Renewable Energy Focus 48 (2024) 100544

Contents lists available at ScienceDirect

Renewable Energy Focus

journal homepage: www.elsevier.com/locate/ref

Analyzing the relationship between oil prices and renewable energy sources in Italy during the first COVID-19 wave through quantile and wavelet analyses

Cosimo Magazzino [a,*], Lorenzo Giolli [b]

[a] Department of Political Science, Roma Tre University, Rome, Italy
[b] European School of Economics, Florence, Italy

ARTICLE INFO

Keywords:
Renewable energy
COVID-19
Long memory
Spectral causality
Wavelet analysis
Italy

ABSTRACT

The paper aims to analyze the evolution of oil prices and renewable energy production in Italy during the first wave of the COVID-19 pandemic crisis with daily data for the period January 2020-September 2020 through several time series techniques (long memory test and spectral causality analysis) and Wavelet Analysis tools. Italy has been the first country all over the world to be severely hit by the pandemic, reacting immediately with strong restrictive measures. The applied results show that oil prices and renewable energy sources were highly correlated during the pandemic shock. Moreover, causality tests reveal a unidirectional flow running from solar, hydro, and wind sources to oil prices, highlighting the relevance of the effect of the energy transition on the oil market. It is also imperative for a country that is a net energy resources importer to achieve a more sustainable way of production and accelerate the energy transition process, especially during phases of high fossil fuel prices.

1. Introduction long-term

During Italy's first wave of the Corona Virus 2019 (COVID-19) pandemic, the intricate relationship between oil prices and renewable energy sources underwent significant shifts. As the nation grappled with the severe economic impact of the crisis, global oil prices experienced a historic collapse. This was primarily due to a sharp drop in demand as travel restrictions and lockdowns curtailed economic activities. Consequently, Italy, a country heavily reliant on oil imports, observed a temporary reduction in its energy expenditures, providing some respite to its struggling economy. Lower oil prices momentarily lessened the burden on consumers and industries dependent on fossil fuels [14].

Simultaneously, the pandemic highlighted the importance of diversifying the energy sector and investing in renewable sources [39]. In an effort to stimulate economic recovery and address environmental concerns, the Italian government accelerated its transition towards cleaner energy. Incentives and policies supporting renewable energy projects were bolstered, encouraging investment in solar, wind, and hydroelectric power. The decrease in oil prices also underscored the volatility and vulnerability of fossil fuel-dependent economies, making renewable energy sources a more stable and attractive option [11]. Italy's commitment to green energy gained momentum during this period, setting the stage for a more sustainable and resilient energy future. While the initial effects of the pandemic were tumultuous, they ultimately contributed to Italy's progress in reducing its reliance on oil and advancing its renewable energy sector [9].

In recent years, the global energy landscape has witnessed a significant transformation characterized by an oil price slump and an intensified focus on transitioning towards cleaner energy sources. This convergence of events has profound implications for economies, industries, and the environment. The oil price slump, which was precipitated by a multitude of factors, has forced the world to rethink its energy strategies and expedite the shift towards sustainable and cleaner alternatives [50].

The oil price slump, which began to manifest itself in the mid-2010s and persisted into the 2020s, can be attributed to several key factors.

Abbreviations: BCSG, Breitung-Candelon Spectral Granger; CO_2, Carbon dioxide; COVID-19, Corona Virus 2019; CWA, Continuous Wavelet Analysis; DCCA, Detrended Cross-Correlation Analysis; DWA, Discrete Wavelet Analysis; EVs, Electric vehicles; GARCH, Generalized Auto-Regressive Conditional Heteroskedasticity; GHG, Greenhouse Gas; GETS, General to Specific; GPH, Geweke/Porter-Hudak; IEA, International Energy Agency; NEX, New Energy Global Innovation Index; OPEC, Organization of the Petroleum Exporting Countries; SVAR, Structural Vector Auto-Regression; WA, Wavelet Analysis.

* Corresponding author.
E-mail addresses: cosimo.magazzino@uniroma3.it (C. Magazzino), lorenzo.giolli@gmail.com (L. Giolli).

https://doi.org/10.1016/j.ref.2024.100544
Received 21 October 2023; Received in revised form 31 December 2023; Accepted 17 January 2024
Available online 19 January 2024

First and foremost, the global oversupply of oil, coupled with slowing demand growth, created a surplus that put downward pressure on prices. This oversupply was partially due to advancements in shale oil production in the United States (US), which allowed for increased domestic production and a reduced reliance on foreign oil. Additionally, geopolitical factors, such as the Organization of the Petroleum Exporting Countries (OPEC)'s decision to maintain high production levels, contributed to the oversupply and declining prices. The COVID-19 pandemic further exacerbated the situation, with lockdowns and travel restrictions causing a sudden drop in oil demand.

This oil price slump has had far-reaching effects on oil-dependent economies, with many facing economic challenges and fiscal deficits. Countries heavily reliant on oil revenue, such as those in the Middle East, have been compelled to diversify their economies and reduce their dependence on oil. Governments worldwide have recognized the need for resilience in the face of such price volatility and are increasingly investing in renewable energy, electric vehicles, and other sustainable technologies.

The shift towards cleaner energy represents a possible reaction to the decline in oil prices and the urgent need to diminish carbon emissions in the fight against climate change. It is not only an environmental necessity but also an economic opportunity. Investments in renewable energy sources, such as wind, solar, and hydropower, have surged as countries seek to decarbonize their energy sectors. Electric vehicles (EVs) have gained momentum, with major automakers pledging to transition to all-electric fleets in the coming decades. Battery technology advancements are making energy storage more efficient and affordable, addressing the intermittency of renewables.

One notable outcome of the oil price slump and the cleaner energy transition is the re-evaluation of fossil fuel companies. Many of them are diversifying their portfolios by investing in renewable energy projects, recognizing that the future of energy lies in sustainability. These companies are also facing increasing pressure from investors and consumers to reduce their carbon footprint and adopt more environmentally friendly practices.

The shift towards cleaner energy sources is not without its challenges. One of the most significant hurdles is the need for substantial infrastructure investments to support renewable energy generation, distribution, and storage. Governments must also implement supportive policies, such as incentives and subsidies, to accelerate this transition. Moreover, there is a need for a skilled workforce trained in renewable energy technologies, creating new job opportunities in the process [26].

In conclusion, the oil price slump has served as a wake-up call for the world, prompting a reevaluation of our energy sources and consumption patterns. The cleaner energy transition is both an economic imperative and a moral obligation. It offers the potential to not only reduce our dependence on volatile fossil fuel markets but also mitigate the catastrophic effects of climate change. As governments, industries, and individuals continue to embrace cleaner energy alternatives, we move one step closer to a more sustainable and resilient future. While challenges lie ahead, the promise of a cleaner, greener world is worth the investment, effort, and determination it demands.

The study aims to deepen the understanding of the complex relationship between these series. This understanding can greatly contribute to policymaking by identifying specific frequency bands that demonstrate a strong correlation between oil prices and renewable energy. Basically, the paper seeks to examine the correlation between oil prices and renewable energy in Italy during the initial phase of the COVID-19 pandemic. Italy was among the first and most significantly affected countries during the early stages of the virus outbreak, experiencing considerable economic downturn as a result. The study specifically concentrates on the dynamics of this relationship in the early period of the pandemic crisis, providing a unique perspective not extensively explored in existing literature and enhancing the novelty of this research. Moreover, to the best of our knowledge, this is the first study to apply the Wavelet Analysis (WA) and the Breitung-Candelon Spectral Granger (BCSG) causality test to this topic.

The outline of the study is as follows: Section 2 shows a concise overview of the literature, the theoretical background, and the novelty aspects of the research. The methodologies applied together with the data used are discussed in Section 3. In the following Section 4 the empirical findings are presented and commented. Finally, Section 5 concludes, by providing some policy recommendations.

