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Unveiling dynamic connectedness: how macroeconomic variables drive consumer and business confidence

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Abstract

Purpose – The study aims to explore the key determinants of consumer and business confidence by analyzing the interconnectedness between macroeconomic factors and economic sentiment.
Design/methodology/approach – This study employs a time-varying parameter vector autoregression (TVP-VAR) asymmetric connectedness model to analyze the dynamic relationship between macroeconomic variables and economic confidence in the United States from 1994 to 2023. The model examines consumer and business confidence indices about U.S. Treasury maturity, the Federal Fund Rate, geopolitical risk, Moody's Seasoned AAA Corporate Bond Yield, short-term interest rates and oil and gas prices.
Findings – Empirical results indicate that negative return spillovers dominate economic confidence transmission, particularly during economic and geopolitical uncertainty periods. The federal fund rate and short-term interest rates are identified as the most significant transmitters of spillovers. The study also finds that oil and gas price fluctuations impact economic sentiment asymmetrically, with stronger effects during financial crises.
Originality/value – This study contributes to the literature by adopting a novel connectedness approach to examine the dynamic interplay between variables. By incorporating both consumer and business confidence indices, it provides a comprehensive perspective on economic sentiment transmission. Furthermore, including asymmetric spillover effects distinguishes this research from existing studies, offering valuable policy insights for managing economic confidence during periods of uncertainty.

Keywords Economic confidence, Energy prices, Geopolitical risks, Treasury maturity, Corporate bond yield, US

Paper type Research paper

1. Introduction

Economic decision-making by individuals, businesses, and governments involves both financial and non-financial considerations (Ahmad and Rangaraju, 2019). To better understand such behavior and improve predictive accuracy, economic analysis increasingly incorporates psychological dimensions, as emphasized in interdisciplinary fields such as behavioral economics, experimental economics, and neuroeconomics (Pech and Milan, 2009). From a behavioral perspective, confidence plays a pivotal role in shaping economic choices. Accordingly, confidence indices—typically focused on consumer and business sentiment—are widely used to assess economic outlooks (Croushore, 2005). Economic confidence reflects the trust and expectations economic agents hold regarding stability, growth, and future opportunities (Clerides *et al.*, 2022). As such, it serves as a key indicator of macroeconomic conditions, influencing and reflecting trends in consumption, production, employment, financial markets, and policy effectiveness (Yang and Xin, 2020).

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Crude oil and gas, the primary energy source, is essential to the world economy. Thus, oil and gas price fluctuations affect a country's social stability and economic development via different channels. For example, rising prices increase the cost of producing goods and services, leading to higher inflation and affecting business and consumer confidence (Barnes and Olivei, 2017). Although fluctuations in energy prices, for example, gas or oil, may significantly affect economic indicators like production costs, consumer purchasing power, and inflation, the main drivers of energy prices are often determined by external factors. Therefore, analyzing the impact of energy prices on macroeconomic indicators is a focus of research (Su *et al.*, 2023).

Recent developments in macroeconomic research emphasize the need to capture the dynamic interactions between economic sentiment and a wide range of macro-financial indicators. While energy prices are important, confidence in the economic outlook is also shaped by shifts in interest rates, credit conditions, and geopolitical tensions, each reflecting distinct channels of influence. Therefore, adopting a broader lens that integrates both demand-side indicators and supply-side elements provides a more comprehensive understanding of confidence formation across time (Qi *et al.*, 2022).

The idea of confidence being influenced by supply and demand dynamics highlights the diversity of macroeconomic shocks. Factors driven by demand, such as the tightening or easing of monetary policy, impact the expectations of households and businesses through channels related to liquidity and credit. On the other hand, disruptions on the supply side, including shocks to energy prices or issues within global supply chains, affect production costs and expectations for long-term investment. By examining both areas, the current research adds to the existing literature by identifying which factors are more influential in various market environments and how their relative impact changes over time (Lahiri and Zhao, 2016).

This study explores the interrelationship among economic confidence, treasury maturity, Federal Fund Rate, geopolitical risk, Moody's Seasoned AAA Corporate Bond Yield, oil and gas prices, and short-term interest rates for the U.S. from 1994 to 2023. Our model contributes to the literature in different dimensions. Although some papers investigate the impact of energy on economic confidence, these studies address economic confidence from a supply or demand perspective. Our study provides a holistic approach to economic confidence by analyzing business and consumer confidence. Moreover, our model handles the large set of variables is crucial for revealing the determinants of economic confidence in the U.S.

