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Dynamic interconnectedness of economic confidence, energy prices, and interest rates: Insights from the euro area

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ABSTRACT

This work examines the time-varying interlinkages among economic confidence, energy prices, geopolitical stress, and short/long-term interest rates in the Euro Area. Our research meticulously explores the interplay between economic confidence and various determinants, including financial indicators, geopolitical stress incidents, and energy prices. Employing innovative approaches such as the time-varying parameter vector autoregression (TVP-VAR) time and frequency-domain connectedness, we uncover the nuanced relationships between economic confidence, financial indicators, and energy prices. We illuminate the systemic nature of shock transmission in the Euro Area, identifying key net transmitters and recipients of shocks, with short-term interconnectedness emerging as a dominant feature, especially during pivotal events such as the global financial crisis, the COVID-19 pandemic, and geopolitical conflicts. Our empirical findings can be summarized as follows: First, both the time and frequency-domain connectedness indexes correctly associate with major financial/geopolitical events. Second, BCI and CCI respond to the GFC asymmetrically. Third, Brent and short/long-term interest rates are the net transmitters of shocks on average. Fourth, there is a considerable augmentation in return spillovers during the period characterized by the pandemic crisis compared to the GFC. Finally, our findings for frequency-dependent connectedness networks indicate that the market is particularly susceptible to short-term shocks. This study has significant ramifications for investors, market players, and policymakers.

1. Introduction

Economic decision-makers, whether individuals, businesses, or government entities, base their decisions on the information available to them. This process considers both financial and non-financial factors, guiding their choices towards optimal outcomes (Hoff and Stiglitz, 2016; Güneş et al., 2024). For a more comprehensive understanding of human behavior and to make more accurate predictions, it is essential to incorporate psychological factors into economic analyses, especially human behavior. Various interdisciplinary fields, such as behavioral economics, experimental economics, and neuroeconomics, have emerged, particularly in the latter half of the 20th century. These diverse disciplines approach the intersection of economics and psychology from various angles and employ different methodologies (Pech and Milan, 2009).

According to the behavioral perspective, confidence is one of the determinants of economic decisions (Vanlaer et al., 2020). Keynes explores the psychological foundations of economic decision-making by introducing the concept of "animal spirits." He posits that aggregate economic behavior is propelled by these animal spirits. Keynesian behavioral economics argues that economic confidence plays a key role in shaping the economy's outcome. In the view of Keynes, a change in consumer and business confidence could have an important impact on their spending and investment decisions that would affect overall demand and economic activity. He underlined the psychological dimension of economic behavior, arguing that emotions, expectations, and uncertainty could be a cause for economic change (Farmer, 2012). Therefore, confidence indices are calculated to reveal the economic

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outlook. Although different indices are developed in the literature, consumer and business-based are generally utilized as a variable in academic papers (Croushore, 2005).

The consumer confidence index (CCI) is a significant economic barometer. As confidence levels increase, consumers tend to become more optimistic about the future, leading to an uptick in their spending habits, and conversely, declining confidence can have the opposite effect. Consequently, consumer confidence can serve as an indicator of consumers' optimism regarding their future income prospects, influencing their spending behaviors. When consumers hold positive expectations for future income, they are more inclined to increase their expenditures, a trend that bolsters the economy and positively impacts the production of goods and materials (Su et al., 2023). Thus, CCI have long been an early warning or a leading indicator for financial markets and the real sector.

The Business Confidence Index (BCI) is an economic indicator that assesses the sentiment and expectations of businesses or business leaders regarding current and future economic conditions within a specific geographic area or industry. It provides insights into the degree of confidence or positivity that businesses hold regarding the economy and their prospects (Khan and Upadhayaya, 2020). Business confidence is an essential variable for revealing the economic soundness of an area or sector, affecting decisions related to investment, employment, and expansion, and providing insights into market sentiment and potential future trends (Lim and Morris, 2023). The Business Confidence Index (BCI) and Consumer Confidence Index (CCI) are essential tools for assessing economic confidence from distinct viewpoints. The BCI reflects businesses' sentiments on current and future economic conditions, encompassing factors like investment intentions, hiring plans, and overall business outlook. Conversely, the CCI measures consumer confidence levels, focusing on aspects such as job security, income expectations, and willingness to spend. By considering both indices, we gain valuable insights into the broader economic sentiment, as both businesses and consumers are fundamental to economic activity. Fluctuations in these indices can indicate changes in confidence levels, thereby influencing spending patterns, investment decisions, and overall economic performance (Su et al., 2023; Khan and Upadhayaya, 2020).

Studies analyze economic confidence from different perspectives. A significant part of the literature analyses the impact of macroeconomic variables on economic confidence (Tsagkanos et al., 2023; Taylor and McNabb, 2007). Some studies focus on important milestones (epidemics, wars, political events, etc.) (Balcaen et al., 2023). Economic policies and regulations are also variables whose effects on economic confidence are investigated (Montes and Nogueira, 2022). A limited number of academicians aim to highlight the impact of commodity and energy prices on economic confidence (Adekoya and Oliyide, 2021; Degiannakis et al., 2014).

Studies analyzing the supply and demand side of confidence together are limited. This study examines the interrelationship between economic confidence, Euro Area 10-year Government Benchmark bond yield, Federal Fund Rate, geopolitical risk, Moody's Seasoned AAA Corporate Bond Yield, oil and gas prices, and short-term interest rates within the Euro Area from 1994 to 2023. Notably, there needs to be more existing research focusing on the effect of energy prices on economic confidence, often limited to individual variables or specific samples. Our research investigates the combined impact of both oil and gas prices on both business and consumer confidence in the Euro Area. Furthermore, our study employs an original methodology, utilizing the innovative connectedness approach. This approach is novel in the literature and offers a robust method for uncovering the intricate relationships between these variables. Our findings may provide valuable insights into understanding how changes in prices affect both the supply and demand aspects of economic confidence (Anastasiou et al., 2023; Varlik and Berument, 2020).

The remainder of the paper is organized as follows: We present the theoretical background in Section 2. Section 3 deals with the literature, and Section 4 describes methodology and data. Section 5 discusses the empirical results, and Section 6 concludes.

2. Theoretical background

Psychology's effects on economics highlight the importance of certain variables in shaping economic choices. Confidence, as a psychological factor, plays a vital role in promoting effective economic decisions. Consequently, this study delves into the discussion of economic confidence regarding the efficiency of economic activities. John Maynard Keynes elucidates the psychological underpinnings of economic decision-making through the notion of "animal spirits". According to Keynes, aggregate economic activity is driven by animal spirits (Keynes, 1937). Katona (1951) argues that economists should incorporate psychological factors into their forecasts. Farmer (2012) emphasizes the utility of animal spirits for governments in their governance processes.

Behavioral economics incorporates psychological aspects into the study of economics, where concepts such as loss aversion, herd behavior, and cognitive biases have the potential to impact economic confidence. Emotions and cognitive biases among individuals can trigger abrupt shifts in confidence levels, sometimes occurring independently of substantial economic alterations (Hursh, 1984). Expectation theory argues that expectations can influence people's economic decisions and economic indicators (Dräger et al., 2016).