2. Literature overview

The relationship between oil prices and renewable energy has been a topic of significant interest and debate in recent years. This literature review aims to provide a comprehensive analysis of the existing research on this complex and multifaceted relationship, given the growing importance of both oil and renewable energy sources in the global energy landscape. With climate change concerns and energy security issues becoming more prominent, understanding how fluctuations in oil prices impact the adoption and growth of renewable energy technologies is crucial. This review examines studies conducted in the past two decades, focusing on the interplay between oil prices and the renewable energy sector, while also considering the broader socio-economic and environmental implications.

To fully comprehend the relationship between oil prices and renewable energy, it is essential to examine the historical trends. Numerous studies have shown an inverse correlation between oil prices and the development of renewable energy sources. High oil prices tend to stimulate interest and investment in renewable energy, while low prices can slow down progress. For instance, during the oil crisis of the 1970s, there was a surge in research and development in renewable energy technologies [49].

The economic factors underlying the relationship between oil prices and renewable energy are the subject of extensive research. Fluctuations in oil prices, often driven by geopolitical events and supply-demand dynamics, can have a profound impact on the economics of renewable energy. Several studies have shown that high oil prices encourage investments in renewable energy, making it more attractive from a cost perspective. Conversely, during periods of low oil prices, renewable energy investments may appear less competitive [3].

Moreover, this relationship is also deeply influenced by government policies and regulations. Numerous countries have recognized the need to reduce their dependence on oil and curb Greenhouse Gas (GHG) emissions, leading to the implementation of various incentives and mandates to promote renewable energy. Studies have consistently shown that strong policy support can decouple the renewable energy sector from oil price fluctuations, creating a more stable growth trajectory [4].

Technological advancements in the renewable energy sector are also a vital factor. Over the past two decades, the cost of renewable energy technologies, particularly solar and wind, has steadily decreased. This trend has made renewable energy increasingly competitive and less reliant on oil prices. Sözen et al. [48] and Jacobsson and Lauber [19] indicated that innovation and technological progress have been key drivers of the renewable energy sector, enabling it to grow independently of oil price fluctuations.

Additionally, the development of energy storage technologies has mitigated the intermittency issues associated with renewables, further reducing their dependence on oil or other fossil fuels.

Furthermore, the link between oil prices and renewable energy is intrinsically tied to environmental concerns and the urgency to combat climate change. Higher oil prices often coincide with greater awareness of the environmental consequences of fossil fuel consumption. Consequently, during periods of high oil prices, there is increased public and political support for renewable energy as a means to reduce GHG emissions [52].

Kyritsis and Serletis [22] used a bivariate Structural Vector Auto-Regression (SVAR) model to analyze the effects of oil price shocks on the stock returns of clean energy and technology companies, through monthly data for the period May 1983-December 2016. The empirical findings highlighted that oil price uncertainty does not affect stock returns, while the two variables exhibit a symmetric relationship.

Balcilar et al. [2] examined how uncertainties in the energy market impacted the transition to renewable energy in the 28 EU countries between 1990 and 2015, utilizing annual frequency data. They unveiled the pivotal role played by oil price and residual energy price uncertainties to promote renewable energy transition.

Murshed and Tanha [34] explored the nonlinear relationship between renewable energy consumption and crude oil prices in four net oil-importing South Asian economies. Employing yearly data from 1990 to 2018, the long-term elasticity estimates revealed the existence of a nonlinear nexus. The findings suggested that initially increasing crude oil prices do not promote renewable energy consumption; however, once a certain threshold level of crude oil prices is reached, further increases are likely to boost renewable energy consumption.

Mukhtarov et al. [33] investigated the impact of elevated oil prices, carbon dioxide (CO_2) emissions, and income on renewable energy consumption in Iran over the period 1980 to 2019, utilizing the General to Specific (GETS) modeling approach. The estimation results revealed a statistically significant and negative influence of both oil prices and CO_2 emissions on renewable energy consumption.

Sahu et al. [43] analyzed the impact of oil price fluctuations on the utilization of renewable energy in the USA from 1970 to 2018. The findings indicated that an increase in crude oil prices, GDP, and population density leads to a rise in renewable energy usage in both the short-term and the long-term.

Magazzino et al. [25] explored the evolving connection between the oil market and European stock market returns by analyzing monthly data from May 2007 to April 2022 across 27 EU states. The applied findings showed clear evidence of a time-varying causality.

Mohammed and Mellit [30] explored the link between oil prices and the indices of renewable energy and technology companies spanning from 2004 to 2021. The findings underscored compelling evidence of an asymmetric effect.

Nevertheless, the applied literature on the relationship between oil prices and renewable energy during the pandemic is scarce. Naser et al. [35] examined the connections between new COVID-19 cases and the WilderHill New Energy Global Innovation Index (NEX) using daily data from January 23, 2020, to February 1, 2023. The findings indicate a noteworthy positive influence of COVID-19 new cases on NEX index returns in the short-term, while a significant negative impact in the long-term. Horky et al. [14] investigated the worldwide interplay between oil and renewable energy returns amid the COVID-19 pandemic, with data from July 2019 to June 2020. The primary discovery indicates that the pandemic serves as a significant connecting element in the relationship between oil energy and renewable energy. Jia et al. [20] using a computable general equilibrium model for China found that the substantial decline in crude oil prices exerts a notable adverse effect on the low-carbon economy.

Moreover, numerous studies have explored the interconnectedness between oil prices, climate change, and renewable energy adoption. Karanfil and Li [21] studied the effects of crude oil price shocks on the stock market volatility of the G-7 countries, showing that stock market volatility is related to demand shocks but not to oil supply shocks. Salim et al. [44] examined the impact of oil price volatility on key macroeconomic indicators of Thailand, using the VAR method. Causality analysis showed the presence of a unidirectional causality flow from oil price volatility to investment, unemployment rate, interest rate, and trade balance. Sadorsky [42] employed multivariate Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH) models to model conditional correlations and to analyze the volatility spillovers between oil prices and the stock prices of clean energy companies and technology companies. The results highlight that a $1 long position in clean energy companies can be hedged for 20 cents with a short position in the crude oil futures market.

Notwithstanding, this relationship is not uniform across all regions. Different countries exhibit varying levels of sensitivity to oil price fluctuations, depending on their energy mix, natural resource endowment, and policy environment. For example, oil-importing nations may be more susceptible to changes in oil prices, whereas those with abundant renewable energy resources might have a more stable renewable energy sector regardless of oil prices [47].

Mutascu et al. (2022) analyzed the co-movements between gasoline and diesel prices in three European countries (i.e., Germany, France, and Italy) with different fuel tax systems in place. The wavelet coherence analysis showed co-movements between gasoline and diesel at all frequencies, as well as during specific periods, but stronger in the long-term.

Magazzino et al. [27] introduced an innovative method to detect the existence of a hidden factor influencing the simultaneous movements of gasoline and diesel prices in France, Germany, and Italy, with daily data spanning from January 3, 2005, to June 28, 2021. The estimations revealed the presence of a latent factor, contributing to the co-movements in fuel prices.

3. The relevance of the case study

While Italy has taken commendable steps toward an energy transition, there are several challenges and shortcomings in its approach. Italy's transition still heavily relies on natural gas, which is considered a transitional fossil fuel. While cleaner than coal and oil, natural gas is not a long-term sustainable solution. Italy should prioritize further reducing its dependence on gas in favor of fully renewable energy sources. The integration of renewable energy sources into the grid is a complex challenge. The country needs to invest in grid modernization to ensure efficient distribution and management of electricity from renewable sources [13,31]. Italy should allocate more resources to research and development in clean energy technologies. Investing in innovation can accelerate the transition and make the country a leader in sustainable energy solutions. Energy transition should not exacerbate social inequalities. Italy must ensure that the costs and benefits of the transition are distributed equitably, especially among vulnerable communities. The success of Italy's energy transition relies on consistent political commitment and policy stability. Frequent changes in government and policy reversals can undermine long-term planning and investments in the sector.

Italy's experience with the oil price slump and its efforts towards an energy transition reflect the broader global challenges and opportunities facing nations in the 21st century. While Italy has made commendable progress in reducing its reliance on fossil fuels and promoting renewable energy sources, there is still work to be done.