Furthermore, the justification for employing a time-varying, bidirectional framework lies in the recognition that macroeconomic connectedness is rarely static. Confidence may respond to and shape macroeconomic variables through feedback loops, particularly during periods of heightened uncertainty. Events such as the Global Financial Crisis, the COVID-19 pandemic, and geopolitical shocks like the Russia–Ukraine conflict introduce nonlinearities, and regime changes that traditional static models fail to capture. The TVP-VAR asymmetric connectedness model allows us to trace evolving spillover patterns, revealing asymmetries in how negative and positive shocks propagate across the system and differentially impact consumer versus business sentiment. (Anastasiou *et al.*, 2023).

Notwithstanding the advantages of our methodology, several limitations warrant consideration. First, the TVP-VAR model involves estimating parameters at different periods, which may introduce sensitivity to structural breaks and heightened levels of volatility. Second, due to our analysis using monthly frequency data, some short-term (i.e. daily or weekly) dynamics and specific high-frequency interactions among variables may be overlooked. While theoretically justified, our selection of the 10-step ahead forecast horizon in FEVD may influence the measurement of connectedness outcomes, and we acknowledge that other forecast horizons may produce different spillover results. The delineation of frequency bands into short-, medium-, and long-term categories is somewhat subjective, and other definitions might influence our conclusion and interpretation. In future work, we may address these limitations by employing higher frequency datasets, conducting robustness checks with shorter (or longer) forecast horizons, or employing alternate methodologies.

The rest of the paper is organized as follows: We discuss the theoretical background in Section 2, Section 3 presents the literature, Section 4 describes methodology and data, Section 5 examines the analysis results, and we conclude this study in Section 6.

2. Theoretical framework

Our framework integrates multiple economic theories chief among them being business cycle theory, rational expectations theory, and behavioral economics to account for both short-term fluctuations and long-term shifts in sentiment. Business cycle theory posits that macroeconomic indicators such as interest rates and output fluctuate over time, creating cyclical patterns in economic activity and corresponding changes in consumer and business expectations (Lucas, 1995; Kydland and Prescott, 1982). These cyclical shifts provide one explanation for the time-varying nature of confidence indices.

The rational expectations hypothesis provides an essential framework, suggesting that individuals form their expectations using all accessible information, which includes anticipated policy measures and market indicators (Muth, 1961; Sargent, 1973). In this framework, confidence indices represent forward-looking assessments that consider current macroeconomic conditions and expectations regarding future economic outcomes. For instance, fluctuations in the Federal Fund Rate or Treasury yields can impact individuals' predictions about inflation and economic growth, thus affecting their levels of confidence.

Nonetheless, economic decision-making frequently diverges from strictly rational actions, making insights from behavioral economics crucial for understanding the asymmetries and nonlinearities in how people respond to confidence. Cognitive biases such as loss aversion, anchoring, and herd behaviors can intensify responses to macroeconomic disturbances (Thaler, 1990; Akerlof and Shiller, 2010; Montes and Nogueira, 2022). Behavioral theories clarify why negative shocks, such as geopolitical tensions or fluctuations in oil prices, often produce stronger and more enduring effects on sentiment compared to positive developments.

Collectively, these theoretical frameworks offer a comprehensive perspective for examining the economic confidence mechanism: business cycles reflect structural changes, rational expectations outline future-oriented behavior, and behavioral economics accounts for departures from ideal decision-making. This holistic strategy is essential for modeling reciprocal spillovers that develop over time and in different economic conditions.

3. Literature review

Although economic confidence is widely discussed in the literature, studies examining the effect of energy prices on confidence are limited. In this section, the economic confidence literature is reviewed by geographical division.

3.1 Economic confidence studies in the U.S.

Economic confidence is one of the determining variables in the decisions of governments, businesses, and households. Economic confidence can also shed light on the economic outlook of a country (de Mendonça *et al*., 2025; Gomes, 2010). Dees and Brinca (2013) find a significant relationship between consumer confidence and consumer consumption in the United States. Kilic and Cankaya (2016) analyze the economic activities affecting consumer confidence in the U.*S. factor*-augmented vector autoregression method shows that industrial production and inventories effectively affect consumer confidence. Lahiri and Zhao (2016) investigate whether macroeconomic variables significantly affect the University of Michigan's Index of Consumer Sentiment. Empirical results show that macroeconomic variables are among the determinants of the consumer index. El Alaoui *et al*. (2020) indicate that factors associated with the stock market, individual income, and unemployment significantly explain U.S. consumer sentiment. Elmassah *et al*. (2022) argue that the U.S. consumer index will be affected differently according to different scenarios of COVID-19.