Researchers also emphasize the psychological dimension of business confidence. The psychological business cycle theory focuses on the psychological mindset of businesspeople and contends that the expectations and strategies of economic actors establish the bridge connecting future and present economic actions. This theory demonstrates that these psychological connections are not exclusive to what is commonly referred to as psychological business cycle theories; instead, they are present in what are known as fundamental theories, albeit not as prominent a role. The fundamental idea is that changes in emotions and expectations can potentially induce shifts in real economic activities. Thus, economic forecasts can be made using variables related to emotions and expectations (Geiger, 2016; Kara, 2016).

The Permanent Income Hypothesis argues that consumers' economic decisions can be influenced by their future information and expectations rather than their current knowledge. This suggests that uncertainty regarding future earnings is a fundamental driver of deviations from the permanent income hypothesis (Juhro and Iyke, 2020).

Likewise, the life-cycle hypothesis argues that consumers aim to sustain an ideal lifestyle by strategically managing their savings and consumptions throughout their lives (Modigliani, 1966). In this model, consumers are typically expected to save during their younger years and draw down savings during retirement. This implies that emotions, such as certainty versus uncertainty and optimism versus pessimism, play a crucial role in guiding consumption decisions (Shefrin and Thaler, 1988).

This study examines the influence of oil and gas prices on economic confidence, drawing from various theories. The Real Business Cycle Theory asserts that energy price fluctuations play a significant role in shaping the business cycle, impacting productivity, production costs, and overall economic activity. Positive energy price shocks stimulate growth, while adverse shocks can trigger downturns (Clarida et al., 1999).

New Keynesian economics, focusing on price stickiness and inflation, highlights how energy price shocks affect production costs and inflation, thereby influencing short-term economic conditions. The resource curse theory delves into the challenges energy-dependent countries face, linking energy price shocks to issues like Dutch disease and economic instability. Lastly, Marginal Utility Theory and the Permanent Income Hypothesis explore the impact of energy price shocks on economic confidence through income and wealth considerations. These theories collectively offer insights into the multifaceted relationship between

energy prices and economic confidence (Kydland and Prescott, 1982).

All these theories underline the significance of consumer and business confidence in economic forecasting and stabilization. Therefore, confidence indexes are used to forecast the economic outlook and unveil the results of economic policies (Van Aarle and Kappler, 2012; Lahiri and Zhao, 2016).

Our model contributes to the literature by analyzing the determinants of economic confidence in the Euro Area from the supply and demand sides. Besides, we also add a new dimension to economic confidence studies by including energy prices in the model.

The contribution of the paper is at least threefold. Firstly, we investigate the time and frequency-domain interlinkages among economic confidence, interest rates, and oil/gas prices in the Euro Area, encompassing the GFC and recent geopolitical upheavals. This marks the pioneering research endeavors into the time-varying associations between economic confidence, short/long-term interest rates, and energy prices within the Euro Area. Consequently, we not only underscore the dynamic attributes of the dynamic interconnections between the indicators but also scrutinize their transmitting and receiving roles.

Secondly, we concentrate on the system wide interconnectedness networks to offer insights into the frequencies that predominantly contribute to system interconnectedness.

Third, due to the prevalence of the transitory (short-term) linkages over the medium- and long-term (persistent) interdependencies, we estimate transitory connectedness networks around the midst of two turmoil times (September 2008 and January 2020, respectively).

3. Literature review

3.1. Economic confidence literature

Analyzing the determinants of economic confidence holds immense significance, as it yields critical insights into the underpinnings of economic stability and growth. This examination enables a deeper understanding of the factors that shape the confidence levels of businesses and consumers within the economy empowering should be helping policymakers, enterprises, and investors to make well-informed decisions. Identifying these determinants is a foundation for tailored policy development aimed at fortifying economic stability, kindling investment, and driving consumer expenditure (Su et al., 2023).

The CCI is an economic indicator that measures the sentiment and optimism of consumers about the state of the economy (Khan and Upadhayaya, 2020). Studies examine financial and non-financial determinants of consumer confidence. Lahiri and Zhao (2016) argue that the University of Michigan's Index of Consumer Sentiment is influenced by macroeconomic variables and economic news. Starr (2012) finds that economic news in the U.S. has a significant effect on consumer confidence. El Alaoui et al. (2020) examine the variables affecting the consumer index in the US in a wide range of variables with financial and non-financial factors. The findings from linear models indicate that factors associated with the stock market, individual income, and unemployment significantly explain U.S. consumer sentiment. Gholipour et al. (2023) shows the asymmetric effect of policy uncertainty on the CCI in Japan. Kirchner (2020) emphasizes that both expected and unforeseen rises in the official cash rate target and the corresponding interest rates affect consumer sentiment negatively.

Li and Ouyang (2023) discuss the topic from an energy perspective. Authors argue that oil price shocks primarily enhance consumer sentiment by elevating their contentment with present income and their outlook on future employment prospects in China. Güntner and Linsbauer (2018) examine whether energy supply and demand shocks affect consumer sentiment in the U.S. Authors emphasize that Consumer sentiment is minimally affected by oil supply shocks. In contrast, other oil demand shocks exert a substantial negative influence for up to two years, and aggregate demand shocks manifest various effects. Edelstein and Kilian (2009) analyze the influence of gasoline prices on consumer expenditure in the US. VAR models demonstrate that shocks in gasoline prices have a notable impact on consumer confidence and play a determining role in shaping consumer spending patterns in the U.S.

The impact of non-financial variables such as political events and COVID-19 on consumer confidence is one of the topics focused on in the literature (Gholipour et al., 2023; Elmassah et al., 2023; De Boef and Kellstedt, 2004).

Business confidence can reflect business sentiment and feedback from macroeconomic policies (Khan and Upadhayaya, 2020). Like consumer confidence studies, business confidence is analyzed in different dimensions in the literature. de Mendonça and Almeida (2019) examine the impact of central bank decisions on business confidence in emerging economies. Their empirical findings indicate that the credibility of monetary policy can play a role in bolstering business confidence.

Adekoya and Oliyide (2021) emphasize the role of economic uncertainty on business confidence in OECD countries. Almeida and Montes (2020) emphasize the relationship between business confidence and crime and violence in Brazil. Teresiene et al. (2021) examine how COVID-19 cases and death counts influence business confidence in the US. Their empirical findings reveal a negative correlation between the number of cases and business confidence. Adekoya and Oliyide (2021) argue that oil prices have a significant effect on business confidence in OECD countries.

Some studies analyze the determinants of economic confidence through investor confidence. These studies investigate the impact of macroeconomic, financial, and non-financial variables and energy prices on investor confidence (Li et al., 2022; Apergis et al., 2018; Sun et al., 2021).

3.2. Economic confidence studies in the euro area

Euro Area studies analyze economic confidence with business, consumer, and investor dimensions. Like other samples, the factors affecting economic confidence in the Euro Area are included in the model as macroeconomic variables, events, commodity, and energy prices.

There is a significant place in the literature for macroeconomic developments globally and at national level. Dees and Brinca (2013) examine the relationship between CCI and consumption spending with the Granger causality and cointegration methods. Empirical results show a significant relationship between CCI and household spending in the Euro Area. Aristei and Martelli (2014) investigate the effect of macroeconomic variables such as inflation, unemployment, and the stock market on Euro Area consumer confidence. Panel data analysis presents a mixed outlook on whether economic and financial variables can effectively capture the information content of consumer sentiment.

