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UNVEILING THE ROLE OF INDUSTRIES FOR EUROPEAN FINANCIAL STABILITY. INSIGHTS FROM THE ENERGY SECTOR

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Abstract. Extensive analysis of intertwinement with other industries caused the energy sector to gain momentum in the recent economic literature. This paper aims to create an indicator that captures the impact of financial stability for energy companies on all other industrial groups. To this end, we use daily data from 2007 until the end of 2021 to compute financial stability metrics for all European companies from the STOXX 600 index. The main contribution of our study is to harness the neural network forecasting power to predict extreme levels of this impact. We motivate this choice with evidence from the literature that documents the improved performance of these methods in predicting crises. Our methodological approach also employs an outlier detection algorithm based on copula (COPOD) to identify situations when the energy sector substantially impacts other industries and develop a framework to predict out-of-sample situations. We found evidence that the Deep Renewal model has superior forecasting accuracy to the standard Croston model. The main conclusion is that the design of this methodological framework allows authorities to monitor the impact of shocks produced by the energy sector on financial stability at the European level and undertake strategic management actions.

Keywords: financial stability, European companies, energy, COPOD, extreme levels, Deep Renewal process.

JEL Classification: D53, Q40, C53.

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1. Introduction

The energy sector holds immense importance due to its central role in both the economy and society, with its sector-specific characteristics like inelastic demand and environmental concerns further enhancing its significance, necessitating comprehensive research efforts. Energy companies play a crucial role in meeting the rising global demand for energy products, a cornerstone of nearly all economic activities. The intricate relationship between energy sector entities and those in other sectors is vital for the economy, which relies heavily on energy resources. The growing prominence of energy markets has led to increasing parallels between energy products and financial assets, impacting pricing evaluations and adjustments. This growing interconnectedness between energy and financial markets means that shocks are transmitted more rapidly and directly. Given the unique dynamics of supply and demand in the energy sector, prices often exhibit fluctuations and peaks, with these market interconnections enabling the transmission of these fluctuations to other industries. Thus, it is imperative to predict future price trends and fluctuations and comprehend their ramifications on the stock market and broader macroeconomic indicators, driven by the profound significance of this industry. The vital connection between the energy sector and financial stability directly and indirectly affects economic activities, performance, societal and economic development, and overall well-being. A financial system experiencing external pressures can disrupt economic operations by limiting access to specific financing or hedging instruments, underscoring the importance of studying this relationship.

Since the 2008 financial crisis, there has been a growing focus on systemic risk in research and practice. This type of risk has resulted in the development of various measures and regulations aimed at enhancing financial stability. It is a systemic risk when a risk can potentially harm other companies or sectors not directly involved in its production. Large institutions that are highly interconnected and influential can cause harm to other companies, making them systemic individually. Similarly, smaller institutions can also spread risks to others, causing them to become systemic. Systemic risk is often viewed as a market failure and is considered when creating economic policies and regulatory measures.

Considering the significance of the energy sector, this paper's primary research question revolves around assessing how this sector influences the financial resilience of the European economy at a systemic level. To address this question, we have devised an indicator designed to assist financial authorities across European nations in monitoring the energy sector's influence on the overall financial stability of various sectors.

To this end, we use stock market data to quantify and predict the energy sector's propensity to spur spill-over effects on all the other sectors. For quantification, we use the Diebold and Yilmaz (2012) methodology to create an indicator that captures the impact of shocks on financial stability rooted in the evolution of the stock prices belonging to energy sector companies. Given its dynamic nature, this indicator allows us to identify situations when the energy sector significantly impacts financial stability. The main objective is to harness the neural network forecasting power to predict extreme levels of this impact based on literature that documents the performance of this methodology in predicting crises. We, therefore, use a state-of-the-art method for outlier detection to identify situations when this indicator has extreme values. Once these moments are well detected, we produce repetitive out-of-sample prediction experiments to forecast such events. Our results show that the methodology used for these predictions is worth considering for setting up early warning systems that could allow authorities to mitigate such moments of high sensitivity to the energy sector.

Detection of these extreme events is performed by the COPOD (copula-based outlier detection methodology developed by Li et al. (2020)) methodology, while for prediction, we follow the methods set forth by Türkmen et al. (2021). Along these lines, we employ the Deep Renewal model compared with the Croston model for intermittent data prediction and test the differences in the forecasting performance of these models.

The study sets out a novel approach and contributes to the literature in several ways. Firstly, we designed an elaborate methodological framework that allows authorities to monitor the impact of shocks produced by the energy sector on financial stability at the European level. Secondly, we developed a mixture of empirical analyses proving the performance of our methodological framework in dynamical forecasting experiments. Lastly, since the dataset connects information from the energy sector with the financial ones and covers the other economic sectors, our approach furnishes innovatory sagacious perspectives for policy formation.

Our motivation for selecting these methodological tools is twofold. On the one hand, the necessity for leading indicators in risk monitoring spurred a wide selection of methodological tools for measuring the contribution of companies and sectors to systemic risks. We propose a contagion indicator that relies on a combination of several highly used risk metrics to account for the impact of the energy sector on all other sectors. On the other hand, we employ a tool from the domain of artificial intelligence (neural networks). The reason is to create a framework that can give our indicator the statute of leading statistics so that it can be part of the toolkit used to trigger policy decisions related to financial stability.

Throughout this paper, our understanding of financial stability follows the definition embedded in the modelling framework set forth by Adrian and Brunnermeier (2016) and Acharya et al. (2017).