Teresiene *et al*. (2021) investigate the impact of COVID-19 cases and death counts on business confidence in the United States. Empirical results show that the number of cases negatively affects business confidence. Khan and Upadhayaya (2020) show that business confidence positively affects investor confidence. Kabiri *et al*. (2023) analyze sentiment in the U.S. economy from 1920–1934. Empirical results show that industrial production, bank loans, S&P500, and credit risk spread affect economic sentiment. Fisher and Statman (2003) reveal the significant relationship between consumer confidence and the stock market in the U.S.

Energy prices are discussed in the literature on economic confidence regarding their potential effects on economic confidence. Güntner and Linsbauer (2018) examine the impact of energy supply and demand shocks on U.S. consumer sentiment. Their findings reveal minimal effects of oil supply shocks on sentiment, while other oil demand shocks significantly decrease sentiment for up to two years. Additionally, aggregate demand shocks show diverse effects. Using VAR models, Edelstein and Kilian (2009) investigated the influence of gasoline prices on consumer spending in the U.S., demonstrating that they significantly impact consumers' confidence and shopping patterns. Bildirici and Badur (2019) analyze how oil and gasoline prices influence business confidence in Turkey and the U.S. They find a bidirectional causality between gasoline prices and confidence, as well as between oil prices and the confidence index in the U.S. under all regimes. Apergis *et al*. (2018) find that the natural gas and oil prices affect investor confidence in the U.S.

Economic confidence studies are restricted in the United States. There is a need to analyze businesses' confidence sufficiently. Our research has the potential to address a significant void in the existing literature by analyzing the effect of oil-gas prices on business and consumer confidence in the U.S. Our methodology is another unique feature of the study.

3.2 Other economic confidence studies

Economic confidence studies analyze consumer, business, and investor confidence. Nevertheless, the literature on economic confidence is just developing. A significant part of the studies takes European countries as a sample.

Studies include macroeconomic indicators, non-financial variables, and energy prices in their models. Ambrocio (2022) finds that the severity of COVID-19 impacts business confidence in the Euro Area. Kirchner (2020) argues that anticipated and unexpected increases in the official cash rate target and associated interest rates are detrimental to consumer sentiment. While business confidence is less influenced by changes in the cash rate target, an increase in the 90-day bank-accepted bill rate negatively impacts business confidence in Australia. de Mendonça and Almeida (2019) investigate the effects of central bank decisions on business confidence in emerging countries. Empirical results show that the monetary policy's credibility can contribute to business confidence. Adekoya and Oliyide (2021) find that economic uncertainty is one of the determinants of business confidence in OECD countries. Rojo-Suárez Alonso-Conde (2020) finds that the consumer confidence index for Japan enhances the performance of consumption-based asset pricing models over production-based models across various anomaly portfolios.

Adekoya and Oliyide (2021) emphasize that oil prices negatively affect business confidence. Shahzad *et al*. (2019) argue that oil demand and supply shocks determine investor confidence. Clerides *et al*. (2022) find that positive gasoline price shocks negatively impact aggregate consumer sentiment in the Euro Area. Li *et al*. (2022) found both lead-lag relationships and heterogeneous dynamic correlations between crude oil prices (shocks) and investor sentiment in China. Li and Ouyang (2023) find that oil price shocks boost consumer sentiment by elevating their satisfaction with current income and their anticipation of future employment. Antonakakis *et al*. (2017) examine the dynamic structural relationship between oil price shocks and stock market returns or volatility. Findings show that supply-side and oil-specific demand shocks play an important role in the context of geopolitical unrest. Moreover, the authors stress that the oil price is financed. Demirer *et al*. (2020) argue that oil prices in emerging economies affect the bond market beyond the equity market. Arzova *et al*. (2023) investigate the impact of oil and gas prices on economic confidence in the Eurozone. Empirical findings indicate that consumer confidence is adversely affected by both oil and gas prices across all regimes. In a volatility regime, oil prices positively impact business confidence. Table 1 summarizes prior studies on economic confidence by geographical scope, analytical methodology, and findings.

In summary, the literature reveals that economic confidence is shaped by diverse macroeconomic factors, yet prior studies often isolate consumer or business sentiment and lack an integrated framework capturing dynamic, asymmetric interactions. The combined effects of oil and gas prices, particularly in the U.S. context, have been largely overlooked. This study fills these gaps using a novel methodology that uncovers time-varying and directional spillovers between macroeconomic variables and confidence indices. The findings contribute to a more coherent theoretical understanding, aligned with behavioral economics, expectation theory, and real business cycle theory.