Van Aarle and Kappler (2012) find that output, retail sales, and unemployment are determinants of consumer confidence in the Euro Area. Sentiment analysis shows that Important events and geopolitical risks are analyzed as determinants of consumer confidence. According to correlation–regression, Teresiene et al. (2021) find that COVID-19 spread is ineffective in the Euro Area. Energy prices are another variable whose impact on consumer sentiment is analyzed. Clerides et al. (2022) analyze the impact of energy prices on economic confidence with SVAR model. Authors find that oil and gasoline prices in the Euro Area harm consumer confidence. Similarly, Binder and Makridis (2022) investigate the relationship between gas prices and consumer confidence with survey data. Empirical results show that gas prices negatively affect consumer confidence.

Economic confidence studies examine the supply side of the economy by analyzing business confidence. Like consumer confidence studies, the effects of macroeconomic variables on business confidence are most analyzed in the Euro Area. Colombo (2013) applies the SVAR model to examine the determination of business confidence in Euro Area. Author argues that economic shocks in the U.S. economy have a negative impact on business confidence in the Euro Area. Michail et al.

(2017) use Factor-Augmented Vector Autoregressive model to examine the determination of business confidence. Empirical results emphasize that fiscal policy is an essential determinant of business confidence.

Other variables (political events, COVID-19, geopolitical risks, energy prices) that may determine business sentiment in the Euro Area have yet to be adequately investigated. There are few analyses in the literature (Ambrocio, 2022; Van Aarle and Moons, 2017; Cavallo and Ribba, 2018). Investor confidence is another dimension of economic confidence analyzed in the literature. These studies reveal the economic and financial determinants of investor sentiment in the Euro Area (Reis and Pinho, 2020; Nitoi, Pochea, 2022; Rehman and Apergis, 2019).

There are limited studies on the determinants of economic confidence within the euro area that can be drawn from the Economic Confidence literature. Besides, these studies apply panel data analysis, causality tests, SVAR model and cointegration test. Our study aims to contribute to the literature by analyzing the determinants of economic confidence in the Euro Area using a connectedness approach.

4. Data and methodology

4.1. Data

In this study, we examine the impacts of oil/gas prices, industrial production, short-term interest rates, and geopolitical risks on both business and consumer confidence in the Eurozone between January 1994 and May 2023. We sourced BCI and CCI and the short-term interest rate from the OECD website (OECD, 2023). We collected oil and gas prices from the World Bank Monthly Prices dataset (World Bank, 2023), industrial production, and Euro Area 10-year Government Benchmark bond yield from the European Central Bank (ECB) statistical data warehouse.

We use the Geopolitical Risk Index (GPR) computed by Dario Caldara and Matteo Iacoviello by the text-mining approach using the presence of words associated with geopolitical tensions in leading international newspapers (Caldara and Iacoviello, 2022) (see Table 1).

Table 2 provides summary statistics for returns, while Fig. 1 illustrates the trends.

Per the results displayed in Table 2, the GPR has the highest return, followed by the SIR, and the 10YGBBY. On the other hand, the 10-year Government Benchmark bond yield exhibits the highest variance, followed by the short-term interest rate and the geopolitical risk index.

BCI, CCI, Brent, and IPI are skewed to the left, while the rest of the returns are left-tailed. Furthermore, all return series are leptokurtic, and the greater J.B. values show they are abnormally distributed.

Table 1
List of variables.

Variable	Abbreviations	Definition
Business Confidence Index	BCI	Business Confidence Index (Monthly)
Consumer Confidence Index	CCI	Consumer Confidence Index (Monthly)
Natural Gas Prices	NG	US Natural Gas Prices (Monthly)
Oil Prices	BRENT	Brent Crude Oil (Monthly)
Short-Term Interest Rates	SIR	Short-term interest rates indicate the rates at which financial institutions engage in short-term borrowing or at which short-term government securities are issued or traded in the market monthly.
Euro Area 10-year Government Benchmark bond yield	10YGBBY	Benchmark bond - Euro Area 10-year Government Benchmark bond yield (Monthly)
Geopolitics Risks	GPR	Geopolitical Risk Index (Caldara and Iacoviello, 2022)
Industrial Production Index	IPI	Euro Area 19 (fixed composition) - Industrial Production Index (Monthly)

Additionally, they exhibit significant autocorrelations and ARCH/GARCH errors.

Fig. 1 illustrates notable peaks corresponding to significant financial and geopolitical crises, including the 2008 Global Financial Crisis (GFC), the oil price spike, the oil price collapse spanning late 2014 to early 2016 (Grigoli et al., 2019; Silva and de Araujo, 2023), the emergence of COVID-19, and the more recent Russian-Ukrainian conflict (RUC) in early 2022. In addition to the explicitly mentioned events, these peaks may also signify changes in regulatory frameworks, technological advancements, and demographic trends, all of which significantly impact economic dynamics. A comprehensive understanding of the nuanced drivers behind each peak can offer profound insights into the underlying mechanisms guiding market behavior, thereby enriching strategic decision-making processes for stakeholders across diverse sectors.

4.2. Methodology

In this study, we used the TVP-VAR-based time and frequency-domain connectedness methodologies, respectively. Table 3 briefly explains these methodologies, and details are presented in Appendix A.1 and A.2.

5. Results

5.1. Dynamic connectedness

The first stage of the study centers on the dynamic connectedness between the return series and plots the TCI with significant financial/geopolitical events in Fig. 2. The TCI fluctuated between 17% and 52% and peaked in June 2020 (51.77%) during the first wave of the COVID-19 pandemic. It is worth remarking that TCI creates proper signs of the prominent incidents during the episode. The index steadily declined until June 1998 and began to soar after the Russian debt moratorium in August 1998 and the subsequent collapse of the hedge fund Long-Term Capital Management (LTCM) in September 1998.

The TCI elevated prominently in August 2007, triggered by BNP Paribas' suspension of three investment funds invested in asset-backed securities tied to subprime mortgage debt, which had become illiquid. The index skyrocketed in September 2008 following Lehman Brothers' filing for bankruptcy protection. The TCI already achieved high levels (36.52%) in May 2010, when the Greek bailout took place. The TCI experienced a significant from mid-2014 to early 2015 driven by the supply conditions.[1] The index dramatically soared in early 2020 following the outbreak of the COVID-19 pandemic and its official declaration by the World Health Organization (WHO) on March 11, 2020. The TCI notably surged following the Russian invasion of Ukraine on March 24, 2022. Table 3 displays findings on the average connectedness of returns.

The average connectedness findings showcase that the 10-year Government Benchmark bond yield and the CCI are the principal sources for transmitting and receiving return shocks. At the same time, the GPR exhibits the lowest level of shock transmission and reception. BRENT, SIR, and 10YGBBY are identified as the primary net propagators, while the remaining indices function as net receivers of these shocks. The overall interconnectedness of returns is 30.5%.

Upon reviewing the data presented in Table 4, it becomes apparent that both Natural Gas Prices and BRENT display a moderate level of sensitivity to fluctuations in both BCI and CCI, as evidenced by their relatively elevated spillover values. This implies that shifts in business and consumer confidence have the potential to exert influence on energy prices, likely stemming from alterations in demand patterns and overall economic activity. Additionally, SIR exhibits significant sensitivity to

[1] https://blogs.worldbank.org/developmenttalk/what-triggered-oil-price-plunge-2014-2016-and-why-it-failed-deliver-economic-impetus-eight-charts.

Table 2
Summary statistics.