To achieve a sustainable and resilient energy future, Italy must continue its transition away from fossil fuels, invest in grid infrastructure, prioritize research and development, ensure social equity, and maintain political commitment. The oil price slump, while a challenging hurdle, can catalyze Italy to accelerate its efforts towards a cleaner and more sustainable energy landscape, contributing to a greener future for the country and the planet as a whole.

4. Data and methodology

The data on oil prices and renewable energy production series for Italy during the COVID-19 pandemic have been derived from the International Energy Agency (IEA) database (https://www.iea.org/data-and-statistics). The series are observed with a daily frequency over the period from January 2nd, 2020 to September 30th, 2020, which represented the most severe phase of the pandemic crisis for the country.

The Geweke and Porter-Hudak (GPH [10] method is employed. This test uses nonparametric methods (i.e., a spectral regression estimator) to estimate the long-term parameter d of a time series. Moreover, to evaluate the robustness of the GPH results, a range of power values (from 0.40 to 0.60) is commonly calculated as well.

The Breitung and Candelon [5] Spectral Granger causality test is an advanced econometric method for investigating causal relationships between time series data. This approach addresses the limitations of traditional Granger causality tests, especially when dealing with non-stationary data common in economic and financial analysis. The BCSG test operates in the frequency domain, leveraging spectral analysis techniques. It extends Granger causality by examining how one time series influences another across different frequency components. To this extent, it decomposes time series data into spectral components using methods like the Fast Fourier Transform or Wavelet Transform. By analyzing the spectral density of these components, researchers can pinpoint frequency bands where one series Granger-causes another. This approach provides a deeper understanding of causal relationships, revealing lead-lag dynamics and frequency-specific interactions. The BCSG test finds applications in diverse fields, including economics, finance, and neuroscience. Its ability to handle non-stationary data and uncover frequency-specific causalities makes it a valuable tool for understanding complex systems. Researchers use it to reveal hidden causal links and enhance predictive modeling, particularly when dealing with intricate, dynamic datasets.

Wavelet analysis is a powerful and versatile mathematical tool used in signal processing, data compression, and various scientific fields [29]. Its numerous advantages make it an indispensable method for analyzing signals and data.

One of the primary advantages of wavelet analysis is its ability to provide both time and frequency localization simultaneously [7]. Unlike traditional Fourier analysis, which offers excellent frequency resolution but lacks time information, wavelets can capture transient events with precision. This characteristic makes wavelets particularly well-suited for analyzing non-stationary signals, such as those encountered in speech, image, and financial data analysis.

Another advantage of wavelet analysis is its multiresolution analysis capability (Strang and Nguyen, 1996). Wavelets allow for the decomposition of a signal into different scales, which helps uncover hidden structures or features at various levels of detail. This hierarchical representation enables efficient data compression and denoising, as one can selectively retain or discard specific wavelet coefficients to preserve essential information while reducing noise.

Additionally, wavelet analysis is adaptable to a wide range of applications, from image and vid***eo compression to the detection of transient events in biological signals, like electroencephalogram or electrocardiogram data [38]. Its flexibility, along with the availability of various wavelet families and parameters, allows researchers and practitioners to tailor their analysis to the specific requirements of their data and problem domains.

The core element in the wavelet analysis is the wavelet transformation. In summary, wavelet analysis offers the advantages of time-frequency localization, multiresolution analysis, and versatility, making it a valuable tool for extracting meaningful information from complex signals and data in diverse fields of science and engineering.

Wavelet analysis can be categorized into two variants: Discrete Wavelet Analysis (DWA) and Continuous Wavelet Analysis (CWA). The former is particularly useful for noise reduction and data compression, while the latter is more advantageous for feature extraction purposes [12,8]. Both variants have found applications in the realm of energy economics or environmental sustainability, as evidenced by Magazzino et al. [28] and Matar et al. (2023).

When applying discrete wavelet analysis to examine the causal relationship between time series, the first step involves decomposing the variables into different frequencies using methods such as the maximal overlap discrete wavelet transform [38]. Subsequently, the decompositions are analyzed using traditional time-domain measures of causality. However, this procedure has been criticized for its inability to convey the time-domain content of causal effects [1,37]. Consequently, this study employs two alternative designs of causal inference within the framework of continuous wavelet analysis, which can effectively address this problem.

Morlet et al. [32] first developed continuous wavelet analysis). As defined in equation [1], a mother wavelet can generate baby wavelets by shifting the location parameter τ and dilating the scale parameter s.

$$\psi\tau, s\,(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right) \tag{1}$$

A cross-wavelet transform can be applied to a pair of time series to examine their comovement.

For series $x(t)$ and $y(t)$, their cross-wavelet transform is calculated. Then we have two primary approaches within the continuous wavelet framework to assess their causal linkages.

$$W_{xy}\,(\tau,s) = W_x\,(\tau,s)\;W^*_y\,(\tau,s) \tag{2}$$

All variables are taken in their natural logarithm transforms. Table 1 shows the descriptive statistics on the constructed dataset. Only wind has a third moment (skewness) value relatively far from 0, and biomass has a kurtosis value far from 3.

The correlation analysis is graphically condensed in Figure 1. Visually, it is possible to detect a slight negative correlation between oil prices and Solar (r=-0.28), Wind and Solar (r=-0.32), Geothermal and Solar (r=-0.41), and Geothermal and Hydro (r=-0.68); on the other hand, a mild positive association exists between Hydro and Solar (r=0.41) and Geothermal and Wind (r=0.25).

5. Empirical findings

Given the nature of our data – with a daily frequency – we choose to run a long memory (fractional integration) test, in order to inspect the stationarity properties of the selected series. The results of the GPH test are given in Table 2.

The GPH test, applied to these series, finds that $d = 0$ (stationarity) can be rejected for oil prices, solar, hydroelectric, and geothermal. Thus, we can derive that these variables should be considered as difference-stationary – as clearly emerges from the test results on the first-difference transformation –, while the remaining two (biomass and wind) are level-stationary, or I(0).

Figure 2 provides the CWT findings for the tested series. The power spectrum is constructed with the frequency on the vertical axis (y) and the time on the horizontal axis (x). Generally speaking, we can see that the market was less volatile during the second half of the time span (approximately since July 2020). Moreover, we can see that the higher volatility is roughly confined to high-frequency (low-scale) periods. In particular, for Biomass, Solar, and Wind a clear dark red area is evident between January and April 2020 at low frequency, while for Biomass and Geothermal it could be detected between May and mid-June. In addition, only for Biomass a high volatility can also be registered at a medium frequency (April-May 2020). Thus, we can infer that the market fluctuations affected the series essentially at a high frequency.

Figure 3 presents the graphs for the WTC analysis. On the x-axis is reported the time; on the y-axis is the frequency (with a low frequency that corresponds to a high scale). Figure 3a shows that the relationship between oil prices and Biomass exhibits a high volatility at a medium frequency, the series are in-phase (the arrows point to the right), with the latter leading (arrows pointing to the right-up). Regarding the relationship between oil prices and Solar, a high volatility is fundamentally found at a low frequency, the series are in-phase, with Solar leading (arrows pointing to the right-up or left-down) (Figure 3b). Similar findings are also registered for the nexus between oil prices and Hydro as well as between oil prices and Wind (Figures 3c-3d). However, here a high volatility can be also observed at a medium-low frequency. Finally, the connection between OilP and Geothermal differs a bit from the others, since the high volatility episodes are located at either a low or

Table 1
Descriptive statistics.

Statistics	Brent Oil Prices	Biomass	Solar	Hydro	Wind	Geothermal
Mean	3.6497	3.9017	4.3393	4.9095	3.7296	2.7351
Std. Dev.	0.3929	0.1032	0.3626	0.2662	0.7460	0.0368
Min.	2.2105	3.4055	3.1082	4.3223	1.9851	2.6319
Max.	4.2521	4.2257	4.7779	5.3398	5.0420	2.7918
Skewness	-0.9632	-1.1005	-1.1083	-0.2461	-0.4249	-0.5159
Kurtosis	3.5970	6.4272	3.5503	1.8865	2.4433	2.4981
JB Adj. χ^2	20.28	36.53	23.94	40.65	8.38	9.42

Sources: authors' elaborations in Stata.