The rest of our paper is structured as follows. Section 2 presents the relevant articles on systemic risk and its use in the energy market, specifying the gap in the literature. In addition, studies on detecting rare events and the choice of methods and processes for their prediction are identified, emphasising financial markets. Section 3 presents the dataset and the methodology for this study, while Section 4 reports the results. Section 5 elaborates discussion. Furthermore, the last section concludes.

2. Literature review

Numerous definitions of financial stability are used in the literature and practice. Although there is no unanimously accepted definition, most believe that financial stability is linked to the absence of systemic episodes that affect the functioning of the financial system, emphasising the financial system's resilience to stress. Financial stability is the financial system's ability to withstand shocks (endogenous and/or exogenous) and not to transmit financial imbalances through the ability to mitigate or absorb them. Often, the lack of stability and the appearance of financial instability, strongly reflected in any economic and financial system, attracts attention. Maintaining a stable financial system is motivated by its ability to allocate resources efficiently and manage financial risks, thereby contributing to economic development and growth.

Most specifications of financial stability refer to systemic risk, which does not have a generally accepted definition. However, some concepts are described in several reference works: "the risk of experiencing a strong systemic event. Such an event adversely affects several systemically important intermediaries or markets" (European Central Bank, 2009); "the risk that the capacity of the entire financial system is impaired, with potentially" (Adrian & Brunnermeier, 2016); "any set of circumstances that threatens the stability of or public confidence in the financial system" (Billio et al., 2012); "systemic risk matters only to the extent there is an impact on the broader economy" (Acharya et al., 2012). Smaga (2014) conducts an extensive review of systemic risk definitions in the literature. Additionally, the author delineates factors contributing to the systemic risk process and contagion spread, offering a conceptual view connecting these appearances, while Caccioli et al. (2018) provide a comprehensive review of models addressing financial systemic risk, emphasising the interconnectedness in the global financial system and discussing various models, including default cascades due to bilateral interbank exposures and overlapping portfolios.

Several methods have been introduced to measure systemic risk (or systemic stability). One of these is to aggregate the stability measures calculated at the firm level (z-score and distance from insolvency) using averages or by weighting each value according to the relative size of the institution. In the end, an assessment of system-wide stability is to be achieved. In the economic literature, this method is considered incomplete because it needs to consider the interconnection between financial institutions (in other words, contagion).

Unlike the previous method, First-to-Default Probability, or the probability of insolvency occurring in several institutions, considers that financial institutions are interconnected and has been proposed as a method of systemic risk measurement for large financial institutions. The disadvantage observed in the literature for this method is that it omits that the failure of a large institution causes more significant effects than a small one.

Another way to assess the financial system's stability is the Systemic Expected Shortfall (SES) method. This method measures the individual contribution of each institution to systemic risk, helping identify systemically relevant institutions, although it cannot estimate when they may have difficulties. In order to cover the need for forecasting that appears as a result of another crisis, the SRISK method has been developed by Brownlees and Engle (2017). It measures the loss of capital that a company may have in a severe market downturn.

Other methods or indicators include systemic loss distribution, financial soundness indicators developed by the International Monetary Fund, excessive credit growth, market volatility, or asymmetric distribution of yields.

The high risk of insolvency faced by oil companies is raised by Restrepo et al. (2018) in a paper that analyses the financial links and principal vulnerabilities in the global financial architecture of energy companies. The financial problems they face are likely to affect the entire energy market. The methodology was developed to evaluate the volatility (including the dynamic volatility index) for the entire sample during the analysed period in Diebold and Yilmaz (2009, 2012, 2014). Then a network is built to observe volatilities between blocks of oil companies in less quiet times, using Greenwood-Nimmo et al. (2016). The study results show that the risk spread is very high among energy companies, with an average of 84.7% in the analysed period (January 2002 – November 2016). This value is much higher than calculated for other sectors or markets: 39.5% for stock markets, 78% for global banks, 74.78% for the credit market, and 76% for the foreign exchange market. The authors also note an enhancement in systemic risk in the oil market in the last two analysed years and increased volatility of connectivity, with very high values during periods of financial (2008–2009, 2010–2011) and political crisis (2014, conflict between Russia and Ukraine). The Diebold and Yilmaz (2012) methodology is recognised in the literature to measure contagion, including the spill-over issues regarding the financial cycle (Chen et al., 2022).

Using graph analysis, Lautier and Raynaud (2012), consider oil the centre of the energy complex, and the energy market is the centre of the price system. Moreover, commodity markets have become increasingly interconnected in recent years, thus laying the groundwork for increasing systemic risk.

In the same vein, Butzbach (2016) examined the interplay of systemic risk and banking regulation, and the work involves elucidating connections between systemic risk and banking diversity, evaluating the effectiveness of macro and micro-prudential policy tools in mitigating diversity-related systemic risks, and proposing a foundational framework for policies aimed at enhancing diversity.

The need to introduce financial regulations in the energy sector was also proposed (Kerste et al., 2015). The authors measured the systemic risk using a method that considers the chance of a company going bankrupt if at least one other company went bankrupt (*the expected fraction of other failing firms*). The study results suggest that the links between firms in difficulty are higher in the energy sector. One explanation for this is that most energy companies use industry companies as counterparties in derivative contracts; it is also a sector with strong vertical integration, with many companies carrying out production and distribution actions. High values for the additional insolvency risk in the energy sector (even higher than for the banking sector) show the effects of an adverse shock in the sector without evidence of the impact on the economy. The results also suggest that the risk of contagion from the energy sector to the banking sector is not very high compared to other non-financial sectors. However, the authors consider this result as not definitive and recommend using another method to consider the average marginal loss over a certain probability threshold (Marginal Expected Shortfall – MES). Although both methods measure the risk conditioned by an extreme event, the one used in the mentioned study calculates the risk according to the chances. In contrast, MES and CoVaR calculate the risk according to the value.

