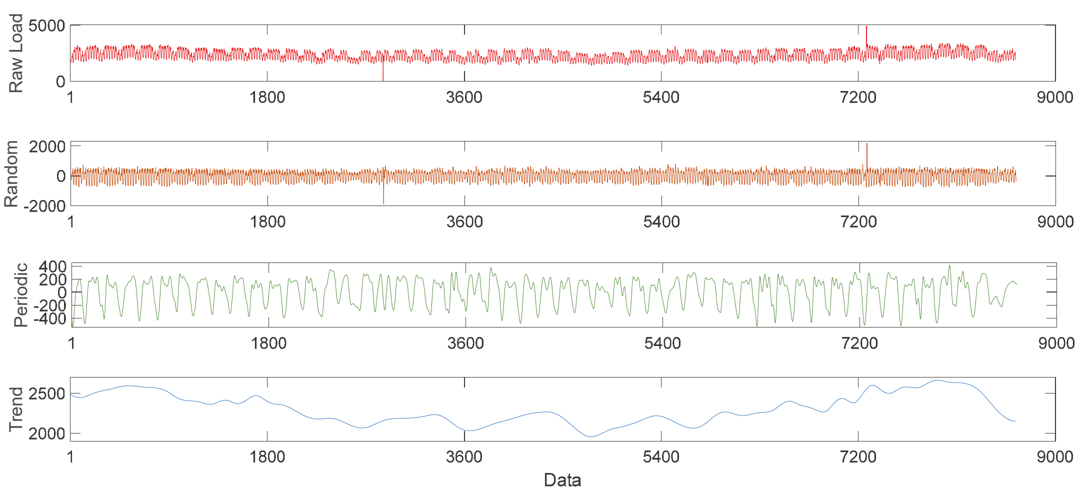


Figure 2. The reconstructed load series.

Combined with Figure 2, we can see that the load value showed a downward trend from January to August, reaching the bottom of electricity consumption in August, and the load value showed an upward trend from August to December. Through the variance and standard deviation, we can find that the January, February, April, and December load values is bigger, and the June, July, August, and September load values is smaller.

Figure 2 is the three load components reconstructed by ICEEMDAN combined with sample entropy. We can see that the periodic component has obvious and stable periodicity; when the fluctuation range of the trend component is small, the load value is high at both ends and low in the middle, and the overall trend is similar to that of the original data. The series with a higher frequency of random component variation is more ambiguous, and the variation range of load value is large and random. Through the above analysis, we can conclude that the reconstructed component conforms to the characteristics of the original load data.

5.3. Prediction Performance of Different Prediction Methods

To select the best prediction algorithm, we chose the BP neural network, support vector regression, and ELM to compare. The predicted results are shown in Table 4. The experimental results are shown in Table 3. The MAPE and MAE of ICEEMDAN-ELM are greater then ICEEMDAN-BP, and MSE is smaller than that of ICEEMDAN-BP. However, the three evaluation indexes of ICEEMDAN-ELM are better than ICEEMDAN-SVR. As MSE is more sensitive to extremum, combining the three evaluations we chose ICEEMDAN-ELM.

Table 4. Prediction results of different algorithms.

Method	MAPE(%)	MAE	MSE
ICEEMDAN-BP	2.28	58.68	9822.40
ICEEMDAN-SVR	3.13	77.10	11,582.00
ICEEMDAN-ELM	2.50	63.84	9625.20

In the experimental process, we find that although ELM has the advantages of high accuracy and a fast training speed, the prediction stability is slightly poor. To further improve the prediction effect, we use the salp swarm algorithm (SAA) to optimize the number of hidden layer neurons and threshold of ELM to improve the accuracy of point prediction. After using SSA optimization, the prediction accuracy of the model has been significantly improved. It can be seen that MAPE, MAE and MSE decreased to 1.98, 50.42 and 6723.70, respectively. Figure 3 is the comparison between the prediction results of SSA-ELM and ELM. From Figure 3, we can see that SSA-ELM has a higher prediction accuracy than ELM. Therefore, we can conclude that using the SSA method to optimize the number and threshold of ELM hidden layer neurons is better than selecting only the optimal number of ELM hidden layer neurons.

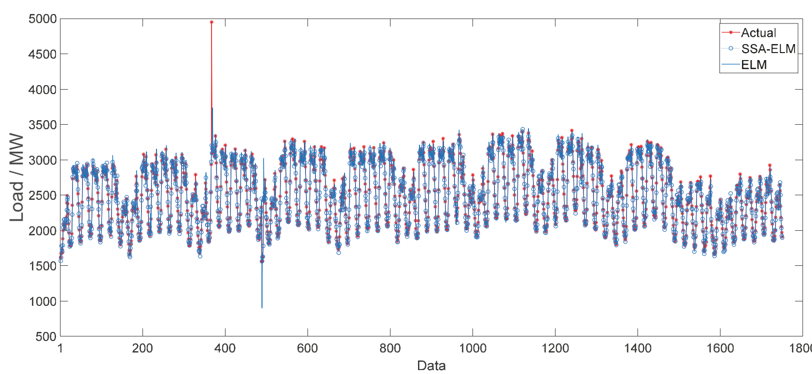


Figure 3. Comparison of actual and predicted values.

5.4. Performance of Reconstructed Model and Ordinary Model

To better evaluate the three different prediction models, we use SSA-ELM to predict the load data processed by different methods. From Table 5, we can see that the prediction effect of the model combined with ICEEMDAN is better than that of the ordinary model without decomposition. On the other hand, we can see that the training time of the reconstructed model is 127.78 s, which is significantly lower than that of the decomposed model. Considering the prediction accuracy, the number of models, and training time, we believe that the overall performance of the reconstructed model is better.

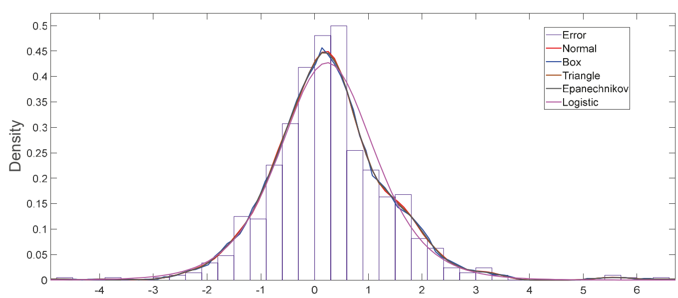
Table 5. Comparison of the reconstructed model and the decomposition model.

Method	MAPE(%)	MAE	MSE	Traing Time (s)
Reconstructed Model	1.98	50.427	6723.70	127.78
Decomposition Model	1.55	38.46	2632.40	451.50
Ordinary Model	2.32	59.69	8898.00	41.00

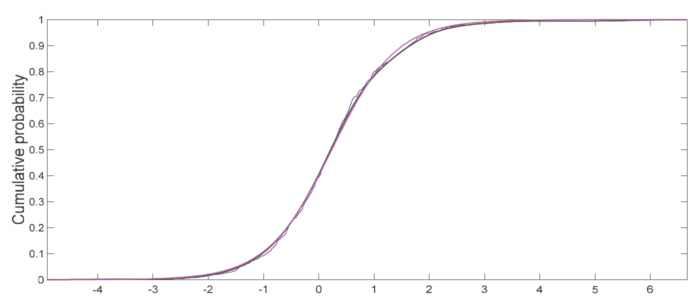
5.5. Interval Prediction Based on Kernel Density Estimation

To better estimate the uncertainty in the load sequence, we used the kernel density estimation method to estimate the load interval. Firstly, we use the maximum real load value of the training set to normalize the error of the training set, and then divide the error into 0–1750 MW, 1750–2350 MW, 2350–2850 MW, and more than 2850 MW, according to the size of the predicted load value. The four intervals are respectively estimated by kernel density estimation and logistic estimation, and the optimal approximation curve is selected. Then, according to the predicted value of the prediction set, the corresponding error percentage is selected to obtain the final prediction interval.

It can be seen from Figure 4 that the fitting effect of kernel density estimation is better than that of logistic estimation in the process of estimating the set error of the 0–1750 MW interval. Further comparison with Figure 4b, it can be found that the normal kernel has a better fitting effect on the cumulative distribution function curve of the training set error, and the error range is [−1.44%, +2.1%] under the 90% confidence interval. Similarly, we found that the prediction effect of 1750–2350 MW Epanechnikov kernel is better through experiments, and the error range of 90% confidence interval is [−2.9%, +2.6%]. For the 2350–2850 MW load interval, Box kernel has a good fitting. The error range is [−3.3%, +4.1%] under 90% confidence interval. The Box kernel above 2850 MW has a good prediction effect, and the corresponding value range is [−3.21%, +3.98%].



(**a**)



(**b**)

Figure 4. 0–1750 MW interval training set error; (**a**) probability density function curve; (**b**) cumulative distribution function curve.

Finally, prediction intervals coverage probability (PICP) is 0.919 and prediction intervals normalized averaged width (PINAW) is 0.112. PCIP is 0.919, indicating that 91.9% of the load values in the test set fall within the prediction interval, and PCIP > interval confidence, which shows that the model in this paper has good prediction performance and can accurately estimate the load change. For PINAW, when the prediction interval width is certain, the larger the variation range of real load data, the smaller the PINAW, which also represents the better performance of the model. To avoid the impact of the highest point of annual load value (4952) on PINAW, we select the second highest point of forecast set value 3416 as the upper limit of load change, and the final PINAW is 0.112. This shows that the width of the prediction interval is within a reasonable range, and the model used in this paper does not obtain high coverage by unlimited increase of the width of the error interval. To sum up, we can conclude that the probability prediction model proposed in this paper has good prediction accuracy.

6. Conclusions

By analyzing the above experiments, we can draw the following conclusions:

(1) Compared with EEMD and EMD decomposition models, we find that ICEMDAN decomposition has better prediction accuracy. In addition, through the comparison of the decomposition model, reconstruction model, and ordinary model, we can find that the reconstruction model performs well in training time and prediction accuracy, and is suitable for load forecasting scenarios. Combined ICEEMDAN with sample entropy is used to decompose and reconstruct the load series, which not only improves the accuracy of load forecasting, but also reduces the number of models, shortens the training time, and improves the forecasting efficiency.

(2) Through the comparison between SSA-ELM and ELM, we can find that the prediction accuracy of the model has been significantly improved after using SSA to optimize the number and threshold of ELM hidden layer neurons. SSA-ELM can effectively improve the stability and accuracy of prediction results.

(3) The kernel density estimation is used to analyze the error interval, which has a good fitting for the error curve and can obtain a more accurate prediction interval. We also found that the choice of different sum functions will affect the fitting effect of error distribution, and then affect the accuracy of interval prediction.

(4) PICP was 0.919 and PINAW was 0.112. These two indicators show that the model achieves high coverage in a reasonable interval width. This means that the method used in this paper can better predict the variation range of load and reflect some unknown load information. It also proves the feasibility of the method used in this paper.

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Assessment of the Target Model Implementation in the Wholesale Electricity Market of Greece

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Abstract: The European Union Target Model aims to integrate European energy market by removing barriers to trade and align markets. The most important goals of the Target Model are to provide consistent prices, enhance liquidity, support cross boarder trading, facilitate interconnections, and coordinate the use of transmission system capacity. In that context, the smooth operation of both forward and spot markets is a core development that directly affects the good operation of the wholesale market. This paper examines the application of the Target Model in the wholesale electricity market of Greece and its impact on electricity prices. The study explores the time period before the implementation of the Target Model, which took place on November 2020, and the first nine months of its execution. Based on the feedback received by the rest of the European countries, which are already part of the European Single Market, this crucial period of time is considered transitional, when many distortions and unethical behaviors take place. Empirical findings indicate a relatively successful implementation of the Target Model in Greece, with price disorders mostly met in the Balancing Market.

Keywords: target model; Greek wholesale electricity market; day-ahead market; intraday market; balancing market; trading volumes

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1. Introduction

Since 1996, the European Union (EU) aims to harmonize and liberalize the internal energy market, by adopting a list of measures to eventually create the "Single European Energy Market". The need to strengthen competition for the benefit of final consumers via reliable prices, transparency, and reliability are some of the key factors that have pushed Europe to support cross-border electricity trade among Member States. The Target Model is the official tool that Member States need to implement towards the completion of the Single Market. Prior to that, most of the countries operated their wholesale electricity markets according to the guidelines of a Mandatory Pool model.

The EU Target Model is based on two broad principles: (i) the development of integrated regional wholesale markets, preferably established on a zonal basis, in which prices provide important signals for generators' operational and investment decisions; and (ii) market coupling based on the so-called 'flow-based' capacity calculation, a method that takes into account that electricity can flow via different paths and optimize the representation of available capacities in meshed electricity grids. More information on the Target Model are available online: https://eur-lex.europa.eu/legalcontent/bg/TXT/?uri=CELEX:52017SC0383 (accessed on 13 September 2021), In general, Market Coupling, which is a crucial component of the Target Model refers to the interconnected cross-border electricity market among the Member States of the European Union. Through the physical interconnection among them, the flow of electricity takes place based on the optimal and shortest route from various production sources towards the final consumer. According to [1], discrepancies between regulatory policies and market designs could distort the normal functioning of the neighboring markets and security of supply. Market Coupling is based on Price Coupling of Regions (PCR), Flow-Based Market Coupling, and the Cross-Border Intraday (XBID) Project. In line with [2], by maximizing the use of cross-border interconnection capacity, market coupling increases the level of market integration and facilitates the access to low-cost generation by consumers located in high-cost generation countries. Thus, it is expected that a high-priced area could greatly benefit from the introduction of this mechanism. Existing literature supports the above argument [3,4].

To achieve market coupling, and for the benefit of all participants, the Mandatory pool was gradually replaced across Europe by the Target model (the Commission pursues the vision of a 'Target Model' using a European governance process (Third package, Directive 2009/72/EC.)). The ultimate goal of the Target Model is to enable the energy produced in one country to be delivered to another Member State participating in this Model. The Member States of the European Union are committed to complying with the fundamental principles which ensure a level playing field. Cross-border electricity trade initially takes place at a regional level and aims to achieve pan-European market coupling and consequently convergence to a single electricity price for the whole of Europe [5]. A prerequisite for the smooth operation of the model is the coordination of national actions between neighboring countries, and the optimal exploitation of cross-border electricity transactions. The implementation of the Target model envisages the creation of four new electricity markets that operate on an energy exchange. Given the above, the purpose of the Target model is to promote competition, convergence of energy prices with the prices of neighboring countries and increase of the overall welfare in the economy. However, considering the case of Greece, the implementation of the Target Model, that took place on the 1 November 2020, provides mixed results [6]. In theory, the goal of a Single European Energy Market is to favor end consumers. However, wholesale electricity prices in Greece have more than doubled since the beginning of November 2020. This sharp rise is partially attributed to the peculiarities of the introduced model, since both marker participants and regulators broadly accept that the market was not completely prepared for that fundamental shift [7–9].

This paper examines the application of the Target Model in the wholesale electricity market of Greece and its impact on electricity prices. To our knowledge, this is the first study to analyze and evaluate this application. The study explores the time period before the implementation of the Target Model and the first nine months of its execution. Based on the feedback received by the rest of the European countries, which are already part of the European Single Market, this transitional period of time is considered crucial, when many distortions and unethical behaviors take place. Empirical findings indicate a relatively successful implementation of the Target Model in Greece, with price disorders mostly met in the Balancing Market. However, those increased prices have caused great market turmoil and unbearable pressure on businesses and small suppliers who are unable to cope financially with the unprecedented situation.

A plethora of academic papers have reviewed the efficiency of Target Model implementation in various counties across Europe. As a starting point, Ref. [10] provides an overall estimation considering the benefits of Target Model implementation across Europe. The authors highlight that additional improvements are feasible by reducing unscheduled flows and preventing the curtailment of renewables with improved market design. In general, the study underlines the necessity to assist interconnections and cross-border trading, given that the final outcome, via the provision of balancing services, leads to increased gains for the overall economy. Based on the challenge to achieve a common electricity market design in a multi-regional context, Ref. [11] analyzed how diverse design approaches, such as cross-border congestion management and capacity mechanisms, affect generation adequacy and welfare in Europe. Their findings confirm the benefits of market coupling in terms of welfare as well as generation adequacy. Earlier investigations of the effectiveness of a common electricity market design suggested a partial successful [12–15]. However, recent studies are clearly in favor of the effectiveness of a Single Electricity Market across Europe [16–18]. For instance, Ref. [19] argue that investment in interconnection reduces wholesale electricity prices in France and Ireland as well as the net revenues of thermal generators.

Considering country-by-country analysis, Ref. [2] evaluated the impact of the Target Model in the Italian electricity market and estimated the welfare benefits using various scenarios. The study concludes that a welfare increase is apparent when market fundamentals are tight. Next, Ref. [20] examined the evolution of the Irish Single Electricity Market under the European Target Model for electricity. The authors focused on the theoretical and practical circumstances under which derivatives markets stimulate competition in the spot and retail markets. In addition, the authors examined the impact of market concentration on the new capacity payment mechanism, and, eventually, provided specific proposals towards the regulatory authorities to enhance the overall performance of the wholesale market. The authors conclude that regulators should promote competition in the forward market and at the same time extend regulation to the price and quantity that the dominant firm bids.

Another study, considering the case of Britain, [21], investigates the EU Target Electricity Model and its effectiveness before and after 2015. The paper provides theoretical and empirical implications of delivering capacity, energy, and quality of supply, by paying special attention to the trilemma problem of the country and considers potential solutions. Ref. [22] provides an exploratory analysis of the price spikes both in the Day-Ahead and Imbalance markets following the implementation of the Electricity Act of 1998 in the Netherlands. The authors argue that market participants gain from more stable economic environment in which they can better forecast future prices and evaluate investment plans. Finally, a recent study considering the case of Spain compares the regulatory framework and the cost of electrical energy among European countries [23]. The limited electricity interconnection capacity of Spain leads to higher energy bill costs and, eventually, lower competition of electricity intense industries.

Prior studies have analyzed the wholesale electricity market of Greece [24]. For instance, Ref. [25] provided a detailed analysis of recent developments in the electricity market of Greece and described the structure of the Hellenic Energy Exchange and the markets that will be formed in the future. The authors presented the basic design variables and respective options for the integration of the Greek wholesale electricity market with the other European markets under the Target. Finally, a recent study by [26] highlights the recent attempt to liberalize the electricity market, which was hindered for a long time by socio-economic forces that favored the monopolistic system of the market. Overall, the authors argue that the road towards a Single European Energy Market is an opportunity for the country to move forward and in parallel to maintain the pace of "coupling" with the most developed energy economies of Europe.

Over the past decade, national authorities demonstrated a strong commitment on energy policy goals and are constantly in line with the EU's overall goal to achieve climate neutrality by 2050. Greece aims to achieve a 62–65% share of renewable energy in the electricity mix by 2030. To accomplish the above objective, the Greek government announced various packages of financial incentives, tax cuts, exemptions, and funding programs. In parallel, ambitious incentives for private companies were introduced, to invest in Renewable Energy Sources (RES) and contribute to the gradual decarbonization of the country. In 2020, the renewed National Energy and Climate Plan and the introduction of the Green Legislative Framework played a key role by continuing to support RES penetration in the energy mix of Greece. It is estimated that gross energy consumption in Greece is expected to fall below 22,000 ktoe by the year 2040, while the share of RES will gradually exceed petroleum products. In line with Figure 1, between 2020 and 2040, RES are expected to play a dominant role in the country's energy production, increasing their share by up to 36%. Currently, Greece has exceeded the 2020 targets for the production of energy from RES. At the same time, Greece faces the highest wholesale energy price in Europe and in parallel one of the lowest retail prices in the EU. In that context, according to Eurostat (2019), the electricity market is considered as a key sector in Greece, since generation, transportation, distribution, supply, and trade of electricity produce 2% of national Gross Added Value of the total economy. Gross electricity generation in 2019 remained relatively steady compared to 2018 levels, reaching 53.3 TWh, while COVID-19 affected the total electricity consumption in Greece, an index which continued to decline for a third consecutive year.

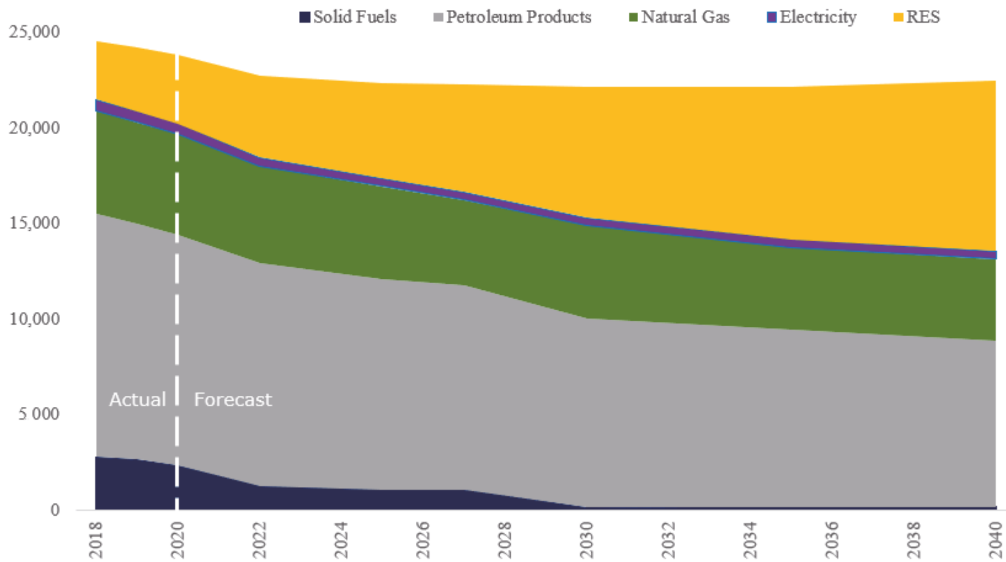

Figure 1. Evolution of Gross Energy Consumption in Greece (ktoe), (2018–2040), Source: National Energy and Climate Plan (2020) and Authors' estimations.

In line with Figure 2, the further decarbonization process of the electricity generation in Greece continues, with the lignite share plummeting to 15.4% in 2020. The share of RES recorded the most significant growth in the electricity mix, increasing by 9.7% during the period December 2019–October 2020. In addition, April 2020 was characterized as a "Snapshot from the Future" when natural gas and RES prevailed in the electricity mix. At the same time, the price of CO_2 emission allowances directly affects electricity prices and contribute to emissions reduction through Europe. Beyond lignite-fired units, natural gas-fired units are also affected by the increasing cost of CO_2 emissions, however, at a lower magnitude. In 2020, RES and Hydro together represented a greater share of total capacity (53%) compared to coal and natural gas combined (47%). According to Figure 3, the incumbent, Public Power Cooperation (PPC), retained a dominant share in electricity generation. PPC's share in the retail market continues the downward trend, reaching 64.2% in May 2020 from 94.3% in January 2016 (Figure 4).

Considering alternative suppliers, three energy groups are active generators in the Greek energy market (Mytilineos, Heron, Elpedison). The oligopoly that prevails due to the small number of thermal producers has distorted competition in the wholesale market. In recent years, NOME-type auctions have played a key role in the electricity market, mainly towards the reduction of PPC retails' market share. Essentially, alternative suppliers entered the market, exploiting cheap energy from NOME and achieving increasing their shares without substantial risk. Energy suppliers that are not vertically integrated into the market are forced to buy energy at high prices with the impact of either losing market share, raising their tariffs, or presenting losses on their balance sheets.

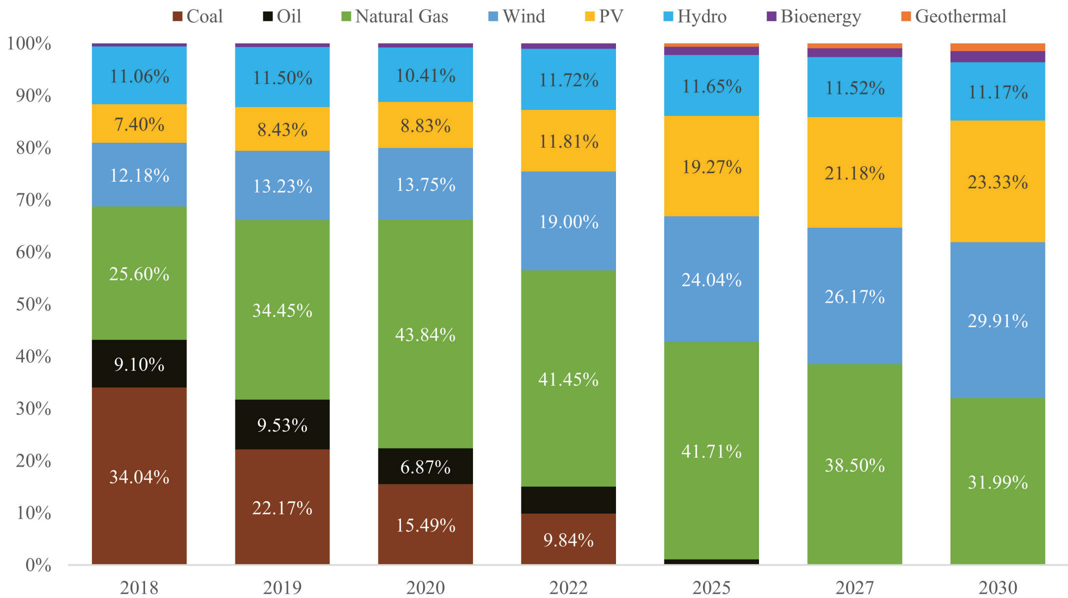

Figure 2. Evolution of Electricity Generation by Source in Greece (%), (2018–2030), Source: National Energy and Climate Plan (2020) and Authors' estimations.

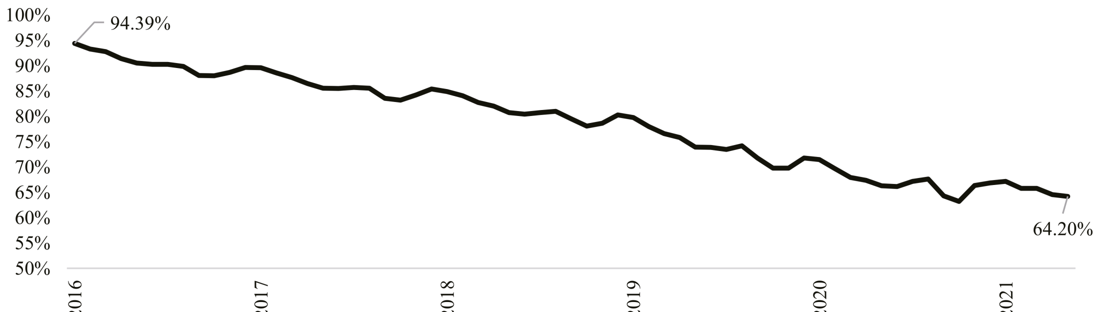

Figure 3. PPC's Market Share (%), (2016–May 2021), Source: Hellenic Energy Exchange and Authors' estimations.

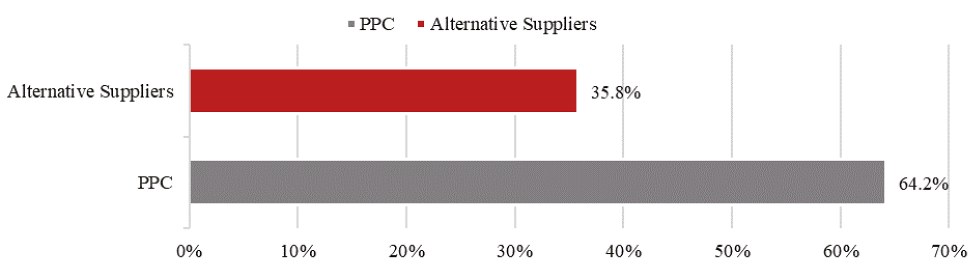

Figure 4. Retail Market Share (%), (2016–May 2021), Source: Hellenic Energy Exchange and Authors' estimations.