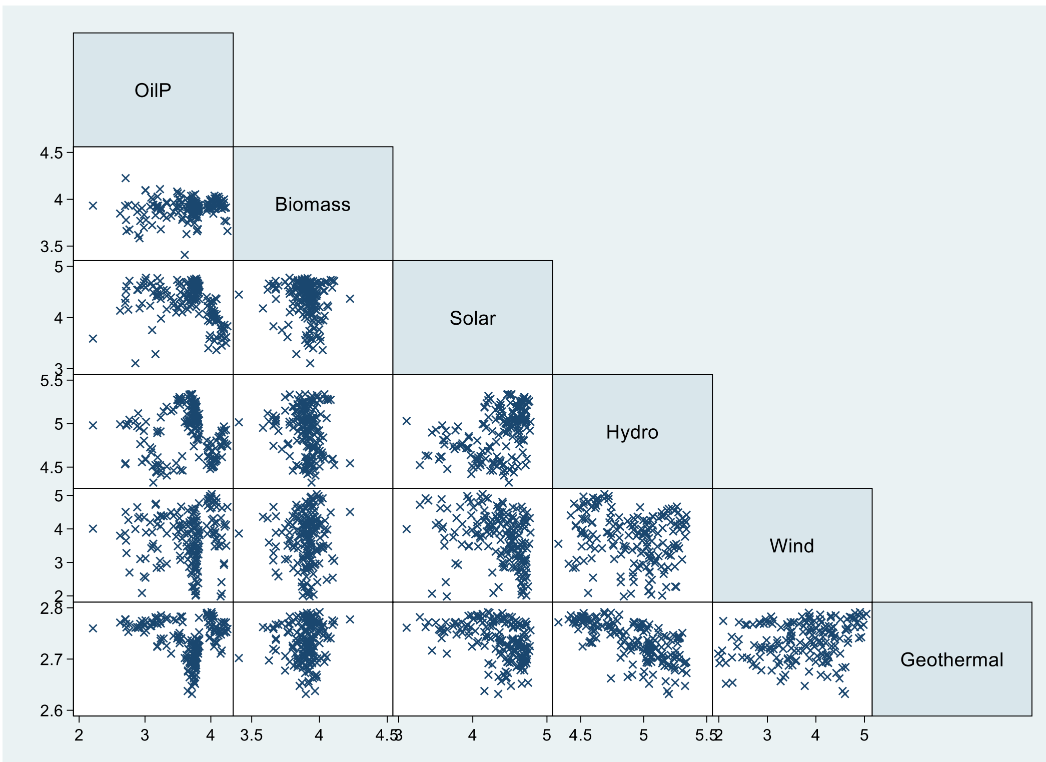

Figure 1. Scatterplot matrices. Sources: authors' elaborations in Stata.

a high frequency, and in the final part of the sample period (Figure 3e).

We can see that at high frequency (short-term), for up to 4 days band of scale, the co-movements between oil prices and renewable energy sources are rather idiosyncratic, with isolated episodes of co-movements. On the other hand, a period of intense co-movements is registered on medium-to-low frequencies as well as medium-to-long-term (for more than 8 days band of scale). Moreover, this clear correlation between oil prices and renewable sources, with renewable energy leading, shows the increasingly important role of renewables in the energy market.

These results are in line with those by Reboredo [41], Zhang and Du [53], Song et al. [45], and Horky et al. [14], as the oil prices seem to be strictly connected with renewable energies under the pandemic shock, when the oil prices revealed high volatility.

In Figure 4, the main results of the BCSG tests are shown. The relationships among the variables are assessed over the time-frequency domain. Each figure displays the Wald statistics over all frequencies $\omega \in (0; \pi)$. The test statistics for the Granger non-causality for the pairs of variables (*OilP*; *Biomass*) and (*OilP*; *Geothermal*) show the absence of any causal flow (Figures 4a-4b and 4i-4j, respectively). On the contrary, a unidirectional causal link is found between the solar source and oil prices, since *Solar* causes *OilP* over the whole spectrum, at least at a 5% significance level for $\omega < 1.16$ and $\omega > 1.53$, and at a 10% level elsewhere (Figures 4c-4d). *Hydro* causes *OilP* at a 10% significance level in the range $\omega \in (01.48; 1.97)$ (Figures 4e-4f). Finally, another unidirectional link running from *Wind* to *OilP* is established when $\omega > 1.33$ (at a 10% level of significance) (Figures 4g-4h).

Furthermore, generally speaking, the test results according to the Geweke-type conditioning are qualitatively similar.

Reboredo [40] and Ma et al. [24] supported the "neutrality hypothesis" (absence of causality) between oil prices and agricultural commodities; while Daglis et al. [6] found a causal link between the solar wind and the oil volatility index.

6. Robustness checks

For robustness checks, the Detrended Cross-Correlation Analysis (DCCA) is applied, to obtain a single scaling parameter for the long-range cross-correlation features of the variables. For each pair of tested series, a rho value is calculated [15]. The final correlation coefficients are shown in Figure 5.

Some interesting features can be detected. The detrended cross-correlation parameters for the pairs (*OilP; Biomass*) and (*OilP; Solar*) fluctuate around 0 in the range (-0.138; 0.198) and (-0.273; 0.143),

Table 2
GPH estimate of the fractional differencing parameter.

Variable	Power	Estimated *d*	Standard Error	*t*	P-Value
OilP	0.40	1.1795	0.2411	4.8919	0.003***
	0.45	1.2102	0.1852	6.5354	0.000***
	0.50	1.2818	0.2257	5.6785	0.000***
	0.55	1.1683	0.1838	6.3547	0.000***
	0.60	1.2225	0.1654	7.3903	0.000***
ΔOilP	0.40	0.3467	0.3524	0.9840	0.363
	0.45	0.3135	0.2596	1.2077	0.262
	0.50	0.2229	0.1949	1.1432	0.277
	0.55	0.2073	0.1959	1.0582	0.307
	0.60	0.2287	0.1464	1.5623	0.134
Biomass	0.40	0.1905	0.3385	0.5629	0.594
	0.45	0.5340	0.3147	1.6971	0.128
	0.50	0.3508	0.2538	1.3820	0.194
	0.55	0.3001	0.2016	1.4884	0.157
	0.60	0.2415	0.1684	1.4341	0.167
Solar	0.40	1.4911	0.2400	6.2125	0.001***
	0.45	1.0988	0.3182	3.4530	0.009***
	0.50	0.6697	0.2981	2.2469	0.046**
	0.55	0.7342	0.2313	3.1737	0.006***
	0.60	0.6622	0.1891	3.5024	0.002***
ΔSolar	0.40	0.4820	0.2303	2.0930	0.081*
	0.45	0.0211	0.3517	0.0601	0.954
	0.50	-0.4954	0.3432	-1.4436	0.177
	0.55	-0.4606	0.2689	-1.7128	0.107
	0.60	-0.5002	0.2168	-2.3073	0.032*
Hydro	0.40	1.3616	0.2653	5.1318	0.002***
	0.45	0.9879	0.3045	3.2440	0.012**
	0.50	0.9695	0.2406	4.0286	0.002***
	0.55	1.0435	0.1959	5.3266	0.000***
	0.60	0.8309	0.1684	4.9343	0.000***
ΔHydro	0.40	0.4086	0.2926	1.3965	0.212
	0.45	-0.0768	0.3585	-0.2143	0.836
	0.50	-0.1533	0.2654	-0.5776	0.575
	0.55	-0.1078	0.1942	-0.5554	0.587
	0.60	-0.2427	0.1570	-1.5459	0.138
Wind	0.40	0.9155	0.5026	1.8215	0.118
	0.45	0.6305	0.4034	1.5630	0.157
	0.50	0.5545	0.3010	1.8418	0.093*
	0.55	0.5618	0.2839	1.9789	0.066*
	0.60	0.3449	0.2262	1.5244	0.143
Geothermal	0.40	0.9107	0.3661	2.4876	0.047**
	0.45	0.6498	0.3257	1.9950	0.081*
	0.50	0.5581	0.2382	2.3433	0.039**
	0.55	0.5418	0.1802	3.0068	0.009***
	0.60	0.6301	0.1481	4.2539	0.000***
ΔGeothermal	0.40	-0.1803	0.2676	-0.6739	0.525
	0.45	-0.3948	0.2513	-1.5708	0.155
	0.50	-0.3981	0.1901	-2.0936	0.060*
	0.55	-0.3550	0.1714	-2.0716	0.056*
	0.60	-0.3323	0.1364	-2.4370	0.024**