	Mean	Variance	Skewness	Ex. Kurtosis	JB	ERS	Q(20)	Q2(20)
BCI	0.007	0.089***	−1.08***	6.74***	732.43***	−2.50**	535.05***	255.31***
CCI	0.001	0.062***	−1.26***	7.13***	835.03***	−2.82***	445.61***	210.90***
NG	0.963*	116.942***	1.33***	7.97***	1031.00***	−4.77***	95.40***	373.73***
BRENT	0.876*	85.176***	−0.42***	1.57***	46.579***	−6.16***	24.39***	124.19***
SIR	2.702	2473.02***	15.53***	269.53***	1073562.28***	−7.83***	3.23	0.81
GPR	3.300**	738.047***	1.76***	7.29***	958.50***	−2.05**	34.26***	1.17
IPI	0.102	3.543***	−2.11***	42.95***	27164.82***	−4.23***	24.34***	194.47***
10YGBBY	1.253	813.422***	2.49***	29.41***	12980.81***	−6.54***	70.38***	154.87***

Notes: J-B stands for the Jarque Bera statistics, and ***, **, and * denote statistical significance levels at the 1%, 5%, and 10% confidence levels, respectively. ERS denotes unit root test as proposed by Stock et al. (1996), while Q (20) and Q2 (20) indicate the Ljung–Box statistics for assessing serial correlation in the raw series and squared residuals. Authors' calculations.

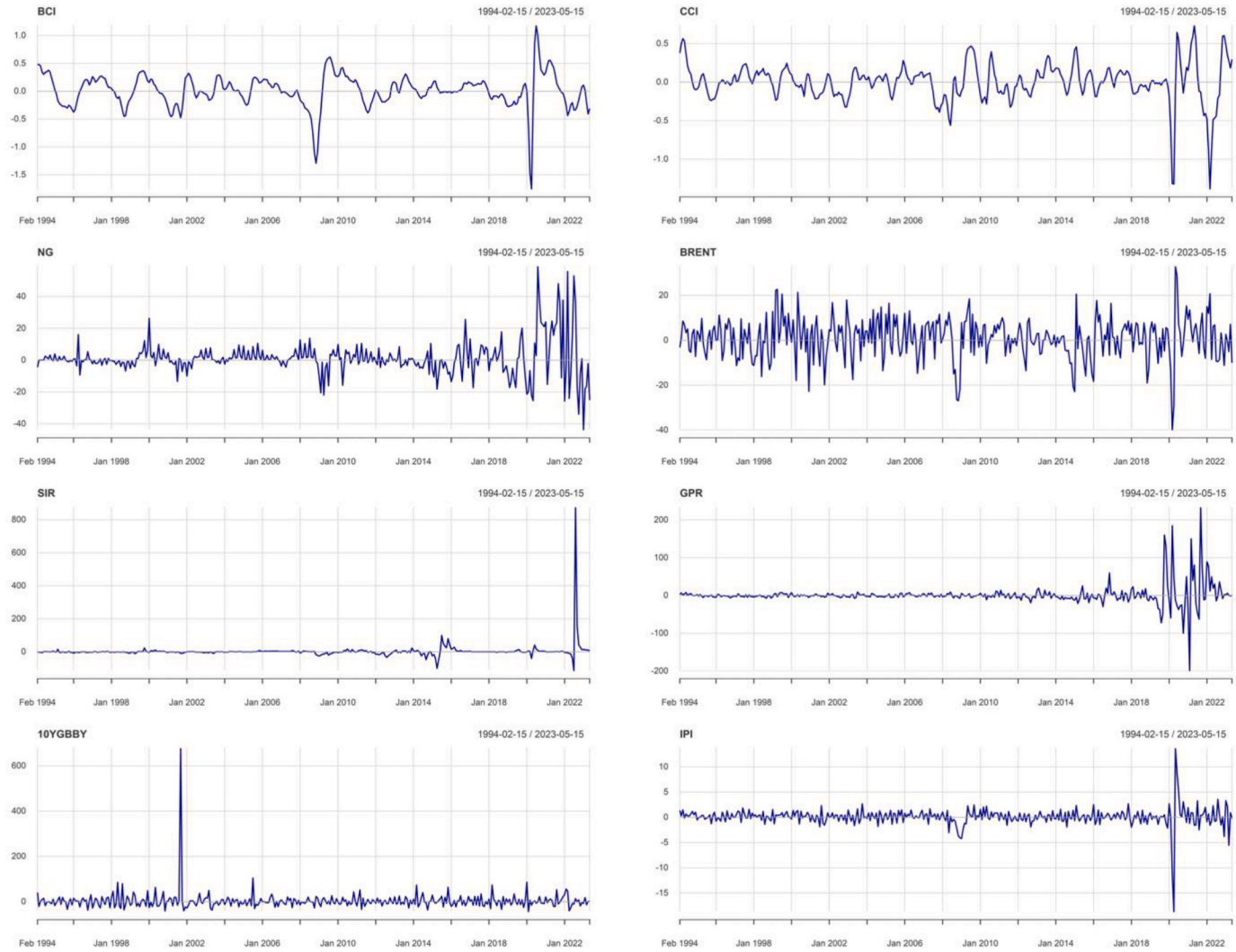

Fig. 1. Trends in the returns.

changes in both BCI and CCI, suggesting that variations in confidence levels may impact short-term borrowing rates or the trading of government securities. Similarly, the Euro Area 10-year Government Benchmark bond yield (10YGBBY) reveals sensitivity to changes in BCI and CCI, albeit to a somewhat lesser degree.

Subsequently, we explore the net directional spillovers among these indices and display them in Fig. 3.

Based on the results illustrated in Fig. 3, there are several key insights to highlight. First, corroborating our previous findings, 10YGBBY, SIR, and BRENT are the net transmitters of shocks over most times of the episode. While 10YGBBY and SIR are the net propagator, BCI and CC are the net receivers of shocks around late 1994, probably due to the ongoing financial turmoil during that period (i.e., the 1994 Türkiye financial crisis, the Mexican peso crisis). BCI, SIR, and IPI propagate a vast amount of shocks, whereas CCI and 10YGBBY receive a significant amount of spillovers during the GFC. It is worth noting that BCI and CCI respond to the GFC asymmetrically and become net transmitters/recipients during the GFC. During the Global Financial Crisis in the Euro Area, the asymmetrical response of the Business Confidence Index (BCI) and Consumer Confidence Index (CCI) can be explained by the

Table 3
Methodological summary.