A study on the European Energy Exchange and the DAX Industrial Index (Pierret, 2013) draws attention to the significance of systemic risk in energy markets: "the risk of an energy crisis that raises the prices of all energy products with negative consequences for the real economy". Proposals are made to measure the total cost and net impact on other companies, starting with adapting the MES methodology. The results show that energy crises are attracting rising costs for the economy. On the other hand, the analysis for the DAX industry index suggests that events in the energy market have had a low impact on the profitability of the sampling analysed. The findings of Nasim and Downing (2023) on the adverse impact of energy price shocks on banking sector performance underscore the critical interplay between energy market dynamics and financial stability, necessitating informed policy responses to mitigate systemic risks and safeguard economic resilience.

Algieri and Leccadito (2017a) use the ΔCoVaR method developed by Adrian and Brunnermeier (2016) to explore whether the energy sector contributes to systemic risk across the economy. Using a sample of 35 companies in the energy sector that are part of the S & P200 energy index, the authors pointed out a risk transfer from the energy sector to the whole economy. The periods when the contagion was very high were significant crises, the 2007–2009 financial crises and Europe's sovereign debt. The analysed period was October 2005 – June 2013. Using the ΔCoVaR method based on quantile regression, Algieri and Leccadito (2017b) identified the measure of contagion risk for the energy, food and metals markets. They found that financial factors in the energy and metals sectors mainly trigger contagion risks. In contrast, financial and economic factors trigger contagion risks in the food sector, with the energy sector contributing more to the contagion than other markets.

Throughout this series of papers, we have pinpointed a noticeable deficiency in the existing literature regarding creating a monitoring tool to detect spill-over effects from the energy sector to the financial sector. Prior research outcomes have failed to establish a unanimous agreement regarding the character and significance of the connections between the energy sector and financial stability. Nevertheless, these studies underscore the critical importance of systemic risk and advocate for a fresh approach to research in this area. These sectors are intricately intertwined with all others directly and indirectly, albeit with varying intensity.

3. Data and methodology

3.1. Description of the statistical data used

The data used in this research were obtained from the Bloomberg platform and included daily prices recorded at the end of trading sessions for May 3, 2007 – December 21, 2021, consisting of 3,819 observations corresponding to trading days. These data were extracted for all the companies that make up the STOXX 600 index, respectively 600 companies listed on European stock exchanges.

In order to allow for calculation consistency, the data corresponding to the unlisted companies for more than 20% of the period under review were deleted. In general, this resulted from the fact that they were listed on the stock exchange following May 3, 2007. After data processing, 488 companies remained in our sample. For all these companies, the daily logarithmic yields were calculated, based on which the systemic risk indicators CoVaR, ΔCoVaR and MES were estimated. 3,818 values of these indicators were obtained for each of the 488 companies.

The aim we pursued in this study was to engender an indicator that reflects the impact of the energy sector on financial stability at the European level. To achieve this goal, we have used the Global Industry Classification Standard (GICS) developed by Morgan Stanley Capital International [MSCI], which divides companies into 24 industrial groups according to the principle of the field that brings the highest income (MSCI, n.d.). According to this setup, the energy sector comprises companies that activate in Energy Equipment and Services and Oil, Gas and Consumable Fuels industries.

3.2. Description of the applied methodology

In crisis prediction, it was evidenced that using neural networks surpasses logistic regressions when used for financial systems (Tölö, 2020). The author used macroeconomic data series for 17 countries for an extended period from 1860 to 2016 and considers that neural networks consistently improve predictions in the financial sector. This is the argument for choosing such a method to further our research.

The literature on outlier detection is divided based on methods tailored to their definition and the field in which they are used. They are often defined as situations when some data significantly deflect from the many (Ahmed et al., 2016; Li et al., 2019). A general way to classify them is by considering non-sequential data with behavioural analysis: point, contextual or collective (Aggarwal, 2017; Feremans et al., 2020). This most straightforward way to classify the outliers is sometimes criticised because it is based on similarity without modelling the temporal structures in the data (Harvey & Peters, 1990; Shumway & Stoffer, 2017). The ambiguity of the invoked context is discussed in the literature, as there are different interpretations concerning adjacent points (Yu et al., 2014) or seasonality (Golmohammadi & Zaiane, 2015).

Amid the various ways used to identify outliers, a new algorithm based on an empirical copula called COPOD was recently developed in a way substantiated as being parameter-free, with a good performance and allowing interpretation (Li et al., 2020). We used this method to identify rare events and then applied the deep renewal process (Türkmen et al., 2021) to predict them.

We use a combination of analysis methods identified in the recent literature to identify how energy companies can affect financial stability.

To measure systemic risk, we referred to methods recognised in the literature.

The method used by Adrian and Brunnermeier (2016) presumes that systemic risk measures consider the increase of tail comovement that may emerge due to the spreading of financial difficulties between institutions. The authors believe that the value at risk (VaR) highlights the risk of a single company or institution "in isolation" and propose other indicators with the following calculation methods:

- $CoVaR_q^{j|C\left(X^i\right)}$ – is the VaR for the whole system, subject to the fact that the company (or group of companies, sector) for which we calculate it is subject to an event or shock $C\left(X^i\right)$;

- $Pr\left(X^j \mid C\left(X^i\right) \le CoVaR_q^{j|C\left(X^i\right)}\right) = q\%$ is the probability that the yields of the whole system will be lower than CoVaR; in our case, q is 1%;
- $\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i = Var_q^i} - CoVaR_q^{j|X^i = Var_{50}^i}$ ($\Delta CoVaR$ is the difference between a *CoVaR* conditioned by a shock applied to a company or sector and *CoVaR* under the conditions in which the respective company or sector is in a so-called "normal" situation, respectively when the yield is equal to the median yield).