Notes: Δ: first differences. ***p<0.01, **p<0.05, *p<0.10.
Sources: authors' elaborations in Stata.

respectively. On the contrary, the coefficients for (*OilP; Hydro*) and (*OilP; Wind*) are almost constantly positive, in the range (-0.123; 0.336) and (-0.155; 0.415), respectively. Finally, *OilP* and *Geothermal* exhibit a pretty stable negative correlation coefficient (-0.399; 0.077). In addition, it is worth noticing that in the final part of the window size all the cross-correlations are negative.

7. Concluding remarks and policy recommendations

The relationship between oil prices and renewable energy is a topic of significant importance in the context of global energy markets and environmental sustainability. Oil prices have traditionally played a central role in shaping energy policy and market dynamics [17] . When oil prices surge, governments, and industries often turn to renewable energy sources as an attractive alternative [3]. However, this relationship is not as straightforward as it may seem.

Firstly, high oil prices can act as a catalyst for investments in renewable energy. When oil prices rise, there is a sense of urgency to reduce dependence on fossil fuels. This leads to increased investments in wind, solar, and hydroelectric power. It also prompts research and development in energy-efficient technologies [51]. However, this relationship can be fickle. When oil prices drop, investments in renewable energy can decrease, as the economic incentive for sustainable alternatives weakens [36].

Secondly, the relationship is also influenced by government policies and incentives. Subsidies and regulatory frameworks can mitigate the impact of fluctuating oil prices on the renewable energy sector [19]. Governments play a crucial role in ensuring a consistent commitment to sustainable energy sources, irrespective of oil price trends.

On the flip side, the relationship between oil prices and renewable energy is not one of strict causality. Renewable energy is driven not only by oil prices but also by factors such as environmental concerns, technological advancements, and public opinion [46]. As technology advances and the cost of renewable energy decreases, the sector becomes more competitive on its own merits, independent of oil price fluctuations [23].

Therefore, the relationship between oil prices and renewable energy can be considered dynamic and complex. While high oil prices can accelerate the transition to renewable energy, it is essential to recognize that a sustainable energy future requires consistent government support and a long-term commitment to green technologies. The interplay of oil prices and renewable energy is just one piece of the puzzle in the broader context of energy policy and climate change mitigation [18].

The empirical findings show a high correlation among the variables during the first wave of the pandemic shock when the oil market registered turmoil. In addition, causality analysis reveals a unidirectional causality from solar, hydro, and wind sources to oil prices, which clearly demonstrates the potent impact that the energy and environmental transition processes can exert on the oil market. The energy transition has prompted many oil companies to diversify and invest in cleaner technologies and renewable energy sources, marking a notable shift in their business strategies. As a result, the global oil market is adapting to a new landscape, where environmental sustainability and energy transition efforts are integral factors, and the traditional dominance of fossil fuels is gradually being challenged. While oil will likely remain a crucial part of the global energy mix for some time, the energy transition is reshaping the market's dynamics and creating a more sustainable and diversified future.

Taking into account these considerations, an adverse impact of higher oil prices on the consumption of renewable energy can be understood as a stronger constraint, stemming from elevated oil prices, on the energy transition process. To put it differently, Italy, being a net energy resources importer, should be more inclined to invest in alternative energy resources when conventional energy prices are high.

As a result of the COVID-19 pandemic crisis, Italy increased the import of oil and gas from North African and Persian Gulf countries. While the possibilities of power trade across these regions are frequently downplayed due to significant geopolitical and macroeconomic challenges, it is essential to address and overcome these obstacles with a focus on fulfilling the Sustainable Development Goals (SDGs). This can be achieved through the implementation of specific public policies aimed at promoting the energy transition process.

In particular, causality analysis results highlighted that the causal flow runs, generally speaking, from renewable energy sources to oil prices (in a unidirectional link). Thus, the incorporation of renewable energy holds considerable importance for enhancing both Italian energy security and the reduction of GHG emissions. It is imperative for the country to adopt systems that more accurately consider the external costs associated with the utilization of fossil fuels. These costs encompass factors such as human healthcare expenses, local environmental harm, and the impact of climate change on the broader macroeconomy.

In addition, given the finite nature of oil resources and the adverse environmental effects associated with fossil fuel usage, there should be a

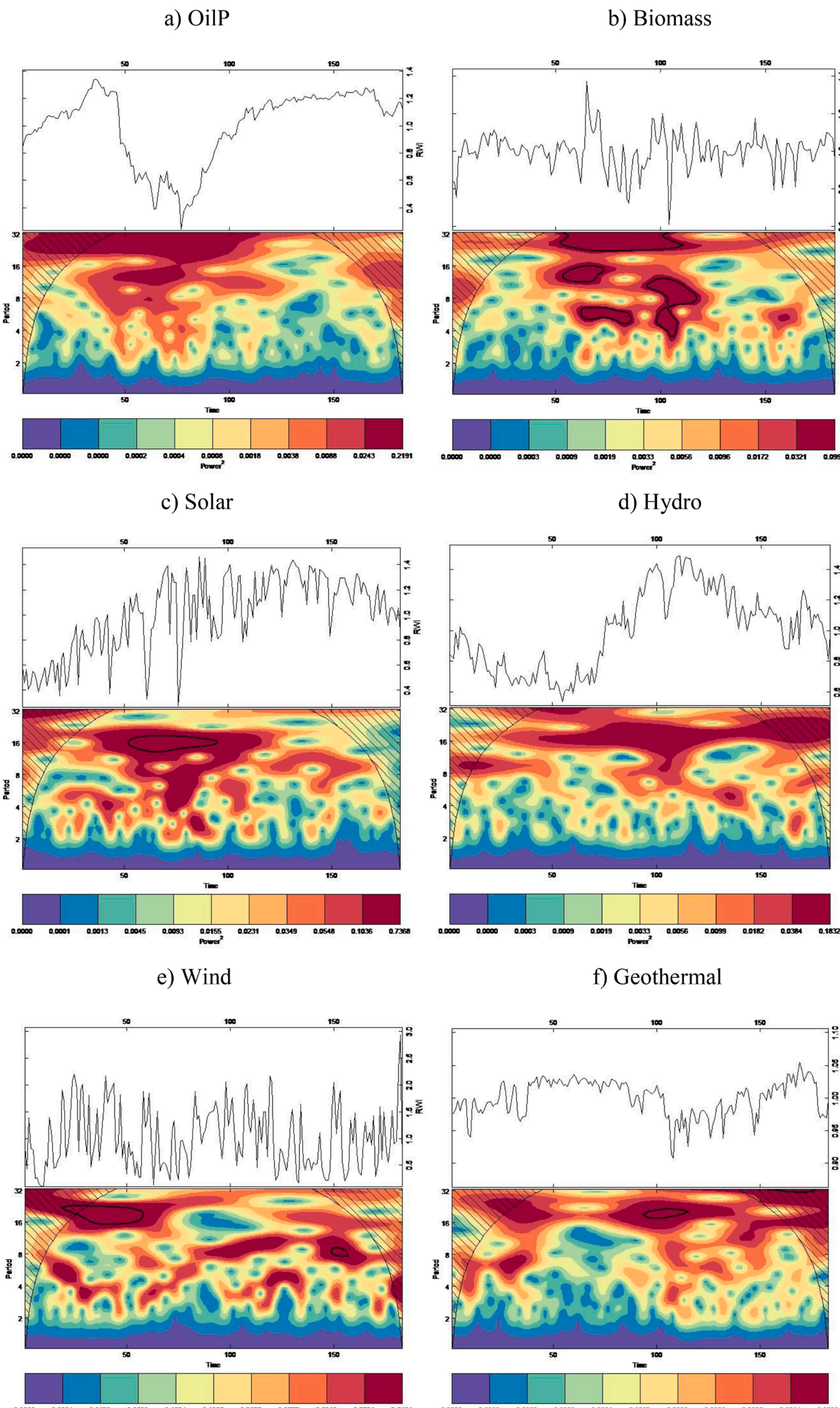

Figure 2. Continuous Wavelet Transform results. Sources: authors' elaborations in R.

focus on directing efforts toward the long-term production and consumption of renewable energy.