Figure 5 shows that, since the financial crisis of 2008, energy demand decreased exponentially and, in 2014, it reached 50,000 GWh. Then, a slight increase occurred, and it reached 50,217.4 GWh in 2019. The appearance of the pandemic stopped the upward trend of demand and, according to the "Reference Scenario" of the Hellenic Transmission System Operator (HTSO), electricity demand will regain its prior level in 2022. In April 2020, when COVID-19 restrictive measures were firstly introduced, a decrease of 9.8% in energy demand was recorded compared to April of 2019. Overall, the first four months of 2020 recorded a decrease in demand of 3.8% compared to the first four months of 2019. The pandemic heavily impacted oil and electricity demand, while natural gas consumption remained stable.

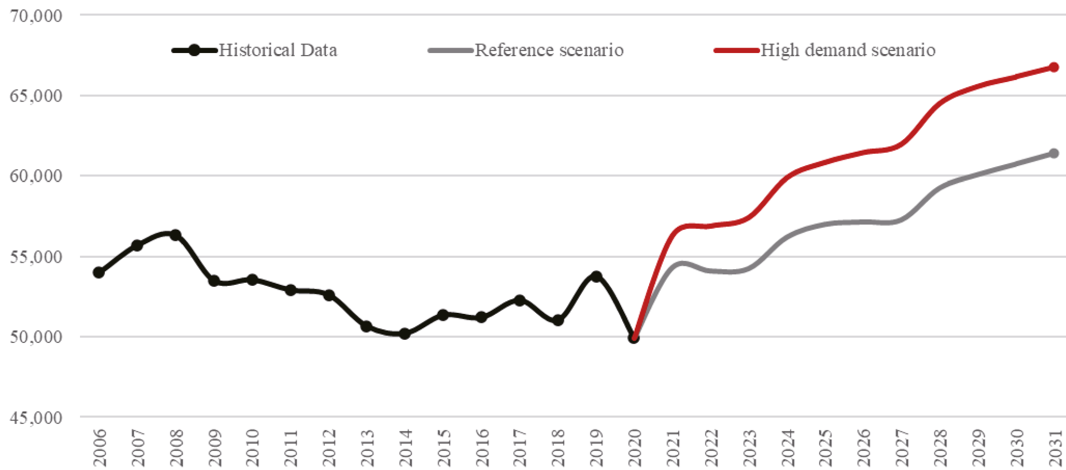

Figure 5. Historical Data and Forecast of Total Annual Demand for Electricity in Greece (GWh), (2006–2031), Source: Hellenic Transmission System Operator and Authors' estimations.

According to prior literature, an efficient design for real-time markets should address the special challenges of electricity system operation and support the intended economic outcomes by providing a spot market basis for development of and reliance on forward contracts [27,28]. Hellenic Energy Exchange S.A., (HEnEx) is the entity responsible for the operation of Spot and Derivatives markets in Greece. HEnEx has established the EnEx Clearing House S.A. (EnEx Clear) as the market Clearing House, in order to undertake the responsibilities of clearing, risk management, and settlement of the transactions. Under the Target Model, HEnEx Members are able to participate in the following markets: Day-Ahead Market (DAM), Intra-Day Market (IDM), Balancing Market (BM), and Forward Market (FWM).

2. The Application of the Target Model in Greece

A key energy market improvement was accomplished as the Target Model, a specific commitment of Greece, was implemented on 1 November 2020. This is considered as an important phase in the direction of Greece to fulfill the requirements of the EU energy policy. The innovative structure of the market which include the Day-Ahead Market, the Intra-day Market, the Balancing Market, and Forward Market is anticipated to provide improved price information and broader involvement and market entree of various services. The scheme "produce and forget" that used to be the case for Greece is transforming into a flexible and dynamic one. The novel market design is well-suited with all EU Members, permitting for the quick Day-Ahead and Intraday coupling with the neighboring countries. Considering the case of Greece, coupling with Italy and Bulgaria has already been achieved, which in turn is anticipated to boost energy security, assist the ongoing growth of RES, and promote competition in the wholesale market.

The latest market formation entails the collaboration of several entities like ADMIE, which is the Transmission System Operator, the Hellenic Energy Exchange, the Clearing

House, and the Athex Clear for the Derivatives Market. Moreover, the Regulatory Authority for Energy (RAE) and the Hellenic Capital Market Commission collaborate for the efficient supervision of the legal structure that oversees the daily function of the markets. The recently formed clearing house, EnEx Clear, is in charge for the financial settlement, the invoicing of participants, and eventually the risk management of the system. Financial institutions, such as banks, are already listed as official General Clearing Members to provide their services for both the spot and derivatives market.

The intense unpredictability of electricity prices has constantly concerned academics, generators, retail suppliers, and traders [29,30]. Those variations could be attributed to several factors that may be either easily predicted or not. Namely, reasons that crucially affect electricity prices are unexpected modifications in demand, unit availability, established interconnections with neighboring countries, fuel price such as natural gas, coal or oil, CO_2 prices, the stochastic generation of RES, macroeconomic conditions, and broader socioeconomic disorders like the pandemic. Consequently, members are able to exploit the hedging opportunities of the Derivatives Market. However, despite the fact that the Derivatives Market has been available to market participants in Greece since March 2020, it is not utilized by them, and liquidity persists at minimum levels, even after 15 months of official operation.

The Market Clearing Price of the Day-Ahead Market is formed at the point where the aggregate supply and aggregate demand curves intersect. Next, the energy exchange is responsible for submitting priority price taking orders by representing previous transactions as submitted on the Forward Market or the unregulated bilateral Over-The-Counter (OTC) market. In that framework, the recently established energy exchange aims to be a vital component in the growth, of the domestic and regional economy over the utilization of the Target Model. Regardless of the COVID-19 outbreak, the market layout of a totally functional gas exchange is presently under formation. In the wake of the electricity market, a natural gas trading platform will be available to participants at a later stage. Hence, including a gas marketplace in the framework of HEnEx is expected to function as a key step for the overall market, along with the recent developments in Northern Greece with the Trans Adriatic Pipeline, and other pivotal projects being supported by the EU [31].

According to Table 1 which depicts the most recent available data provided by the HEnEx, Day-Ahead Market accounts for more than 98.5% (or 3972 GWh) of the total volume traded during May 2021. Hence, the biggest share of market value derives from DAM (€254.7 Million), since the Intraday Market accounts for 1.5% (54.1 GWh) of the total volume by taking into consideration the three Intraday Auctions (LIDA 1, LIDA 2, & LIDA 3). Next, we identify small discrepancies between the Day-Ahead Market Price and the Intraday Prices. Figure 6 shows that, in May 2021, DAM price was equal to 63.16 €/MWh, while the average Intraday price was slightly lower at 63 €/MWh (LIDA 1 (62.53 €/MWh), LIDA 2 (63.12 €/MWh) and LIDA 3 (63.52 €/MWh)). The analysis that follows provides detailed information considering the comparison between DAM and IDM prices and shows that prices between the two markets were almost identical from November 2020 until June 2021.

Table 1. Summary of the main figures from DAM & LIDAs (April & May 2021), Source: Hellenic Energy Exchange and Authors' estimations.

May 2021 **April 2021**	**DAM**	**LIDA 1**	**LIDA 2**	**LIDA 2**
Price (€/MWh)	63.16 64.17	62.53 63.17	63.12 64.88	63.52 66.80
Volume (GWh)	3972 4176	28.2 37.8	14.6 17.0	11.3 9.7
Value (MM€)	254.7 271.1	1.91 2.28	0.98 1.08	0.78 0.64

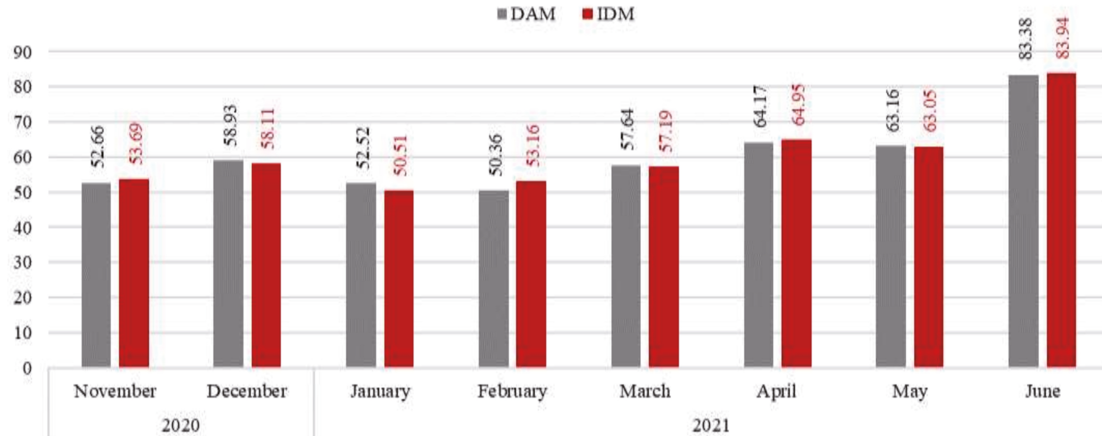

Figure 6. Day-Ahead & Intraday Prices (€/MWh) (November 2020–June 2021), Source: Hellenic Energy Exchange and Authors' estimations.

Next, in terms of the electricity mix for May 2021, the sell volume of the Day-Ahead Market is dominated by the natural gas (38%) and RES (33%), while imports (18%), hydro (7%), and lignite (5%) account for the remaining share of generation (Figure 7). Considering the Intraday Market, again, natural gas (49%) and RES (29%) account for 78% of the total generation (Figure 8). Moreover, on the buy side of the Day-Ahead Market, considering again May 2021, the majority of the volume directed to Low Voltage (LV) Load (56%), Medium Voltage (MV) Load (19%) and High Voltage (HV) Load (15%) (Figure 9). In the Intraday market, we identify natural gas-fired units absorbing 50%, RES aggregators 28%, and LV load 14% (Figure 10).

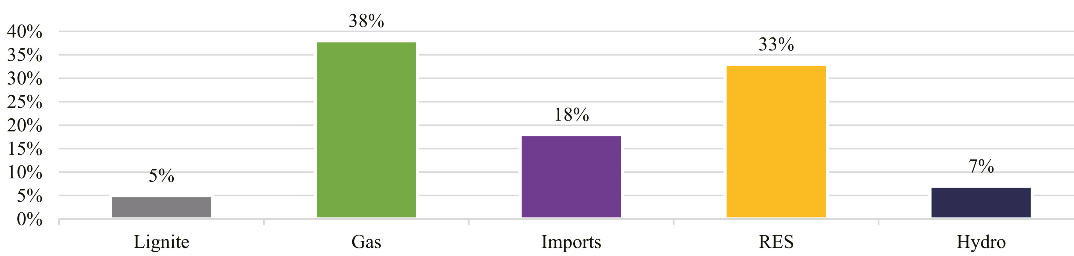

Figure 7. Day-Ahead Market, Sell Volume mix (%), (May 2021), Source: Hellenic Energy Exchange and Authors' estimations.

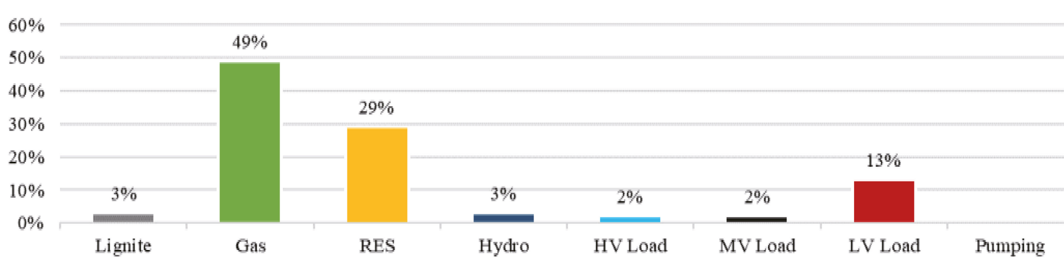

Figure 8. Intraday Volume—Sell Volume mix (%), (May 2021), Source: Hellenic Energy Exchange and Authors' estimations.

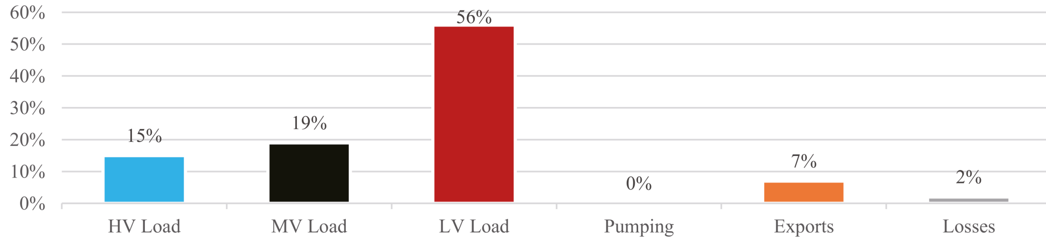

Figure 9. Day-Ahead Market—Buy Volume mix (%), (May 2021), Source: Hellenic Energy Exchange and Authors' estimations.

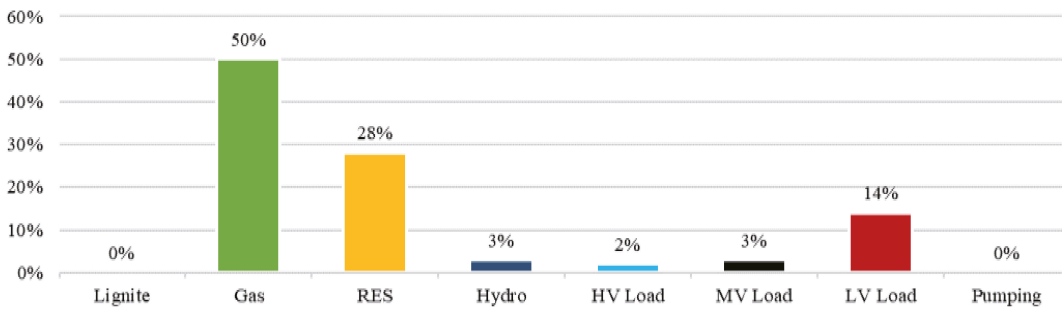

Figure 10. Intraday—Buy Volume mix (%), (May 2021), Source: Hellenic Energy Exchange and Authors' estimations.

As Figure 11 illustrates, since 2008, the daily average market clearing price in Greece fluctuated from 10 €/MWh to 123 €/MWh, with an average price considering the period 1 January 2008 until 1 June 2021 at 54.1 €/MWh. In terms of the overall fluctuation, and prior to the implementation of the Target Model, we identify spikes in electricity prices (values higher than 100 €/MWh) only four times in a period of a 13.5 year period. Specifically, the first spike is identified by the end of 2008, the second at the beginning of 2012, the third in mid-2014, and the fourth in early 2017. However, only following the implementation of the Target Model, the average daily Market Clearing Price skyrocketed to 128 €/MWh. Prior to the launch of the Target Model, a significant drop occurred in wholesale electricity prices during the 1st period of COVID-19 lockdown (March 2020–April 2020), reaching 28.5 €/MWh in April 2020.

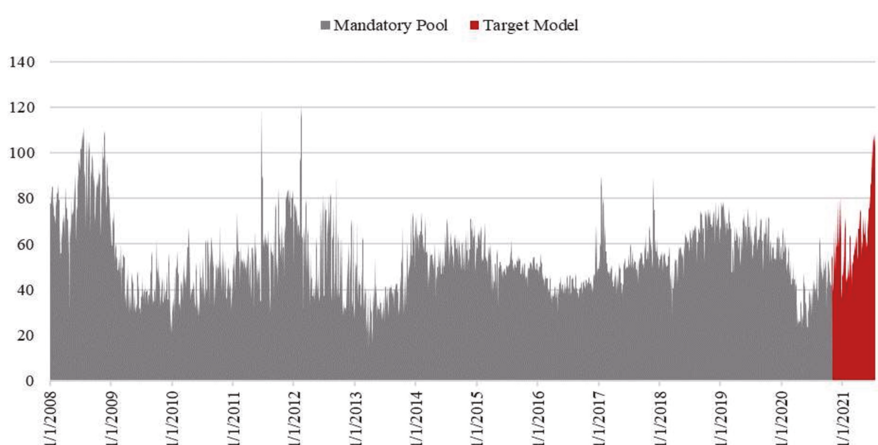

Figure 11. Daily Average Market Clearing Price in Greece (€/MWh), (2008–July 2021), Source: Hellenic Energy Exchange and Authors' estimations.

3. Empirical Findings

3.1. Day-Ahead Market and Intraday Market

A price increase in the Day-Ahead Market causes intense concern, which, during the first nine months of Target Model operation, recorded an increase of 97.8%, since the average price soared from 47.2 €/MWh in October 2020 to 93.4 €/MWh in July 2021. Interestingly, despite the fact that the total electricity consumption reduced by almost 10% from March 2021 to April 2021, the price followed an upward trend from 57.64 €/MWh in March to 64.17 €/MWh in April (an increase of 11.3%). On a year-to-year comparison, the price levels during April 2020 were equal to 28.51 €/MWh, thus the price increase was more than 125%. Based on Figure 12, the upward trend of Day-Ahead Market price continued until July 2021. In detail, during June 2021, the price at DAM was set at 83.38 €/MWh, an increase of 32% compared to May 2021 when the price was recorded at 63.16 € MWh. On an annual basis, during June 2020, the DAM price was 34.04 €/MWh, meaning that the growth was equal to 144% (see Figure 13 for Day-Ahead Market prices and Table 2 for Intraday Market prices).

The aforementioned developments are not entirely attributed to the implementation of the Target Model. The overall demand increase due to high temperatures is one of the main reasons that led to a spectacular rise in the price of electricity, which, on 25 June 2021, reached 128.15 €/MWh. In line with the prices recorded during June 2021 and July 2021, with prices exceeding the benchmark of 100 €/MWh, it is anticipated that the increase in price levels will be maintained during the following period. At the same time, the constantly increasing natural gas prices crucially affect electricity cost in Greece, since natural gas accounts for 38% of electricity generation in the DAM. The natural gas import price since June 2020 follows an upward trend, while consumption hits an all-time high record during 2020. Precisely, natural gas import price in Greece during the COVID-19 outbreak dropped to 5.4 €/MWh in March 2020 yet recovered to 13.4 €/MWh by December 2020.

Market coupling systems exist both in Day-ahead trading and in Intraday markets, and this interconnection among markets ensures efficient electricity trading. Furthermore, the participation in short-term markets, the initiation of bilateral contracts, and the removal of prior restrictions on trading are expected to boost liquidity, with a positive impact on the balancing market. In this direction, a significant change that is taking place is the implementation of continuous trading in the Intraday market within the first quarter of 2022. At the same time, during October 2021, the wholesale gas market will be activated. Initially, spot transactions will be available to market participants and, in the second stage, futures products as well, thus acting as a starting point for the establishment of a regional energy hub.

Figure 14 illustrates that, the impact of Co_2 prices is already apparent on coal-fired units since their total operational cost today is more than 75 €/MWh (35 €/MWh fuel cost + 40 €/MWh CO_2 cost). In addition, the increased CO_2 prices will generate additional pressure to the daily operation of natural gas-fired plants and eventually lead to higher electricity prices. The corresponding levels of total operational cost for natural gas-fired units is more than 65 €/MWh (55 €/MWh fuel cost + 10 €/MWh co2 cost). Even though the emissions from natural gas (117 pounds of CO_2 emitted /btu) are lower compared to coal (215 pounds of CO_2 emitted /btu), given the current and projected prices of CO_2 emissions, natural gas-fired units are anticipated to drive electricity prices at increased levels in all three Scenarios (see Figures A1 and A2 in Appendix A for more details. Main assumptions: auction price €/t CO_2 not to drop at lower than 50 €/t CO_2, fuel cost remains steady in all three Scenarios at 55 €/MWh)).

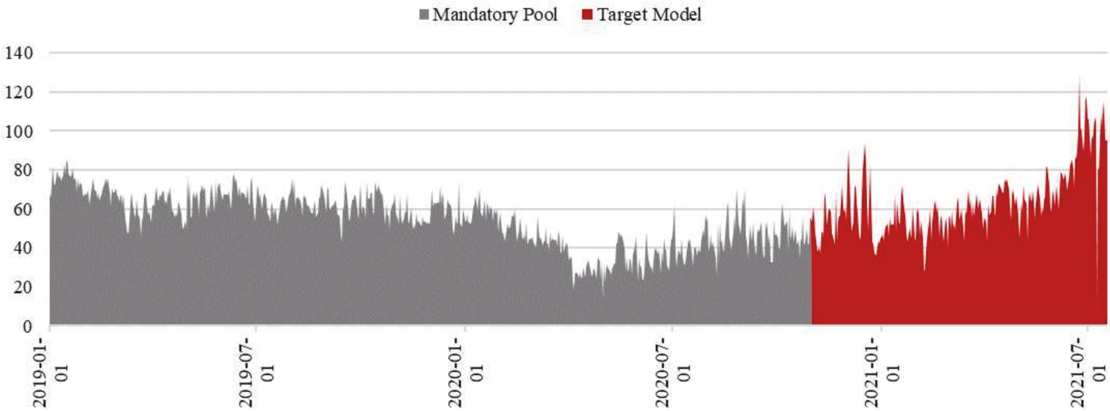

Figure 12. Daily Average Market Clearing Price in Greece (€/MWh), (2018–July 2021), Source: Hellenic Energy Exchange and Authors' estimations.

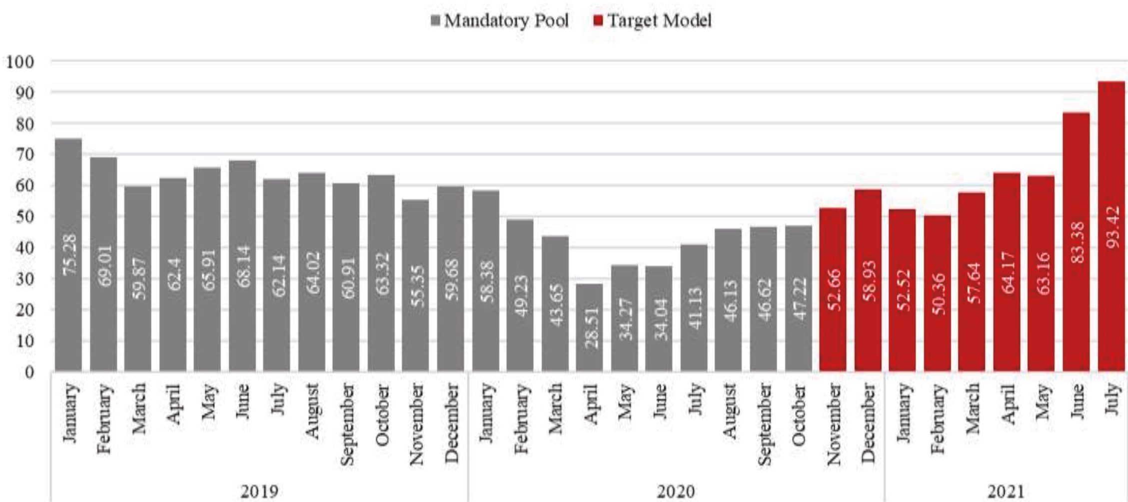

Figure 13. Monthly Average Market Clearing Price (€/MWh), (2019–July 2021), Source: Hellenic Energy Exchange and Authors' estimations.

Table 2. Monthly average Intraday prices (€/MWh), (November 2020–June 2021), Source: Hellenic Energy Exchange and Authors' estimations.

	LIDA 1	**LIDA 2**	**LIDA 3**	**Average IDM**
Nov-20	53.21	51.84	56.03	53.69
Dec-20	60.26	59.09	54.98	58.11
Jan-21	53.57	49.9	48.07	50.51
Feb-21	50.67	54.31	54.52	53.16
Mar-21	55.66	56.82	59.11	57.19
Apr-21	63.17	64.88	66.8	64.95
May-21	62.53	63.12	63.51	63.05
June 2021	82.96	83.12	85.75	83.94

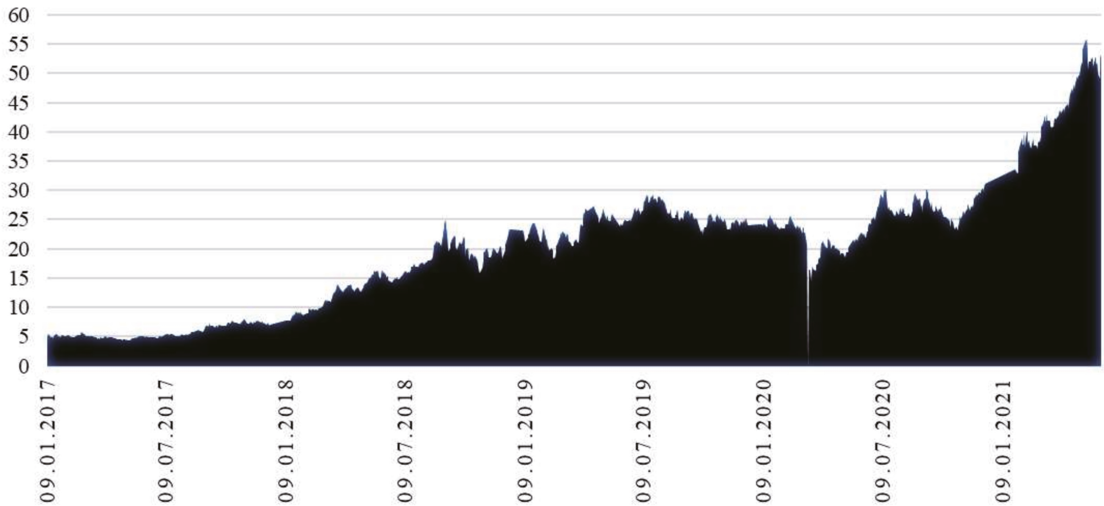

Figure 14. CO_2 European Emission Allowances (€/ton), (2017–May 2021), Source: EEX and Authors' estimations.

In 2022, the Target Model is expected to incorporate the optimization algorithm, EUPHEMIA. The EUPHEMIA algorithm is a key tool for calculating and linking individual electricity prices across Europe as well as for optimal cross-border capacity allocation. It offers transparency in the calculation of energy price and its distribution. The procedure of the algorithm is as follows: first, the participants submit their orders to the respective energy exchange; the algorithm accumulates the orders and, according to specific criteria, those orders are accepted or rejected. The criteria on the basis of which it operates are the maximum prevalence of social welfare (according to the consumer surplus, the producer surplus and the congestion rent in the area) and the flow of capacity so that no congestion is caused. The following table provides illustrative information considering imports and exports of electricity for both explicit and implicit allocation. Greece is a net importer of electricity to cover the domestic demand. According to Table 3, the main countries from which Greece imports electricity are Albania (235 GWh), North Macedonia (166 GWh), and Bulgaria (125 GWh from Explicit Allocation and 135 GWh from Implicit Allocation). On the contrary, Greece exported electricity towards Italy via Implicit Allocation (152 GWh) and towards North Macedonia via Explicit Allocation (75 GWh).

Table 3. Imports/Exports at Day-Ahead Market, May 2021 (GWh), Source: Hellenic Energy Exchange and Authors' estimations.

	Exports—Explicit Allocation	Imports—Explicit Allocation	Exports—Implicit Allocation	Imports—Implicit Allocation
Albania	17	235	0	0
North Macedonia	75	166	0	0
Bulgaria	12	125	7	135
Italy	0	0	152	25
Turkey	6	37	0	0

3.2. Balancing Market

The Balancing Market, which is the market responsible for the smooth operation of the system as electricity approaches the actual delivery, was the one that presented the biggest problems as its cost multiplied compared to the corresponding cost from the previous model of mandatory pool. In November 2020, the balancing market quadrupled compared to the previous model (Figures 15 and 16). Only during the last two months of 2020, when the

Target Model was initiated, the burden on the Balancing Market was estimated at €135 million euros while the total annual burden of 2020 at €200 million. Based on the liquidation of the Balancing Market for the period from November 30 to December 6, the cost amounted to 43.37 euros per megawatt hour. For the same period, the corresponding weighted average price of the Day-Ahead Market (DAM) was 66.18 euros per megawatt hour. This means that the cost of the Balancing Market amounted to 66% of the market value. The prices formed in the Balancing Market force the companies to increase the tariffs by 15% to 20% even in the low voltage (households). Medium increases are already being borne by similar increases (large commercial companies). The cost of energy is close to 70 euros per megawatt hour, while in the same period there were contracts on the market with 55–60 euros per megawatt hour. The surge in the price of electricity caused a great upheaval in the market in December 2020 with consumers massively terminating electricity contracts.