	Antonakakis et al. (2020)	Barunik and Ellington (2020)
Total connectedness index (TCI)	$C_t(H) = \frac{\sum_{i,j=1,i\neq j}^{n}\widetilde{\Phi}_{ij,t}(H)}{\sum_{i,j=1}^{n}\widetilde{\Phi}_{ij,t}(H)} * 10 = \frac{\sum_{i,j=1,i\neq j}^{n}\widetilde{\Phi}_{ij,t}(H)}{n} * 100$	
Local network connectedness		$C(\mu,d) = 100 \times \sum_{j,k=1, j\neq k}^{N} [\widetilde{\theta}(\mu,d)]_{j,k} / \sum_{j,k=1}^{N} [\widetilde{\theta}(\mu)]_{j,k}$
Total directional connectedness (TDC) TO others	$C_{i\rightarrow j,t}(H) = \frac{\sum_{j=1,i\neq j}^{n}\widetilde{\Phi}_{ji,t}(H)}{\sum_{j=1}^{n}\widetilde{\Phi}_{ji,t}(H)} * 100$	$C_{j\rightarrow\bullet}(\mu,d) = 100 \times \sum_{k=1, k\neq j}^{N} [\widetilde{\theta}(\mu,d)]_{kj} / \sum_{k=1}^{N} [\widetilde{\theta}(\mu)]_{kj}$
TDC FROM others	$C_{i\leftarrow j,t}(H) = \frac{\sum_{j=1,i\neq j}^{n}\widetilde{\Phi}_{ij,t}(H)}{\sum_{j=1}^{n}\widetilde{\Phi}_{ij,t}(H)} * 100$	$C_{j\leftarrow\bullet}(\mu,d) = 100 \times \sum_{k=1, k\neq j}^{N} [\widetilde{\theta}(\mu,d)]_{j,k} / \sum_{j,k=1}^{N} [\widetilde{\theta}(\mu)]_{j,k}$
NET TDC	$C_{i,t}(H) = C_{i\rightarrow j,t}(H) - C_{i\leftarrow j,t}(H)$	

contrasting reactions of businesses and consumers to economic uncertainty. Businesses, more sensitive to market conditions, likely transmit their pessimism through cost-cutting measures and reduced investments, thus becoming net transmitters of confidence. Conversely, consumers may receive confidence through government interventions and adjustments in spending habits, mitigating the decline in their confidence levels. This dynamic interplay between businesses and consumers results in the observed asymmetry, with each group influencing the other in different ways throughout the crisis (Fernandez-Perez et al., 2024). It should be noted that the transmitted spillovers from the SIR dramatically surge towards the end of the period, which can be triggered by the ECB's decisions to raise interest rates to historically record levels to fight against the inflationary precedence over a weakening economy.

5.2. Frequency-dependent interlinkages

Focusing on the frequency-dependent interconnectedness network of returns, we adhere to the approach outlined by Kang et al. (2019) and calculate interconnectedness networks for short-term (1 month–6 months), medium-term (6 months–12 months), and long-term (more than 12 months) returns. We illustrate these networks alongside noteworthy geopolitical or financial events in Fig. 4.

Frequency-dependent connectedness networks indicate that the temporary interdependence is stronger than the medium- and persistent interdependencies, aligning with previous studies (Ferrer et al., 2021; Kang et al., 2019; Hanif et al., 2021). Precisely, the frequency-dependent connectedness indices signal significant stress events during the period. Moreover, the medium- and long-term connectedness indices exhibit highly comparable motifs throughout the episode, except for the GFC. It is worth mentioning that persistent connectedness dramatically surged between 2008 and 2009, compared to the transitory and medium-term interlinkages, consistent with the findings of Barunik and Ellington (2020). Furthermore, the transitory connectedness of returns hit its apex roughly late 2019/early 2020 due to the pandemic outbreak. Sharing a common trend, the indices notably surged due to the Russian-Ukrainian conflict in early 2022.

In the final phase of the study, due to the prevalence of the transitory (short-term) linkages over the medium- and long-term (persistent) interdependencies, we estimate transitory connectedness networks around the midst of two turmoil times (September 2008 and January 2020, respectively) and plot them in Fig. 5.

Several noteworthy findings emerge from the connectedness networks. First, it merits accentuation that there exists a considerable

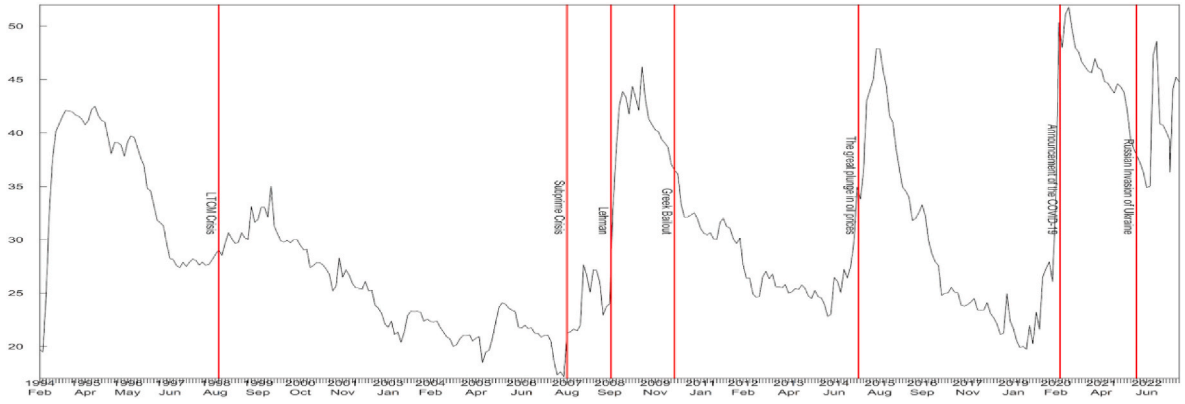

Fig. 2. Tci for returns.

Table 4
Average spillovers.

	BCI	CCI	NG	BRENT	SIR	GPR	IPI	10YGBBY	FROM
BCI	53.53	9.06	3.97	5.38	11.00	2.25	5.09	9.71	46.47
CCI	17.43	46.74	4.76	5.71	10.96	2.53	5.99	5.89	53.26
NG	1.74	2.05	74.81	4.57	6.80	2.30	3.47	4.25	25.19
BRENT	4.38	2.27	2.37	73.33	5.30	3.94	3.91	4.48	26.67
SIR	1.61	2.04	2.40	2.34	80.40	1.43	4.70	5.09	19.60
GPR	3.51	4.19	1.76	2.83	1.97	83.02	1.23	1.49	16.98
IPI	7.32	3.61	3.99	4.40	9.98	2.19	62.18	6.34	37.82
10YGBBY	1.05	1.12	2.44	2.47	7.28	1.89	1.79	81.97	18.03
TO	37.04	24.34	21.69	27.70	53.29	16.52	26.18	37.24	244
NET	−9.43	−28.92	−3.50	1.04	33.70	−0.46	−11.64	19.22	TCI = 30.5

Notes: Findings are computed by TVP-VAR with lag 2 (BIC) and a 10-step FEVD. Authors' calculations.