Climate change poses a formidable challenge to global energy security as rising temperatures, extreme weather events, and sea-level rise threaten the stability and reliability of energy infrastructure (Bang, 2010). The burning of fossil fuels, a major contributor to climate change, exacerbates the problem, creating a feedback loop that intensifies environmental risks and compromises energy systems. Adapting to climate change requires a transition towards cleaner and more sustainable energy sources, such as solar, wind, and geothermal power. This shift not only addresses the environmental crisis but also enhances energy security by diversifying the energy mix and reducing dependence

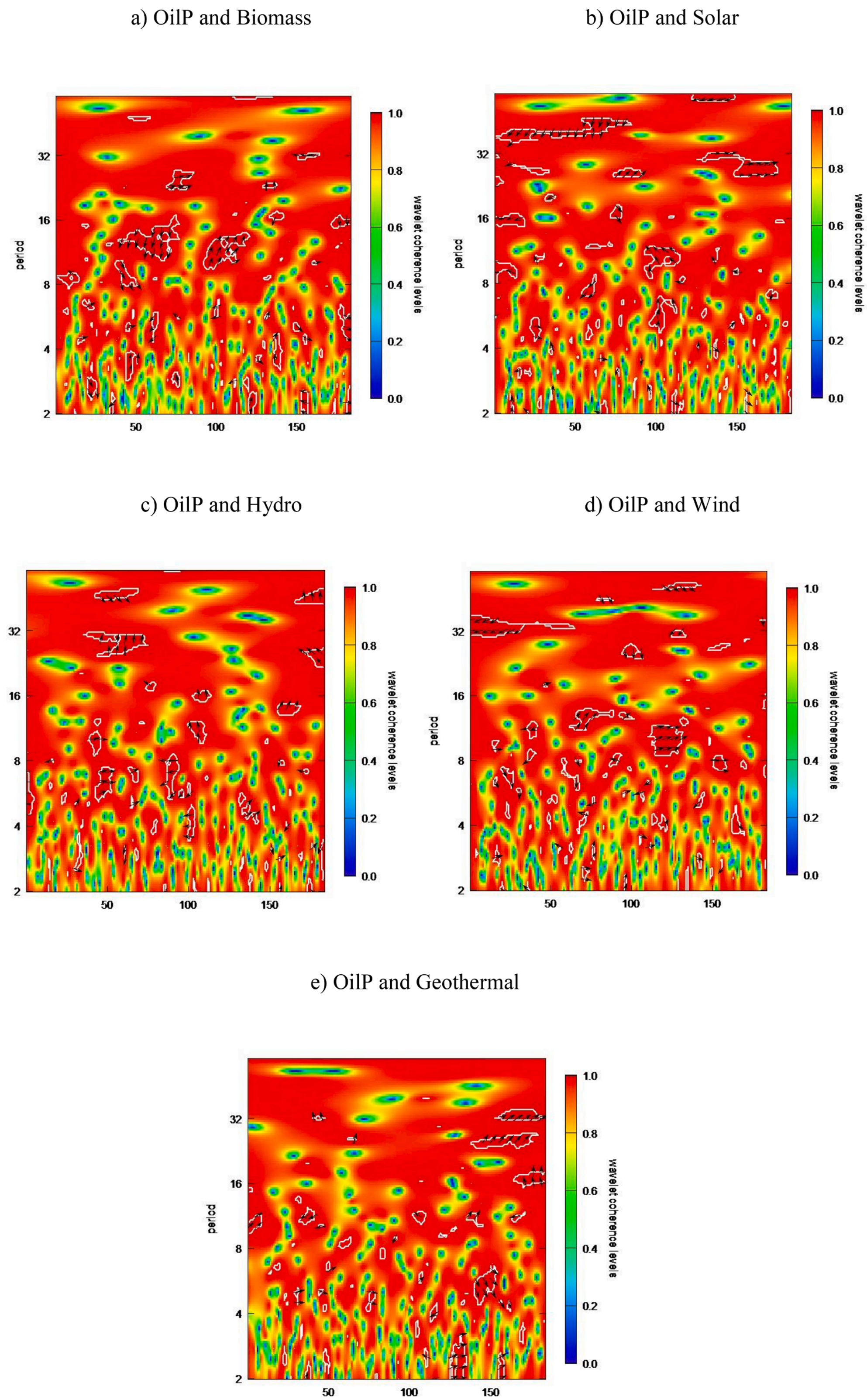

Figure 3. Wavelet Transform Coherence results. Sources: authors' elaborations in R.

on finite and polluting resources. International cooperation and policies, such as the Paris Agreement, play a crucial role in addressing the intersection of climate change and energy security, promoting a low-carbon future that prioritizes both environmental sustainability and resilient energy infrastructure [16].

The main limitation of this study is connected to the data availability on socio-economic factors, which could be used as control variables and might eventually influence the nexus between oil prices and renewables. In addition, alternative empirical strategies can be adopted to empirically test the relationships of interest (Machine Learning algorithms, Regime-Switching models, DCC-GARCH). In addition, although the analyzed period represents the most severe phase of the pandemic crisis