Acharya et al. (2017) developed a new methodology based on expected losses:

- *MES* – is the average marginal loss above a certain probability threshold during an aggregate market shock; the indicator measures the individual contribution of each company or sector to systemic risk and is calculated using the following formula:

$$MES_\alpha^i = \frac{\partial ES_\alpha}{\partial y_i} = -E\left[r_i \mid R \le -VaR_\alpha\right]. \quad (1)$$

- *MES* is calculated based on the average loss indicator above a certain probability threshold (Expected Shortfall – ES), respectively the average value of logarithmic returns that have values lower than the *VaR* for a certain confidence level α:

$$ES_\alpha = -E\left[E \mid R \pounds -VaR_\alpha\right]. \quad (2)$$

- *ES* expressed that taking into account the individual contributions of the companies that are part of the study can be formulated as follows:

$$ES_\alpha = -\sum_i^n y_i E\left[r_i \mid R \le -VaR_\alpha\right], \quad (3)$$

where r_i is the yield of each company, *R* is the system's yield (the group analysed), y_i is the share of the company *i* within the group (based on the market capitalisation).

For our analysis, each sector's average values for each day of the three systemic risk indicators (*CoVaR*, Δ*CoVaR* and *MES*) were calculated, obtaining 24 data sets for each of the three indicators.

The methodology developed by Diebold and Yilmaz (2012) was used to estimate the degree of contagion, which estimates the extent to which the dynamics of one variable contribute to the uncertainty of predicting another variable when all these variables are included in a Vector Autoregression system (VAR).

For this purpose, mobile samples of 120 transaction days (corresponding to approximately a half-year period, respectively six calendar months) were used for which the FROM indicators were estimated, which reflect the contribution of the S8 (Energy) sector to the increase of prediction uncertainty for all other 23 economic sectors. The TO indicators were similarly estimated to obtain the NET variant (TO-FROM). There were 3,699 such values (for each 120-day sample built with the 3,818 trading days) for each of the three systemic risk indicators. To obtain a first picture of the evolution of the energy sector, we estimated such values for the yields and volatilities of the energy sector.

Acharya et al. (2012) point out a shortcoming of the *CoVaR* methodology: it does not consider the volatility of the financial institution but only its correlation with the market. Therefore, we try to mitigate this deficiency and build an aggregate indicator that captures both the influence of a shock or shocks on the system (captured by *CoVaR* and *ΔCoVaR*) and the influence of an aggregate risk (captured by *MES*). Thus, the aggregate indicator *ContagEn* quantified the influence of the energy sector on the financial stability of the other sectors at the European level and was constructed by calculating the average of the two FROM indicators corresponding to the two systemic risk measures (*ΔCoVaR* and MES). For the calculation of the indicator, the operation of scaling the indicators *ΔCoVaR* (FROM) and *MES* (FROM) within the range (0–100) is used, obtaining the indicators $I_{\Delta CoVaR,t}$ and $I_{MES,t}$ from day t. The *ContagEn* indicator for the energy sector will be calculated according to the formula:

$$ContagEn_t = \frac{I_{\Delta CoVar,t} + I_{MES,t}}{2}. \tag{4}$$

The *ContagEn* indicator represents the average value of systemic risk transmitted by the energy sector to the other sectors of the economy. It takes values between 0 and 100, 100 representing the maximum level.

We employ the COPOD methodology to detect outliers (Li et al., 2020). It is based on a three-stage interpretability algorithm that has as input of form $X = (X_{1,i}, X_{2,i}, \dots, X_{d,i})$, with $i = 1, 2, \dots, n$ and as output a score vector that can be written $O(X) = [X_1, X_2, \dots, X_n]$. The obtained score is considered to be a relative measure for the X_i. This value has been compared with the other values. X_i will be an outlier as $O(X_i)$ is higher.

After the outliers' identification step, the next objective is to predict them using Croston and Deep Renewal models. Intermittent demand forecasting was addressed by Croston (2017), who proposed a methodology that allows for an independent application of exponential flattening to inter-demand times and positive consecutive demands. His method is considered a recognised benchmark for software forecasting this data type (Türkmen et al., 2021).

4. Results

To capture the evolution of the degree of contagion, we calculated the averages of the systemic risk indicators (Δ*CoVaR* and *MES*) for all companies in each sector, obtaining a value of the average systemic risk in each sector. There were 24 indicators related to the 24 sectors according to the GICS classification. The heatmap of Diebold – Yilmaz for Δ*CoVaR* (all sectors, the whole sample) can be observed in Figure 1, while MES for all sectors for the whole sample is presented in Figure 2. The colour scale on the right-hand side of each chart shows the intensity of the spill-over effect, ranging from smaller values in dark red to higher values in blue.

4.1. Computation and evolution of ContagEn

The values obtained for ΔCoVaR and MES indicators (the European energy sector for the FROM case – what this sector transmits to the rest of the economy) are presented in Figure 3. Figure 4 displays the values obtained for the ΔCoVaR and MES indicators for the NET situation; they represent the difference between what this sector receives and what it transmits.

We found a reasonably significant difference between the average amount of systemic risk transmitted by the energy sector to other sectors of the European economy and the received one, the latter being superior, with much higher values and firm reaction peaks for both indicators presented (CoVaR and MES), with multiple peaks recorded for the ΔCoVaR indicator, but with the highest value recorded for the MES indicator.