4. Data

In our empirical modeling, we examine the impacts of oil/gas prices, treasury yield spread, corporate bond yield, and geopolitics risks on economic confidence in the United States, covering the period from January 1994 to November 2023. We utilize the Business and Consumer Confidence Index variables and source data from the OECD Database (OECD, 2023). Additionally, we acquire oil and gas price data from the World Bank Monthly Prices dataset (World Bank, 2023). We employ the short-term interest rate variable, which we obtain

Table 1. Summary of previous studies focused on the United States

Study	Methodology	Key variables	Main findings
Dees and Brinca (2013)	VAR	Consumer Confidence, Consumption	Consumer confidence significantly influences household consumption
Edelstein and Kilian (2009)	VAR	Gasoline Prices, Consumer Expenditures	Gasoline price shocks strongly affect consumer sentiment and spending patterns
Kilic and Cankaya (2016)	FAVAR	Industrial Production, Inventories, Confidence	Industrial activity is a significant driver of consumer confidence
Lahiri and Zhao (2016)	Regression Analysis	Macroeconomic Indicators, Sentiment Index	Macroeconomic variables are major determinants of U.S. sentiment indices
Güntner and Linsbauer (2018)	SVAR	Oil Supply and Demand Shocks, Sentiment	Oil demand shocks reduce consumer sentiment; supply shocks have a limited effect
Kabiri *et al*. (2023)	Historical Index Construction	Bank Loans, S&P500, Credit Spread, Sentiment	Financial variables influence historical economic sentiment (1920–1934)
Bildirici and Badur (2019)	Regime-Switching Model	Oil and Gas Prices, Confidence Index	Bidirectional causality exists between energy prices and business confidence in the U.S.
This study	TVP-VAR Asymmetric Connectedness	Oil and Gas Prices, Interest Rates, Geopolitical Risk, Confidence Indices	Time-varying, asymmetric spillovers show that negative shocks dominate transmission to confidence; the novel framework captures dynamic macro-financial interactions

Source(s): Authors' own work

from the OECD Database (OECD, 2023). We obtained data on the Federal Fund Rate, 10 years constant treasury maturity minus 2 years treasury maturity, and Moody's seasoned AAA corporate bond yield from Federal Reserve Economic Data (FRED, 2023). We use the Geopolitical Risk Index calculated by Dario Caldara and Matteo Iacoviello (Caldara and Iacoviello, 2023).

We have selected the macroeconomic variables in our model based on strong theoretical reasoning and empirical research. Key interest rate variables, including the Federal Fund Rate, short-term interest rates, Treasury yield spread, and corporate bond yields, reflect the transmission channels of monetary policy, backed by literature of Keynesian and expectation-based theories. Given their importance in real business cycle models, we included oil and gas prices and observed asymmetric effects on economic confidence. As a manifestation of uncertainty or investor optimism, geopolitical risks fit within behavioral economic theory. We address the issue of endogeneity among the variables using the TVP-VAR framework, where all variables are treated as jointly endogenous and capture dynamism and lag structures of feedback loops over time. This framework captures time-varying relationships across multiple economic regimes, thereby addressing econometric issues of simultaneity and omitted variable bias (see Table 2).

Following Adekoya *et al*. (2022), We divided the returns into their positive and negative components as follows:

$$R_t = \{0, if z_t < 01, if z_t \geq 0 \tag{1}$$

$$z_t^{+=R_t.z_t} \tag{2}$$

$$z_t^{-=(1-R_t)..z_t} \tag{3}$$

Where zt—and z_t^+ represent the negative and positive returns. We implement the series' log monthly differences. Table 3 and Figure 1 report the return's descriptive statistics and plots

Table 3 reveals that BCI, NG, WTI, SIR, GPR, FFR, and AAA consistently yield positive returns on average, whereas the remaining indexes exhibit negative means. Notably, the 10–2 Treasury Yield Spread has the highest variance and records the lowest mean value. The spread shifted to negative territory since July 7, 2022, indicating a looming economic recession in the U.S. Except for BCI and CCI, all returns demonstrate a rightward-tailed distribution,