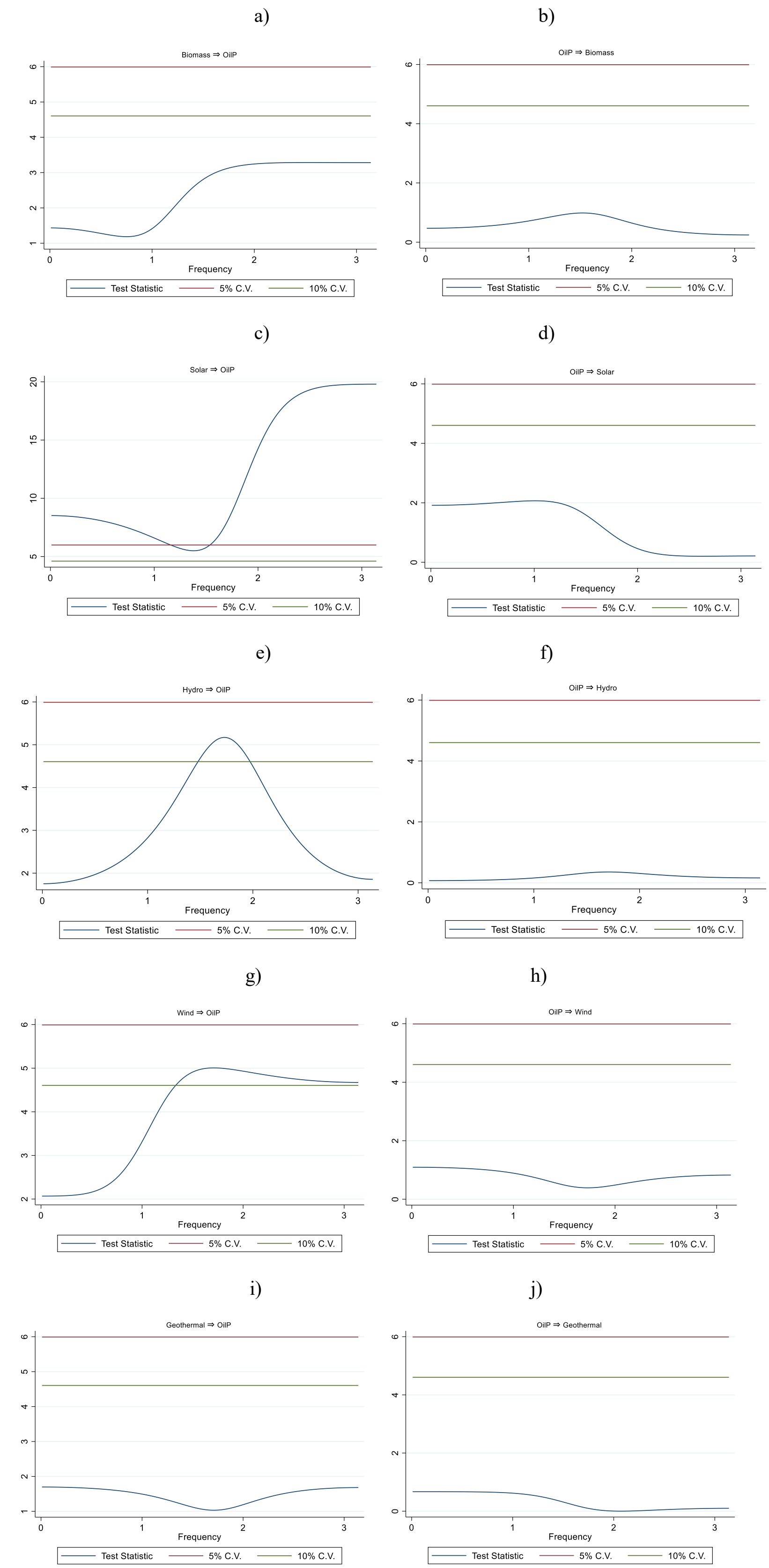

Figure 4. Breitung-Candelon Spectral Granger causality test results. Notes: Confidence level on *y-axis*. Hosoya-type conditioning was used. Sources: authors' elaborations in Stata.

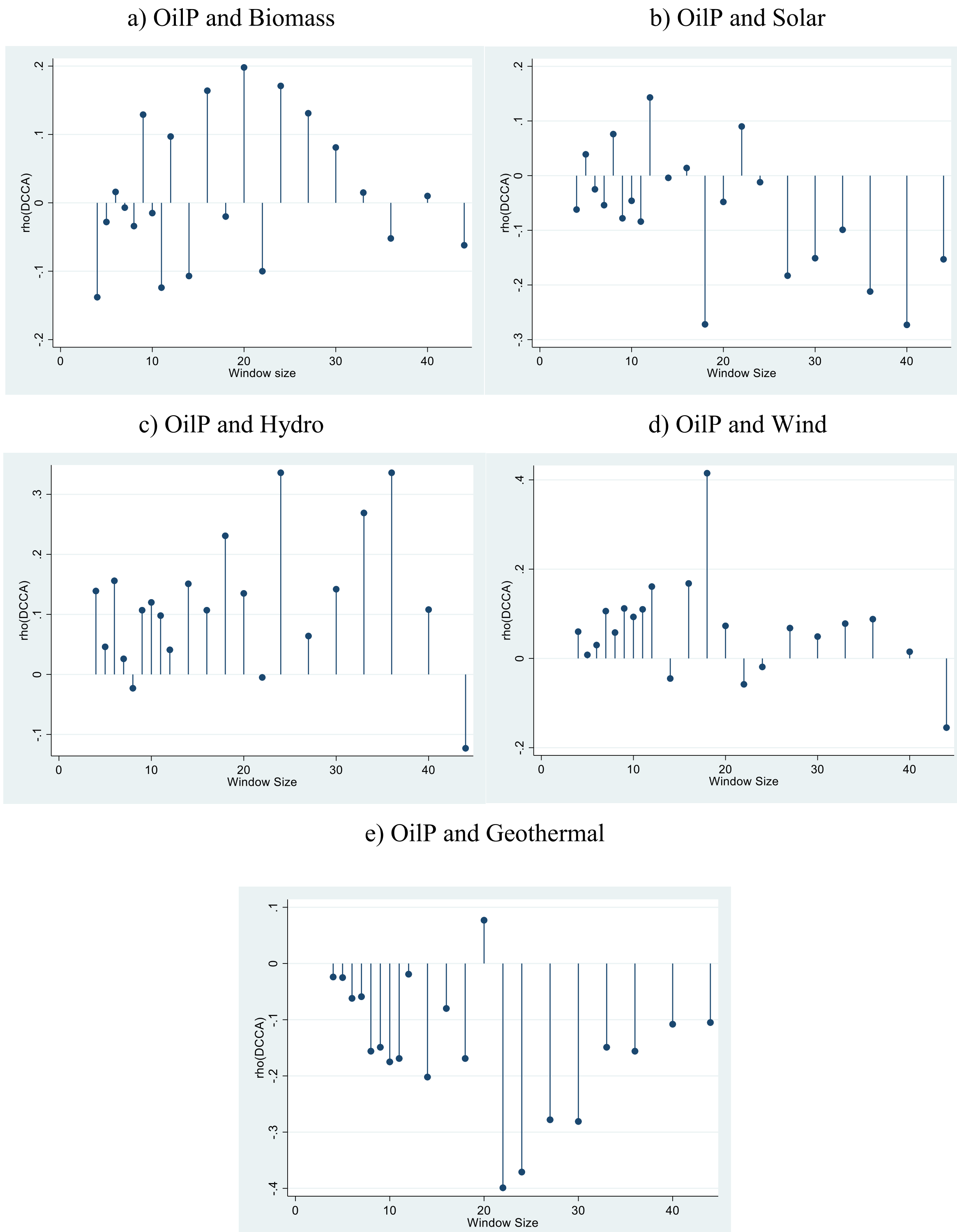

Figure 5. Detrended Cross-Correlation Analysis results. Sources: authors' elaborations in R and Stata.

in Italy, the pandemic effects must have been experienced or expanded (at least in a residual form) somewhat beyond the early stage. Since it is questionable to imagine an abrupt change or something like a singularity after the period considered in the present study, future research may expand the time horizon. Finally, future research may aim to analyze different countries that adopted alternative measures to contrast the spread of the COVID-19 pandemic, with a different endowment of natural resources or opposite energy strategies, using novel empirical approaches (Artificial Intelligence tools, common factor models, switching regime models).

CRediT authorship contribution statement

Cosimo Magazzino: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Project administration, Resources, Software, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Lorenzo Giolli:** Methodology, Validation.

Declaration of competing interest

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

Data availability

Data will be made available on request.