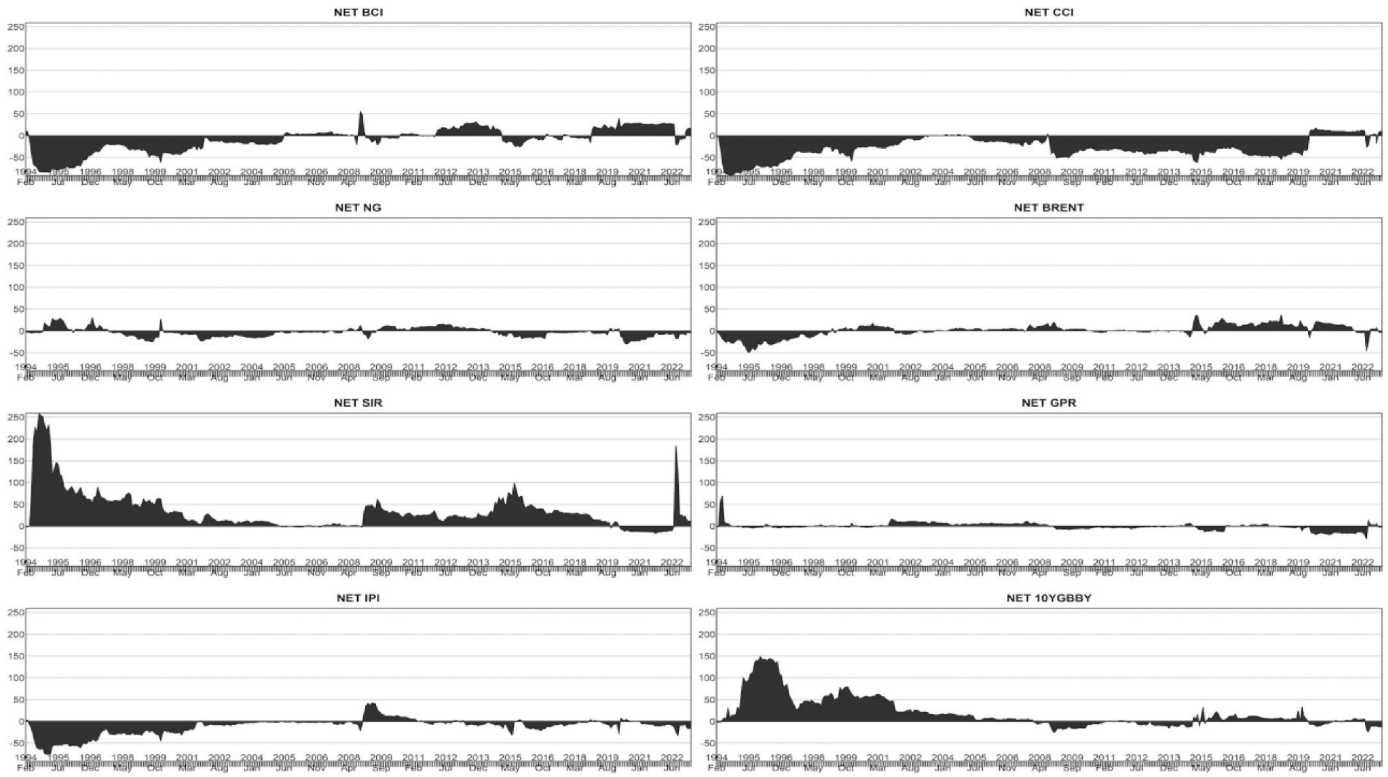

Fig. 3. Net directional spillovers for the returns.

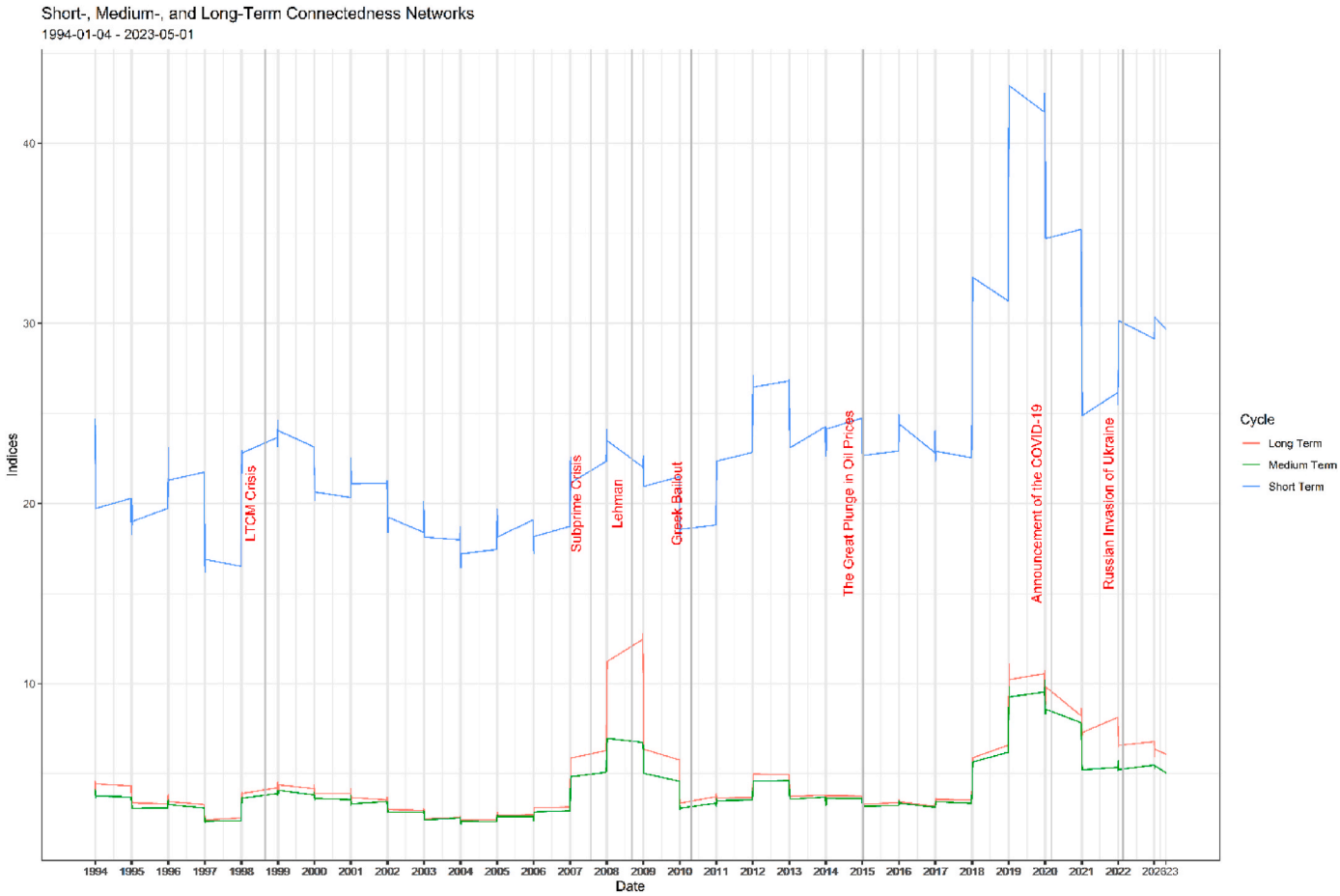

Fig. 4. Frequency-dependent return connectedness networks.