The evolution for the period included in the analysis of the *ContagEn* indicator, which represents the average value of systemic risk transmitted by the energy sector to the other

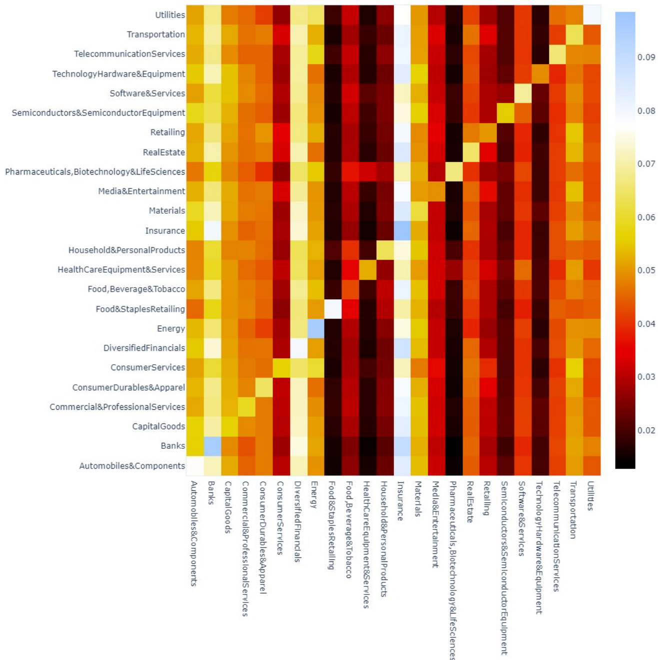


Figure 1. Heatmap of Diebold – Yilmaz for ΔCoVaR all sectors for the whole sample

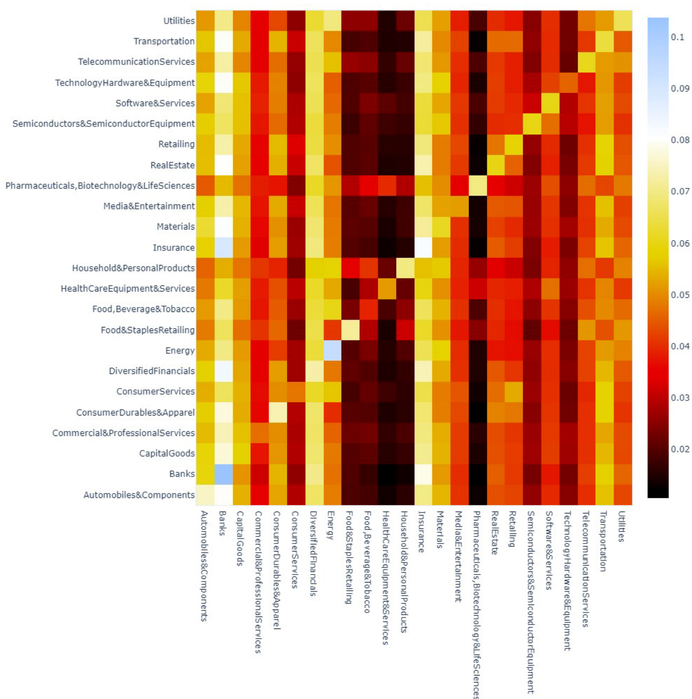


Figure 2. Heatmap of Diebold – Yilmaz for MES all sectors for the whole sample

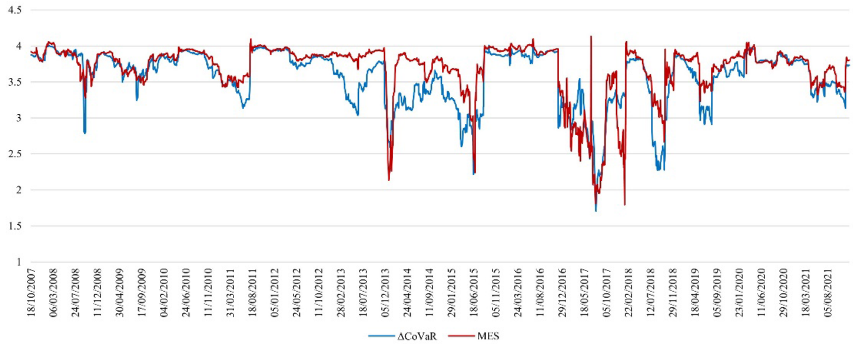


Figure 3. Evolution of ΔCoVaR and MES indicators for the energy sector (FROM, May 2007 – December 2021)

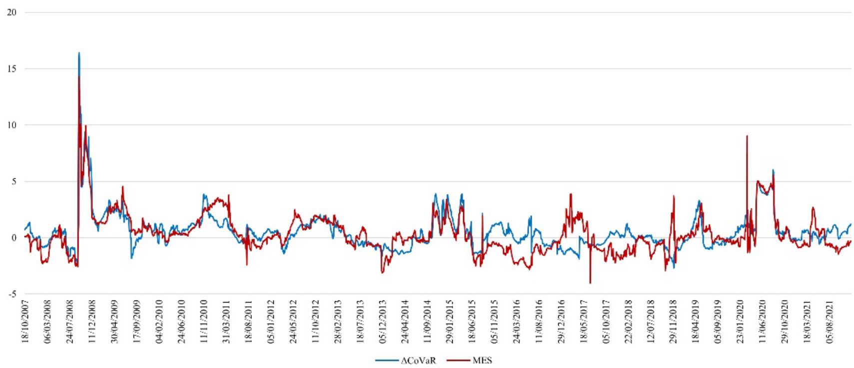


Figure 4. Evolution of ΔCoVaR and MES indicators for the energy sector (NET, May 2007 – December 2021)