Table 2. List of variables

Variable	Abbreviations	Definition
Business Confidence	BCI	Business Confidence Index
Consumer Confidence	CCI	Consumer Confidence Index
Natural Gas Prices	NG	US Natural Gas Prices
Oil Prices	WTI	Western Texas Intermediate
Short-Term Interest Rates	SIR	Short-term interest rates represent the rates at which financial institutions engage in short-term borrowing
Federal Fund Rate	FFR	The federal funds rate denotes the interest rate that banks levy when lending their surplus funds to other financial institutions overnight monthly
Geopolitics Risks	GPR	Geopolitical Risk Index (Caldara and Iacoviello, 2023)
10 Years Constant Treasury Maturity Minus 2 Years Treasury Maturity	102YrsSpr	The 10–2 Treasury Yield Spread is the difference between the 10-year and 2-year treasury rates
Moody's Seasoned AAA Corporate Bond Yield	AAA	Moody's Corporate Bond Rating

Source(s): Authors' own work

Table 3. Descriptive statistics

	BCI	CCI	NG	WTI	SIR	GPR	102YrsSpr	FFR	AAA
Mean	0.003	−0.002	1.017	0.933*	1.283*	3.604	−2.655	1.894**	0.005
Variance	0.096	0.063	207.722	94.29	199.539	1753.974	21931.31	330.249	16.169
Skewness	−1.443***	−1.216***	1.090***	0.527***	0.994***	11.856***	7.498***	2.672***	0.006
Excess Kurtosis	8.221***	6.657***	6.638***	9.793***	13.344***	186.110***	147.247***	24.296***	3.254***
JB	1132.401***	749.254***	728.136***	1447.081***	2714.983***	525052.795***	326772.394***	9231.414***	157.993***
ERS	−2.596	−3.001	−6.398	−7.684	−4.322	−4.043	−8.421	−5.893	−5.514
Q(20)	455.538***	393.765***	15.504	24.992***	185.125***	8.617	13.131	123.543***	20.308**
Q2(20)	125.424***	210.198***	13.475	123.166***	55.295***	0.05	0.382	90.969***	47.257***

Kendall	BCI	CCI	NG	WTI	SIR	GPR	102YrsSpr	FFR	AAA
BCI	1.000***	0.386***	0.083**	0.139***	0.029	−0.022	0.006	0.094***	0.089**
CCI	0.386***	1.000***	−0.047	0.033	−0.063	−0.049	−0.038	0.094***	−0.005
NG	0.083**	−0.047	1.000***	0.175***	0.066	−0.059	−0.013	0.01	0.075**
WTI	0.139***	0.033	0.175***	1.000***	−0.032	0.007	0.041	0.038	0.123***
SIR	0.029	−0.063	0.066	−0.032	1.000***	0.012	−0.177***	0.331***	0.136***
GPR	−0.022	−0.049	−0.059	0.007	0.012	1.000***	−0.041	−0.035	0.033
102YrsSpr	0.006	−0.038	−0.013	0.041	−0.177***	−0.041	1.000***	−0.156***	0.162***
FFR	0.094***	0.094***	0.01	0.038	0.331***	−0.035	−0.156***	1.000***	−0.006
AAA	0.089**	−0.005	0.075**	0.123***	0.136***	0.033	0.162***	−0.006	1.000***

Note(s): ***, **, * indicates 1%, 5%, and 10% significance levels, respectively. ERS indicates the unit root test of Stock *et al*. (1996). Q(20) and Q2(20) denote the Ljung–Box serial correlation statistics
Source(s): Authors’ own work