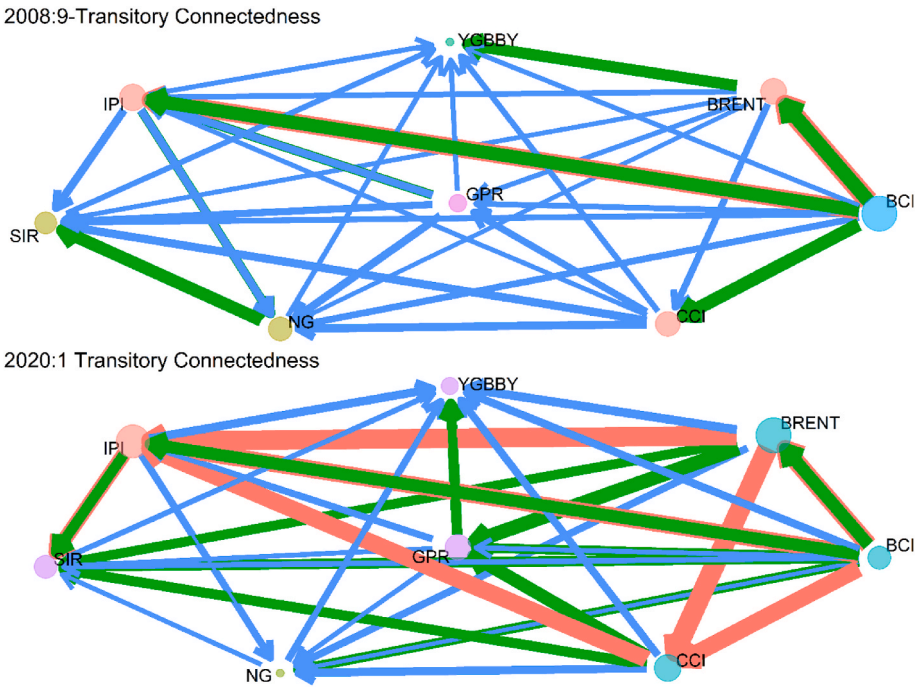

Fig. 5. Transitory Connectedness Networks
Notes: Arrows indicate the direction of connectedness; thickness color (red, blue, and green) shows the strength of linkages, and nodes' size shows the total TO spillovers from that node.

augmentation in return spillovers during the period characterized by the pandemic crisis. This empirical observation agrees with antecedent academic inquiries, as substantiated by the investigations conducted by Mensi et al. (2021) and Umar et al. (2022). Second, Brent-CCI, Brent-IPI, CCI-IPI, and BCI-CCI node pairs have the strongest interdependencies in the second network, indicating immense spillovers among these nodes. Third, IPI and Brent are the most significant transmitters of shocks in the first and second connectedness networks, respectively. Third, IPI stands out as the primary source of shock transmission in the first connectedness network, while Brent takes on the role of the principal shock transmitter in the second network.[2]

6. Conclusion

The study delves into time-varying interlinkages between economic confidence and various factors, including financial indicators, geopolitical stress, and energy prices, within the Euro Area from January 1994 to May 2023. The analysis employs time and frequency-domain connectedness approaches to unravel the dynamics of economic confidence and its interconnectedness with other economic variables. The study highlights that economic confidence is a crucial aspect of economic decision-making, both from a consumer and business perspective. Notably, it revealed the significance of psychological factors in shaping economic decisions, aligning with the insights from behavioral economics and expectation theory. Moreover, the study emphasized the importance of considering macroeconomic variables, significant events, energy prices, and geopolitical risks when assessing economic confidence.

In terms of connectedness, the analysis showcased that the Euro Area's economic confidence is sensitive to various shocks and spillovers. The study identified critical net transmitters and recipients of shocks, shedding light on the interconnectedness of different economic variables. The overall connectedness index provided insights into the systemic nature of shocks within the Euro Area's economic landscape.

Our TVP-VAR connectedness results indicate that the TCI correctly associates with prominent events over the episode. Moreover, short/long-term interest rates and oil prices are the net transmitters of shocks over most times of the episode. Particularly, BCI and CCI respond to the GFC asymmetrically and become net transmitters/recipients during the GFC. Short-term interest rates have a significant amount of spillover effects to other variables towards the end of the episode, which can be linked to the ECB's actions of elevating interest rates to historically unprecedented levels in response to the prevailing inflationary pressures amid a deteriorating economy.

Frequency-dependent interconnectedness networks unveiled that short-term linkages tend to dominate over medium- and long-term interdependencies, with notable surges in interconnectedness during significant events such as the global financial crisis, the COVID-19 pandemic, and geopolitical conflicts. This underscores the importance of monitoring the connectedness, especially in the short term, as it can serve as an early warning and provide valuable insights into the state of the economy.

Our findings hold relevance for governments, businesses, and households. Governments can influence economic confidence through economic policy choices, imparting signals to businesses and households. Furthermore, the repercussions of energy price fluctuations on economic confidence are essential for policymakers. Governments retain the discretion to extend support, such as grants or tax advantages, for gas and oil prices, playing a central role in alleviating the economic burdens associated with soaring oil and gas expenses. Additionally, they can stimulate sustainable energy approaches by incentivizing consumers and enterprises. These measures are crafted to promote adopting energy-efficient practices, investments in renewable energy sources, and the transition toward cleaner technologies.

Moreover, policymakers can enact measures directed at overseeing and steadying energy costs, especially during times of elevated inflation. These approaches could include measures like price regulations, the

[2] The estimated sizes for BCI, CCI, NG, Brent, SIR. GPR, IPI, and YGBY for the first and second connectedness networks are as follows: 0.0359, 0.0374, 0.0320, 0.0311, 0.0390, 0.0371, 0.0358, 0.0276, and 0.0515, 0.0794, 0.0584, 0.0561, 0.0737, 0.0390, 0.0514, 0.0438.

creation of strategic reserves, or financial aid to adeptly navigate price variations, shielding consumers and enterprises from abrupt and substantial price surges. Governments can also embark on awareness initiatives centered on energy preservation and applying alternative energy resources in residential settings.

This study has some limitations. Our study analyses the impact of energy prices, financial variables and geopolitical risks on economic confidence. Since monthly data are used, some financial and non-financial data are not included in the analysis. Future studies may include the real exchange rate, inflation, output, retail sales and unemployment variables in the analysis with a different methodology.

Appendix

A.1. TVP-VAR connectedness

Antonakakis et al. (2020) introduced a TVP-VAR connectedness approach which is an extension of the Diebold and Yılmaz (2014) approach. In this methodology, the variance-covariance matrix varies via a Kalman filter estimation with forgetting factors in the spirit of Koop and Korobilis (2013).

$TVP-VAR_{(p)}$ model is defined as follows:

$$y_t = B_t x_{t-1} + \varepsilon_t \quad \varepsilon_t \,|\Omega_{t-1} \sim N(0, \Sigma_t) \tag{A.1}$$

$$vec(B_t) = vec(B_{t-1}) + \varrho_t \quad \varrho_t|\Omega_{t-1} \sim N(0, \Xi_t) \tag{A.2}$$

With

$$x_{t-1} = \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ . \\ . \\ . \\ y_{t-p} \end{pmatrix} \quad B_t' = \begin{pmatrix} B_{1t} \\ B_{2t} \\ . \\ . \\ . \\ B_{pt} \end{pmatrix} \tag{A.3}$$

Where Ω_{t-1} denotes all information available until t-1; y_t, and x_{t-1} denote n x 1 and np x 1 vectors, respectively. B_t and B_{it} are n x np and n x n dimensional matrices, respectively. ε_t and ϱ_t are n x 1 and n^2p x 1 dimensional vectors, respectively. Σ_t and Ξ_t are n x n and n^2 p x n^2 p dimensional matrices, respectively. $vec(B_t)$ is the vectorization of B_t and is a n^2p x 1 dimensional vector.

TVP-VAR is transformed to its vector moving average (VMA) form based on the Wold representation theorem, and thus the generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD) are computed. Consequently, the VMA representation of y_t can be defined as $\sum_{j=0}^{\infty} A_{jt}\, \varepsilon_{t-j}$, where A_{jt} is the n x n dimensional matrix.