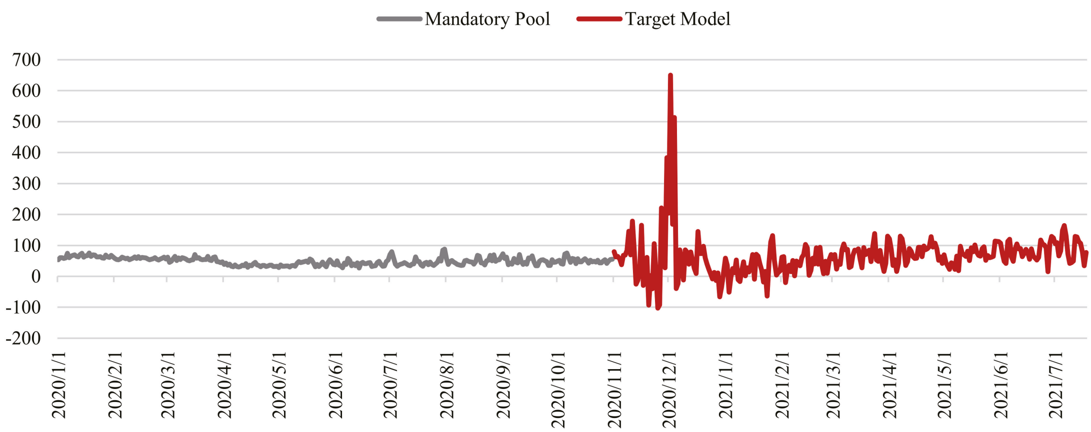

Figure 15. Daily Imbalance Price in Greece (€/MWh), (January 2020–July 2021), Source: Hellenic Transmission System Operator and Authors' estimations.

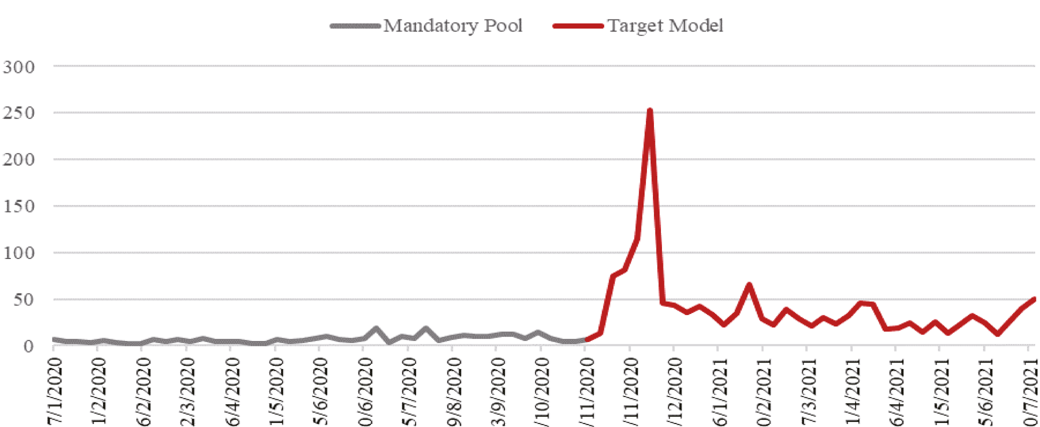

Figure 16. Weekly Standard Deviation of imbalance prices in Greece, (January 2020–July 2021), Source: Hellenic Transmission System Operator and Authors' estimations.

4. The Response of the Regulator

Due to the deteriorating situation resulting from the implementation of the Target Model, the regulator was aware of the potential impact of this situation and, in order to curb the rise in wholesale energy costs, on 13 February 2021 (Figure 17), made the Decision (54/2021) to impose a threshold on the bids of the producers regarding the downward balancing action (The Decision was taken in cooperation with the European Commission and the Ministry of Environment and Energy). RAE also modified the Integrated Scheduling Process (ISP) algorithm. The ISP refers to an action performed by the System Administrator in order to configure the unit allocation program and the distribution of balancing power to the entities that provide it. The exercise is executed three times: once immediately after the resolution of the Day-Ahead Market and twice more after the resolution of each of the two intraday auctions held within the framework of the Intraday Market. It can additionally be performed at the request of the TSO, in case any serious changes occur during the operation of the System, such as serious damage related to loss of unit, loss of interface, and forecast failures.

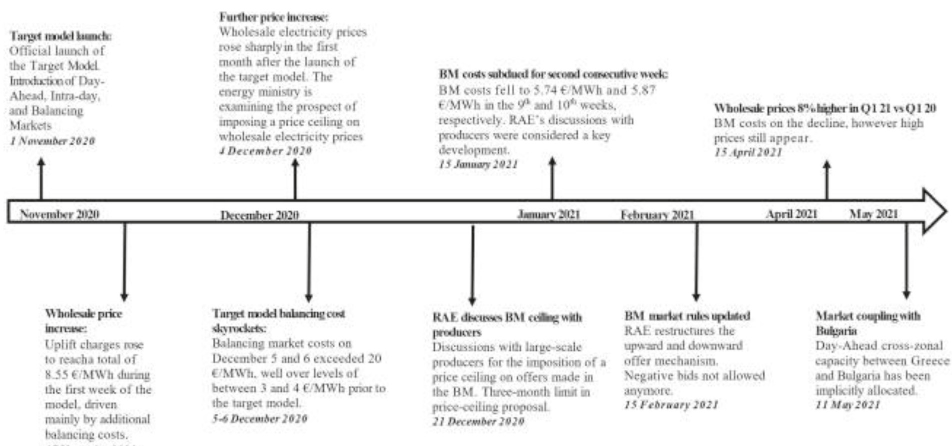

Figure 17. Timeline of important developments following the Target Model implementation in Greece.

Based on the above decision, RAE modified the ISP algorithm in such a way as to eliminate the submission of tenders for quantities of energy that are lower than the technical minimum production quantity. In the explanatory memorandum, RAE notes that it recognizes that there is an issue of abusive behavior in the balancing market and states that the measures it promotes aim to balance the market by keeping it essentially able to operate, and, secondly, the restoration of conditions of good operation and competition. In particular, the adoption of these measures strengthened the operational framework of the Balancing Market, by discouraging the occurrence of abusive behaviors and preventing the avoidance of standard rules in order to benefit, to the detriment of the system's economy and a healthy competition. Another action of RAE regarding the inconsistent operation of the Target model was the imposition of a penalty of five million euros on the TSO, due to the failure of completing the Western Corridor in the Peloponnese. Although the above arrangements prevented the continuous rise in balancing costs, the situation does not remain viable, and more adjustments are needed for the smooth operation of the energy exchange:

- The causes of the malfunction—Improper operation of the Target model in Greece
- Price liberalization given that producers providing balancing services were able to provide prices up to 100 times their actual variable unit costs.
- Oligopoly on the producers of thermal units.

- Inability of the system administrator algorithm to prevent unethical bids.
- Congestion of the high voltage network in the Peloponnese due to overload.
- Low interconnection power transmission of electricity from other countries
- Low liquidity in the Forward and Intraday market. Both the number of participants and the volume of transactions should increase, aiming to reduce the need for balancing energy and, consequently, the corresponding costs.

Measures to Be Taken

Demand response: The expected development of RES has considerable impacts on the average daily pattern of electricity generation in the current decade. Demand Response concerns the storage of energy that comes from RES during peak hours so that it can be stored and used when demand is increased. According to the TSO, it is estimated that in 2025 the thermal units will only cover the remaining quantities apart from the generation from RES. Nowadays, Demand Response is not available to support the wholesale electricity market in Greece, yet it is crucial for smoothing the typical load curve in the future. In addition, the use of batteries as a means of energy storage is anticipated to provide long-term profits for the overall economy. Hence, the authorities need to establish concrete steps to allow participation of Demand Response and Storage in all stages including in the Balancing Market.

Central scheduling: The Balancing Market is governed by the principle of Central Dispatching per unit. The Marker Operator considers the generation offers and, according to an algorithm optimization solution, provides the most efficient nominations to each to the entity providing balancing services. These entities submit bids in the market area per unit, per load zone, and per interconnection border. This model is applied to Greece, Poland, Italy, and Ireland, while the model of Self-Scheduling is selected in other European countries. In countries where the Self-Scheduling model is applied, first the backup auction process takes place, then follows the Day-Ahead Market, the Intraday Market, and finally the self-scheduling nomination. In this way, the simultaneous action of upward and downward balancing is prevented, a fact that is usually observed in the Greek electricity market. The imposition of a penalty for the simultaneous action of upward and downward balancing is one of the best measures to minimize this phenomenon.

5. Next Steps

- Power Purchase Agreements (PPAs)—Several GWs of merchant driven projects are expected to come online by 2030 and a supportive framework for PPAs is key for their deployment. In that context, the national authorities are seeking to establish a subsidy support-scheme by supporting renewable electricity absorbed by energy-intensive industries and other enterprises. Balancing costs are an important part of the equation, and the scheme is anticipated to subsidize balancing market costs by using recovery fund money as part of the effort. According to the plan, the support mechanism will be made available to energy consumers whose energy cost exceeds 20% of operating costs. Besides industrial producers, the mechanism's availability could be expanded to also cover hotels in the tourism sector, retail food chains, and other enterprises operating on a mass scale. RES investors opting to establish bilateral PPAs with industrial consumers are expected to be given licensing priority for the projects over peers planning to secure tariffs via RES auctions. The licensing priority for PPAs is a measure to counteract the fact that projects that have been awarded a contract via the auction system (Auction prices have decreased significantly in the previous auctions, especially in the last common auction, where the weighted average price dropped by 30% compared to the Starting Price. For more details on auction results, see Table A1 in Appendix A) are likely to enjoy more favorable treatment for project financing. The scheme needs to be endorsed by the European Directorate for Competition. For the moment, there is only one PPA signed in Greece—Mytilineos has signed a PPA with Egnatia group for 200 MW solar at 33 €/MWh (It is worth noting that Mytilineos acquired over 1 GW of assets in the late stage of development by Egnatia group, which suggests that the pricing might not necessarily show a representative fair value of a PPA).

- Capacity Remuneration Mechanism (CRM)—Greece aims to create a new permanent CRM following the temporary CRM from 2020. Additionally, Greece is pushing for a strategic reserve scheme in order to compensate lignite units which need to stay on the system for capacity adequacy purposes despite being unprofitable. At the moment, Greece has submitted a proposal highlighting the need and operation details of a strategic reserve scheme along with a set of answers posed by the EU commission in June 2021. The new CRM needs to be aligned with EU regulations. Greece submitted in June 2021 a draft of the Market Reform Plan for the national Day-ahead, Intraday and Balancing markets that were launched in November 2020. In July 2021, DG Comp is set to start consultations which will take four months before the final Market Reform Plan can be published. In parallel with the consultations of the Market Reform Plan, a new capacity adequacy report from the Greek TSO will be prepared for the EU commission as a supplement to the Greek energy ministry's proposal for the strategic reserve scheme—a final Market Reform Plan by the last quarter of 2021 that can be legally implemented as early as the first quarter of 2022. The setup of a strategic reserve scheme could be activated in the first quarter of 2022 together with the updates from the Market Reform Plan. The legislation of the new CRM would be activated after the strategic reserve scheme ends and will include, among others, Demand Response.

The Transition to Full-Scale Target Model for RES

Existing literature provides illustrative information considering the impact of the Target Model on RES [32] and the role of RES Aggregators [33]. Figure 18 depicts the upcoming scheme in Greece, which contains substantial operational charges such as clearing, imbalance, and non-compliance costs. Under the introduced scheme, it is mandatory for generators with a capacity bigger than 500 KW to sell their production in wholesale market, either by utilizing own resources or via the existing aggregators. Apart from their aforementioned obligation, RES producers need to also be considered for accurate forecast projections. As long as the interim phase of the Target Model is available, and until the introduction of the full-scale Target Model, participants will be credited with 1 €/MWh, which corresponds to a Fixed Management Premium. During this phase, RES producers are burdened by the Temporary Mechanism of Optimal Forecast Accuracy that equals 12.98 €/MWh for 2021. Overall, RES producers under the Sliding FiP framework receive a premium which is the difference between the Reference Price (or Auction Price) with the monthly Reference Market Price (RMP) per technology.

For the Greek wholesale electricity Market, the RMP is derived from the hourly generation that corresponds to each RES technology. The calculation considers the aggregate production coming from the total number of identical technologies. RMP is part of an exercise that yields the "Sliding Premium" which is the same for every producer per RES technology. Therefore, this process guarantees that total revenues in terms of each technology are resulting from the multiplication of the Reference Price (or Auction Price) with the total production for the specific time unit. Historical data of Reference Market Price by month reveal that, on average, compensation prices for all RES technologies are 48.8 €/MWh. The COVID-19 effect is apparent in this figure as well since prices for all RES technologies dropped around 33 €/MWh. However, as Figure 19 illustrates, a sharp increase in prices followed along with the gradual withdrawal of mobility restrictions. Even during the 2nd wave of lock down of lockdown restrictions in Greece (November 2020 until May 2021), RES compensation prices remained at increased levels (around 55 €/MWh). Average Reference Market Price of all RES Technologies from November 2019 until May 2021 (excluding COVID-19 effect) equals 52.2 €/MWh.

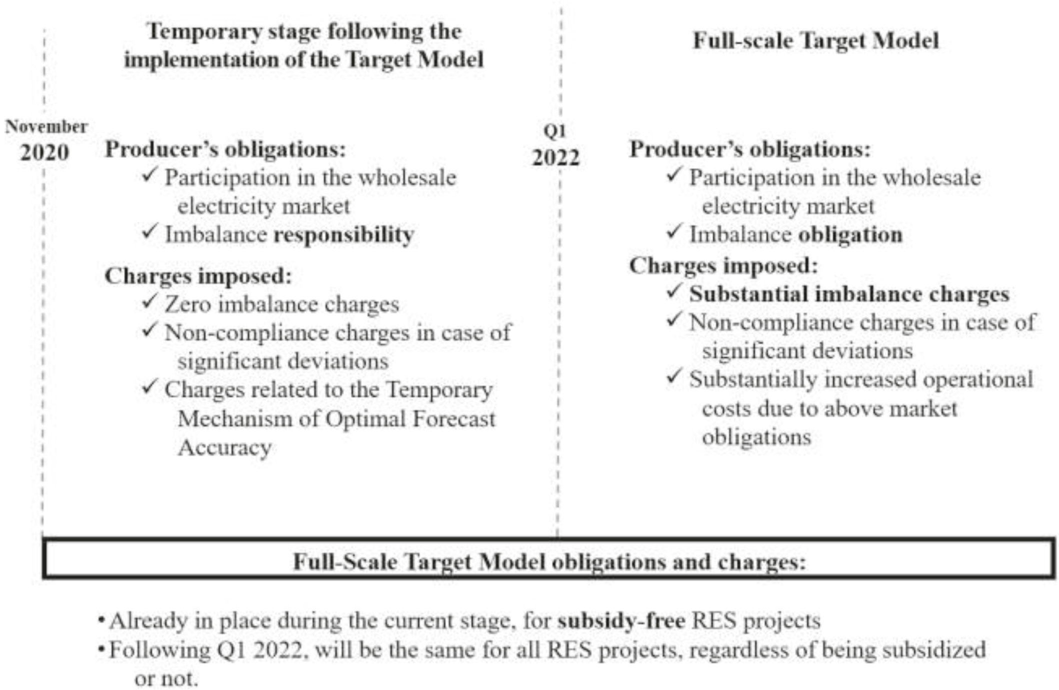

Figure 18. New RES Framework under the Target Model in Greece, Source: Hellenic Energy Exchange and Authors' estimations.

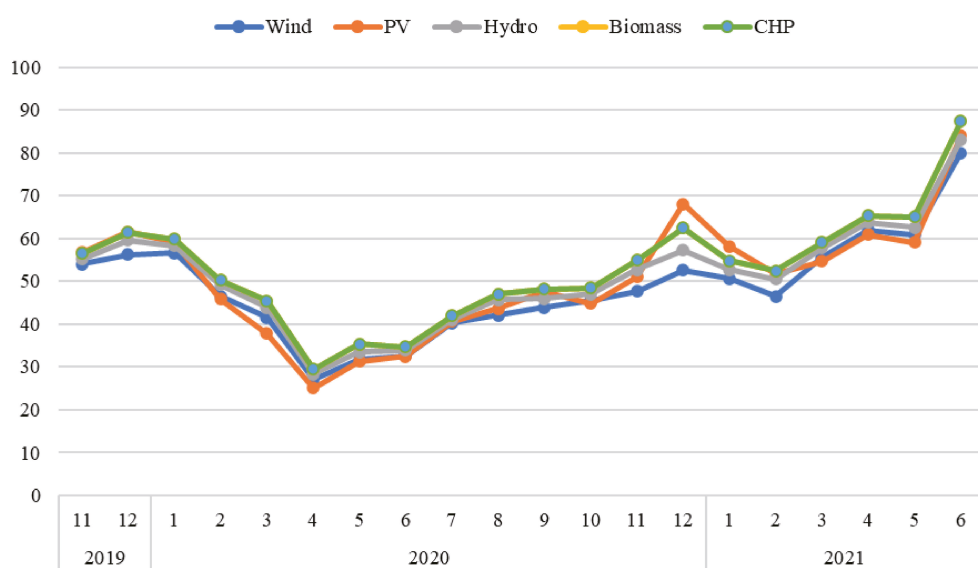

Figure 19. Reference Market Price in Greece (€/MWh), (November 2019–June 2021), Source: Hellenic Energy Exchange and Authors' estimations.

6. Conclusions

This paper investigated the implementation of the Target Model in the wholesale electricity market of Greece and its impact on electricity prices. The study explores the time period before the implementation of the Target Model and the first nine months of its execution. In countries like Greece, where a monopoly or oligopoly of producers prevails in the wholesale electricity market, in combination with low capacity in connectivity with other neighboring countries, an upward trend on electricity prices is mostly anticipated. The above, combined with the lack of supervision in order to prevent manipulative behavior, could partially lead to the postponement of energy related investment plans. Energy producers are the only ones who benefit from the price increase and the overall market turmoil since those companies are able to exploit the legislative and technical gaps and implement unethical strategies in order to achieve extremely high profitability.

The peculiarity in this case is that the market itself provides room for the above exploitation since the submitting bids are within the limits set by the European Union. Especially in times of high demand, where there is a low supply from the producers, it is necessary to check by the competent regulator in order to determine whether they meet the reality or whether they use the regulations of the Target model to achieve profit maximization through the Balancing Market. As market participants understand better the dynamics of the new market and RAE monitors competition and costs, the Target Model is expected to become more fluent and efficient eventually increasing competition and reducing costs. In addition, RES seems to be responsible for a large share of the cost of the Balancing Market. This fact is due to the inability of accurately predicting their production, due to their stochastic nature. In addition, in line with [34], the increase of RES to an electricity market has an ambiguous effect on wholesale prices. The merit order effect has a downward pressure on prices while, with market power, higher inframarginal rents will tend to increase prices. Considering the case of Greece, we observe simultaneous increase in RES share and higher prices which yields to the existence of market power. This could be mainly attributed to the increased share of one RES aggregator in the market, which is equal to 54%. It is apparent that the aforementioned finding has important consequences for the domestic wholesale prices.

Part of prior studies found that Target Model implementation was accompanied by welfare increase, which is not yet the case of the Greek wholesale market. Some benefits that are anticipated to be evident on the wholesale market of Greece are the consumers benefit from lower prices as a buyer will be automatically matched with the cheapest generation in Europe, and the fact that balancing markets will be integrated so that consumers benefit from lower balancing costs and improved security of supply across the EU. However, a study from the United Kingdom (UK) illustrates how market design solutions characterized by good intentions could have adverse effects, depending on the details of how they are implemented in practice [35]. The author lists some drawbacks in the case of UK such as the increased cost of relieving congestions, increased risk of discrimination by system operators, increase in the potential scope for abuse of market power by generators, and failure to capture positive externalities and perverse incentives. We observe that our findings are in line with the case of Spain, where the limited electricity interconnection capacity of the country led to higher energy bill costs and, eventually, lower competition of electricity intense industries [23].

At the same time, our research is in line with prior empirical findings towards the direction of extended regulation to the price and quantity of the dominant firm bids. As can be seen from the countries of the European Union where the Target model has been implemented, it takes a period of one and a half years for the market to function properly and for healthy competition to prevail. One of the main limitations of the study is that the study explores only the first nine months of its execution; thus, future research should utilize new data and reevaluate the effectiveness of Target Model implementation in the wholesale market of Greece. This study documents in detail all the developments that took place up to this point, but this is yet to be seen in the future if the Target model achieves functioning properly and effectively in Greece and eventually benefiting the final consumers.

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Appendix A

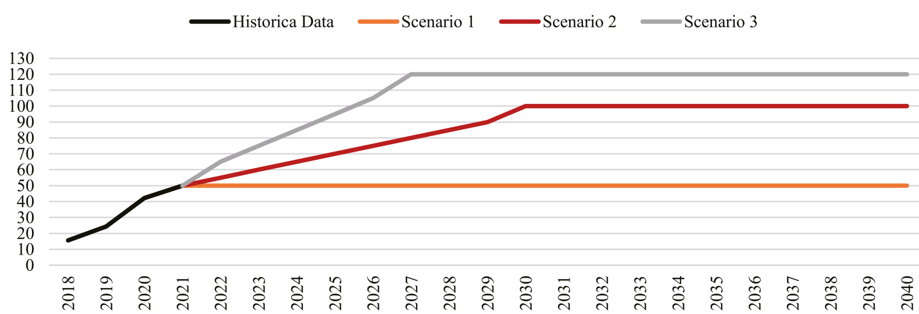

Figure A1. Projection of CO2 Price evolution €/t, Source: Authors' projections.

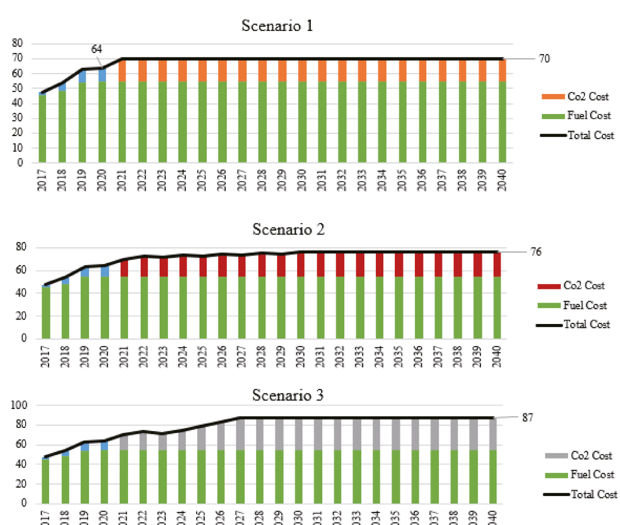

Figure A2. Estimation of average annual total cost of Natural Gas-fired Units (€/MWh), (2017–2040), Source: Authors' projections.

Table A1. RES Auctions Results (PV & Technology Neutral), Source: Regulatory Authority for Energy (RAE).

	Participation/Applications (MW)	**Final Auctioned Capacity (MW)**	**Starting Price (€/MWh)**	**Highest Bid (€/MWh)**	**Lowest Bid (€/MWh)**	**Weighted Price (€/MWh)**
July 2018						
Category I (PV < 1 MWp)	94.07	53.52	85.00	80.00	75.87	78.42
Category II (1 MWp < PV < 20 MWp)	93.44	53.40	80.00	71.00	62.97	63.81
December 2018						
Category I (PV < 1 MWp)	108.40	61.95	81.71	68.99	63.00	66.66
Category II (1 MWp < PV < 20 MWp)	151.32	86.47	71.91	71.91	63.00	70.39
April 2019						
Category IV (technology neutral) (Technology Neutral: Common Auction for PV > 20MW & Wind > 50MW)	637.78	437.78	64.72	64.72	53.00	57.03
July 2019						
Category I (PV < 20 MWp)	200.26	142.8	69.26	67.7	61.95	62.78
December 2019						
Category I (PV<20 MWp)	147.65	105.00	66.02	65.99	53.82	59.98
April 2020						
Category IV (technology neutral) *	712	502.94	61.32	54.82	49.11	51.59
July 2020						
Category I (PV < 20 MWp)	94.07	141.93	63.00	62.45	45.84	49.80
May 2021						
Category V (technology neutral) (Technology Neutral: Common Auction for PV < 20MW & Wind < 50MW)	1090.27	350	53.86	41	32.97	37.60

* Technology Neutral: Common Auction for PV > 20MW & Wind > 50MW.

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energies

Review

Towards a Global Energy-Sustainable Economy Nexus; Summing up Evidence from Recent Empirical Work

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Abstract: The recent trend in New Economics is the establishment of measures of sustainable wealth and welfare which take into account all the parameters of economic, environmental, and social life and progress, juxtaposed to the conventional and myopic GDP. This review summarizes results from a series of recent papers in the energy-growth nexus field, which have perused a proxy for the sustainable GDP instead of the conventional GDP and discusses the difference in results and policy implications. The energy-growth nexus field itself has generated a bulk of work since the seminal study of Kraft and Kraft (1978), but still the field needs new perspectives in order to generate results with a consensus. The bidirectional causality between energy consumption and sustainable economy provides evidence for the Feedback Hypothesis, a statement that essentially warns that it is too early for sustainability to be feasible without fossil energy consumption, and vice versa. The unidirectional causality reveals, on the one side, that an economy cannot grow without the plentiful consumption of energy (the Growth Hypothesis) and, on the other side, that the growth of the economy fuels energy consumption (the Conservation Hypothesis). Failure to corroborate causality between energy consumption and economic growth is evidence for the Neutrality Hypothesis.

Keywords: energy-growth nexus; sustainable economy; new economics; critical review

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1. Introduction

According to the International Energy Agency [1] the world energy consumption has increased by 45% since 1980 and will be 70% higher by 2030. Therefore, future energy policy is bound to remain focused on saving, efficiency, and renewable energy usage. European Union energy targets for 2030 have been set as follows: 40% reduction in greenhouse gas emissions (compared to 1990 levels), at least 32% share of renewable energy consumption, and 32.5% energy savings compared with the business-as-usual scenario [2] The EU is devoting significant efforts to reduce energy consumption in the main consumption areas such as residential, tertiary, transport and industry. However, both primary and final energy consumption are slightly above their 2020 targets because not all sectors have managed to decrease their consumption. One such sector was transport and the largest increase in energy consumption was noted in the tertiary sectors (20.2%) which overshadowed the progress made in industry (−14.6%) and the households (−4.5%) [2]. Despite the applied policies, it is not an easy task to harness energy consumption given the demands for economic growth, the increasing population, the heating energy demand, the household characteristics towards single person families, and the energy prices which have not fully incorporated the incurred environmental costs pertinent to their exploitation and consumption.

Despite the need for energy conservation (with energy conservation we refer to the reduction of energy consumption in all sections of economy), energy inputs are necessary in production and thus the configuration of the impact of energy cuttings on economic growth remains important. Energy efficiency is an ongoing process, it has gone through a major breakthrough, but there is still much structural distance to be covered until its full potential is exploited by all sectors. Thus, increases in efficiency of thermal power generation have been made, due to a shift from coal to gas, and a change in the power mix has also been achieved with a higher share of renewables [3]. The financial crisis has been acknowledged to having slowed down efficiency progress, a situation that will be prolonged with the health crisis caused by the COVID-19 pandemic. Overall, there is not a single and widely acknowledged indicator of energy efficiency and this can only be revealed through reduced energy consumption (conservation). On the other hand, we need to remember that there is not a single index to measure energy efficiency, and this can only be perceived through a combined overview of the energy intensity reduction, energy consumption reduction and energy savings [3]. Taking into account the fact that energy efficiency (through the aforementioned dimensions) is at the foreground of energy policy and the political and economic agenda worldwide, it is no doubt because the energy-growth nexus economics field remains timely despite the controversy in its results and the lack of consensus [4,5].