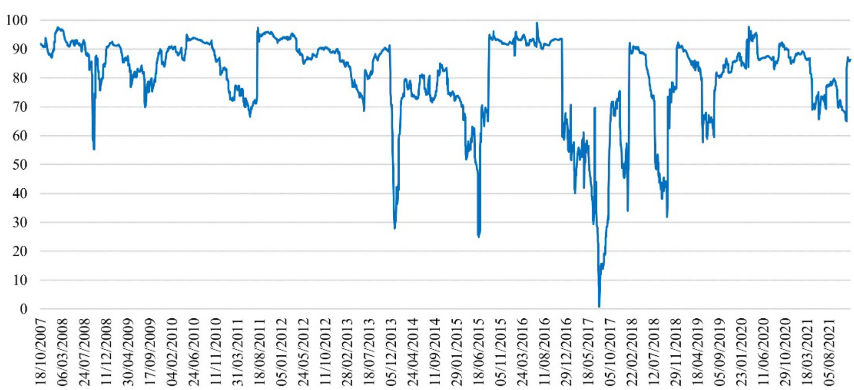


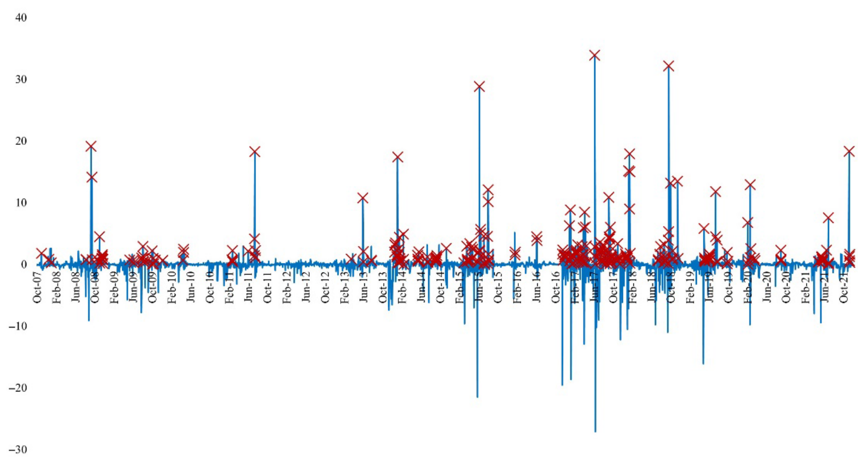
Figure 5. Evolution of the ContagEn indicator (May 2007 – December 2021)

sectors of the economy, is presented in Figure 5. We obtained values over 50 in 94.13% of cases but over 85 in only 52.36%. Extreme values, over 95, are obtained in only 3.40% of cases.

The upper fluctuations are lower, and without excessive transmission peaks to the other sectors, results are valid for all variants of calculated indicators. Our results are similar to those obtained by Kerste et al. (2015) or Pierret (2013) regarding risk transfer to other sectors. However, we note a greater power of risk transmission in times of crisis, as suggested by the results obtained by Algieri and Leccadito (2017a) and Restrepo et al. (2018). These include the financial crisis of 2007–2009, periods of the European sovereign debt crisis, and the COVID-19 crisis.

The highest values are observed for the dates (28, 29, and 30 June 2016) after the announcement of the Brexit referendum that triggered uncertainty in the energy market (*ContagEN* values were 99.14, 97.89, and 97.68). The second significant event is the awareness of the spread of the SARS-CoV-2 virus in March 2020 (*ContagEn* indicator value is 97.67). The rise of oil prices started at the beginning of 2008 and peaked in July 2008, which is reflected in high values for *ContagEn* for the first half of the year. In early August 2011, while still high compared with historical standards, oil prices fell amid weak economic conditions in Europe and the United States. The last three events are responsible for the highest values of the indicator, with the most prolonged influence belonging to the developments of 2008. The value of September 2015 (96.04) is also noteworthy, a year in which there were significant decreases in the price of oil amid rising supply and the refusal of the Organization of the Petroleum Exporting Countries to reduce production. In early February 2016, the prices reached the minimum of that period; the effects were captured by the indicator *ContagEn* (95.91). In December 2018, there were also sharp decreases in oil prices, with undesirable effects on the financial markets (the value of the *ContagEN* indicator was 92.31).

Outliers were detected using the COPOD algorithm for the first-order differences computed on the *ContagEn* index. Identifying outliers relies on these series' persistent dynamics; therefore, we used the first two lags as features (explanatory variables) in the COPOD methodology.



Note: Outliers are represented by the red marks on top of log returns computed on the *ContagEn* index.

Figure 6. Dynamics of first-order differences in ContagEn and outliers detected with COPOD methodology

For our analysis, the positive spikes only concern us since they correspond to moments when the market was susceptible to the energy sector, i.e., when the companies from the energy sector transfer shock to the other sectors at the European level. These large movements are depicted in Figure 6.

There are 292 positive outliers detected for a sample of 3,696 log returns that cover the period from October 2007 (the first part of 2007 was needed for the first fit of the Diebold-Yilmaz methodology to compute the first value for *ContagEn*) until December 2021. The next step in our analysis, which is our paper's main objective, consisted of investigating the forecasting capabilities of these significant increases (positive spikes) of *ContagEn*.

Figure 7 uncovers the statistical properties of the identified positive outliers by depicting their frequency across all time intervals for which we deliver our forecasts. This chart also provides information about the difficulties encountered by the forecasting methodologies. We notice, for instance, that approximately 79% of prediction intervals hold up to ten outliers, 15% have between eleven and fifteen outliers, and approximately 5% have more than 15 outliers. Intervals with three outliers are the most frequently met. Since a more significant number of outliers in the out-of-sample interval represents a more difficult task for the predictors, we can expect an essential variation in the performance of these algorithms.