References

[1] L. Aguiar-Conraria, N. Azevedo, M.J. Soares, Using wavelets to decompose the time–frequency effects of monetary policy, Physica A: Statist. Mech. Its Appl. 387 (12) (2008) 2863–2878.
[2] M. Balcilar, D. Roubaud, M. Shahbazb, The impact of energy market uncertainty shocks on energy transition in Europe, Energy J. 40 (1_suppl) (2019) 55–80.
[3] S. Borenstein, The market value and cost of solar photovoltaic electricity production, Natl. Bureau Econ. Res. (2008).
[4] N. Apergis, J.E. Payne, Renewable energy consumption and economic growth: Evidence from a panel of OECD countries, Energy Pol. 38 (1) (2010) 656–660.
[5] J. Breitung, B. Candelon, Testing for short- and long-run causality: a frequency-domain approach, J. Econ. 132 (2006) 363–378.
[6] T. Daglis, S. Yfanti, P. Xidonas, K.N. Konstantakis, P.G. Michaelides, Does solar activity affect the price of crude oil? A causality and volatility analysis, Financ. Res. Lett. 55 (A) (2023) 103833.
[7] I. Daubechies, Ten lectures on wavelets, Society for Industrial and Applied Mathematics, Philadelphia, PA, 1992.
[8] J. Fernández-Macho, Time-localized wavelet multiple regression and correlation, Phys. A 492 (1) (2018) 1226–1238.
[9] P. Gallo, J.M. Guerrero, R. Musca, E.R. Sanseverino, J.C. Vasquez Quintero, G. Zizzo, Effects of COVID19 pandemic on the Italian power system and possible countermeasures, Electr. Pow. Syst. Res. 201 (2021) 107514.
[10] J. Geweke, S. Porter-Hudak, The estimation and application of long memory time series models, J. Time Ser. Anal. (1983) 221–238.
[11] E. Ghiani, M. Galici, M. Mureddu, F. Pilo, Impact on electricity consumption and market pricing of energy and ancillary services during pandemic of COVID-19 in Italy, Energies 13 (2020) 3357.
[12] A. Grinsted, J.C. Moore, S. Jevrejeva, Application of the cross wavelet transform and wavelet coherence to geophysical time series, Nonlinear Processes Geophys. 11 (5) (2004) 561–566.
[13] A.R. Gurrieri, G. Morelli, M. Mele, C. Magazzino, Gli Smart Meters, una misura di sostenibilità verde, L'Industria 1 (2023) 153–184.
[14] F. Horky, M. Mutascu, J. Fidrmuc, Oil and renewable energy returns during pandemic, Environ. Sci. Pollut. Res. 30 (2023) 25836–25850.
[15] D. Horvatic, H.E. Stanley, B. Podobnik, Detrended cross-correlation analysis for non-stationary time series with periodic trends, Europhys. Lett. 94 (2011) 18007.
[16] B.N. Ike, Climate change, energy security risk, and clean energy investment, Energy Econ. 129 (2024) 107225.
[17] International Energy Agency (IEA) (2019). World Energy Outlook 2019. https://www.iea.org/reports/world-energy-outlook-2019.
[18] S. Jacobsson, A. Johnson, The diffusion of renewable energy technology: An analytical framework and key issues for research, Energy Policy 28 (9) (2000) 625–640.
[19] S. Jacobsson, V. Lauber, The politics and policy of energy system transformation – explaining the German diffusion of renewable energy technology, Energy Policy 34 (3) (2006) 256–276.
[20] Z. Jia, S. Wen, B. Lin, The effects and reacts of COVID-19 pandemic and international oil price on energy, economy, and environment in China, Appl. Energy 302 (2021) 117612.
[21] F. Karanfil, Y. Li, The impacts of oil price shocks on stock market volatility: Evidence from the G7 countries, Energy Policy 82 (2015) 135–142.
[22] E. Kyritsis, A. Serletis, Oil Prices and the Renewable energy sector, Energy J. 40 (1_suppl) (2019) 337–364.
[23] Lazard. Lazard's Levelized Cost of Energy Analysis - Version 14.0; 2021. https://www.lazard.com/media/450784/lazards-levelized-cost-of-energy-version-140.pdf.
[24] Z. Ma, R. Xu, X. Dong, World oil prices and agricultural commodity prices: the evidence from China, Agric. Econ. 61 (2015) 564–576.
[25] C. Magazzino, M. Adamo, M. Shahbaz, On the relationship between oil market and European stock returns, Environ. Sci. Pollut. Res. (2023).
[26] C. Magazzino, M. Mele, A new machine learning algorithm to explore the CO_2 emissions-energy use-economic growth trilemma, Ann. Operat. Res. (2022).
[27] C. Magazzino, M. Mele, C.T. Albulescu, N. Apergis, M.I. Mutascu, The presence of a latent factor in gasoline and diesel prices co-movements, Empir. Econ. (2023).
[28] C. Magazzino, M. Mele, C. Drago, S. Kuşkaya, C. Pozzi, U. Monarca, The trilemma among CO_2 emissions, energy use, and economic growth in Russia, Sci. Rep. 13 (2023) 10225.
[29] S. Mallat, A Wavelet Tour of Signal Processing, Academic Press, Cambridge, 1998.
[30] K.S. Mohammed, A. Mellit, The relationship between oil prices and the indices of renewable energy and technology companies based on QQR and GCQ techniques, Renew. Energy 209 (2023) 97–105.
[31] G. Morelli, C. Magazzino, A.R. Gurrieri, C. Pozzi, M. Mele, Designing smart energy systems in an industry 4.0 paradigm towards sustainable environment, Sustainability 14 (2022) 3315.
[32] J. Morlet, G. Arens, E. Fourgeau, D. Giard, Wave propagation and sampling theory, Geophysics 47 (2) (1982) 203–221.
[33] S. Mukhtarov, J.I. Mikayilov, S. Maharramov, J. Aliyev, E. Suleymanov, Higher oil prices, are they good or bad for renewable energy consumption: the case of Iran? Renew. Energy 186 (2022) 411–419.
[34] M. Murshed, M.M. Tanha, Oil price shocks and renewable energy transition: Empirical evidence from net oil-importing South Asian economies, Energy Ecol. Environ. 6 (2021) 183–203.
[35] H. Naser, F. Al-aali, Y. Abdulla, R. Ebrahim, The impact of oil price and COVID-19 pandemic on clean energy stocks: an empirical approach using ARDL, Arab Gulf J. Sci. Res. (2023).
[36] W.D. Nordhaus, Alternative fuels and global carbon abatement, Proc. Natl. Acad. Sci. 104 (18) (2007) 7219–7223.
[37] O.R. Olayeni, Causality in continuous wavelet transform without spectral matrix factorization: theory and application, Comput. Econ. 47 (3) (2016) 321–340.
[38] D.B. Percival, A.T. Walden, Wavelet Methods for Time Series Analysis, Cambridge University Press, Cambridge, 2000.
[39] B. Rakshit, Y. Neog, Effects of the COVID-19 pandemic on stock market returns and volatilities: Evidence from selected emerging economies, Stud. Econ. Financ. (2021).
[40] J.C. Reboredo, Do food and oil prices co-move? Energy Pol. 49 (2012) 456–467.
[41] J.C. Reboredo, Is there dependence and systemic risk between oil and renewable energy stock prices? Energy Econ. 48 (2015) 32–45.
[42] P. Sadorsky, Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies, Energy Econ. 34 (1) (2012) 248–255.
[43] P.K. Sahu, S.A. Solarin, U. Al-mulali, I. Ozturk, Investigating the asymmetry effects of crude oil price on renewable energy consumption in the United States, Environ. Sci. Pollut. Res. 29 (2022) 817–827.
[44] R.A. Salim, S. Rafiq, H. Bloch, Impact of crude oil price volatility on economic activities: An empirical investigation in the Thai economy, Resour. Policy 34 (3) (2009) 121–132.
[45] Y. Song, Q. Ji, Y.J. Du, J.B. Geng, The dynamic dependence of fossil energy, investor sentiment and renewable energy stock markets, Energy Econ. 84 (2019) 104564.
[46] B.K. Sovacool, How long will it take? Conceptualizing the temporal dynamics of energy transitions, Energy Res. Soc. Sci. 13 (2016) 202–215.
[47] B.K. Sovacool, M.A. Brown, Competing dimensions of energy security: an international review, Energy Policy 38 (1) (2010) 81–90.
[48] A. Sözen, E. Arcaklioğlu, F. Kiliç, The historical development of wind energy and the role of government policies in supporting renewable energy production, Renew. Sustain. Energy Rev. 107 (2019) 109–118.
[49] D.I. Stern, C.J. Cleveland, Oil prices and the U.S. macroeconomy: A structural VAR analysis. The Energy Journal (2004) 31-47.
[50] S. Ullah, Impact of COVID-19 Pandemic on Financial Markets: a Global Perspective, J. Knowl. Econ. 14 (2023) 982–1003.
[51] U.S. Energy Information Administration (EIA). (2014). Annual Energy Outlook 2014. https://www.eia.gov/outlooks/aeo/pdf/0383(2014).pdf.
[52] X. Wang, Z. Feng, Oil prices and carbon emissions in the United States: The role of fuel price fluctuations, Energy Econ. 88 (2020) 104747.
[53] G. Zhang, Z. Du, Co-movements among the stock prices of new energy, high-technology and fossil fuel companies in China, Energy 135 (2017) 249–256.