At the same time, the 17 sustainable development goals which were stipulated by United Nations in 2015 and have been included into the UN 2030 Agenda, do connect directly or indirectly to energy matters in at least four of the goals; the 7th goal is about affordable and clean energy, the 11th goal is about sustainable cities and communities, the 12th goal is about responsible consumption and production, and the 13th goal is about climate action. On top of that, the evolution of New Economics have introduced new perspectives in the real measurement of wellbeing which take into account all sustainability goals and many additional aspects in order to establish a measure of real wealth that could be juxtaposed to the conventional measure of the Gross Domestic Product (GDP). The usage of a sustainable GDP in place of the traditional GDP in the energy-growth nexus research field will enable comparisons between the effects of energy conservation on welfare. Societies need the knowledge of the trade-off between the reduction of energy consumption and the effect on their wellbeing.

Hypotheses encountered in the conventional energy-growth nexus are the following four:

- Growth Hypothesis: Energy consumption Granger causes GDP growth. This signifies an economy much reliant on energy consumption for its growth. It is applicable to early industrial economies which applied emphasis on their economic growth at all costs and this energy consumption has caused environmental degradation.
- Feedback Hypothesis: Energy consumption Granger causes GDP growth and vice versa. GDP growth Granger causes energy consumption. This causal relationship denotes a circle of coupling between energy consumption and economic growth. This circle cannot be interrupted unless structural changes and conservation technologies are adopted in economies.
- Conservation Hypothesis: GDP growth Granger causes energy consumption. Thus with proper structural and technological correction, conservation is feasible without interrupting economic growth.
- Neutrality Hypothesis: No causal relationship is observed between GDP growth and energy consumption. This situation can be met in either very rich and advanced economies or basic rural societies in poor countries, in which production is evolved for the maintenance of a subsistence level, but not for the sake of economic growth and wealth accumulation.

New considerations encountered in the sustainability extended energy-growth nexus are suggested as follows:

- If energy conservation affects both GDP growth and sustainable economic growth, societies should think of procrastinating energy conservation until further renewable energies penetration becomes feasible.
- If energy conservation affects GDP growth but not sustainable economic growth, the conservation adaptation will be less painful in terms of wellbeing. If societies are focused on wellbeing rather than growth, then this situation may not be problematic.

- If energy conservation affects neither conventional GDP growth, nor sustainable GDP growth, then it safely takes place with no repercussions on growth.
- If energy conservation does not affect GDP growth, but affects sustainable economic growth, then this situation needs a lot of consideration for the identification of possible rigidities that may be causing such a result.

This paper summarizes and compares results of different studies in the energy-sustainable growth nexus for various groups of countries around the world and compares the results with the respective conventional energy-growth nexus studies.

The rest of this paper is organized as follows: The current part (Section 1) is the introduction, Section 2 is the background material, Section 3 briefly refers to the employed methodologies in each paper, Section 4 summarizes and discusses the results of the different studies, while Section 5 offers the conclusion.

2. Background Material on Sustainable Economic Growth

The relationship between energy and sustainable economic development is studied with various indexes. For example Zhang and Su [6] study the rural household energy sustainable development in China with a composite indicator. Wang et al. [7] have also constructed a composite indicator for energy sustainable development in China. On the other hand, in the energy-growth nexus, Esseghir and Khouni [8] insert a focus on the discussion on sustainability, though without using a specific index in that aspect. The ISEW indicator for Europe has not been applied before within the energy-growth nexus.

The energy-growth nexus concerns the papers studying the relationship between energy consumption and economic growth and the direction of causation among the variables which best describe how an economy functions. Until recently, the literature until has not been unanimous but is rather controversial. A big picture of that situation has been provided in Kalimeris et al. [9]; Menegaki [10] and Ozturk [11]. Economic growth in most of these papers has typically been shown with GDP per capita. In different cases in which these papers performed a sector analysis rather than a country–economy as a whole, other proxies were employed for economic activity, such as industrial production which has been employed in the study by Marques et al. [12]. Overall, energy-growth studies mainly aim to discover the role of energy consumption as a factor of production in an economy. Therefore, they draw conclusions about the sensitivity of economic growth to various energy policy tools, which aim to make the economy rely less on energy consumption and consequently produce less greenhouse emissions, resulting in less fossil fuel resources depletion.

As aforementioned, these studies typically place the GDP per capita variable in the position of the dependent variable, while the independent variables are basic drivers of production, such as capital formation, labour, greenhouse gas emissions, energy consumption, electricity consumption, or production, trade etc. The elasticities of these magnitudes, with respect to GDP, constitute important information for policy making in each economy or groups of economies. However, given the principles of the so-called "New Economics" and their base of genuine progress and sustainable economic welfare and sustainable GDP, we agree that the energy-growth nexus research is rather short sighted, because it does not say anything about the genuine effect and the contribution of energy consumption on sustainable economic welfare.

In order to explain the aforementioned statement in a better way, we mean to suggest that: The GDP of each country has a different base and is generated in ways that may have different effects on human welfare. Therefore, a high-income country may have generated excessive pollution and induced extreme urbanization, accompanied by a low quality of life or family breakdown caused by the extended working hours of the working force. The list of the negative effects is rather long in this respect. Conversely, a less developed economy, usually accompanied with a lower GDP per capita, may have a cleaner natural environment, more essential human bonds, less family disintegration, and generally consist of people who enjoy their wellbeing and existence more. Furthermore, an industrialized country generates more environmental degradation than a country that produces services.

Petrochemical activities, construction, or agriculture are usually very polluting activities in an economy. Next, we provide the energy intensity of GDP for an indicative set of countries across the world (Table 1). The differences in intensity reflect the different structure of the GDP in each country with the participation of energy.

Table 1. Energy intensity of GDP across the world.

Country	Energy Intensity (koe/%15p)
Colombia	0.057
United Kingdom	0.058
Turkey	0.06
Portugal	0.064
Italy	0.064
Romania	0.066
Spain	0.067
Mexico	0.069
Germany	0.07
Egypt	0.07
Indonesia	0.071
Japan	0.076

Source: Enerdata.net [13]. Note: koe stands for kilogram of oil equivalent.

GDP does not distinguish economic activity that improves welfare from the one that reduces welfare [14]. This and other drawbacks of the GDP as a measure of wellbeing and genuine comprehensive progress, had been acknowledged from the day it was established. For instance, GDP disregards transactions performed in the unofficial and unrecorded economy. Nevertheless, these transactions are consuming energy capital and labour. These transactions are not recorded in the official accounts of the economy thus, they do not appear to generate income, but they consume energy, capital and contribute to the generation of pollution.

The same applies with market failures from environmental and social externalities that are not reflected in the GDP but contribute to the depletion of resources and formal capital. Furthermore, these externalities may inflate the GDP with much defensive expenditure, which arise from disservices generated from the externalities [15]. For example, a poor road network (this is capital) may be one of the reasons for a high number of car accidents and fatalities. The expenditure incurred to have cars repaired or people hospitalized should not be measured as GDP. This rationale of New Economics [16] that has started permeating the modern economic world, brings forward the need to re-examine the relationship of the conventional energy-growth nexus by focusing on income indicators that are as inclusive as possible.

Until today, and from what we do know from the literature, very little research has been devoted on this new promising area. For example, You [17] has employed genuine savings instead of the GDP variable and concludes that renewable energy increases China's genuine savings, while fossil energy contributes to the increase of GDP growth. Genuine savings is a variable readily available by international statistical agencies. Conversely, the ISEW explained in this paper and applied in the energy-growth nexus (in all the reviewed papers) is a more comprehensive indicator because it included data from all the three sustainability fields: economic, environmental, and societal.

The Construction of the Index for Sustainable Economy

Welfare is a controversial and multi-aspect concept. Therefore, a comprehensive indicator is needed to reflect it. Some of the aspects of welfare are the following: living standards (housing conditions, housing area, size etc.), health, the feeling of neighbourhood, education, time use, democratic engagement, leisure, culture, environment, public infrastructure, natural resources, emissions, equal access to resources and their sustainable use; corruption and transparency, waste assimilation capacity, sustainable consumption and production, demographics, recycling rates, adult literacy, mean duration of schooling, knowledge, social relations, climate change (extreme weather phenomena), urban sprawling, commuting, noise pollution, globalization, volunteerism, criminality, unemployment costs, loss of farmland and wetland, net foreign borrowing, happiness (happy life years), peace, and safety.

As we understand, some of the above aspects are tangible and some are not. From the tangible dimensions some of them have not yet been measured. The immaterial ones are mainly psychological aspects that may lead to happiness and wellbeing. It is more difficult to calculate the value of the immaterial ones than the material or tangible ones. There are means to calculate intangibles, such as revealed or stated preference techniques. However, even if their value has been estimated for one economy, there is no institutional tool to impose or even encourage other economies to do the same. Therefore, cross country comparisons cannot be made if there is no cross-country agreement on the calculation of those values. This increases the difficulty of the calculation of a complete ISEW, which can host all possible parameters affecting human wellbeing within an economy. Countries that have made a lot of institutional progress have had more progress in advanced statistical data keeping while others with low institutional development have not managed to do this.

The convention held by the European Commission, entitled "2007 Beyond", has presented a series of 24 similar indicators. Each one of them deals with a different and specific aspect of human welfare. However, none of them is so comprehensive and inclusive, something which would make an ideal indicator. For instance, the adjusted net savings (ANS) or genuine savings, the capability index, (according to which, the quality of life is defined by what people achieve with their resources), the ecological footprint indicator (which evaluates the balance between the demand and supply for renewable resources in a certain population or economic activity and the capacity to assimilate waste), the environmentally sustainable national income-ESNI (defined by the number of years that a certain economy with its current production capacity is away from an ideal benchmark that is considered to be sustainable), the human development index-HDI (which measures life-span and years of healthiness, together with access to education and knowledge and a decent standard of living that does not deprive one of basic facilities and goods), the Happy Planet Index- HPI, (ratio of the product of the experienced welfare and life expectancy to the ecological footprint) as well as many others. Goosens et al. [18] distinguish these indicators and place them into three categories: those replacing GDP, those supplementing GDP, and those adjusting it. The ISEW belongs to the ones which are adjusting GDP to reflect the experienced welfare.

The first version of the ISEW was generated by Daly and Cobb [19] for the US and then was further improved in 1994. There are both numerous supporters and opponents of the ISEW. The index has received a lot of criticism for measuring welfare and sustainability together within one index [20] and for the way it treats stocks and flows methodologically [21]. Responses to the former criticism state that the ISEW indicator is an aggregate indicator for both current and future wellbeing. Future welfare is an aspect of utility for the current generation. The latter receives satisfaction from knowing they will not damage the utility of their descendants [22]. This was additionally supported by Lawn [23]. He drew principles from Irving Fisher's "net psychic income" and he explains why each component in the ISEW contributes to the psychic income. Despite the hesitations stated by the ISEW opposers, the existent ISEW is better than nothing (Lawn and Clarke, [24]). This is explained by the fact that the Index has covered a lot of distance to the measurement of sustainability but not all of that. Posed in a different way by Posner and Costanza [25], it is better to be approximately correct than completely wrong. Bleys and Whitby [26] report some of the most important obstacles and opportunities in the calculation of the ISEW.

From what it is known, the calculation of the ISEW has been sparsely implemented only for several European countries: regional Italy [27], Belgium [28], France [29] and Greece [16]. Therefore, the official expression of the proposed ISEW in the reviewed papers here, is described in Equation (1):

$$\text{ISEW} = \text{Cw} + \text{Geh} + \text{Kn} + \text{S-N-Cs} \tag{1}$$

where Cw denotes the weighted consumption, Geh denotes non defensive public expenditure, Kn stands for the net capital growth, S stands for the unpaid work benefit, N stands for the depletion of natural environment and Cs denotes the cost from social problems, which has not been taken into account in the calculations of the reviewed papers due to lack of proper data. Understandably, environmental, or ecological degradation is a wide concept which encompasses many more problems, for which, however, we had no data available to rely on. For instance, the cost of water pollution or the cost of the loss of land and wetlands is not readily published in the publicly available official databases that are usually employed, namely Eurostat, OECD, and World Bank. The same applies for the lack of reliable social data. Since we have not been able to include costs from social problems, Equation (1) is simplified to Equation (2), as demonstrated by Menegaki and Tugcu [30] and Menegaki and Tiwari [31] and the rest of the reviewed papers:

$$\text{ISEW} = \text{Cw} + \text{Geh} + \text{Kn} + \text{S-N} \tag{2}$$

The method approach in Equations (1) and (2) is also recommended in [18] Gigliarano et al. [27], Menegaki and Tsagarakis [32]. The first two papers concern regional Italy and have included a large variety of available environmental and social data. However, in the reviewed papers contained in this study, this has not been possible. Thus, in each of the reviewed papers first, we have calculated the ISEW for the sampled countries and then we have estimated the conventional energy-GDP growth and new energy-ISEW for those countries, where it was feasible upon data availability for the variables, setting up the energy-growth nexus for the countries the study was focusing on each time. Table 2 explains the details of the calculation and the origin of the data in the sampled papers. Please note that since the current paper is a review of past published papers, new methods of calculation of the involved ISEW components have been evolved. The future researcher must take that into consideration. For example, it would be interesting to recalculate the index with the cost of carbon being \$100 or \$200/ton [7,28]. The same applies with the cost of renewable energies, which is reduced over time as technology improves.

Table 2. The ISEW components, sign, calculation methods and data sources as it has been originally presented in the reviewed papers.

Component	Sign	Calculation Method	Source/Available from
1. Adjusted personal consumption with durables (C_w)	+	We multiplied personal consumption and durables' expenditure (PC) with Gini coefficient (G) and poverty index (P) as: PC × (1 − G) × (1 − P)	PC: http://data.worldbank.org/indicator/NE.CON.PRVT.CDT.CD. (accessed on 1 January 2015) Gini coefficient: http://data.worldbank.org/indicator/SI.POV.GINI. (accessed on 1 January 2015) Poverty index (headcount ratio): http://data.worldbank.org/indicator/SI.POV.2DAY. (accessed on 1 January 2015)
2. Education expenditure (G_{eh})	+	Public expenditure on education(current operating expenditures in education, including wages and salaries and excluding capital investments in buildings and equipment). Assuming that half of it is defensive, we multiply this amount with 50%.	http://data.worldbank.org/indicator/NY.ADJ.AEDU.CD. (accessed on 1 January 2015)
3. Health expenditure (G_{eh})	+	Public health expenditure is also multiplied with 50% for the same reason as above.	http://data.worldbank.org/indicator/SH.XPD.PUBL. (accessed on 1 January 2015)

Table 2. *Cont.*

Component	Sign	Calculation Method	Source/Available from
4. Net capital growth (K_n)	±	We have used data on fixed capital accumulation (FCA). We subtracted consumption of fixed capital(CFC) to find the net capital and then calculated its growth rate.	FCA: http://data.worldbank.org/indicator/NE.GDI.TOTL.CD. (accessed on 1 January 2015) CFC: http://data.worldbank.org/indicator/NY.ADJ.DKAP.CD. (accessed on 1 January 2015)
5. Mineral depletion (N)	−	Mineral depletion is the ratio of the value of the stock of mineral resources to the remaining reserve lifetime (capped at 25 years). It covers tin, gold, lead, zinc, iron, copper, nickel, silver, bauxite, and phosphate.	http://data.worldbank.org/indicator/NY.ADJ.DMIN.CD. (accessed on 1 January 2015)
6. Energy depletion (N)	−	It is the ratio of the value of the stock of energy resources to the remaining reserve lifetime (capped at 25 years). It covers coal, crude oil, and natural gas.	http://data.worldbank.org/indicator/NY.ADJ.DNGY.CD. (accessed on 1 January 2015)
7. Forest depletion (N)	−	Net forest depletion is calculated as the product of unit resource rents and the excess of roundwood harvest over natural growth.	http://data.worldbank.org/indicator/NY.ADJ.DFOR.CD. (accessed on 1 January 2015)
8. Damage from CO_2 emissions (climate change-long-run environmental damage) (N)	−	It is estimated to be $20 per ton of carbon (the unit damage in 1995 U.S. dollars) times the number of tons of carbon emitted. World bank estimations are based on Samuel Fankhauser's "Valuing Climate Change: The Economics of the Greenhouse" (1995).	http://data.worldbank.org/indicator/NY.ADJ.DCO2.CD. (accessed on 1 January 2015)

Note: This type of the ISEW calculation has been applied by Menegaki and Tsagarakis [27]. The notation following the definition of components in this table, is the one represented in Equation (2).

3. Methodology

The current section will provide a summary of the methodologies used in the series of papers the current review focuses on. Those methodologies are varied depending on the different characteristics of the data and the diagnosed problems. The section is further divided into three sub-sections on unit root testing, cointegration and causality, respectively. The section serves an informative purpose because the current study is a review of previous studies and not a new empirical one. Thus, this section does not describe the employed methodologies from scratch as this can be done in the relevant original papers. These papers are: Menegaki and Tugcu [33], Menegaki et al. [34], Menegaki and Tugcu [35], Menegaki and Tiwari [31], Menegaki and Tugcu [17], Menegaki and Tugcu [30].

3.1. Unit Roots Testing

Testing for unit roots is the first stage in every study in the energy-growth nexus. First, the study by Menegaki and Tugcu [35] in page29, uses the cross-sectionally augmented IPS test for the investigation of unit roots in cross-sectionally dependent data. Previously, in page 29–31 they have used the Pesaran CD test [36], Pesaran scaled LM test [36] and Baltagi et al. [37] bias-corrected scaled LM test. The presence of cross-sectional dependence was confirmed in three out of four statistics. Second, the study by Menegaki et al. [34] in page 1261 has employed ADF Fisher, PP Fisher (Maddala and Wu, [38] and Choi, [39]) and CIPS (Zt-bar) test (Pesaran, [40]). Third, the study by Menegaki and Tugcu [35] has employed the Pesaran IPS and GIPS (Pesaran et al. [40]) test in page 896 in constant and constant and trend versions. Fourth, the study by Menegaki and Tiwari [31] in pages 499–500 employs a battery of unit root tests such as the Levin et al. [41], the Im et al. [42], the augmented Dickey-Fuller test [43] the Phillips-Perron test [44] and the Breitung *t*-test [45] Hadri Z-test [46] and Heteroskedastic consistent Z test. Fifth, the study by Menegaki and Tugcu [30] in page 81 tests panel unit roots with Im et al. [41] and Choi [47]. None of the variables was stationary at levels, so they took first differences. Sixth, the study by Menegaki and Tugcu [33] in pg 156 has also used the augmented IPS (Pesaran, [48]), after acknowledging the existence of cross-sectional dependence (Pesaran, [40]).

3.2. Cointegration

Accordingly, this sub-section describes the type of cointegration analysis employed in each of the sampled studies. First, the study by Menegaki and Tugcu [33] in page 31 used a panel cointegration procedure developed by Westerlund [49] which considers the cross-sectional dependence that has been previously acknowledged. Second, the study by Menegaki et al. [34] in page 1261–1262 employed the ARDL cointegration framework which directly hosts both short run and long run relationships. Third, the study by Menegaki and Tugcu [35] in page 897 (Table 4 in the referenced paper) uses the panel ARDL model with a Pooled Mean Group (PMG) estimator. The advantage of this estimator is that it allows the intercepts, the short run coefficients, and error variances to differ across groups of countries, but it constraints the longrun coefficients to be the same. Fourth, the study by Menegaki and Tiwari [31] in pages 501–502 applies the Pedroni cointegration test [50] and based on evidence from the Hausman test they have decided in favour of a dynamic fixed effects model to depict the cointegration relationship estimated with a Generalized Method of Moments (GMM), which revealed that there was no problem of autocorrelation. They have also employed a quantile regression to corroborate the previous results. Fifth, the study by Menegaki and Tugcu [32] in page 83 has also used the Westerlund [49], whereby the underlying idea is to test for the absence of cointegration by determining whether the individual panel members are error correcting. Over the long run, cointegration is employed to investigate whether the variables move along the same path. The confirmation of cointegration also indicates the existence of a causality relationship at least in one direction of the relationship. Menegaki and Tugcu [30] in page 157 have used the Pedroni [51] cointegration with seven test statistics. Four out of the seven statistics are estimated based on pooled data across countries, and three out of the seven are based on averages of the individual autoregressive coefficients for each country.

3.3. Causality

The causality analysis is usually the last step in the energy-growth nexus studies. Causality analysis is necessary to reveal the direction of the causal relationship, which is not revealed in the cointegration analysis. This sub-section provides information as to which causality methods have been employed. First, the study by Menegaki and Tugcu [33] in page 31–32 have employed the Dumitrescu and Hurlin [52] to examine the panel causality context in their data. Second, the study by Menegaki and Tiwari [31] in page 1264 employed panel VECM Granger/Block exogeneity Wald tests. Third, Menegaki and Tugcu [35], within their ARDL approach, have separate long run and short run effects through the elasticities and semi-elasticities in page 897. Fourth, the study by Menegaki and Tiwari [31] in page 503 employs a VECM Granger causality/Block exogeneity Wald tests. Fifth, the study by Menegaki and Tugcu [27] in pages 84–85 has used Konya [53] which is a bootstrap panel Granger causality test and is examined as a set of SUR (seemingly unrelated regression). This test relies on the lag structure and hence this should be carefully decided. Sixth, the study by Menegaki and Tugcu [30] in page 157 has employed a pairwise Granger causality test.

4. Results and Discussion

This section provides summary results of the major and focal points reached in each study about the relationship of energy consumption and sustainable economy vis-a-vis the results from the conventional energy consumption and GDP growth.

Study 1: Sustainable economic growth and energy consumption in Asian countries

[Full study can be found at: Menegaki, A.N., Tugcu, C.T., 2018. Two versions of the Index of Sustainable Economic Welfare (ISEW) in the energy-growth nexus for selected Asian countries. Sustainable Production and Consumption 14, 21–35]

This study has separated energy consumption into renewable and non-renewable. It has also used international trade, natural resources rents, financial development, and the consumer price index as covariates. The dependent variable was sustainable economic growth in two versions: "loose" and "strict". The used data ranged from 1990 to 2015. The results have revealed a bidirectional relationship between each of the two versions of sustainable economic growth and the rest of the covariates as well as between GDP growth and the rest of the covariates. There is only a unilateral relationship between the strict version of sustainable economic growth and international trade, but that was not significant at 5%.

Particularly, there is a bidirectional relationship between economic growth and energy consumption (either renewable or non-renewable) and between sustainable economic growth and energy consumption (either renewable or non-renewable). Thus, the Feedback Hypothesis is overall supported and this shows that energy conservation will negatively affect conventional and sustainable economic growth. The latter will then affect energy consumption and this dependence is mutual and of a spiral type. This constitutes some evidence that economic growth (not least the sustainable one) is coupled with energy consumption and without it, it will be fragile. Asia has achieved very high economic growth rates in recent years but has not managed to correct the inequalities. Environmental degradation could not be escaped and, therefore, Asian countries belong to the 70% of the world's most vulnerable countries in front of climate change. Based on the parameters constituting the sustainable economic growth, it is apparent that Asian countries are also characterized by poor performance in vital indicators, such as public health expenditure. The progress in major energy goals, such as the improvement in the electrification rates, the increased penetration of renewable energies, and particularly the progress in energy efficiency have not been able to support the required structural change that would enable the confirmation of the conservation or neutrality hypotheses. The latter, if confirmed, signal the existence of energy decoupled economies which are more sustainable. It is interesting to reflect on the result of the Feedback Hypothesis between sustainable economic growth and energy consumption, which shows that energy consumption Granger causes sustainable growth. This has ramifications on the Environmental Kuznets Curve Hypothesis, according to which developing economies cannot help degrading the environment at the first stages of their development until a point is reached, which is the turning point of the EKC, where economies actively start improving their natural environment. Overall, it would be an interesting point of further research to corroborate the findings of the energy-sustainable growth nexus with relevant findings from the EKC curves. One of the most striking implications from the results in the Asian group of countries is that governments need not take different measures for conventional and sustainable economic growth, given that their Granger causal behaviour appears the same.

Study 2: Sustainable economic growth and energy consumption in Europe

[The full study can be found at: Menegaki, A.N., Marques, A.C., Fuinhas, J.A., 2017. Redefining the energy-growth nexus with an index for sustainable economic welfare in Europe. Energy 141, 1254–1268]

Detailed results from this study can be found in Menegaki et al. (2017). The study has compared the causal behaviour between conventional economic growth with energy consumption and sustainable economic growth with energy consumption from fossil fuels and renewable resources. Covariates have used the following variables: financial sector, carbon emissions, labour, electricity produced from renewables, electricity produced from non-renewables, capital, exports, natural resource rents and inflation.

Short run causality analysis has revealed bidirectional causality between energy consumption and sustainable economic growth. Sustainable economic growth also positively affects labour, exports, financial development, rents, electricity produced from renewable, and electricity produced from non-renewables. Energy consumption also positively affects inflation, carbon emissions, labour and capital. The corresponding analysis with conventional economic growth has revealed similar causation findings, except for the variable of labour; the latter was not significant in the conventional economic growth framework.

As far as the negative contribution of the rents to economic growth (conventional or sustainable) is concerned, it has been captured in literature (Fuinhas et al., with a negative sign for specific natural resources, such as oil production. This may be attributed to the high dependence on these resources which allow rent earning, but at the same time hinder the diversification of productive structures of these countries. Nevertheless, this effect is very small in this empirical study, because European countries rely much less on oil production for revenues. Inflation was significant only in the conventional economic growth framework, which may be an indication that sustainable economic growth is robust to price fluctuations. The effect of inflation on conventional economic growth has also been documented in Asia has achieved very high economic growth rates in recent years but has not managed to correct the inequalities Asia has achieved very high economic growth rates in recent years but has not managed to correct the inequalities.In countries with high inflation, businesses suffer, and their operational environment is not favourable. Regarding the significance of labour in the sustainable economy, we need to remember that the reporting for conventional economic growth does not take into account the contributions of unofficial labour and the disservices from unemployment. Therefore, the latter acknowledgements throw some light as to why labour appears significant in the sustainable economy and not the conventional economic growth.

A result that causes scepticism is the positive significance of fossil fuelled electricity only in the conventional economic growth model. This finding is in line with previous literature which supports that renewables hamper economic growth. The current study corroborates this, given the significant negative sign of renewables in the sustainable economic growth framework. The larger coefficient estimated for capital in the welfare nexus than the conventional one shows that shocks, such as the financial crisis which entailed severe investment cuttings, could compromise the implementation of sustainable development in Europe. Sustainable economies need to increase or renew their capital base. Overall, the small differences between the welfare and the economic framework show that these frameworks are not perfect substitutes.

Study 3: Sustainable economic growth and energy consumption in G7 countries

[The full study can be found at: Menegaki, A.N., Tugcu, C.T., 2017. Energy consumption and Sustainable Economic Welfare in G7 countries; A comparison with the conventional nexus. Renewable and Sustainable Energy Reviews 69, 892–901]

G7 countries play important roles in the global political and economic scene. Their decisions affect the global financial architecture, and they are usually regarded as exemplar policy actors by developing countries. The study on G7 countries has employed capital, labour, and research and development (R&D) expenditure as a proxy for education and energy consumption. The sustainable economic growth has assumed two versions: "light" and the "strict".

The Feedback Hypothesis is confirmed only between strict sustainable economic growth and energy consumption, while between the light sustainable economic growth and energy consumption we observe the Conservation Hypothesis. The same hypothesis is also confirmed in the GDP framework. The rest of the covariates all have a positive significant effect, except for labour with a negative sign in the strict welfare and energy consumption, which enters with a negative sign in the light welfare framework.

Based on the results derived from this set of countries, G7 most likely will be resilient to energy conservation measures and their sustainable development progress will not be hindered. Within the framework of the strict welfare, G7 economies show a feedback behaviour which means that resilience is not strong enough.