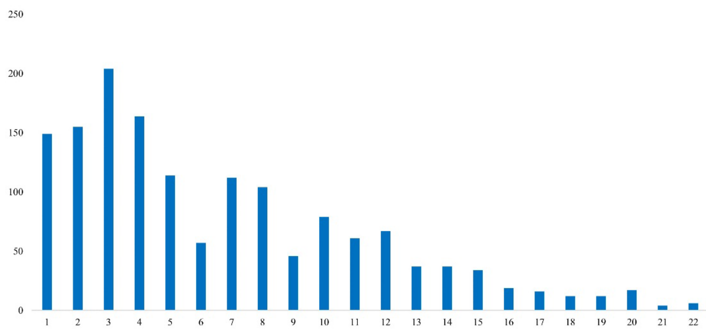


Figure 7. Frequency of outliers for forecasting intervals

4.2. Robustness check

We evaluate the appropriateness of our selection for the Deep Renewal model by comparing it to the Croston model, a conventional approach commonly employed for analysing intermittent data. We will use this model as a benchmark for the Deep Renewal algorithm, which is documented as a powerful tool that uses neural network methodology to forecast intermittent time series.

We fit both models repetitively on rolling windows of 500 observations that move with a step of one day and produce forecasts for the next 30 days. Under this setting, our first fitting interval is October 23, 2007, to September 22, 2009, and the first prediction covers the next 30 days, ending on November 3, 2009. Our last forecasting interval ended on December 21, 2021.

This prediction exercise allows us to develop a framework to measure the performance of the forecasting methods employing differences between the actual values of the outliers and their forecast values. We used two types of metrics: the Mean Squared Error (MSE) and the quantile losses at 10%, 50% and 90% levels. Figure 8 shows the distribution of these measures across all prediction experiments for both Croston and Deep Renewal models. We notice that all these representations reveal a more significant concentration of values in the lower part of the losses for the Deep Renewal model, which means that these charts indicate that the Deep Renewal model in this repetitive sequence of forecasting exercises outperforms the Croston model.

We extended our investigation by grouping the four metrics into categories according to the number of outliers we forecast per interval. For instance, we put all the values of MSE for predictions from the Croston model, corresponding to situations when the out-of-sample intervals (the ones for which we produced our forecasts) contained one outlier in a group (we denote it by $G_{MSE,C,O1}$). Further, we put the MSE for predictions from the Deep Renewal models, corresponding to situations with one outlier in the forecast interval in a separate group ($G_{MSE,DR,O1}$). According to this arrangement, we obtained 22 groups $G_{MSE,C,Oi}$ and the corresponding 22 groups $G_{MSE,DR,Oi}$, for $i = 1 \dots 22$.

We continued with the same setting for the values of the quantile losses, ending up with 22 other groups for the quantile loss at 10% ($G_{Q10,C,Oi}, G_{Q10,DR,Oi}$), 22 groups for the quantile loss of 50% ($G_{Q50,C,Oi}, G_{Q50,DR,Oi}$) and finally, 22 groups for the quantile loss of 90% ($G_{Q90,C,Oi}, G_{Q90,DR,Oi}$).

For each pair of groups, we computed Welch's test of differences between the two groups to investigate the extent to which the Deep Renewal model succeeds in producing better metrics than the Croston model. Welch's test is considered less dependent on hypotheses that cannot be easily verified, and when applied, the statistical power is not much diminished (Delacre et al., 2017).

For each set of differences $G_{QX,C,Oi} - G_{QX,DR,Oi}$ (we denote it as $Pval_{Metric}$), we obtained 22 p-values, which we represent in Figure 9.

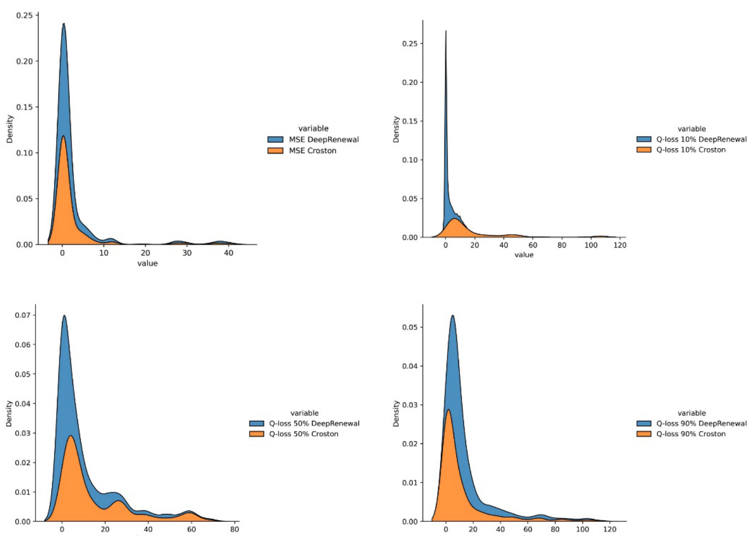
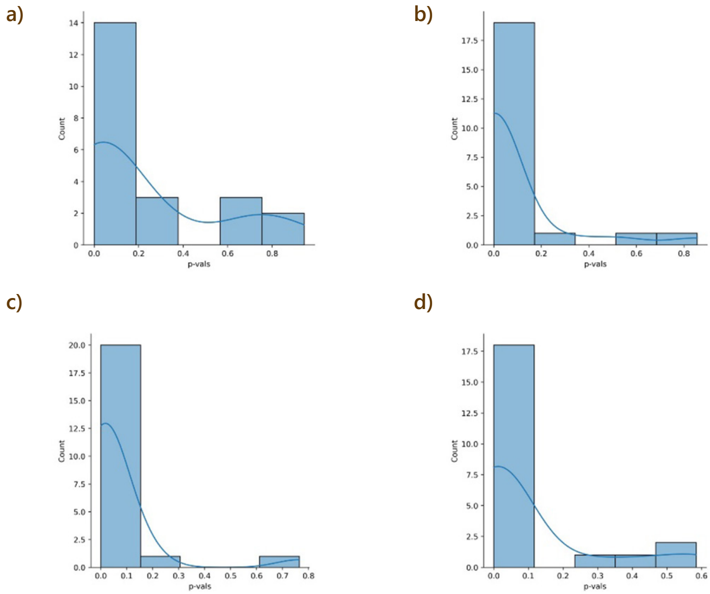