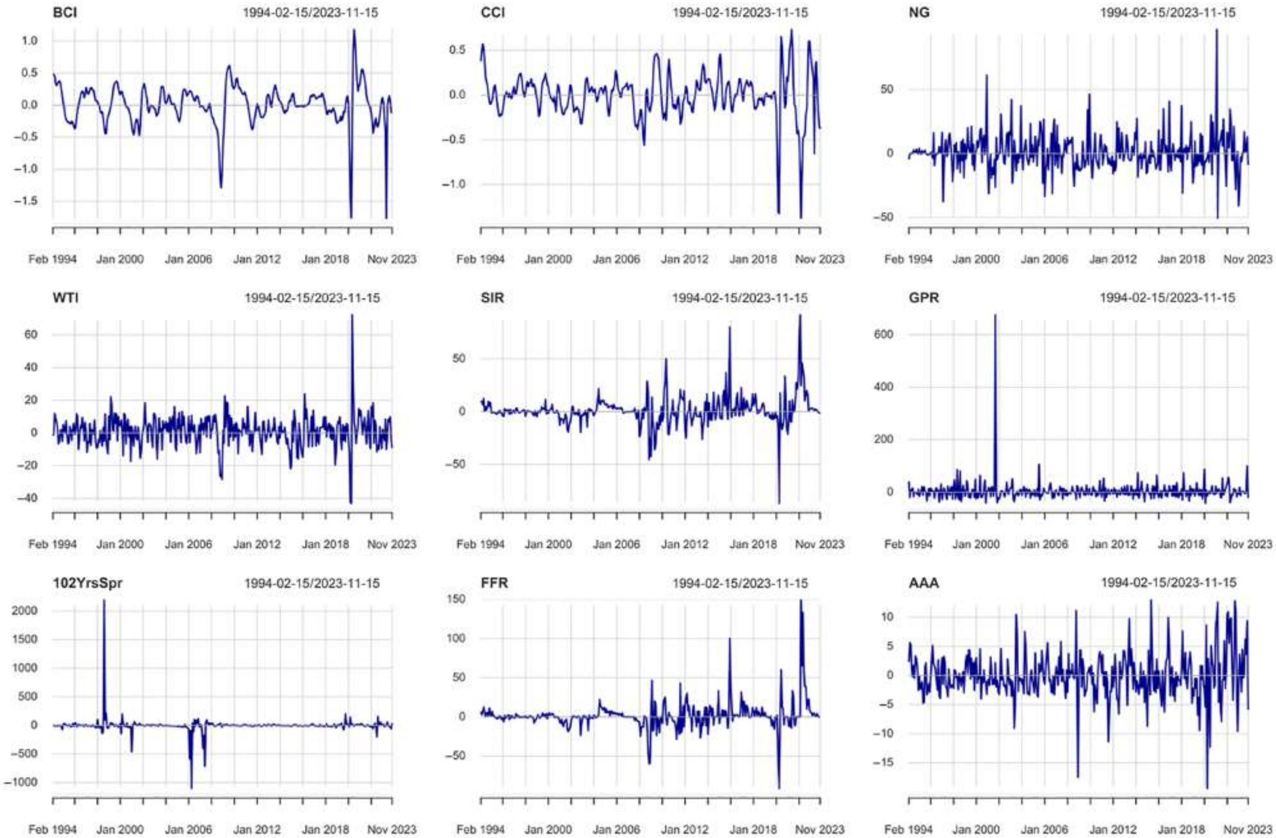

Figure 1. Trends in returns. **Source:** Authors' own work

exhibiting leptokurtic characteristics. The JB values indicate abnormal distribution for all series. Moreover, all returns exhibit significant autocorrelation and display ARCH/GARCH errors. The subsequent table presents unconditional correlations among return series.

Returns show notable increases during significant financial and geopolitical upheavals such as the 2008 global financial crisis (GFC), the oil price collapse spanning late 2014 to early 2016 (Grigoli *et al.*, 2019), the COVID-19 pandemic, and the recent Russian-Ukrainian conflict (RUC).

5. Methodology

Our empirical model, which builds upon these theoretical underpinnings, is designed to capture the interaction of structural, monetary, and psychological macroeconomic factors that influence economic confidence. Keynesian and expectation-based theories, which highlight how interest rates and policy signals influence sentiment, align with the inclusion of variables like the Federal Fund Rate, Treasury Yield Spread, and corporate bond yields. In the meantime, the integration of oil and gas prices acknowledges energy shocks as major contributors to macroeconomic volatility and confidence, reflecting insights from the theory of resource curses and real business cycle theory. Lastly, behavioral economic principles are directly operationalized using business and consumer confidence indices, which capture economic agents' psychological reactions and subjective expectations.

The business and consumer confidence indices are behavioral proxies that measure how people react psychologically to financial and economic events. Our study's theoretical foundations strongly support the time-varying, nonlinear, and directionally distinct nature of spillovers among these variables, which we can account for using the asymmetric TVP-VAR connectedness model.

The TVP-VAR connectedness approach can account for structural shifts and estimate changing relationships between variables, essential in analyzing long periods involving financial crises, policy changes, and geopolitical shocks. The model's ability to capture the magnitude and direction of spillovers over time, especially through asymmetric connectedness measures, also fits well with behavioral and expectation-based psychosocial frameworks that focus on the importance of nonlinear and dynamic sentiment processes. Alternative models, such as standard VAR or a rolling-window VAR, do not capture or accurately portray periods of evolving interconnectedness as they either assume fixed parameters or are sensitive to the window choice. As such, TVP-VAR models provide a more robust and flexible framework to uncover dynamic transmission mechanisms between macroeconomic indicators and confidence indices.