Study 4: Sustainable economic growth and energy consumption in American countries

[The full study can be found at: Menegaki, A.N., Tiwari, A.K., 2017. The index of sustainable economic welfare in the energy-growth nexus for American countries. Ecological Indicators 72, 494–509]

This study is based on data from 1990 to 2013 on 20 American countries. These data are: labour, capital, carbon emissions, energy use, renewable energy, rents, and trade. This study examines the relationship between energy consumption and economic growth (conventional and sustainable). Results do not reveal a relationship between energy consumption and growth whatsoever, but they clearly provide support for the Growth Hypothesis between renewable energy and GDP growth. On the other hand, results also support the Feedback Hypothesis between renewable energy sustainable economic growth. Another important finding is that the speed of adjustment for GDP growth is -0.380, while for the sustainable growth, it is -0.625. This entails that if the equilibrium situation in each case is perturbated, the sustainable growth can come to equilibrium at a higher speed (almost double) than the GDP growth.

As far as the energy consumption variable is concerned, this variable is only affected by capital under the sustainable economy framework. Renewable energy resources are affected by trade under both frameworks (GDP growth and sustainable economy). Had we stayed with conventional analysis in the first place, the non-existence of Granger causality between energy and GDP would have been mistaken for the Neutrality Hypothesis. In such a situation conservation measures on energy are not expected to retard economic growth. Contrary to this, the additional information we receive from the renewable energy-sustainable economy, namely the confirmation of the Feedback Hypothesis, provides a useful warning for policy makers: Therefore, applying conservation measures in renewable energy consumption will eventually cause a de-growth result and this, in turn, will impact on the development of renewable energies and it will slow down their penetration in the American countries.

Last, but not least, the results from Menegaki and Tiwari [31] inform us in the sustainable economy framework that the same amount of energy or renewable energy Granger causes a smaller effect on sustainable economy than the GDP economy. This is a sound indication that the sustainable economy is more stable and less prone to the fluctuations that can be caused by the application of energy conservation measures.

Study 5. Sustainable economic growth and energy consumption in emerging economies

[The full study can be found at: Menegaki, A.N., Tugcu, C.T., 2016. The sensitivity of growth, conservation, feedback & neutrality hypotheses to sustainability accounting. Energy for Sustainable Development 34, 77–87]

The study is based on 15 emerging economies and uses two versions of sustainable economy. The light and the strict version of sustainable economic growth vis a vis the conventional economic growth as denoted by the GDP growth. Thus, besides the aforementioned variables, the rest of the employed variables are capital, labour, openness of economy (imports and exports) and of course energy consumption. Based on the estimated results, in 8/15 countries, the confirmed hypothesis does not vary between the conventional growth framework and the sustainable economy (strong version). For 13 out of 15 countries, the same hypothesis is observed between the basic and the solid version of sustainable economy. For 8 out of 15 economies the same hypothesis is observed between GDP and the two versions of sustainable economy. Different causalities between the light and strong version of the sustainable economy are noted only for Poland and South Africa. Moreover, Brazil and Malaysia confirm the Feedback Hypothesis in the GDP framework, while for the sustainable economy framework the Growth Hypothesis is supported. Thus, had policy makers ignored the different results applicable between the conventional and the sustainable economy, it would have resulted in the possibility of changing energy consumption by changing welfare. A different situation applies for Colombia and Indonesia. The Growth Hypothesis applies in the GDP economy, while the Feedback Hypothesis applies for the sustainable economy. The latter entails that conservation measures will have repercussions on sustainability and, in turn, on energy.

Study 6. Sustainable economic growth and energy consumption in Sub-Saharan countries

[The full study can be found at: Menegaki, A.N.; Tugcu, C.T. Rethinking the energy-growth nexus: Proposing an index of sustainable economic welfare for sub-saharan africa. *Energy Res. Soc. Sci.* **2016**, *17*, 147–159]

The African region has been in the foreground of the summits of G8 since 2000. Due to its socio-economic and environmental characteristics, this region can play an important role for combating climate change. Thus, the way official assistance, with respect to energy is designed, is important, and such studies can inform policy making towards the right decisions. The study is based on 42 countries within the data span between 1985 and 2013. Besides GDP growth, sustainable economy growth, and energy consumption, the following variables are used: capital, carbon emissions, trade, and inflation. Granger causality results have provided support for the Feedback Hypothesis between energy consumption and the sustainable economy growth. A similar bidirectional relationship has been confirmed between capital and sustainable economy and between trade and sustainable economy. Moreover, we note a unidirectional Granger causality running from sustainable economy to rents and from carbon emissions to sustainable economy. The support for the Feedback Hypothesis between sustainable economy and energy consumption means that each magnitude affects the other and no conservation measures can take place without compromising sustainability. According to Menegaki and Tugcu [11], this finding can be expected to occur in the context of underdeveloped or developing economies which are in need of a minimum threshold of energy consumption that cannot be avoided, and it will put the sustainable economy on track. Thus, it may be the case that it is too early for the studied countries to be controlled in their energy consumption.

5. Concluding Remarks

The new trend of economic thinking and planning, with respect to sustainable economic growth and not the traditional economic growth as revealed by GDP, has led to the investigation of the so called energy-growth nexus from this new perspective. The current paper summarizes the gist causality results from a series of six studies which have been devoted to the investigation of the energy-sustainable economic growth relationship in various groups of countries worldwide. While the idea was first applied to a set of Sub-Saharan countries, mainly because it was a region suffering from poverty and because of the role it could play in the global sustainability, the interesting results the first study reached gave the initiative for the gradual study of an additional set of countries, covering almost the whole world.

Nowadays, besides the abundant studies in the conventional energy-growth nexus field which have been implemented for various single countries and groups of countries, there are a number of studies dealing with the relationship between energy consumption and a sustainable economy. A striking result is that almost all studies, and thus all country sets, provide support for the Feedback Hypothesis between energy consumption and sustainable economy. Despite the different econometric methods and the different timespans and covariates, the studies end up resulting in the same common finding, namely the bidirectional causal relationship between energy consumption and sustainable economy, which entails that sustainability cannot be yet achieved with energy conservation. Despite energy conservation being an action towards sustainability, energy consumption is still much required for the implementation of a sustainable economy. It is most surprising that this result is apparent worldwide with no differentiation between developed and underdeveloped countries. This might reflect the many dimensions of the sustainability agenda, such as the late and insufficient adoption of renewable energies by most countries due to their high cost, and the only recent adoption of circular economy practices, climate change mitigation etc. Generally, the worldwide evidence of the Feedback Hypothesis in the energy-sustainable economy relationship is a signal that sustainability requires a major structural transformation of economies, which is both energy and fossil energy intensive.

Of course, it is understood that the sustainable economy index that the series of studies has employed is far from perfect. However, the criticism received for the Index of Sustainable Economic Welfare is widely known, but still the lack of a better index allows withstanding of this criticism. Next, the main conclusions derived from the sampled studies are presented and compared.

5.1. Study 1 (Asia)

Contrary to other country groups, in the group of Asian countries no different implications appear for economic growth, either conventional or sustainable. Thus, policy makers in the energy sector can apply a uniform energy policy. However, since conservation measures will restrain growth generally, it would be advisable that the policy makers refrain from that altogether. This may be due to the fact that Asian countries in our sample are developing countries, and this entails that that they have not yet reached the time point at which they can decouple their growth from energy consumption.

5.2. Study 2 (Europe)

Particularly for the European sample of countries, the positive effect of capital investment is larger in the sustainable nexus than the conventional, which reveals that when economies are faced with financial shocks, such as an economic crisis, reducing investment can also reduce sustainable economic growth. Significant differences exist between the long and short run in the energy-growth relationship of European countries. In the short run, conservation policies put more strain on the GDP rather than the sustainable economy. The opposite applies for the long run horizon. As far as the comparison of results in the conventional energy-growth nexus is concerned, the positive effect of capital investment is lower in the conventional energy-growth nexus as compared to the sustainable one. This highlights the importance of not cutting down on investment, a fact that can seriously delay sustainable growth. Despite this, the study reveals that sustainable growth also affects energy consumption, both in the short and the long run. Thus, energy conservation policies, albeit taking place in the short run, bear long-term implications.

5.3. Study 3 (G7 Countries)

G7 are the seven richest economies, so it is important to observe the energy-growth relationship in them. Basic sustainable growth (as a separate sustainability indicator and defined in the relevant study) is affected negatively by energy consumption, which is some evidence that G7 countries have reached a point in their history of economic growth and development where additional energy consumption can do no better. The same is not suggested with conventional economic growth however, and this underlines the importance of studying these two contexts together (the conventional energy-growth model with the sustainable economy-growth model). In this relationship the energy-growth is mutually caused by each other, thus any energy conservation measures will bring economic growth to a halt. This case study reveals that sustainable economic growth is more fragile in G7 countries than in the Asian or European ones. This may be due to the fact that the seven richest countries have relied much on energy consumption and environment exploitation in order to reach their high growth level.

5.4. Study 4 (American Countries)

In the American group of countries, we find that energy does not affect either type of economic growth. While this lends support for the Neutrality Hypothesis, the picture is different in the separate case of the effect of renewable energy, unveiling a feedback hypothesis which entails that renewable energy conservation will lead to a de-growth of American economies. The situation revealed in this case study is quite different from all the above cases and with no implications for policy making, because it appears that growth is not dependent on energy consumption. The structure of the economy is different and probably with an advancement in energy efficiency which enables growth decoupled from energy. Thus energy conservation will bear no negative consequences for growth.

5.5. Study 5 (Emerging Economies)

This study suggests caution towards the results received between the different versions of sustainable GDP and the different results reached when comparing the conventional energy-growth nexus with the sustainable energy-growth nexus. It is understandable that the constructed ISEW is far from perfect and has been built based on the available information concerning basic sustainable GDP components. The method used in this study enables reaching results for each country separately. In nine countries, causality results are stable across the conventional growth and the different definitions of sustainable growth that are identified in the study. These countries are Chile, China, Colombia, India, Mexico, Morocco, Philippines, Thailand, and Turkey. In the rest of the countries, there are different results, either between the conventional and sustainable aspect of growth, or between the different versions of sustainability. Hence, one cannot make comparisons between this group of countries and the rest stated in this review.

5.6. Study 6 (Sub-Saharan Countries)

For Sub-Saharan countries it is found that energy conservation policies will restrict sustainable development. Due to its characteristics, this region will play a fundamental role in combating climate change. The huge income inequalities in Sub-Saharan countries require the usage of a more comprehensive measure of economic growth, such as the sustainable GDP. This study has resulted in a bidirectional relationship between energy consumption and sustainable growth, which means that these two magnitudes fuel each other. On the other hand, no relationship is revealed between energy consumption and economic growth, which supports the existence of the Neutrality Hypothesis. Thus, energy conservation will negatively affect sustainable growth but will not affect conventional growth and thus must be taken into consideration by policy makers who pursue sustainability. Conversely to the American sample of studies, where neutrality is evidenced in both cases of economic growth (conventional and sustainable), the Sub-Saharan case study reveals that neutrality is the case only for the conventional economic growth and not its sustainable counterpart.

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Forecasting Natural Gas Spot Prices with Machine Learning

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Abstract: The ability to accurately forecast the spot price of natural gas benefits stakeholders and is a valuable tool for all market participants in the competitive gas market. In this paper, we attempt to forecast the natural gas spot price 1, 3, 5, and 10 days ahead using machine learning methods: support vector machines (SVM), regression trees, linear regression, Gaussian process regression (GPR), and ensemble of trees. These models are trained with a set of 21 explanatory variables in a 5-fold cross-validation scheme with 90% of the dataset used for training and the remaining 10% used for testing the out-of-sample generalization ability. The results show that these machine learning methods all have different forecasting accuracy for every time frame when it comes to forecasting natural gas spot prices. However, the bagged trees (belonging to the ensemble of trees method) and the linear SVM models have superior forecasting performance compared to the rest of the models.

Keywords: natural gas; spot price; machine learning; forecasting

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1. Introduction

Natural gas has been proposed as a solution to increase the security of the energy supply and to reduce environmental pollution around the world. It is the second most widely used energy commodity after oil [1]. With the replacement of coal and the widespread use of natural gas, gas spot price forecasting has become one of the most critical issues in many sectors. The accurate forecasting of natural gas spot prices is of high importance, as these forecasts are used in the energy market, in power system planning and in regulatory decision making, covering both supply and demand in the natural gas market.

Due to the significant economic results obtained from forecasting, many techniques have been explored and studied, especially in electric load forecasting, such as artificial neural networks (ANN), as seen in [2] and SVM, as seen in [3] and many other works. The current studies on energy market forecasting mainly focus on crude oil prices [4]. Thus, publications in the field of natural gas price forecasting are relatively rare [1].

One of the few studies that has tried to directionally forecast natural gas price movements for the U.S. market is that of [5], which analyzed trader positions published on a weekly basis. [6] forecasted gas prices one day ahead, but they relied on monthly forward products and futures instead of focusing on current prices. They combined wavelet transform (WT) with fixed and adaptive machine learning/time series models: multi-layer perceptron (MLP), radial basis functions (RBF), linear regression, and GARCH (Generalized Autoregressive Conditional Heteroskedasticity). According to their results, the best models for electricity demand/gas price forecasting are the adaptive MLP/GARCH.

Another study analyzing gas prices is that of [7]. They trained several nonlinear models with the aid of a Gamma test: local linear regression (LLR), dynamic local linear regression (DLLR), and artificial neural networks (ANN). They used daily, weekly, and monthly Henry Hub spot prices from 1997 to 2012. They concluded that the forecasting model of daily spot prices using ANN can provide an accurate view. Moreover, ANN models have superior performance compared to LLR and DLLR models.

Ref. [8] tried to determine whether natural gas future prices can predict natural gas spot prices. They used daily observations for the spot and futures prices for natural gas for all trading days between 1 January 1997 and 3 March 2014 collected from the U.S. Energy Information Administration (EIA) for a total of 4294 observations. According to their results, gas futures prices are not superior in forecasting natural gas spot prices when compared to a random walk (RW) model.

Ref. [9] compared the long-horizon forecasting performance of traditional econometric models with machine learning methods (neural networks and random forests) for the main energy commodities in the world: oil, coal and gas. Their results showed that machine learning methods outperform traditional econometric methods and that they present an additional advantage, which is the ability to predict turning points.

Ref. [10] combined machine learning methodologies (XGboost, SVM, logistic regression, random forests, and neural networks) with dynamic moving windows and expanded windows to forecast crises in the U.S. natural gas market for a period spanning from 1994 to 2019. According to their results, the best forecasting accuracy was achieved with the XGboost combined with the dynamic moving window, reaching 49% accuracy and a false alarm of no more than 25%.

Ref. [11] presented a literature survey of the published papers forecasting natural gas prices, amongst others. According to their survey, predicting the exact future evolution of natural gas price is impossible.

According to the literature review, it can be observed that machine learning methodologies produce higher prediction accuracy compared to standard econometric methods. Therefore, in this paper we trained models that have the potential to successfully predict gas prices. The models trained in this paper are the support vector machines (SVM), regression trees, linear regression, Gaussian process regression (GPR), and ensemble of trees models. We focus on the short-term forecasting of the natural gas spot price 1, 3, 5, and 10 days ahead, and we compare the effectiveness of the machine learning models in natural gas price forecasting with a random walk model.

For the training of the models, we used the lags of the natural gas spot prices and a set of 21 explanatory variables that were selected based on the relevant literature (for instance, [1,8,12]) and determined their ability to enhance the predictive ability of natural gas price forecasting. The selected variables were then fed into the forecasting models through a training–testing learning process, resulting in the most efficient and least error-prone models for natural gas price forecasting.

The paper is organized as follows: in Section 2, we will briefly discuss the methodologies and the data used in our study, while in Section 3, we describe our empirical results. Finally, Section 4 will conclude the paper.

2. Methodology

2.1. Support Vector Machines

Support vector machines (SVM) are a set of methods for data classification and regression based on the maximization of the interclass distance: the basic concept of the SVM is to define the optimal (optimal in the sense of the model's generalization to unknown data) linear separator that separates the data points into two classes. To facilitate this, the algorithm employs the "kernel trick": the initial data space is projected through a kernel function to a higher dimensional space (feature space) where the dataset may be linearly separable [13]. In this paper, we use four kernels, the linear, the quadratic, the cubic, and three different Gaussian kernels: fine, medium and coarse, following a different structure in the data each time.

2.2. Gaussian Process Regression

Gaussian processes are a flexible class of non-parametric machine learning models that are primarily used for modeling spatial and time series data. Gaussian models are commonly used to solve difficult machine learning problems. They are particularly useful and attractive due to their flexible non-parametric nature and their computational simplicity. A common application of Gaussian processes is regression. Gaussian process regression (GPR) is based on the determination of an appropriate kernel function or a measure of similarity between data points whose locations are known. Compared to other machine learning methods, the advantages of GPR lie in its ability to seamlessly integrate multiple machine learning tasks, such as parameter estimation. Moreover, it has excellent performance and needs a relatively small training dataset to perform predictions. However, a known problem that arises is that due to the computational complexity of the predictions, according to [12], it becomes infeasible for GPR to be effective for large datasets. In this paper we trained four different GPR models coupled with the most important kernel functions with same length scale for each predictor:

(1) Rational Quadratic GPR: a Gaussian process model that uses the rational quadratic kernel;
(2) Squared Exponential GPR: a Gaussian process model that uses the squared exponential kernel;
(3) Matern 5/2 GPR: a Gaussian process model that uses the matern 5/2 kernel;
(4) Exponential GPR: a Gaussian process model that uses the exponential kernel.

2.3. Decision Trees

Ref. [14] proposed decision trees as a forecasting modeling technique in statistics, data mining, and machine learning. It employs a decision tree (as a forecasting model) to shift from observations of an item (represented by the branches) to inferences about the object's target value (represented in the leaves). Regression trees are decision trees in which the target variable can take continuous values (typically real numbers). In this paper we use three different tree models:

(1) Fine Tree where the minimum leaf size is 4;
(2) Medium Tree where the minimum leaf size is 12;
(3) Coarse Tree: where the minimum leaf size is 36.

2.4. Ensemble of Trees

An ensemble of trees is formed by several individual trees that are added together. Although decision trees are one of the most efficient and interpretable classification algorithms, they suffer from low generalization ability nonetheless. Thus, they provide a low bias in-sample but a high variance out-of-sample. Ensemble techniques have been shown to solve this problem. They combine several decision trees to produce better prediction performance, as opposed to using a single decision tree. The basic principle underlying the ensemble model is that a group of weak learners is combined to form a strong learner. The main techniques for training ensemble decision tree models are bagging and boosting [15].

2.4.1. Bagging

Bagging (bootstrap aggregation) is used when our goal is to reduce the variance of a decision tree. In this process, the basic idea is to generate several subsets of data from the training sample, which is selected randomly by replacement. Each subset of data is used to train the corresponding decision tree model. As a result, we end up with a set of different models. Finally, the average of all predictions obtained from different trees is used, which is more powerful and accurate than a single decision tree (Figure 1).

2.4.2. Boosting

Boosting is another ensemble technique that aims to improve the accuracy of predictions generated by one or many models. This technique starts by fitting an initial model (e.g., a tree or linear regression) to the data. Then, a second model is constructed that focuses on accurately predicting cases where the first model does not perform well by using a weighted data sample. The combination of these two models is better than either individual model separately. The boosting process is then repeated several times. Each successive model attempts to correct the weaknesses and errors of the combined boosted set of all of the previous models (Figure 2). Combining the entire set at the end converts the weak learners into a better performing model.

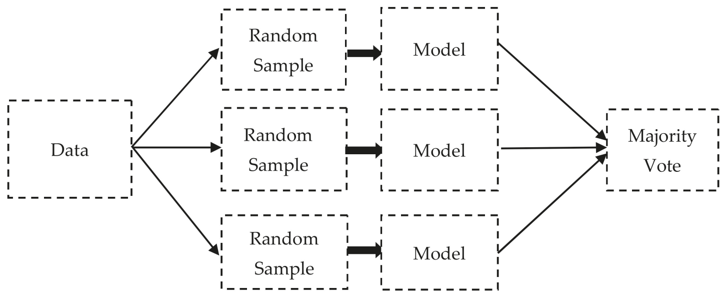


Figure 1. Bagging [16].

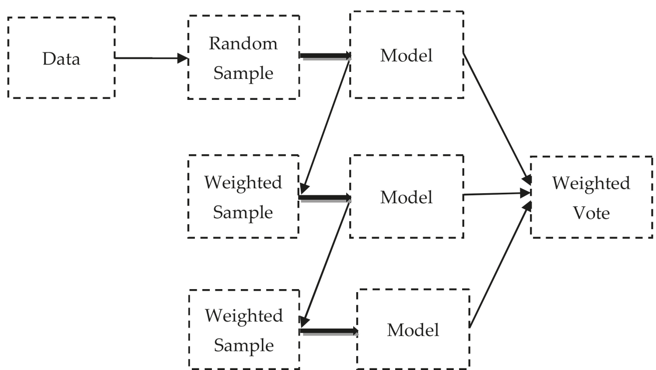


Figure 2. Boosting [16].

2.5. Cross-Validation

A common issue in this area of work is the problem of overfitting. A model can theoretically be conditioned to precisely fit the training data, hence exhibiting very high accuracy in-sample. Nonetheless, such a model would be useless in forecasting, as it will likely exhibit a low fit in the test (out-of-sample) data. In such cases, the model is trained to only fit the training data and not the underlying phenomenon. To avoid this, in the empirical part of the study, we employed a k-fold cross validation procedure. The in-sample data, which are used to train the model, are divided into k parts (folds) of equal size. Then, in each of the k iterations, one fold is used as the testing set, while the remaining k-1 folds are used as the training set. This is repeated for all k folds. In this scheme, the model's accuracy is evaluated by the average performance over all of the k folds for each set of the model's parameters. Figure 3 provides a graphical representation of a 3-fold cross validation procedure.

2.6. The Dataset

For the training and the testing of our models, we compiled a dataset consisting of 2423 daily natural gas spot price values from the Energy Information Administration (EIA) database and 21 related economic variables from the Federal Reserve Bank of Saint Louis and Yahoo Finance databases. They span the period from 3 December 2010 to 18 September 2020 (Table 1). In addition, the momentum of the last 5 and 10 days (Momentum 5 and 10 are defined as the sum of the times that natural gas spot price increases in the last 5 and 10 days, respectively) as well as the 5- and 10-day moving average was calculated and added to the independent variable set. With the exception of interest rates, all of the variables were converted to natural logarithms.

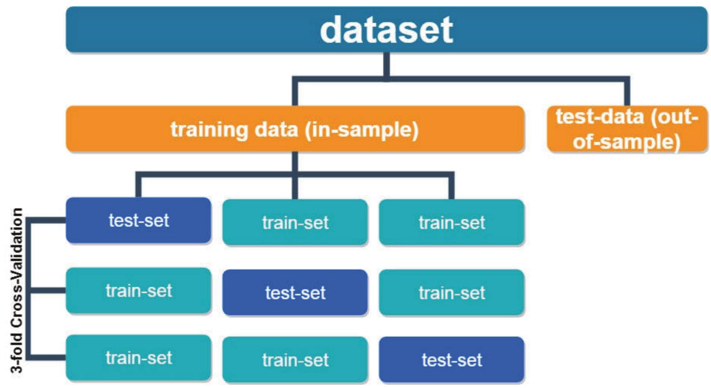


Figure 3. A three-fold cross validation for a given set of model parameter values. Each fold serves as a test sample, while the remaining folds are used to train the model. The average prediction accuracy for each set of parameters over the k-folds is used to assess the model [17].

Table 1. List of explanatory variables with mean, standard deviation, skewness, kurtosis, and variance.

#	Name	Mean	Standard Deviation	Skewness	Kurtosis	Variance
Panel A: Stock Indices						
1	NASDAQ Composite Index	5289.44	2132.48	0.61	−0.4	4,549,055
2	S&P 500 Index	2112.97	607.77	0.18	−0.92	369,500
3	Dow Jones Industrial Average Index	18,797.36	5195.66	0.3	−1.04	27,003,372
Panel B: Exchange Rates						
4	USD/EUR	0.19	0.09	0.3	−1.29	0.008
5	JPY/USD	4.62	0.14	−0.82	−0.61	0.019
6	USD/GBP	0.37	0.1	0.19	−1.5	0.010
Panel C: WTI Spot Price						
7	Cushing, OK WTI Spot Price FOB	4.17	0.37	−0.57	0.34	0.1401
Panel D: Interest Rates						
8	Effective Federal Funds Rate	0.638	0.77	1.17	−0.15	0.5974
9	5-Year Breakeven Inflation Rate	1.7	0.32	−0.84	1.57	0.107
10	10-Year Breakeven Inflation Rate	1.94	0.33	−0.44	0.36	0.1142
11	1-Year Treasury Constant Maturity Rate	0.75	0.82	1.1	−0.23	0.6757
12	10-Year Treasury Constant Maturity Rate	2.22	0.61	−0.4	0.51	0.3736
13	Bank Prime Loan Rate	3.76	0.75	1.18	−0.12	0.5732
Panel E: Future Contracts						
14	Natural Gas Futures Contract 1	1.1	0.26	−0.171	−0.51	0.0686
15	Natural Gas Futures Contract 2	1.11	0.25	−0.174	−0.62	0.0626
16	Natural Gas Futures Contract 3	1.13	0.24	−0.163	−0.69	0.0573
17	Natural Gas Futures Contract 4	1.15	0.23	−0.096	−0.75	0.0519
18	OK Crude Oil Future Contract 1	4.181	0.371	−0.53	0.15	0.138
19	OK Crude Oil Future Contract 2	4.189	0.358	−0.37	−0.45	0.1283
20	OK Crude Oil Future Contract 3	4.195	0.348	−0.27	−0.81	0.1213
21	OK Crude Oil Future Contract 4	4.199	0.341	−0.22	−0.95	0.1165

In order to test the generalization ability of the trained models, the dataset was divided into two parts: the first 90% was used as the training data set (in-sample, consisting of 2180 observations), and the remaining 10% of the most recent observations was the test data set (out-of-sample, consisting of 243 observations).

3. Empirical Results

The prediction accuracy of each model for both the out-of-sample and in-sample data was measured using the Root Mean Square Error (RMSE) metric. Thus, the optimal model was selected as the one that minimizes the RMSE:

$$\mathrm{RMSE} = \frac{\sqrt{\sum_{t=1}^{T} (\hat{y}_t - y_t)^2}}{T} \tag{1}$$

where $\hat{y}$ = the forecasted value, y = the actual value, and T = the number of observations.

Our forecasts were produced for several alternative forecasting horizons, i.e., $t + 1$, $t + 3$, $t + 5$, and $t + 10$. We completed the same task with a random walk model in order to compare our machine learning results to a naïve prediction model.

Before moving to structural models (The ones that include the independent variables of our data set.), we first tried to identify the best autoregressive representation, i.e., to produce the best AR(q) model (autoregressive model). The AR(q) model is a simple model that uses past (lagged) values of natural gas spot prices to forecast the future natural gas spot price.

$$\boldsymbol{X}_t = c + \sum_{i=1}^{q} \varphi_i \boldsymbol{X}_{t-i} + \varepsilon_t \tag{2}$$

where $\boldsymbol{X}$ is the natural gas spot price, q is the maximum number of lags, and φ_i the parameter vector of the lags to be estimated.

In order to identify the optimal number of lags, we train several linear SVM models by varying the number of lags we used each time, starting with an AR(1) up to an AR(15).

We concluded that by using the first 14 lags, we minimize the in-sample RMSE (0.04196). These results are presented in Figure 4.