The *GIRF* $\left(\psi_{ij,t}(H)\right)$ represents the responses of all variables *j*, following a shock in i computed with an *H-step* ahead of forecast. *GIRF* $\left(\psi_{ij,t}(H)\right)$ is given as follows:

$$GIRF_t\ \left(H,\ \rho_{j,t}, \Omega_{t-1}\right) = E\left(y_t + H \,/\, e_j = \rho_{\,j,t}, \Omega_{t-1}\right) - E\left(y_{t+j}\,|\Omega_{t-1}\right) \tag{A.4}$$

$$\psi_{j,t}\ (H) = \frac{A_{H,t}\ \Sigma_t\ e_j}{\sqrt{\Sigma_{\,j\,j,t}}} \quad \frac{\rho_{\,j,t}}{\sqrt{\Sigma_{\,j\,j,t}}} \quad \rho_{\,j,t} = \sqrt{\Sigma_{\,j\,j,t}} \tag{A.5}$$

$$\psi_{j,t}\ (H) = \Sigma_{\,j\,j,t}^{\ -1/2}\ A_{H,t}\ \Sigma_t e_j \tag{A.6}$$

where e_j is an n x 1 selection vector which takes 1 with the selection of the jth element, and 0 otherwise. Therefore, the *GFEVD*$\left(\phi_{ij,t}(H)\right)$ is estimated based on $\phi_{ij,t}(H)$ as follows:

$$\phi_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \psi_{ij,t}^2}{\sum_{j=1}^{n} \sum_{t=1}^{H-1} \psi_{ij,t}^2} \tag{A.7}$$

With $\sum_{j=1}^{n} \phi_{ij,t}(H) = 1$ and $\sum_{i,j=1}^{n} \phi_{ij,t}(H) = n$.

The TCI:

$$C_t(H) = \frac{\sum_{i,j=1,i\neq j}^{n} \phi_{ij,t}(H)}{\sum_{i,j=1,i\neq j}^{n} \phi_{ij,t}(H)} * 100 = \frac{\sum_{i,j=1,i\neq j}^{n} \phi_{ij,t}(H)}{n} * 100 \tag{A.8}$$

TDC to others, i.e., how i transmits its shock to all other variables *j*:

$$C_{i\rightarrow j,t}(H) = \frac{\sum_{i,j=1,i\neq j}^{n} \phi_{ij,t}(H)}{\sum_{j=1,}^{n} \phi_{ij,t}(H)} * 100 \tag{A.9}$$

TDC from others, i.e., how i retrieves shock from all other variables *j*:

$$C_{i\leftarrow j,t}(H)=\frac{\sum_{i,j=1,i\neq j}^{n}\phi_{ij,t}(H)}{\sum_{j=1,}^{n}\phi_{ij,t}(H)}*100 \tag{A.10}$$

Net TDC:

$$C_{i,t}(H)=C_{i\rightarrow j,t}(H)-C_{i\leftarrow j,t}(H) \tag{A.11}$$

A.2. TVP-VAR Frequency-domains connectedness network

Barunik and Ellington (2020) introduced a dynamic network form that shows the effects of transitory and persistent shocks *j* on the future variance *k* as follows:

Define $(X_{t,T})_{1\leq t\leq T,T\in N}$ with $X_{t,T}$, where *t* represents the time index and *T* as the "*sharpness of the local approximation of the time series* $(X_{t,T})_{1\leq t\leq T,T\in N}$ *by a stationary one*" (Baruník and Ellington, 2020). $(X_{t,T})_{1\leq t\leq T,T\in N}$ is structured as follows:

$$X_{t,T}=\phi_1(t/T)X_{t-1,T}+\ldots+\phi_p(t/T)X_{t-p,}+\Sigma_{t,T} \tag{A.12}$$

where $\Sigma_{t,T}=\Sigma^{-\frac{1}{2}}(t/T)\rho_{t,T}$ with $\rho_{t,T}\sim NID(0,I_n)$, and $\phi(t/T)=\left(\phi_1(t/T),\ldots.\phi_p(t/T)\right)^T$ are time varying autoregressive coefficients. In fixed time neighbourhood of $\mu_0=t_0/T$, a stationary process $\overline{X}_t(\mu_0)$ approximates the process as

$$\overline{X}_t(\mu_0)=\varnothing_1(\mu_0)\overline{X}_{t-1}(\mu_0)+\ldots+\varnothing_p(\mu_0)\overline{X}_{t-p}(\mu_0)+\Sigma_t \tag{A.13}$$

with $t\in\mathbb{Z}$, satisfying the suitable regularity conditions $\left|X_{t,T}-\overline{X}_T(t_0)\right|=O_p(|t/T\mu_0|+1/T)$. Time varying $VMA(\infty)$ representation of the process is:

$$X_{t,T}=\sum_{h=-\infty}^{\infty}\psi_{t,T}(H)\Sigma_{t-h} \tag{A.14}$$

Here, $\psi_{t,T}\approx\psi(t/T,h)$ and $sup_t\|\psi_t-\psi_t\|^2=O_p(h/t)$ for $1\leq h\leq t$ as $t\rightarrow\infty$. "*The spectral density of* $X_{t,T}$ *at frequency d is defined as*" (Ellington and Baruník, 2020):

$$S_X(\mu,\varpi)=\sum_{h=-\infty}^{\infty}E\left[\overline{X}_{t+h}(\mu)\overline{\overline{X}}_t^T(\mu)\right]e^{-i\varpi h}=\left\{\psi(\mu)e^{-i\varpi}\right\}\Sigma(\mu)\left\{\psi(\mu)e^{+i\varpi}\right\}^T \tag{A.15}$$

The dynamic adjacency matrix is defined as:

$$[Q(\mu,d)]_{j,k}=\frac{\theta_{kk}^{-1}\int_a^b\left|\left(\psi(\mu)e^{-i\varpi}\epsilon(\mu)\right|_{j,k}{}^2d\varpi\right.}{\int_{-\pi}^{\pi}\left[\left(\psi(\mu)e^{-i\varpi}\right)\Sigma(\mu)\left(\psi(\mu)e^{+i\varpi}\right)^T\right]_{j,j}d\varpi} \tag{A.16}$$

where $d=\{(a,b):a,b\epsilon(-\pi,\pi),a<b\}$.

The 'local network connectedness':

$$C(\mu,d)=100\,x\sum_{\substack{j,k=1\\ j\neq k}}^{N}[\overline{\theta}(\mu,d)]_{j,k}\Big/\sum_{j,k=1}^{n}[\overline{\theta}(\mu)]_{j,k} \tag{A.17}$$

Here,

$$[\overline{\theta}(\mu,d)]_{j,k}=[\theta(\mu,d)]_{j,k}/\sum_{k=1}^{N}[\theta(\mu)]_{j,k} \tag{A.18}$$

From connectedness for $k\neq j$, is defined as:

$$C_{j\leftarrow}(\mu,d)=100\,x\sum_{\substack{k=1\\ k\neq j}}^{N}[\overline{\theta}(\mu,d)]_{j,k}\Big/\sum_{j,k=1}^{N}[\overline{\theta}(\mu)]_{j,k} \tag{A.19}$$

To connectedness for $k \neq j$, is defined as:

$$C_{j\rightarrow}(\mu, d) = 100\, x \sum_{\substack{k=1 \\ k\neq j}}^{N} [\overline{\theta}(\mu, d)]_{kj} \Big/ \sum_{kj=1}^{N} [\overline{\theta}(\mu)]_{kj} \tag{A.20}$$

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