Adekoya *et al.* (2022) developed the TVP-VAR-based asymmetric connectedness method, utilizing negative and positive absolute returns. This method builds upon Antonokakis *et al.* (2020) TVP-VAR approach, an augmented version of Diebold and Yılmaz's (2014) methodology.

$TVP-VAR(q)$ is defined as follows:

$$y_t = B_t x_{t-1} + \varepsilon_t \varepsilon_t \vee \Omega_{t-1} N(0, \Sigma_t) \tag{4}$$

$$\overrightarrow{(B_t)} = \overrightarrow{(B_{t-1})} + \gamma_t \gamma_t \vee \Omega_{t-1} N(0, \Xi_t) \tag{5}$$

with

$$y_{t-1} = \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-q} \end{pmatrix} B_t' = \begin{pmatrix} B_{1t} \\ B_{2t} \\ \vdots \\ B_{qt} \end{pmatrix} \tag{6}$$

here Ω_{t-1} represents all information available until $t-1$; x_t and y_{t-1} represent $n \times 1$ and $nq \times 1$ vectors. B_t and B are $n \times nq$ and $n \times n$ matrices, ε_t and γ_t are $n \times 1$ and $n^2q \times 1$ vectors, and Σ_t and Ξ_t are $n \times n$ and $n^2q \times n^2q$ matrices, respectively.

The VMA representation of y_t is defined as $\sum_{j=0}^{\infty} A_{jt}\mu_{t-j}$, where A_{jt} is the $n \times n$ matrix.

$GIRF(\Psi_{ij,t}(H))$ is introduced as follows:

$$GIRF\left(H, \rho_{j,t}, \Omega_{t-1}\right) = E\left(y_t + H \vee e_j = \rho_{j,t}, \Omega_{t-1}\right) - E\left(y_{t+j} \vee \Omega_{t-1}\right) \tag{7}$$

$$\Psi_{j,t}(H) = \frac{A_{H,t}\Sigma_t e_j}{\sqrt{\Sigma_{jj,t}}} \frac{\rho_{j,t}}{\sqrt{\Sigma_{jj,t}}} \beta_{j,t} = \sqrt{\Sigma_{jj,t}} \tag{8}$$

$$\Psi_{j,t}(H) = \Sigma_{jj,t}{}^{-1/2} A_{H,t}\Sigma_t e_j \tag{9}$$

here, e_j is an $n \times 1$ selection vector. The $GFEVD(\widetilde{\Phi}_{ij,t}(H))$ is obtained relying on $\widetilde{\Phi}_{ij,t}(H)$ as:

$$\widetilde{\Phi}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \Psi_{ij,t}^2}{\sum_{j=1}^{n} \sum_{t=1}^{H-1} \Psi_{ij,t}^2} \tag{10}$$

with $\sum_{j=1}^{n} \widetilde{\Phi}_{ij,t}(H) = 1$, and $\sum_{i,j=1}^{n} \widetilde{\Phi}_{ij,t}(H) = n$.

The total connectedness index (TCI):

$$C_t(H) = \frac{\sum_{i,j=1, i \neq j}^{n} \widetilde{\Phi}_{ij,t}(H)}{\sum_{i,j=1}^{n} \widetilde{\Phi}_{ij,t}(H)} * 100 = \frac{\sum_{i,j=1, i \neq j}^{n} \widetilde{\Phi}_{ij,t}(H)}{n} * 100 \tag{11}$$

Overall directional connectedness to others:

$$C_{i \to j,t}(H) = \frac{\sum_{j=1, i \neq j}^{n} \widetilde{\Phi}_{ji,t}(H)}{\sum_{j=1}^{n} \widetilde{\Phi}_{ji,t}(H)} * 100 \tag{12}$$

Overall directional connectedness from others:

$$C_{i \leftarrow j,t}(H) = \frac{\sum_{j=1, i \neq j}^{n} \widetilde{\Phi}_{ij,t}(H)}{\sum_{j=1}^{n} \widetilde{\Phi}_{ij,t}(H)} * 100 \tag{13}$$

Net total directional connectedness:

$$C_{i,t}(H) = C_{i\to j,t}(H) - C_{i\leftarrow j,t}(H) \tag{14}$$

$$C_t(H) = \left(\frac{n}{n-1}\right)\frac{\sum_{i,j=1,i\neq j}^{n}\widetilde{\Phi}_{ij,t}(H)}{n} = \frac{\sum_{i,j=1,i\neq j}^{n}\widetilde{\Phi}_{ij,t}(H)}{n-1} \tag{15}$$