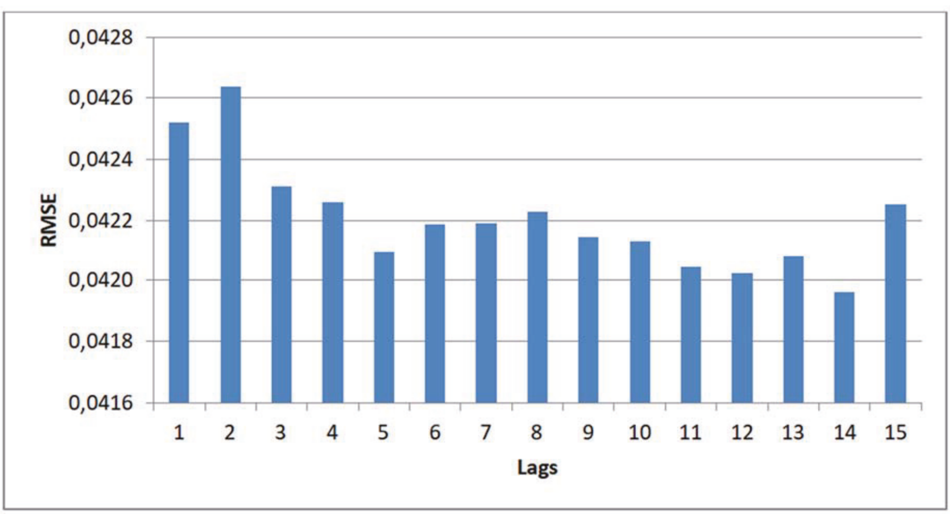


Figure 4. RMSE for AR models.

After identifying the best autoregressive representation, we built structural models. These include the 14 lags and all of the explanatory variables described earlier as independent variables to produce forecasts one day ahead. For this, we trained several alternative machine learning models and also produced the results for the random walk model. The in-sample and out-of-sample RMSEs of these models are presented in Table 2. An important issue in such forecasting models is to avoid overfitting in the in-sample or out-of-sample datasets. In the literature, this is known as the bias–variance trade-off. An efficient forecasting model is one that provides a balanced performance both in-sample and out-of-sample, i.e., the bias and variance are comparable. For this reason, we rejected all of models that provided evidence of overfitting and continued our empirical analysis with the rest. In the last column of Table 2, we note the models that overfit and are not used in the rest of our analysis. Interestingly, the tree models (plus bagged and boosted trees) do not overfit, and all of the GPR models overfit alongside most of the SVM models (with the exception of the linear SVM).

Table 2. In-sample and out-of-sample (OOS) RMSE of all models.

Models	In-Sample RMSE	OOS RMSE	Overfitting
RW	0.042643	0.057435	no
Linear Regression	0.038421	0.062872	no
Interactions Linear	0.1009	1.560244	yes
Robust Linear	0.039067	0.05736	no
Fine Tree	0.04992	0.071181	no
Medium Tree	0.045707	0.083954	no
Coarse Tree	0.047189	0.083388	no
Linear SVM	0.038581	0.056694	no
Quadratic SVM	0.044703	0.161214	yes
Cubic SVM	0.058968	0.456275	yes
Fine Gaussian SVM	0.098278	0.461634	yes
Medium Gaussian SVM	0.042352	0.243223	yes
Coarse Gaussian SVM	0.046224	0.079625	yes
Boosted Trees	0.065151	0.06169	no
Bagged Trees	0.041597	0.061089	no
Squared Exponential GPR	0.039915	0.216353	yes
Matern 5/2 GPR	0.039915	0.164098	yes
Exponential GPR	0.039989	0.098513	yes
Rational Quadratic GPR	0.040069	0.120337	yes

3.1. Time Frame $t + 1$

According to the results presented in Figure 5, we observed that for the time horizon $t + 1$, the optimal in-sample model was the linear regression model with RMSE = 0.038421 and that the best out-of-sample forecasting model was the linear SVM model with RMSE = 0.056694. The robust linear model also showed very good results, as it had the second lowest RMSE in the out-of-sample data and the third lowest in the in-sample data. Finally, the random walk model seemed to adequately predict the out-of-sample data. Therefore, we can generally conclude that linear models are able to predict the natural gas spot prices one day ahead with high accuracy and that the best model (linear regression) has good generalization ability (Figure 6).

3.2. Time Frame $t + 3$

The results for the forecasting window $t + 3$ are presented in Figure 7. We observed that for time horizon $t + 3$, the optimal in-sample model was the bagged trees model with RMSE = 0.057793 and that the best out-of-sample forecasting model was the boosted trees model with RMSE = 0.077136. According to the above, it is clear that the best models at time horizon $t + 3$ are tree based models. The out-of-sample performance of the bagged trees model is presented in Figure 8.

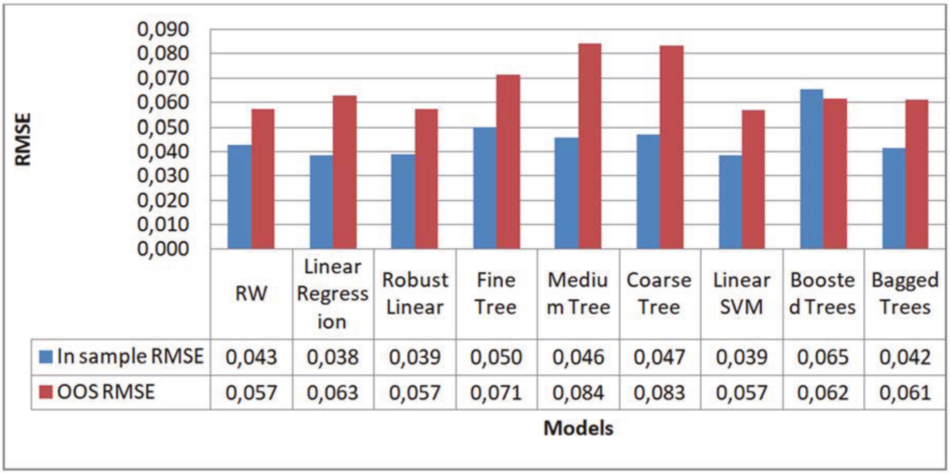


Figure 5. RMSE for $t + 1$ forecasting.

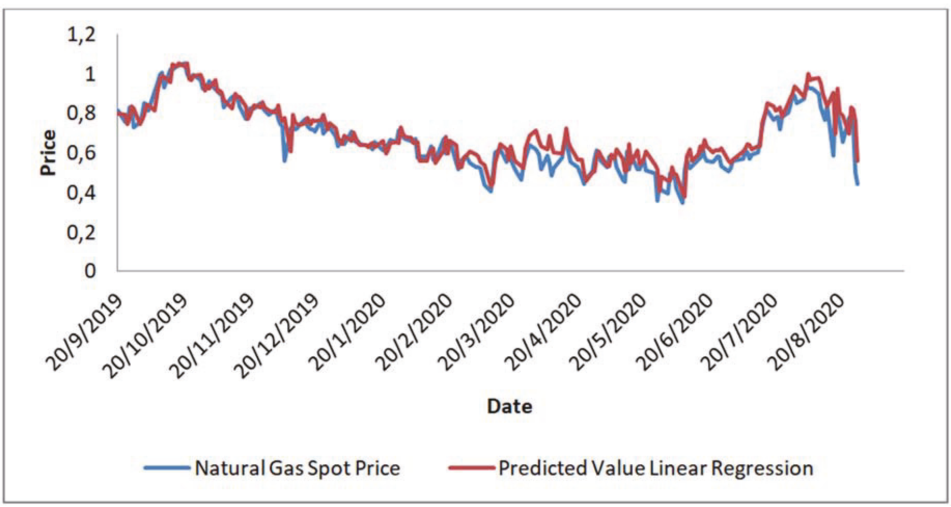


Figure 6. Comparison of the actual natural gas spot prices and the predicted prices with the linear regression model for $t + 1$ in the out-of-sample part of the dataset.

3.3. Time Frame t + 5

The results for the forecasting window at $t + 5$ are presented in Figure 9. In this window, we found that the optimal in-sample model was the bagged trees model with RMSE = 0.061787 and that the best out-of-sample forecasting model was the linear SVM model with RMSE = 0.083687. The bagged trees model also shows good generalization ability (Figure 10). It is worth noting that the random walk model also showed good performance, as it holds the second lowest out-of-sample RMSE = 0.087654.

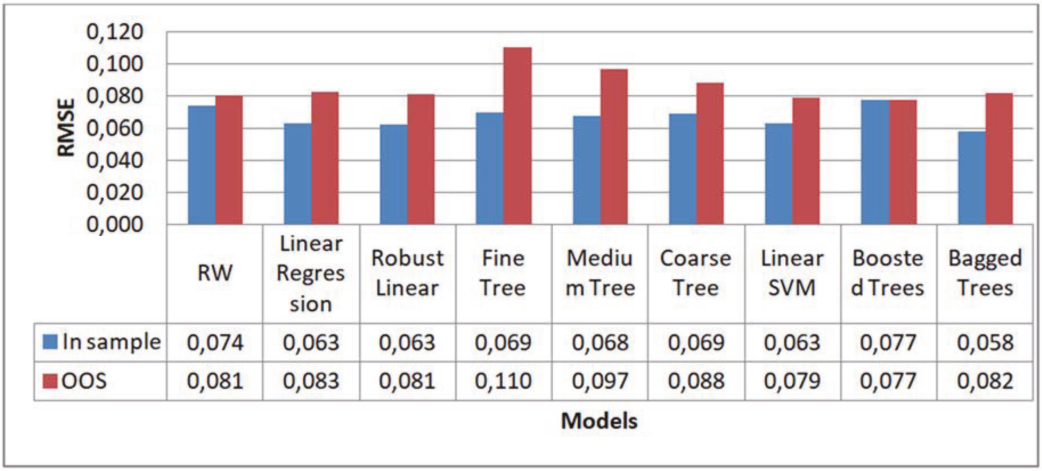


Figure 7. RMSE for $t + 3$ forecasting.

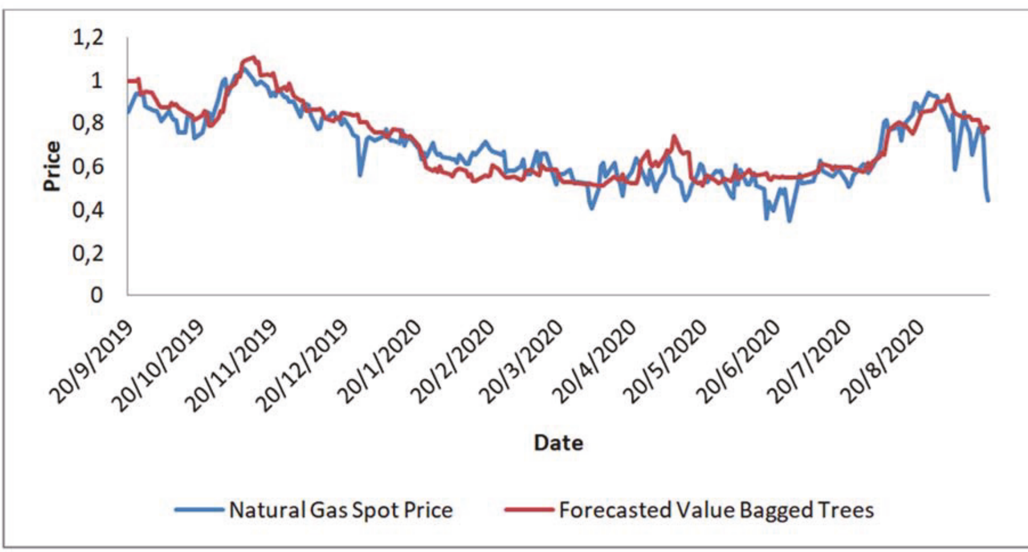


Figure 8. Comparison of the actual natural gas spot prices and the predicted prices with the bagged trees model for $t + 3$ in the out-of-sample part of the dataset.

3.4. Time Frame t + 10

Finally, for the $t + 10$ forecasting window the results are presented in Figure 11. We observed that the optimal in-sample model was the bagged trees model with RMSE = 0.064968 and that the best out-of-sample forecasting model was the linear SVM model with RMSE = 0.102711. Additionally, the random walk model showed good results, as it achieved the second lowest out-of-sample RMSE = 0.109871. The best model for time horizon $t + 10$ (bagged trees) has also good generalization ability (Figure 12).

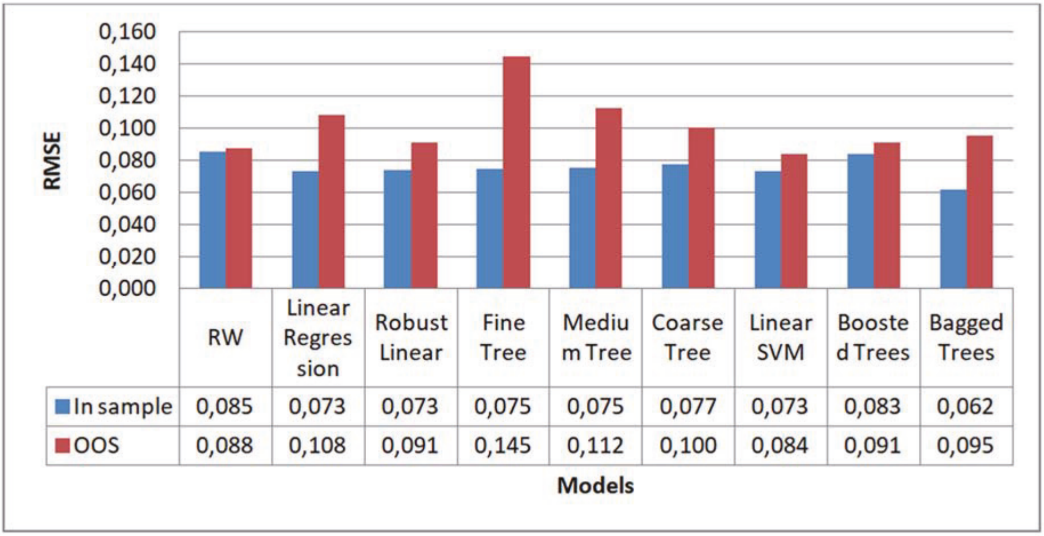


Figure 9. RMSE for $t + 5$ forecasting.

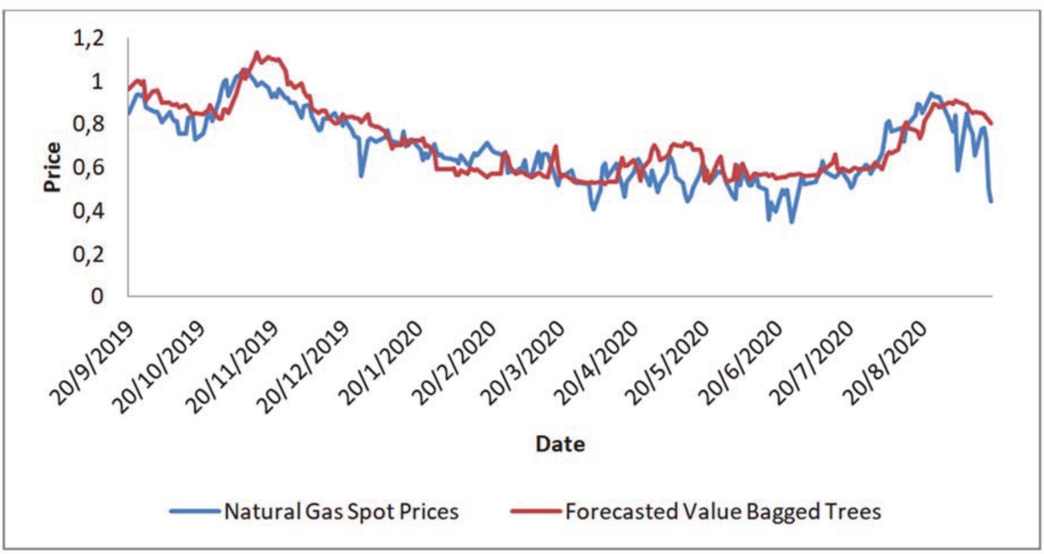
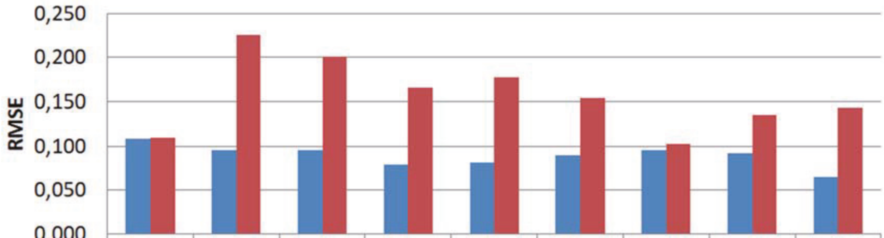


Figure 10. Comparison of the actual natural gas spot prices and the predicted prices with the bagged trees model for $t + 5$ in the out-of-sample part of the dataset.

Interestingly the random walk model showed very good results for the out-of-sample part of the dataset at all time instances, while at the same time, we can conclude that all of the linear models have the ability to predict natural gas prices with high accuracy and showed very good performance with small RMSE values. The bagged trees models also showed very good predictive ability, having the lowest in-sample RMSE error at all time instances except for $t + 1$.



	RW	Linear Regression	Robust Linear	Fine Tree	Medium Tree	Coarse Tree	Linear SVM	Boosted Trees	Bagged Trees
In sample	0,108	0,096	0,095	0,079	0,082	0,090	0,095	0,092	0,065
OOS	0,110	0,225	0,201	0,166	0,177	0,154	0,103	0,136	0,144

Figure 11. RMSE for t + 10 forecasting.

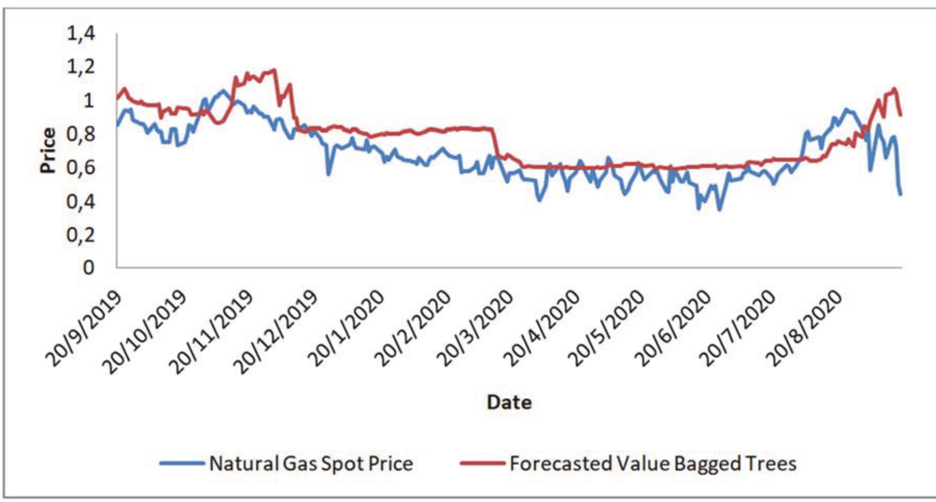


Figure 12. Comparison of the actual natural gas spot prices and the predicted prices with the bagged trees model for t + 10 in the out-of-sample part of the dataset.

4. Conclusions

The accurate forecasting of any asset has obvious practical implications. It can help individuals on both the supply and demand sides to reduce associated risk by better anticipating future changes in prices and by being prepared and acting on time to optimize their participation and behavior in the relevant market via positive or negative storage, substitution from and to this market, and the alteration of budget plans and in general decreases uncertainty, which has adverse effects on both suppliers and consumers. Moreover, government officials can use such information for larger scale planning, as they can anticipate prices swings.

The effective forecasting of natural gas prices is obviously important for all market participants: suppliers, distributors, consumers, investors, and regulatory agencies. It is also a powerful and important tool that has become increasingly important for various stakeholders in the natural gas market, helping them to make better decisions for risk management, reducing the demand-supply gap, and optimizing resource utilization based on accurate predictions. For investors trading in the U.S. energy equity markets, the current boom around green energy investing offers significant hurdles. If and how these investors learn to cope with various information frictions, navigate through broad fluctuations in market risk appetite and uncertainty, and deal with unexpected changes in energy laws and regulations will be crucial to their investment decisions [18].

In this paper, we tested the effectiveness of various machine learning algorithms in forecasting natural gas spot prices. We trained multiple machine learning models and a naïve random walk model. In machine learning models, we used the optimal number of lagged natural gas spot prices and 21 other explanatory variables (regressors). These were selected based on economic theory and the relevant literature. Hence, these regressors included macroeconomic and stock market indicators, exchange rates, interest rates, the spot prices and future contracts of Oklahoma West Texas Intermediate Crude Oil, the corresponding future contracts of natural gas, the momentum of the last 5 and 10 days, and the 5- and 10-day moving average. The models were trained to forecast horizons one, three, five and ten days ahead ($t + 1$, $t + 3$, $t + 5$ and $t + 10$).

The dataset included 2423 daily observations for the time period from 3 December 2010 to 18 September 2020. This dataset was divided into two subsets, with the first part covering the range from 19 November 2010 to 19 September 2019, or 2180 observations that were used to train our models, and the second part spanning the period from 20 September 2019 to 18 September 2020, or the remaining 243 observations, which were used to test the generalization ability of the models to unknown data that were not used in the training process. In order to avoid the issue of overfitting, we employed a 5-fold cross validation method.

The optimal AR representation was found to be 14 lags using a linear SVM model. Next, we added all of the explanatory variables to train the 19 models. In 10 of these models, we detected overfitting; thus, they were not used in the subsequent analysis. These models were the interactions linear, SVM (quadratic, cubic, fine Gaussian, medium Gaussian, coarse Gaussian) and GPR (squared exponential, matern 5/2, exponential, and rational quadratic) models. The models that did not show overfitting were the random walk, linear regression, robust linear, fine tree, medium tree, coarse tree, linear SVM, boosted trees, and bagged trees models.

According to the results, the optimal model for in-sample data at $t + 1$ is a linear regression model, and for $t + 3$, $t + 5$, and $t + 10$ bagged trees models are optimal. For the out-of-sample data, the best models are linear SVM models for $t + 1$, $t + 5$, and $t + 10$ and a boosted trees model for $t + 3$. The aforementioned models do not overfit since the RMSE's for the in-sample and out-of-sample data are comparable.

Therefore, from our research, we conclude that the most effective methods for natural gas spot price forecasting are the linear SVM and the bagged trees.

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Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

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energies

Review

Renewable Energy, Economic Growth and Economic Development Nexus: A Bibliometric Analysis

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Abstract: The present research aims to conduct a systemic review on Renewable Energy, Economic Growth and Economic Development and look for links between the papers published between 2008 and May 2021. Using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology, it was possible to reach a sample of 111 articles selected by Web of Science and a sample of 199 academic articles selected by Scopus in that specific period. The analysis of the group of Renewable and Non-renewable Energy Consumption, Economic Growth and Economic Development shows that most of the articles published in this subsample use the quantitative methodology in economic sciences. The results indicate that research on the subject has a growing trend and that most of the articles are post-2015 publications. In addition, China has been the leading nation in published works. The journal Renewable and Sustainable Energy Reviews is considered the most relevant in this category, and Sustainability has the most publications. Finally, a research gap was identified to be explored, lacking studies aimed at understanding the consumption of renewable energies and economic development and studies that focus on renewable energies and economic growth in less developed economies.

Keywords: bibliometric analysis; development economics; economic growth; energy; renewable energy

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1. Introduction

The investigation of what drives economic growth and development is thematic and will never cease to be relevant in academia. The nexus between economic growth and energy consumption has been a significantly explored subject in academia over the years; for example, in recent years, this nexus was investigated by several researchers [1–9]. These and other studies pointed to a relevant relationship between energy consumption and economic growth, and the results obtained are of paramount importance in the development of policies and strategies according to the behavior of economic growth in the face of energy consumption.

After observing an increase in carbon dioxide emissions, research began to find evidence that related this increase with an increase in economic activity; therefore, we began to investigate the gap in which energy consumption was inserted, as in, [10–12]. Ref. [13] conducted a bibliometric review on this topic and concluded that there is a relationship of bidirectional causality between economic growth and CO_2 emissions; thus, stimulating a reduction in emissions will reduce economic growth [13].

The existence of difficulty in reconciling economic activity and energy consumption with the conservation of the environment is clear, as is the need to encourage sustainable economic growth. Having said this, the present paper proposes to build a bibliometric review that takes into account studies investigating the relationship between renewable energy, economic growth and economic development nexus in order to understand which direction this field of study is taking.

The present research accessed the WoS and Scopus database to search keywords, titles and abstracts related to the terms renewable energy, economic growth and economic development between the years 2008 and May 2021. The selection of articles used in the research was made through the PRISMA methodology. This research was also proposed to quantify the impact of the papers and journals published on the subject in that period, using some descriptive information to identify which journal(s) and which author(s) is the most relevant within the sample collected. Finally, an analysis was made, with the help of VOSviewer software, to find clusters and links between the terms used and the researchers.

The remainder of this study is structured as follows. Section 2 presents a brief literature review. Section 3 discusses the research methodology of the paper; Section 4 presents results, findings and discussion of this paper based on the study aims. Section 5 provides some concluding remarks, limitations of this study and suggestions for future papers.

2. Literature Review

In this section, a brief literature review on bibliometric reviews and systemic reviews is made. The authors of [14,15] set out to study the footprints of degradation. While one focused on environmental degradation itself [14], the other focused on the carbon footprint [15]. Studies differ methodologically; ref. [14] published a bibliometric analysis, while [15] published a systematic review. Ref. [14] researched the keywords “water footprint”, “carbon footprint”, “land footprint”, “biodiversity footprint”, “chemical footprint”, “nitrogen footprint”, “phosphorus footprint”, “PM2.5 foot-print”, “PM10 footprint” and “ozone footprint” in the Web of Science (WoS) database for the period 1986–2019 after screening processes reached a sample of 4352 articles. The results indicate that the U.S. and China are the countries that have conducted the most research on the subject in the period aforementioned and are those with the highest cooperation among themselves. In addition, it was emphasized that “water footprint” and “carbon footprint” are the most studied terms in relation to the others used in the research. Finally, the authors concluded that the most recent research focuses on the carbon footprint related to supply production chains, greenhouse gas emissions, water consumption in agriculture and environmental issues related to construction [14]. In the study proposed by [15], we used the same database, except for the 1992–2019 interval, and only searched the keyword “carbon footprint”, obtaining a sample of 7450 articles. The results indicate that research on the subject began to grow in 2008, and four topics were “international trade”, “life cycle assessment”, “ecological footprint”, and “supply chain”. There was also a significant interaction between the US and European Union (EU) research; however, in recent years, research from China has been increasing and standing out. The Journal of Cleaner Production is the most prominent. Finally, research in Economic and Political Economics seems to be the most recent ascending [15] theme. Ref. [16] developed a systematic review on carbon leakage with the following questions: What are the generation channels and the factors of the leakage? What methodologies are used to evaluate the leak? Which topics need more attention to formulate more effective climate policies? [16]. The research used the keywords “carbon leakage” and “emission transfer” in the WoS database for the period 2000–2020, with screening techniques reaching 407 articles for research. The researchers concluded that many studies have focused on the loss of competitiveness in the intense emission sectors, caused mainly by international trade, and there is not enough debate about the negative leak channel. In addition, the authors point out the absence of quantitative methodologies for carbon leaks [16].

With the intention of providing an overview of the work performed on the Environmental Kuznets’ Curve (EKC), ref. [17] proposed a bibliometric analysis. Using the WoS database, he analyzed the publications made in the period of 1999–2010, with the PRISMA approach, and reached a sample of 1775 articles to study. The results of the study indicate that research has grown exponentially in recent years and that China, the U.S., Turkey and Pakistan are the countries with the highest academic publication on the subject. In addition, the authors surveyed the journals that published the most in that period, which are Environmental Science and Pollution Research, Journal of Cleaner Production, Ecological Economics and Energy Policy. The author with the most publications is Muhammad Shahbaz [17]. Furthermore, on the topic of EKC, [18] used the WoS database to conduct a study of publications on the subject in the last two decades (1999–2019). From a universe of 59,225 documents, 2384 were investigated in this research. The results found by the authors, based on co-citation, indicate that the most relevant journal on this topic is Ecological Economics; in addition, of the ten most relevant journals, Elsevier publishes seven. The countries with the highest number of citations are China, the USA and Turkey. The same order was obtained by [17]. The most influential researcher is Muhammad Shahbaz, with the same result obtained by [17]. It is no coincidence that the most relevant institution is the Beijing Institute of Technology, where Muhammad Shahbaz is a professor [18]. Moreover, [19] proposed a systemic and bibliographic review on industry 4.0. The study used two databases for the survey of Scopus as well as WoS articles published until 2020. The terms used for research were "Industry 4.0", "Industrie 4.0" and "Fourth Industrial Revolution", following PRISMA protocols, and a sample of 745 articles were obtained. The authors concluded that industry 4.0 is motivated by profit; the value of digital transformation is materialized as corporate profit. In addition, the authors highlighted factors that can determine success or failure, which depend on favorable conditions such as government incentives and an abundance of resources for the digital transition in Industry 4.0 to be achieved [19].