Figure 8. The distribution of losses resulted from fitting the Croston model and the Deep Renewal model



Note: a) $Pval_{MSE}$, b) $Pval_{Q10}$, c) $Pval_{Q50}$, d) $Pval_{Q90}$.

Figure 9. Distributions of p-values for Welch tests across differences in model performances when outliers took place

We notice that the highest columns for these p-values are those for trim levels, usually lower than 10%, which shows that the differences between performances of the Deep Renewal model and the Croston model are significant in most of the cases in which the number of outliers is different in the forecasting interval. Corroborating with the information produced in Figure 8, we can conclude that the Deep Renewal model generates better predictions than the benchmark model.

5. Discussion

The emergence of new phenomena and processes in the energy sector, with multiple interconnections, and diverse propagation in a complex (Andrei et al., 2023) and complicated context of energy ecosystem, contributes to the increased difficulty in understanding and researching the analysed subjects. Besides these issues, the current crisis in the European energy markets is fuelled by the increased prices for electricity, natural gas, and oil, the extreme volatility of prices, and supply problems that encourage research in all mentioned fields.

Our focus on financial stability is motivated by the fact that it is not an independent purpose. However, it maintains the objectives of efficient and sustainable capital allocation and the proper functioning of the economy. From this perspective, our results confirm the findings of Adrian and Brunnermeier (2016), Billio et al. (2012) and continue the methodological setup from Lupu et al. (2020, 2021).

Several novel results can be outlined from our research. First, we highlight that the energy sector conditions affect financial stability. Our intended methodological framework renders feasibility to monitoring shocks that originate in the energy sectors and may threaten European financial stability. Second, our methodological structure produces sensitive empirical results prompted by a dynamic forecasting experiment. The data combination (financial and economic sectors) allows for complex connections and helps formulate policies and recommendations.

As such, they predict positive outliers of our spill-over indicator (*ContagEn*), equivalent to pointing out situations with crises-generating events. An analysis of our *ContagEn* indicator shows no excessive transmission peaks to the other sectors (results valid for all variants of calculated indicators). These conclusions are similar to those of other authors regarding transferring risks to other sectors (Kerste et al., 2015; Pierret, 2013). On the other hand, the power to transmit shocks increases in times of great crisis or the case of energy sector-specific events (sharp price changes, sanitary crises, political uncertainty).

Additionally, as mentioned by Tufail et al. (2022), precise financial inclusion can complement these actions and facilitate the transition to a green economy. Furthermore, energy justice priorities, a concept gaining increasing attention (Qian et al., 2022), can also be considered.

6. Conclusions

Nowadays, the energy industry is gaining importance due to its economic implications.

The main objective of our research is to quantify the degree to which the energy sector affects financial stability at the European level and predict situations when these impacts are most substantial. We quantify these phenomena by constructing an indicator that captures the contribution of energy companies to financial stability (*ContagEn*). Forecasting is developed in an out-of-sample setting of repetitive experiments in which we compare performances of the Croston model (as a benchmark) and a neural network model specially developed for intermittent data forecasting. The data used for this purpose consists of daily prices recorded at the end of trading sessions for May 3, 2007, to December 21, 2021, for all companies listed on European stock exchanges included in the STOXX 600 index, divided into 24 sectors. Initially, the systemic risk indicators CoVaR, ΔCoVaR and MES were estimated. Our analysis relies on previous findings that the energy sector does not transmit intensely constantly.

In addition, these findings have policy implications. Our methodological framework allows for creating tools that can monitor and predict situations where the economy becomes highly reliant on the energy sector. These tools can aid in developing necessary policy measures to reduce such dependencies before they become harmful to the system. Policymakers must increase such actions, especially in light of the European energy crisis, where there are moments of extreme volatility. Following the example of financial stability measures, such policies may be designed as capital buffers triggered by the extent to which significant shifts in the dependence on the energy sector are predicted for the following time frame.

Although it became a standard in the literature, one of the study's limitations concerning assessing the degree to which the energy sector influences financial stability at the European level is that the analysis is limited to listed companies. Due to its design, this study primarily examines the spread of contagion exclusively within financial markets. Therefore, it is essential to note that one of its limitations is the absence of an analysis of contagion at the level of the real economy.

Another limitation would be that the vertical and horizontal integration of the energy companies in the analysed sample (if any) is not considered. However, this aspect is vital if we analyse the transmission of risk within the sector, an analysis that could qualify as a future research direction. We can also consider another aspect of future development: examining the spill-over effects across different countries. In our paper, we concentrate on the most significant European companies to provide a general overview of the interconnectedness within the entire region. However, refining our selection by including the most important companies from each country could also uncover intriguing insights.

Disclosure statement

The authors did not report any potential conflict of interest.

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