With the objective of detailing the stage and the current research trends on Thermal Energies Storage (TES), [20] elaborated a bibliometric analysis on the subject. The Scopus database was used for the research that used all available coverage until 21 September 2020. The authors divided the results of the research into three categories, including buildings, districts, and roads and bridges [20]. As far as buildings are concerned, the results indicated that it is and the most studied category. The USA was the country to publish the first relevant studies on the subject, and the most researched line is the demand for cooling by optimized control techniques. While in Europe, of latent heat thermal energy storage through passive techniques and demand management strategies, in China, there is a focus on material study, and economic analysis seems to be the trend of the most recent studies for buildings. Studies on TES applied to districts began to increase in 2013 and are led by Europe. TES at the district level was investigated at the system level, mainly applications of solar systems and cogeneration systems. The most recent studies have investigated economics and techno-economic. Finally, studies applied to roads and bridges do not attract many researchers. Norway, Japan and China are the countries with the most Publications [20]. Ref. [21] conducted a bibliometric study between 2000 and 2019 on TES in order to understand the trend and future of this field of research. The authors' analysis concludes that latent-heat TES has been the focus in recent years, but thermochemical TES and its hybrid TES technologies appear to be the next focus of researchers [21].

A bibliometric and systematic review was proposed by [22] to understand the standards of key performance indicators (KPI) and multicriteria decision-making models (MCDM/A) in the context of renewable energy technologies (RET). The following questions were raised: "Is there a pattern in the use of performance criteria to select and assess RET performance?"; "Is there a pattern in the use of multicriteria models for decision making to select and assess RET performance?". To find these answers, 142 articles from the WoS database were selected between 1998 and 2019. The authors concluded that there is a growing trend in this research, mainly from 2015. According to the authors, the results of this study demonstrated a preference in the use of synthesis models rather than overlap, the importance of considering political and technical indicators beyond those related to the Triple Bottom Line in decision-making and the importance of MCDM/A in achieving the sustainable development goals of the United Nations agenda [22].

A mapping of a 21st-century problem, poverty energy, was proposed by [23]. Thus, a bibliometric analysis was made using the Web of Science database, and for the 1999–2019 temporal sample, they obtained 1018 articles in the sample. The results show that 2003 was the founding year of energy poverty research. Nine hundred eighty-two institutions developed research on the subject. In addition, the results indicate that the largest cooperation occurred between the UK, USA, Australia and Italy. Among the periods, Energy Policy publishes on the subject for the longest period, while Renewable and Sustainable Energy Reviews publishes the studies with greater influence; Sovacool is the researcher with the highest number of publications and the most influential. Finally, the authors highlighted four areas that should be research trend in the coming years: energy poverty in developing countries, impacts of energy poverty on vulnerable groups, root causes of energy poverty and consequences of emission reduction policies [23].

3. Materials and Methods

In this section, we explain the database, period and methodology applied in the selection of the investigated articles and the techniques applied for analysis. There are several databases for scientific document searches, for instance, the Web of Science (WoS) and Scopus. This investigation chose to use the database provided by WoS and Scopus for the period 2008 to 21 May 2021. The year 2008 is the first year of commitment to reducing carbon emissions of the Kyoto protocol subscriber countries; this first cycle being finalized in 2012, the chosen period covers the years of the first cycle and the subsequent period.

The first step of this investigation was the choice of the sample, using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology proposed by [24]. The PRISMA methodology is a guideline developed to deal with unsatisfactory systematic reviews, which focuses on making the research transparent; therefore, the researcher needs to be aware of the purpose of the review, what the procedure was, and finally, what the findings were [24].

According to [24], the PRISMA methodology was developed to be applied in systemic reviews that assess the effects of interventions in the health area. The PRISMA approach provides guidance that contributes to a methodological improvement to identify, evaluate and synthesize studies; this technique consists of applying a checklist with 27 items in order to have a more accurate screening. Although developed to be applied in the health area, the checklist is relevant and applicable for systematic reviews with mixed methodologies, which include quantitative and qualitative studies [24], a scenario faced by this research.

First, all the documents in the Web of Science (WoS) database related to the three terms of the research (Renewable Energy, Economic Growth and Economic Development) were researched for the period 2008 to 21 May 2021. Immediately, 3382 documents were identified. When applying the procedures, only open access documents were considered; this limited the search to 1.025, excluding 2357 documents. Then only the following areas of research, Environmental Science, Energy Fuels, Environmental Studies, Economics, Management and Business, thus eliminating 426 documents and having 599 documents. Then, the type of documents and language was limited, taking into account only scientific articles and in the English language, leaving 428 articles with the possibility of making the final sample. Finally, titles and abstracts were analyzed; in this stage, 317 articles were disregarded, thus leaving 111 to make up the Web of Science sample. Figure 1 summarizes the screening process.

Second, all the papers in the Scopus database relating to the words Renewable Energy, Economic Growth and Development Economic were identified. The search with these words was directed in keywords, title and abstract, resulting in 2836 identified documents. Following the identification was the screening stage where only open-source documents were chosen to be analyzed, resulting in 790, so there was a reduction of 2046 documents. The second stage of screening was to exclude the research areas that are not related to the focus of the investigation of this research, considering only the following fields of study: Environmental Science, Energy, Social Sciences, Economics, Econometrics and Finance, and Business, Management and Accounting. With this restriction, 377 documents were eliminated, leaving 413 with the possibility of entering the study. Then, we limited the types of documents. We took into account only articles, finding 300 articles. In addition, these were limited to the English language, which resulted in the exclusion of 9 articles, making 291 eligible. Finally, an analysis was made of the abstracts, titles and keywords of these 291 articles to determine which ones would be considered for the investigation of this systematic review, based on the information found. Ninety-two articles were disregarded, so 199 articles were considered for analysis, as can be seen in Figure 2. The protocol applied to the Scopus database can be found in Appendix A of this research.

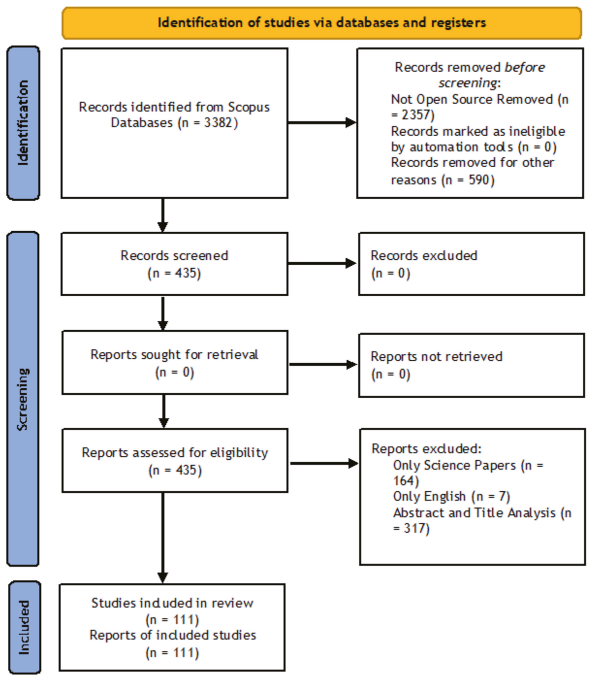

Figure 1. Identification of Studies Via Web of Science Database.

The eligibility of the articles used in this research was mirrored in the strategy applied by [13]. In the stage of determining the eligibility of the articles, the title, abstract and keywords of the individually selected articles were reviewed. In this final stage of screening, we identified the articles that could be part of the study sample. Having exposed this, the articles included in the research explore the link between economic growth, renewable energy consumption and economic development. It should be emphasized that at this stage, only scientific articles were taken into account, so documents such as thesis, dissertations, articles published in a non-English language, editorial notes, books, book chapters, among other types of documents, were disregarded. Finally, it was possible to obtain the 199 articles used in this research, which relate to the keywords in question, from a sample of 74 international journals between 2008 and 21 May 2021.

This research chose to work with the Scopus database due to its great coverage and multidisciplinary. In addition to being peer-reviewed, updated frequently and has resources that assist researchers in the development of work. According to [25], the biggest advantages of the Scopus database are the inclusion of open access articles, tools to find authors, a wide catalog of scientific and technological journals, automatic generation of h-index, more content published in Europe compared to WoS [25].

The screening criterion applied in the Web of Science (WoS) database, which final filter according to the Prisma technique, shows a sample of 111 documents; moreover, 50 articles that represent 45% of the searches found in the WoS database are also listed in the Scopus database.

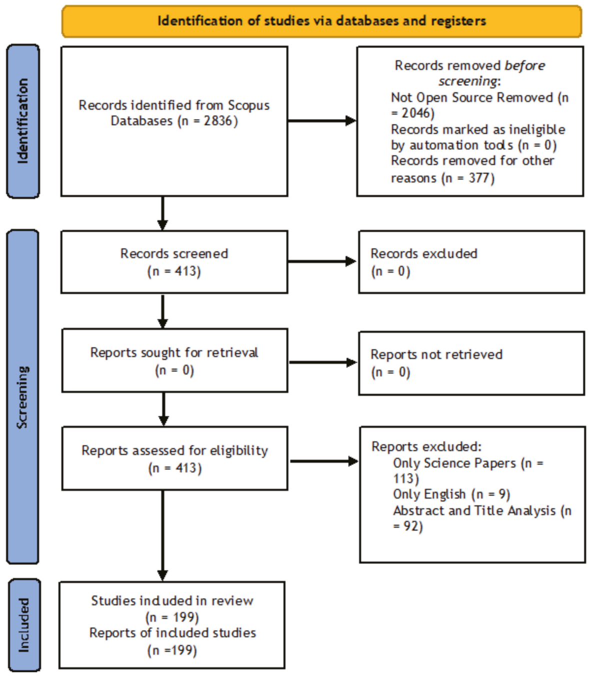

Figure 2. Identification of Studies Via Scopus Database.

After defining the investigated studies, this research analyzes the information of the articles, considering some indicators: number of publications, h-index and citations, as was performed in [26]. However, it is important to emphasize that the literature does not yet have an accurate and conclusive methodology to evaluate articles, journals, and so on, let alone be able to determine their value. This field of research, which tries to measure the value of an article, the researcher or even the institution, is criticized. A criticism pointed out by [26] assumes that an article published in a journal of greater relevance should have a higher value than one published in a median journal, but this is a challenge since each article, regardless of where it is published, will be assigned the same value [26]. The databases, trying to work around these difficulties (for example, the Scopus database), have three metrics that are based on the citations received to assign quantitative values, whether to the author, article, journal or institution, they are: CiteScore (CS), SCImago Journal Ranking (SJR) and the Source Normalized Impact per Paper (SNIP), while, in the WoS database the metrics are available in the Journal Citation Reports (JCR) from Clarivate Analytics

The CiteScore from Scopus is not similar to the impact factor calculated by JCR of the Web of Science (WoS). The difference occurs only in the period used to make the calculation. The CS considers the number of citations in the last 3 years and divides these by the number of publications in the same period, while the ones calculated by WoS are based on the interval of the last 2 years. Nevertheless, according to [26], these metrics are not 100% reliable since it is possible to circumvent them using self-citations [26]. Another Scopus metric used to rank journals is the SJR, which measures the weighted citations received by the journal; the weighting of the citations takes into account the subject field and the prestige (SJR) of the journal it cites.

As a certificate that auto citations are a problem for these metrics, the same problem should be taken into account when the absolute number of citations is considered as a metric. However, in this case, when dealing with already conceptualized studies, this problem tends to be less significant since it is expected that reputable articles are more cited. Intuitively, there is a number of citations that is much higher than the number of articles [26] since they are considered as references. Hereby, the number of citations can be taken into account with the purpose of measuring the influence of an institution, author or journal [26]. Nonetheless, there may be flaws, for example, a great article recently published and that has not yet become popular or even research conducted in a very specific scientific field.

Finally, there is the h-index, proposed by [27], which combines the number of publications and citations. Taking this research as a reference, which has an h-index of 34, this tells us that at least 34 articles published in the period investigated received 34 or more citations. Just as the other metrics, it also has criticisms. For instance, an extreme case pointed out by [26]: if a researcher publishes more than 100 articles and three received more than 1000 citations, while the rest are not cited, the index of this researcher will only be three [26]. Instinctively, it is possible to conclude that this hypothetical researcher has an academic relevance significantly higher than three. Despite the criticisms, this index is useful and relevant in academia; therefore, it is appropriate to the scope of this research in the criterion of evaluating the relevance of research, researcher, journal or institution.

In addition, with the help of VOSviewer software, textual analysis is made in order to identify the relationships between articles, keywords and researchers in the Renewable Energy, Economic Growth and Economic Development theme. The VOSviewer software allows for a relationship network construction between the articles published in the specified period.

4. Discussion

In this section, we analyze and discuss the information from the sample, starting with a temporal reading of the evolution of the publications in the years investigated. The following Figure 3 informs us of the annual amount of articles published on the subject from 2008 to May 2021.

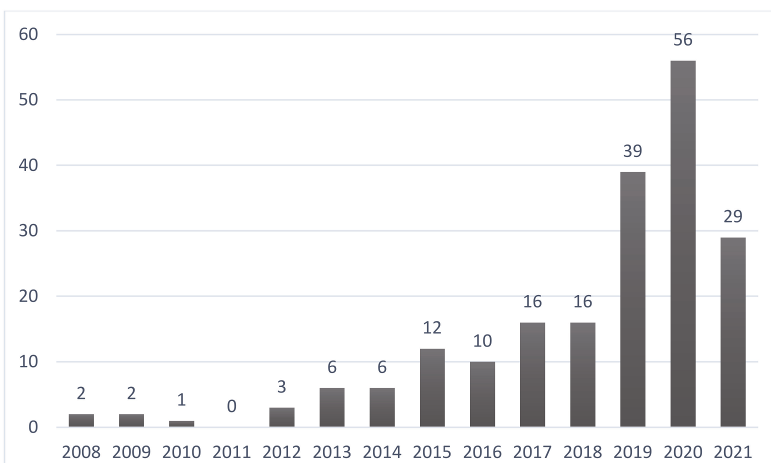

Figure 3. Number of Annual Publications (2008–May/2021).

The X-axis represents the years of research, while the Y-axis represents the number of articles published. A growth trend is easily noticeable, with the exception of 2010, 2011 and 2016. The number of articles published annually grew by the year. The considerable increase in publications in the last 5 years is remarkable; these years concentrate 78.39% of the papers published in that period. The decrease in the number of articles from 2020 to 2021 is most likely due to the sampling period of the research since it does not include the year 2021 as a whole; therefore, we cannot consider it as an indictment of a drop in publications. It is possible that by the end of the year 2021, there will be a number of publications similar to 2020, providing the theme continues with the growth trend.

The growth of publications in the second half of the decade of the 2010s may be the result of the first cycle of commitments of the Kyoto Protocol (2008–2012), which should have fostered research to analyze the effects. Within the scope of this research, in the sample raised, many studies consider emissions and effects on economic activity. It is believed that the first cycle of responsibilities of the Kyoto protocol has a fundamental role in increasing research on renewable energy consumption, non-renewable and which way these matrices are less harmful to the environment affect economic activity.

In Figure 4, we chose to make a geographical analysis, that is, to identify how many and which countries have the most publications on the subject in that period. At first, when considering any number of publications, we obtained 63 countries with research published on this theme of the 194 existing countries. This reveals that only 32% of nations developed research on renewable energy, economic growth and economic development up to the moment of this research. However, it should be noted that this does not mean that only 30% of the countries in the world were investigated in relation to this theme, but that the research is concentrated on around 30% of the countries. In order to facilitate understanding, we did not consider all 63 countries; we chose to make a minimum count of publications, which is five. Thus, the following graph considers only those countries that had more than five publications during the period of the development of this study.

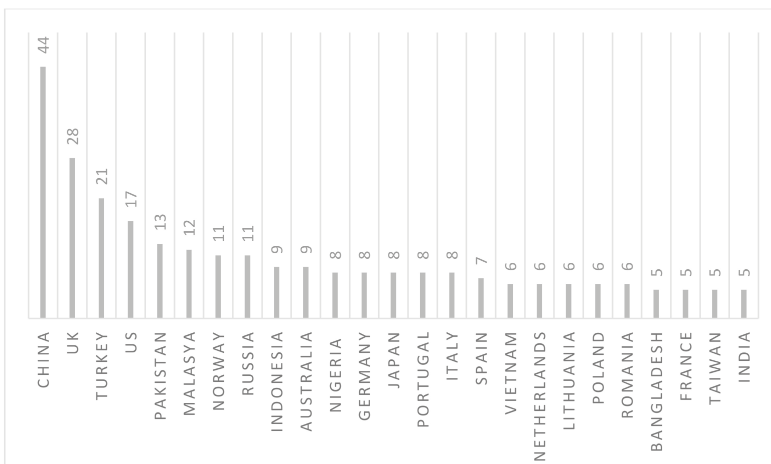

Figure 4. 25 Countries with more publications between 2008 and May 2021.

Only 25 countries have more than five articles published; China is noticeably an outlier. The number of Chinese publications is greater than the other countries; consequently, China is responsible for 22.11% of the publications in that period. Another attention-calling factor is that on all continents, there is at least one country with at least five publications on the subject, except Latin America.

Being a multidisciplinary research area, many journals publish about this theme. Seventy-four periodicals were published in that period. In Table 1, the periodicals are ranked according to the metrics stipulated by the WoS and Scopus databases.

Table 2 above shows us the number of articles in the area that were cited in some way in the research period. There are a total of 167 articles. It should be noted that this number is lower than the total sample, which is 199. This is because some articles (32 or 16.080%) have not yet been cited. When analyzing the citations, it seems that the number is low when compared to other research areas in which there are articles that have more than

1000 references. In this sample, no article reached such a number. It was clear that most of the published papers have less than 50 citations, which should change in the future as there is expected to be an increase in articles with more than 50 citations since the increase in publications on this subject is notorious in recent years.

Table 1. Source Ranking.

R	Journal Name	H-Index	Citations	Publications	Percentage	>200	>100	>50	<50	CS	SJR
1	Renewable and Sustainable Energy Reviews	295	74	4	2.010	0	0	1	3	30.4	3.632
2	Global Environmental Change	177	228	1	0.503	1	0	0	0	20.2	4.304
3	Water Research	303	28	1	0.503	0	0	0	0	15.6	2.932
4	Renewable Energy	191	45	4	2.010	0	0	0	4	10.8	2.052
5	Resources, Conservation and Recycling	130	37	1	0.503	0	0	0	1	14.6	2.215
6	Journal of Industrial Ecology	102	332	1	0.503	1	0	0	0	12.8	1.808
7	Energy Economics	152	87	3	1.508	0	0	0	3	2.7	0.977
8	Energy Policy	217	774	15	7.538	0	3	3	9	10.2	2.168
9	Science of the Total Environment	244	443	9	4.523	0	2	1	6	10.5	1.661
10	Journal of Environmental Management	179	24	2	1.005	0	0	0	2	9.8	1.321
11	Entrepreneurship and Sustainability Issues	25	5	1	0.503	0	0	0	1	7.0	1.171
12	Environmental Sciences Europe	35	5	1	0.503	0	0	0	1	4.8	1.774
13	Progress in Planning	48	24	1	0.503	0	0	0	1	8.4	0.913
14	Urban Studies	147	0	1	0.503	0	0	0	1	6.6	1.618
15	Mitigation and Adaptation Strategies for Global Change	71	25	1	0.503	0	0	0	1	5.9	1.112
16	Technological and Economic Development of Economy	47	119	3	1.508	0	0	1	2	6.0	0.622
17	British Journal of Management	108	21	1	0.503	0	0	0	1	6.8	1.522
18	Aerosol and Air Quality Research	55	7	1	0.503	0	0	0	1	5.9	0.965
19	Financial Innovation	18	66	1	0.503	0	0	1	0	4.2	0.847
20	New Political Economy	56	42	1	0.503	0	0	0	1	5.4	1.748
21	Environmental Science and Pollution Research	113	144	16	8.040	0	0	0	16	5.5	0.788
22	Energy Reports *****	33	113	6	3.015	0	0	0	6	2.7	0.977
23	Energy Strategy Reviews ****	33	414	3	1.508	1	0	0	2	7.8	1.336
24	Energy Journal	77	9	1	0.503	0	0	0	1	4.4	1.480
25	Review of International Political Economy	70	15	1	0.503	0	0	0	1	3.6	1.823
26	Climate and Development	35	1	1	0.503	0	0	0	1	4.8	1.047
27	Journal of Security and Sustainability Issues	23	34	3	1.508	0	0	0	3	3.1	0.375
28	Environmental and Resource Economics	92	0	1	0.503	0	0	0	1	4.2	1.401
29	International Journal of Energy and Environmental Engineering	30	16	1	0.503	0	0	0	1	3.9	0.528
30	Borsa Istanbul Review	21	0	1	0.503	0	0	0	1	4.3	0.684
31	Energy, Sustainability and Society	25	43	2	1.005	0	0	0	2	4.2	0.658
32	Environment, Development and Sustainability	56	2	2	1.005	0	0	0	2	3.8	0.548
33	Sustainability (Switzerland) *	85	383	39	19.598	0	0	0	39	3.2	0.581
34	Economic Analysis and Policy	29	21	1	0.503	0	0	0	1	3.6	0.776
35	Energy Exploration and Exploitation	30	22	2	1.005	0	0	0	2	2.8	0.489
36	International Journal of Energy Economics and Policy **	33	99	17	8.543	0	0	1	16	3.5	0.371
37	Journal of International Studies	17	4	1	0.503	0	0	0	1	3.7	0.541
38	Journal of Sustainable Development of Energy, Water and Environment Systems	14	11	1	0.503	0	0	0	1	3.7	0.400
39	Environmental and Climate Technologies	17	5	1	0.503	0	0	0	1	2.3	0.326
40	Journal of Economics, Finance and Administrative Science	13	0	1	0.503	0	0	0	1	1.4	0.308
41	Atmosphere	37	3	1	0.503	0	0	0	1	2.9	0.698
42	Frontiers in Energy Research ****	30	6	5	2.513	0	0	0	5	2.6	0.641
43	Thermal Science	43	3	2	1.005	0	0	0	2	2.4	0.495

Table 1. *Cont.*

R	Journal Name	H-Index	Citations	Publications	Percentage	>200	>100	>50	<50	CS	SJR
44	EAM: Ekonomie and Management	22	9	1	0.503	0	0	0	1	2.3	0.322
45	Environmental Economics and Policy Studies	23	6	1	0.503	0	0	0	1	2.9	0.483
46	Structural Change and Economic Dynamics	48	1	1	0.503	0	0	0	1	3.5	0.621
47	Polish Journal of Environmental Studies	54	6	3	1.508	0	0	0	3	2.4	0.366
48	Asia and the Pacific Policy Studies	14	14	2	1.005	0	0	0	2	2.7	0.533
49	Environment and Development Economics	62	2	1	0.503	0	0	0	1	2.8	0.787
50	Energy Sources, Part A: Recovery, Utilization and Environmental Effects	45	34	1	0.503	0	0	0	1	3.3	0.319
51	Emerging Markets Finance and Trade	34	47	1	0.503	0	0	0	1	2.6	0.444
52	International Journal of Innovation and Sustainable Development	20	8	1	0.503	0	0	0	1	3.9	0.528
53	International Journal of Renewable Energy Development	12	5	2	1.005	0	0	0	2	3.9	0.528
54	Economic Annals—XXI	14	1	1	0.503	0	0	0	1	1.5	0.234
55	Economy of Region	14	0	2	1.005	0	0	0	2	1.9	0.351
56	Geojournal	12	28	1	0.503	0	0	0	1	2.2	0.232
57	Cogent Economics and Finance	16	112	1	0.503	0	1	0	1	2.0	0.252
58	Management and Marketing	11	1	1	0.503	0	0	0	1	1.9	0.218
59	Social Science	19	11	1	0.503	0	0	0	1	2.3	0.239
60	Latin American Economic Review	8	50	1	0.503	0	0	1	0	2.4	0.346
61	Banks and Bank System	16	0	1	0.503	0	0	0	1	1.0	0.216
62	Comparative Economic Research	8	5	1	0.503	0	0	0	1	1.3	0.195
63	Geography, Environment, Sustainability	8	1	1	0.503	0	0	0	1	1.2	0.286
64	International Organizations Research Journal	7	6	1	0.503	0	0	0	1	1.1	0.295
65	Copenhagen Journal of Asian Studies	13	0	1	0.503	0	0	0	1	1.2	0.175
66	Pakistan Development Review	26	7	1	0.503	0	0	0	1	1.0	0.143
67	Environmental and Socio-Economic Studies	3	4	1	0.503	0	0	0	1	0.6	0.381
68	Informação e Sociedade	6	0	1	0.503	0	0	0	1	0.4	0.256
69	Wit Transactions on Ecology and the Environment	21	4	2	1.005	0	0	0	2	0.6	0.142
70	Russian Journal of Economics ******	12	1	1	0.503	0	0	0	1	0.2	NA
71	Environment and Planning C: Government and Policy [2]	69	9	1	0.503	0	0	0	1	3.5	0.998
72	European Research Studies Journal *[3]	34	44	1	0.503	0	0	0	1	2.6	0.274
73	Journal of Reviews on Global Economics [1]	6	12	1	0.503	0	0	0	1	0.2	0.227
74	Ekonomica Vilniaus Universitetas	NA	1	1	0.503	0	0	0	1	NA	NA
	Total		4163	199	100						

* Listed since 2009; ** Listed since 2011; **** Listed since 2013; ***** Listed since 2014; ****** Listed since 2015; [1] Coverage period 2016–2019; [2] Listed until 2017; [3] Listed until 2018; R = Ranking; >200 Number of articles with more than 200 citations; >100 Number of articles with more than 100 citations; >50 Number of articles with more than a 50 citations; <50 Number of articles with less than a 50 citations.

Taking the total h-index (34) of this research into account, it is noted that it is not a high value as it only comprises 17.085% of the sample. The number of articles with more than 400, 200, 100 and 50 citations is expected to increase since, as previously mentioned in this study, a growth trend is observed in research on renewable energy, economic growth and economic development.

Table 2. General Citation on Renewable Energy, Economic Growth and Development Economic on Scopus.

Citations	2008–May/2021	
	Number of Papers	% of Papers
≥400 citations	1	0.503
≥200 citations	2	1.005
≥100 citations	6	3.015
≥50 citations	9	4.523
≤50 citations	149	74.874
Total	199	83.920

Source: prepared by the authors with data from Scopus.

Table 3 shows us the most cited articles in the research period, in one of the criteria selected to determine relevance. These are the 20 most relevant papers of that period. One is able to notice a good distribution in the journal ranking, which may be an indication that good studies on the subject can be found in most journals listed in this research. Another point is that most of these 20 articles are post-2015, which reinforces the hypothesis that research on the subject still has a horizon of growth.

Table 3. Most Cited Articles in the Period (2008–May/2021).

Journal	JR	TC	Title	Author(s)	Year
Energy Strategy Reviews	23	405	The role of renewable energy in the global energy transformation	Gielen, Dolf Boshell, Francisco Saygin, Deger Bazilian, Morgan D. Wagner, Nicholas Gorini, Ricardo	2019
Journal of Industrial Ecology	6	332	How circular is the global economy? An assessment of material flows, waste production, and recycling in the European Union and the world in 2005	Haas, Willi Krausmann, Fridolin Wiedenhofer, Dominik Heinz, Markus	2015
Global Environmental Change	2	228	Energy, land-use and greenhouse gas emissions trajectories under a green growth paradigm	Van Vuuren, Detlef P. Stehfest, Elke Gernaat, David E.H.J. Doelman, Jonathan C. (. . .)	2017
Science of the Total Environment	9	131	Dynamic impact of trade policy, economic growth, fertility rate, renewable and non-renewable energy consumption on ecological footprint in Europe	Alola, Andrew Adewale Bekun, Festus Victor Sarkodie, Samuel Asumadu	2019
Energy Policy	8	127	China in the transition to a low-carbon economy	Zhang, Zhong Xiang	2010
Cogent Economics and Finance	57	112	Effect of economic growth on CO_2 emission in developing countries: Evidence from a dynamic panel threshold model	Aye, Goodness C. Edoja, Prosper Ebruvwiyo	2017
Science of the Total Environment	9	103	Modelling coal rent, economic growth and CO_2 emissions: Does regulatory quality matter in BRICS economies?	Adedoyin, Festus Fatai Gumede, Moses Iga Bekun, Festus Victor Etokakpan, Mfonobong Udom Balsalobre-lorente, Daniel	2020

Table 3. *Cont.*

Journal	JR	TC	Title	Author(s)	Year
Energy Policy	8	101	The energy and CO_2 emissions impact of renewable energy development in China	Qi, Tianyu Zhang, Xiliang Karplus, Valerie J.	2014
Energy Policy	8	100	The environmental Kuznets curve in Indonesia: Exploring the potential of renewable energy	Sugiawan, Yogi Managi, Shunsuke	2016
Energy Policy	8	89	Onshore wind power development in China: Challenges behind a successful story	Han, Jingyi Mol, Arthur P.J. Lu, Yonglong Zhang, Lei	2009
Energy Policy	8	79	The driving forces of change in energy-related CO_2 emissions in Ireland: A multi-sectoral decomposition from 1990 to 2007	O' Mahony, Tadhg Zhou, Peng Sweeney, John	2012
Technological and Economic Development of Economy	16	75	Evaluation of renewable energy alternatives using MACBETH and fuzzy AHP multicriteria methods: the case of Turkey	Ertay, Tijen Kahraman, Cengiz Kaya, Ihsan	2013
Financial Innovation	19	66	The relationship between energy consumption, economic growth and carbon dioxide emissions in Pakistan	Khan, Muhammad Kamran Khan, Muhammad Imran Rehan, Muhammad	2020
Renewable and Sustainable Energy Reviews	1	58	Energy security and renewable energy policy analysis of Pakistan	Aized, Tauseef Shahid, Muhammad Bhatti, Amanat Ali Saleem, Muhammad Anandarajah, Gabrial	2018
Science of the Total Environment	9	54	An assessment of environmental sustainability corridor: The role of economic expansion and research and development in EU countries	Adedoyin, Festus Fatai Alola, Andrew Adewale Bekun, Festus Victor	2020
Science of the Total Environment	9	53	Heterogeneous impacts of renewable energy and environmental patents on CO_2 emission—Evidence from the BRIICS	Cheng, Cheng Ren, Xiaohang Wang, Zhen Yan, Cheng	2019
International Journal of Energy Economics and Policy	36	51	The role of renewable, non-renewable electricity consumption and carbon emission in development in Indonesia: Evidence from distributed lag tests	Saudi, Mohd Haizam Mohd Sinaga, Obsatar Roespinoedji, Djoko Razimi, Mohd Shahril Ahmad	2019
Latin American Economic Review	60	50	The dynamic linkage between renewable energy, tourism, CO_2 emissions, economic growth, foreign direct investment, and trade	Ben Jebli, Mehdi Ben Youssef, Slim Apergis, Nicholas	2019
Energy Policy	8	49	Hydropower, social priorities and the rural-urban development divide: The case of large dams in Cambodia	Siciliano, Giuseppina Urban, Frauke Kim, Sour Dara Lonn, Pich	2015
Emerging Markets Finance and Trade	51	47	Financing Renewable Energy Projects in Major Emerging Market Economies: Evidence in the Perspective of Sustainable Economic Development	Kutan, Ali M. Paramati, Sudharshan Reddy Ummalla, Mallesh Zakari, Abdulrasheed	2018

JR = Journal Ranking; TC = Total Citations.

The taxonomy of the publication was another aim in this research, hereby, the studies selected through the PRISMA methodology were qualified in four subgroups by the authors, I being—Renewable and Non-Renewable Energy Consumption, Economic Growth and Economic Development; II—Transition to a low-carbon economy and energy efficiency;

III—Environmental Degradation; IV—Others. Most of the articles in this sample fall into category II—Renewable Energies, Economic Growth and Economic Development, and the expected result, according to the Scopus database, 127 of 199 (63.819%), is in this category. Although category II relates to the keywords used in the scope, it is not the focal point of the publications. These are more related to energy efficiency and countries with the objective of reducing their carbon emissions and cover around 15.075% (30 documents) of the research. The Environmental Degradation is responsible for 8.04%, in other words, 16 documents. Finally, the other category, with fewer studies, encompasses researches that relate to the subjects but are very specific cases and covers 13.065%, or 26 published papers on that period. When analyzing the methodologies applied in the researches that are part of the sample of this study, a prevalence of quantitative methodologies is observed of the 199 studies. One hundred and sixty-one, or 80.904%, apply quantitative methods to obtain the results of their studies. In the following paragraphs, an analysis of the studies within the given subsamples is performed.

The analysis of group I (Renewable and Non-Renewable Energy Consumption, Economic Growth and Economic Development) shows that most of the articles published in this subsample use quantitative methodology while 89.763% of the studies use some common methodologies in economic sciences. Most studies are analyses of statistical inferences of countries or a country studied in isolation. There are many studies covering various economies [28–34], for example [35–38]. Ref. [35] conducted a study covering 123 countries, 146 countries for Ref. [36], 53 countries for Ref. [37], and in [38], 24 countries are heterogeneous economies. However, when observing the studies that opt for groups, there is a direction to investigate specific groups with some similarities, whether geographical, economic and cultural, among others. Ref. [39] investigated 37 economies considered developed. OCDE member countries were studied from various perspectives by [40–45]. The results obtained by [45] indicate that in the long term, trade openings and technological developments tend to stimulate the consumption of renewable energy in OCDE countries. Emerging economies were investigated by [46–50], still, in the emerging economies, there were more targeted studies, such as papers [51–53]. According to [51], for these economies, the flow of foreign direct investment (FDI) and the development of the financial market are fundamental in promoting the consumption of renewable energies, in addition to reducing emissions and promoting economic growth. The BRICS economies were also investigated in isolation: Brazil was studied by [54–56], Russia by [57], China and India by [58] and China by several [59–65], and there were also investigations for Chinese provinces such as [66,67]. Moreover, Brazil, China and the USA were studied by [68], China and USA in [69], and China, USA, France and Japan by [70]. Continents were also the target of this type of research: Europe was studied by [71–83]. The result obtained by [71] indicates a balance between environmental degradation, economic growth, commercial opening, consumption of renewable and non-renewable energies and fertility rate. Furthermore, it was observed that the consumption of non-renewable energies increases the degradation of the environment, while the consumption of renewables contributes to conservation. As in the case of the BRICS, European countries were studied separately: Portugal by [84]. Portugal, Spain, Denmark and the USA by [85], Ukraine by [86,87], Turkey by [88,89], Romania by [90], Czech Republic and Slovakia by [91], Wales by [92], Poland by [93,94], Estonia, Latvia and Lithuania by [95], Scotland by [96] and Russia [97]. The American continent, to be more precise, Latin America, was also the target of research by [98–101]. The study [99] concluded that the consumption of renewable energies, tourism, and FDI tend to reduce environmental degradation, while foreign trade and economic growth are responsible for the deterioration of the environment. Refs. [102–104] analyzed Bolivia and Ecuador, respectively. Saudi Arabia [105] and Iran [106] were studied in the Middle East. This relationship was studied for the Asian continent, where the Environmental Kuznets' Curve [107] was validated, for the South Asian economies by [108]. Ref. [109] investigated South Asian and Southwest economies, and the results obtained indicate that the consumption of renewable and non-renewable energies promotes economic growth [109].

Belt Road countries were investigated by [110,111], SAARC and ASEAN countries [112], as well as, South Korea [113], Bangladesh [114], Malaysia [115–118], Indonesia [119–123], Vietnam [124], Taiwan [125], Pakistan [126–130], Kazakhstan [131,132], and Thailand [133]. Not many studies dealing with the African continent [134] investigate the continent, [135] sub-Saharan Africa, [136] Rwanda, [137] Cameron, Nigeria [138], [139] Ethiopia and [140] Tunisia. In Oceania, only [141] investigated Australia. OPEC member countries were studied by [142] and concluded that electricity production improves access to energy and promotes the economy. In addition to quantitative methodologies, other methodological approaches were applied; however, they were the minority in this subsample (10.318%). Similar to quantitative studies, there is an analysis of large groups, such as [143,144], which were analyzed a very different group of economies. The research addressed Europe [145,146], the United Kingdom [147] and Russia [97]. Refs. [148,149] analyzed China, while [150] studied India and China together; Islamic countries were studied by [151], and finally Bangladesh, Indonesia and the USA by [152–154], respectively.

The studies of subsample II (Transition to a Low-Carbon Economy/Energy Efficiency) are a total of 30, of which 22, or 73.333%, are quantitative surveys. Quantitative studies in this sample have a broad profile, such as [155,156]. The results of [156] point out that renewable energy and energy efficiency technologies are the central points for an energy transition. Renewable energy is the key to limiting greenhouse gas emissions and limiting the increase in global temperature by 2° [156]. The continents were also investigated: Asia was studied in [157–159], and the African continent in [160]. The most localized studies have a concentration on research focused on China [161–163]. The results found by [161] indicate that the targets of electricity production through renewable sources in China contributed to an increase of 1.8% between 2010 and 2020. In addition to these, [164] studied India and China. India was also addressed in [165]. Still, on the Asian continent, Pakistan, Vietnam, Kazakhstan and Japan were studied by [166–169], respectively. In Europe, Ireland was surveyed in [170], Turkey by [171], Netherlands by [172], Germany, United Kingdom and Norway in [173]. Regarding the USA, it was found that by achieving innovation targets, there is a reduction in carbon dioxide emissions [174]. In the Middle East, Saudi Arabia was studied by [175], and finally, [176] proposed to investigate quantitatively the impact of public policy of gradual reduction in fossil fuel consumption given through government subsidies; the results indicate that this contributes positively to the performance of macroeconomic factors [176]. In non-quantitative approaches, [177] investigated trends for the global energy market in the medium and long term and concluded that there is a global interest in renewable and non-conventional energies, as well as in improving energy efficiency to reduce an environmental impact on energy generation [177]. Europe was studied by [178,179], while China was studied by [180,181], Russia by [182], the economies of Mexico and Vietnam by [183] and Nigeria in [184].

There is subsample III, in which the documents relate to the keywords used in the research, but the focus of the research is on the degradation of the environment. Having said this, this group has 16 articles, 12 of which are quantitative papers, while the rest applied other methodologies. In the field of quantitative studies, [185] studied 32 countries considered in development. While [186] focused on the BRICS, for these economies, the consumption of renewable energies and the FDI tend to reduce carbon dioxide emissions, the opposite relationship found for GDP, and bank credit with CO_2, the increase in these variables is accompanied by an increase in environmental degradation, as well as exports [186]. In addition to this research, South Africa was also studied by [187,188], and India, together with Malaysia, Indonesia, Kenya, Mexico, Colombia, and Poland, were investigated by [189]. The European Union was addressed by [190], and concluded that economic factors accelerate environmental degradation; only Turkey was analyzed in isolation from Europe by [191,192]. ASEAN member countries were investigated by [193] and showed that macroeconomic factors contribute to degradation. Still, in Asia, Vietnam and Taiwan were studied by [194,195], respectively. The African continent was studied by [196] and Ghana by [197]. The study with non-quantitative approaches by [198] focuses on the possibilities of development in the global use of energy, land exploration, emissions and climate change in order to maintain constant sustainable development. The results indicate that a combination of these factors by opting for sustainable alternative, can lead to a strong energy transition towards renewable sources; however, in addition, it is also necessary to apply strict climate policies to reduce the trend of the rising global temperature [198]. Ref. [199] studies how the banking sector can contribute to decarbonization. Finally, [200] is the only country study that investigates Nigeria.

Lastly, in category IV (Others), unlike the aforementioned, where there is a clear predominance of quantitative methodologies, there is a balance. Of the 26 papers falling into this category, 13 (50%) are quantitative, while the other half use other approaches. In this category there are comprehensive studies, which do not necessarily work with continents/countries, for example [201–205], moreover [206] conducted a micro study. In studies dealing with territories for the European continent [207], it was concluded that renewable energy development policies improve the social factors studied (government policy, general public awareness, the market, lobbying activity) [207]. Russia was studied in [208], and the United Kingdom and Germany in [209] together with the USA and Brazil. On the Asian continent, Iran, China and Cambodia were investigated by [210,211] and [212], respectively. Ref. [213] studied the decision-making between financing and not financing renewable energy matrices on the African continent and concluded that investor confidence in regulatory effectiveness is the main concern, besides local construction capacity and political instruments [213]. In non-quantitative approaches, there are also studies without a sample directed to country/continent, such as [214–219]. Ref. [219] proposes two scenarios, a conservative one in which there is no change in the current situation of energy production and a transition, which assumes ambitious targets in the evolution and incentives of renewable energies. The results show that renewable sources may be responsible for providing between 35 and 50% of the world's electricity production by 2040, while the share of fossil fuels tends to decrease [219]. Ref. [220] demonstrated that common law adept countries responded better to renewable energy investment opportunities; in other words, the study points out that legal and regulatory institutions are to blame for the global imbalance in the development of energy [220]. In Europe, only Italy and Macedonia have surveys in this category, [221] and [222] respectively. While only Chinese provinces were surveyed in [223–225], and at the country level, in Asia, only Nepal in [226].

Due to the diverse results obtained in the studies, there is no academic/scientific consensus on the way in which energy consumption affects economic dynamics. There are economies in which the influence is positive, others negative and even economies in which the results are not statistically significant. This is likely to be the effect of specific characteristics of each sample observed in the studies. Despite this, a conclusion regarding the consumption of renewable energies was possible. They are fundamental in mitigating greenhouse gas emissions; therefore, there is evidence that they are essential in conserving the environment.

The prevalence and varieties of quantitative approaches in the studies are an indication that information is available so that decision-makers and policymakers can formulate strategies based on statistical evidence.

It is worth noting that when observing the countries taken into account in the above-mentioned studies, they are developed economies. There are many studies for Europe, USA, OCDE member countries, and many studies for developing economies, such as the case of BRICS, but little is investigated for less wealthy economies, as most African and Caribbean economies are countries that find themselves at the bottom of a low point of economic development. Thus, there are indications of a gap to be explored, develop, or even replicate studies already conducted for the most relevant economies, for these countries with lower economic power, in order to ascertain how the consumption of renewable energies affects the economy of these nations.

Along with, according to the analysis of the articles in this sample, a focus on relating energy consumption, whether renewable and non-renewable, with macroeconomic indicators, such as labor force, trade, foreign direct investment, with economic growth, not taking into account variables or socioeconomic indicators, is noticeable. This marginalization of metrics to evaluate economic and social development may be an indication, as it was previously pointed out that there is a growth horizon in the studies of this theme. It is natural that socioeconomic development is promoted from economic growth. Therefore, academia is on the way to understanding the various effects of renewable energies on economic activity, and from this understanding to expand into economic development.

Figure 5 informs us of the most used keywords. A universe of 637 keywords was obtained; however, when we limit it to a minimum of five occurrences, this number drops to 17, thus, following relevance criteria previously stipulated that Figure 4 was made with the existing relationships between these 17 words that were most used by the authors as keywords.

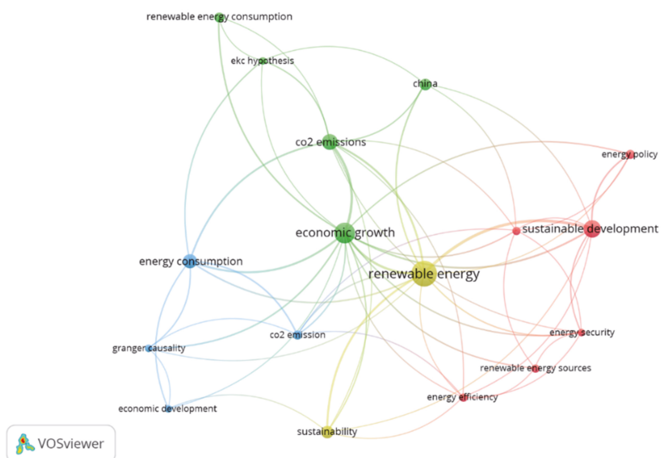

Figure 5. Keywords Occurrence Analysis.

Immediately, it is possible to observe that there are four clusters (given the different colors on the image), all of which somehow connect with the keyword "economic growth", which is the most used term by researchers, followed by "renewable energy". It is noted that, of the three terms selected in this work, two stand out. This may be an indication that the academy is focused on investigating the relationship between economic growth and energy consumption, a subject that was already investigated, however not overdone, since the focus is now on renewable energy matrices. With regard to the term of economic development, this subject, although extremely relevant, when related to economic growth and renewable energy, appears to be marginalized; that is, there is not much targeted research, so it is possible to conclude that there is a gap that should be explored by researchers.

It is also noted in the keywords with more occurrences there is a certain emphasis on CO_2 in conjunction with keywords that relate to sustainability. This implies an apparent interest in studying how greenhouse gas emissions may be impacting growth and or economic development. To a certain extent, the rise in the temperature of the planet may be one of the factors that have driven research to understand how renewable energies affect economic dynamics.

In addition, Figure 6 shows us that there are indications (given the yellow color) that these keywords, in sets, date to 2015 post surveys, once more, another indication that there is still much to be explored. Finally, China is noted as one of the most cited terms, and this may be one of the reasons why the country has greater prominence in the number of publications on the subject.

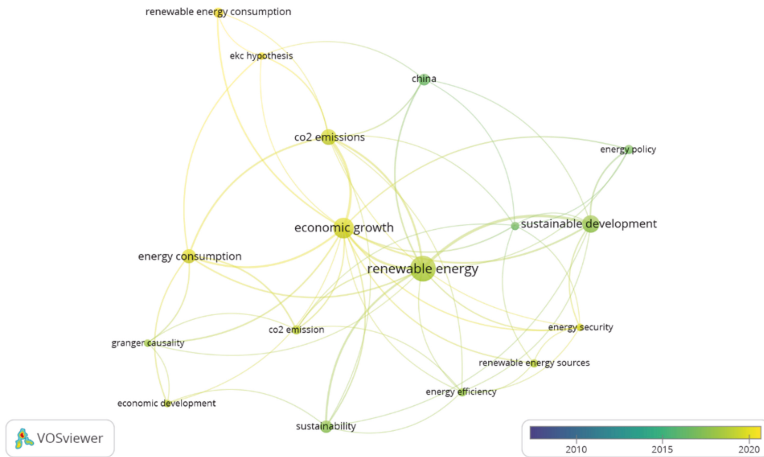

Figure 6. Keywords Overlay Visualization.

When the links between renewable energy, economic growth and economic development are observed, it is noted that there is no evidence of research relating to economic development and renewable energies, as can be seen in Figure 7 below. According to Figure 7, the existence of two clusters is clear; one between economic growth and renewable energies and the other between economic growth and economic development. The research gap that can be explored is even more evident since there is no direct link between economic development and renewable energies.

However, if we use energy consumption instead of renewable energies, a link is noted with economic development, as can be seen in Figure 8. Once again, this result reinforces the hypothesis of the absence of studies relating the consumption of renewable energies with development.

Finally, an analysis of the possible clusters and links between the researchers was also performed. The number of citations is a relevance indicator, even though it is not an accurate metric. In VOSviewer, the software to perform such analysis only considered authors with more than five citations, so the number of authors analyzed is 404 (instead of 665), which is the total number of researchers in this sample. Even though the number of researchers was reduced to 404, a link was found between only 46 of them, as can be seen in Figure 9.

Figure 7. Link Between Renewable Energy, Economic Growth and Economic Development.

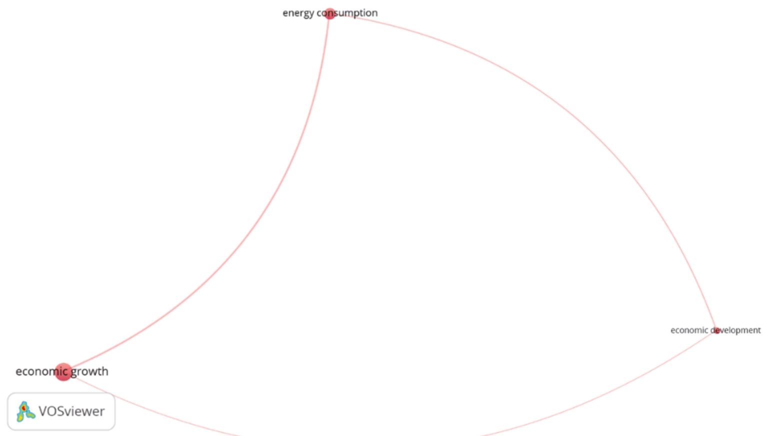

Figure 8. Link Between Energy Consumption, Economic Growth and Development Economic.

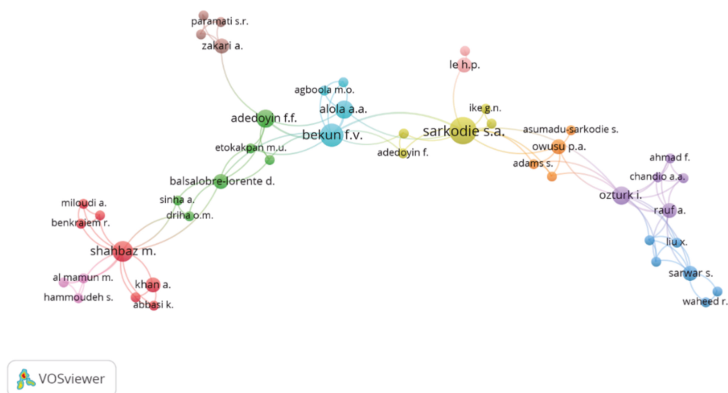

Figure 9. Authors' Network Visualization.

By observing the number of colors, one can see 10 clusters. However, although there are 10, only 4 clusters stand out because they have more branches; therefore, they are connected to more researchers. These are one led by Bekun in blue, followed by Sarkodie in yellow, then Ozturk is in purple, and finally, the cluster formed by the Shahbaz in red. Notoriously, this relationship does not occur randomly since they are the authors with the highest number of documents published on the stipulated criteria. Sarkodie has eight publications based on the topic in that period, while Bekun has five publications, Shahbaz four publications, and Ozturk three publications.

Among the most referenced studies in the period, Bekun and Sarkodie, of the authors with the highest number of publications, are unique, with works listed among only 20 most referenced in the period. While Shahbaz, already recognized for his academic contribution in research that relates to economics and the environment, as highlighted in [17,18], appears to be relevant in studies relating to renewable energy and economics.

The work developed by these authors in the period investigated also does not study less developed economies, except Ozturk studying energies and ecological sustainability in the Belt and Road Initiative Countries [110], and Sarkodie investigating Ghana's economy in [197], all other studies focus on developed or developing economies. This is a strong indication that these less capable economies are being marginalized in the context of understanding how renewable energies can affect their economic growth and development, and this negligence may be another factor of delay in their development.

5. Conclusions

This research focused on investigating articles published in the Scopus database that studied the relationship between renewable energy, economic growth and economic development between 2008 and May 2021. The results of screening through the PRISMA methodology provided a sample of 111 articles selected by the WoS database and 199 articles selected by the Scopus database. There is a prevalence of quantitative methodologies to the detriment of other approaches. Regarding the ranking of the journals with the highest impact, Renewable and Sustainable Energy Reviews were in first place, followed by Global Environmental Change and in third was Water Research. However, the journal with the largest number of publications was Sustainability (Switzerland).

Despite the effort to overcome the difficulty in quantitatively measuring an article, journal or author, this is the major limitation of this research. The metrics used for quantifying are susceptible to failure; thus, they are not accurate because there is no defined methodology that is applicable to the type of approach used in this study. In addition to this, the selected sampling period was also considered since it does not take the year 2021 into account. To be more precise, it is only considered until 21 May. Nevertheless, the number of publications found for this year should not be ignored. Another limiting factor of the research is found in the sample used, considering the information available in the Scopus database in the construction of the analyzed sample, not taking into account all the studies that exist in Web of Science (WoS), which may have relevant studies that of course were not taken into consideration.

The analysis of the data obtained among both databases leads us to conclude that studies with respect to renewable energy, economic growth and economic development are just beginning since it is possible to observe a growth trend. Most of the studies published on that period occurred after 2015, and the articles considered to have the greatest impact are publications that date back to more recent years, which appears to be the result of the end of the first cycle of commitments of the Kyoto Protocol.

It is notorious that the topic is being researched on all continents, and surprising that China is a leader in publications, given that it is one of the countries whose economic growth has been the most damaging to the environment.

This research was able to identify research gaps; studies have focused on understanding how renewable energies have affected economies around the globe, but the observed gap is precisely in one of the keywords used in this research. No studies were observed that connect renewable energies and economic development; therefore, it is suggested that it is a theme to be addressed by academia in the future. There is also a lack of studies dedicated to less developed economies, so there is no evidence of how the factors observed in this study can affect the economic activity of these countries; for these economies, there is a lack of information to outline the best strategies and policy development to promote greater growth. In addition, with the possibility of continuing to work with this sample, it is also proposed in future research to analyze the quality of the research reviewed in this article, with the objective of finding unexplored gaps, which can later be addressed.

This type of study, proposed in this research, is strategic for decision-makers and policymakers in demonstrating that the effects of a variable on the economy. In the case of this research, the nexus between economic growth, renewable energy consumption and economic development may be different between economies. Hence, it is an indication that before any strategic decision-making to promote economic growth, consumption of renewable energies or economic development, statistical studies should be promoted, with the aim of having an evidence-based decision and thus making efficient decisions.

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editing, H.O.; visualization, V.M. Both authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

The search protocol is dated, which is a study limiter. The Scopus database updates its article base quite frequently, making it impossible to replicate and analyze all the papers in it.

On the Scopus (https://www.scopus.com), accessed on 21 May 2021, search page, which has restricted access, requiring a login, we researched the three keywords used in our research (Renewable Energy, Economic Growth and Economic Development), obtaining a total of 2836 documents. Articles published in Biochemistry, Genetics and Molecular Biology, Medicine, Physics and Astronomy, Immunology and Microbiology, Pharmacology, Toxicology and Pharmaceutics, Arts and Humanities, Psychology, Health Professions and Veterinary was not taken into consideration. Below can be seen the final research protocol, which resulted in a sample of 291 documents, which later went through another screening stage that culminated in the 199 articles analyzed in this study.

Table A1. Search Protocol.

TITLE-ABS-KEY (RENEWABLE AND ENERGY, AND ECONOMIC AND GROWTH AND DEVELOPMENT AND ECONOMIC) AND PUBYEAR > 2007 AND (LIMIT-TO (OA, "all")) AND (EXCLUDE (SUBJAREA, "ENGI") OR EXCLUDE (SUBJAREA, "EART") OR EXCLUDE (SUBJAREA, "AGRI") OR EXCLUDE (SUBJAREA, "MATH") OR EXCLUDE (SUBJAREA, "BIOC") OR EXCLUDE (SUBJAREA, "MATE") OR EXCLUDE (SUBJAREA, "COMP") OR EXCLUDE (SUBJAREA, "CENG") OR EXCLUDE (SUBJAREA, "MEDI") OR EXCLUDE (SUBJAREA, "MULT") OR EXCLUDE (SUBJAREA, "PHYS") OR EXCLUDE (SUBJAREA, "CHEM") OR EXCLUDE (SUBJAREA, "IMMU") OR EXCLUDE (SUBJAREA, "ARTS") OR EXCLUDE (SUBJAREA, "DECI") OR EXCLUDE (SUBJAREA, "HEAL") OR EXCLUDE (SUBJAREA, "PHAR") OR EXCLUDE (SUBJAREA, "PSYC") OR EXCLUDE (SUBJAREA, "VETE")) AND (LIMIT-TO (DOCTYPE, "AR")) AND (LIMIT-TO (LANGUAGE, "ENGLISH"))

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