Chatziantoniou *et al.* (2022) enhanced this measure, modifying the TCI as follows;

$$C_t(H) = \left(\frac{n}{n-1}\right)\frac{\sum_{i,j=1,i\neq j}^{n}\widetilde{\Phi}_{ij,t}(H)}{n} = \frac{\sum_{i,j=1,i\neq j}^{n}\widetilde{\Phi}_{ij,t}(H)}{n-1} \tag{16}$$

5.1 TVP-VAR frequency connectedness networks

Barunik and Ellington (2024) showed a dynamic network that indicates transitory and persistent effects of shocks from j on the future variance of k as the following:

Define $(Z_{t,T})_{1\leq t\leq T,T\ N}$ with $Z_{t,T} = (Z^1_{t,T}, \ldots, Z^N_{t,T})^T$, where t denotes the time index and T as the "*precision of the time series local approximation of* $(Z_{t,T})_{1\leq t\leq T,T\ N}$ *with a stationary one*" (Barunik and Ellington, 2024).

$(Z_{t,T})_{1\leq t\leq T,T\ N}$ is structured as follows:

$$Z_{t,T} = \varphi_1(t/T)Z_{t-1,T} + \ldots + \varphi_p(t/T)Z_{t-p,T} + \Sigma_{t,T} \tag{17}$$

where $\Sigma_{t,T} = \Sigma^{\frac{-1}{2}}(t/T)\rho_{t,T}$ with $\rho_{t,T}\, NID(0, I_N)$, and $\varphi(t/T) = (\varphi_1(t/T), \ldots, \varphi_p(t/T))^T$ are TVP_VAR coefficients. In fixed time neighborhood of $\mu_0 = t_0/T$, a stationary process $\widetilde{Z}_t(\mu_0)$ approximates the process $Z_{t,T}$ as

$$\widetilde{Z}_t(\mu_0) = \varnothing_1(\mu_0)\widetilde{Z}_{t-1}(\mu_0) + \ldots + \varnothing_p(\mu_0)\widetilde{Z}_{t-p}(\mu_0) + \Sigma_t \tag{18}$$

with $t \in Z$, satisfying the suitable regularity conditions $\left|Y_{t,T} - \widetilde{Y}_t(t_0)\right| = O_P(|t/T - \mu_0| + 1/T)$. Time-varying $VMA(\infty)$ representation of the process is:

$$Z_{t,T} = \sum_{h=-\infty}^{\infty}\psi_{t,T}(h)\Sigma_{t-h} \tag{19}$$

Here, $\psi_{t,T} \approx \psi(t/T, h)$ and ${}_1\|\psi_t - \psi_t\|^2 = O_p(h/t)$ for $1 \leq h \leq t$ as $t \to \infty$. "*The spectral density of* $Z_{t,T}$ *at frequency d is defined as*" (Barunik and Ellington, 2024):

$$S_Z(\mu, \varpi) = \sum_{h=-\infty}^{\infty} E\left[\widetilde{Z}_{t+h}(\mu)\widetilde{Z}_t^{\,T}(\mu)\right]e^{-i\varpi h} = \{\psi(\mu)e^{-i\varpi}\}\Sigma(\mu)\{\psi(\mu)e^{+i\varpi}\}^T \tag{20}$$

The dynamic adjacency matrix is defined as:

$$[\theta(\mu, d)]_{j,k} = \frac{\sigma_{kk}^{-1}\int_a^b \left|[\psi(\mu)e^{-i\varpi}\ (\mu)]_{j,k}\right|^2 d\varpi}{\int_{-\pi}^{\pi}\left[\{\psi(\mu)e^{-i\varpi}\}\Sigma(\mu)\{\psi(\mu)e^{+i\varpi}\}^T\right]_{j,j}d\varpi} \tag{21}$$

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

For The “local network connectedness”:

$$C(\mu,d) = 100 \times \sum_{\substack{j,k=1 \\ j \neq k}}^{N} \left[\widetilde{\theta}(\mu,d)\right]_{j,k} \Big/ \sum_{j,k=1}^{N} \left[\widetilde{\theta}(\mu)\right]_{j,k} \tag{22}$$

Here,

$$\left[\widetilde{\theta}(\mu,d)\right]_{j,k} = [\theta(\mu,d)]_{j,k} \Big/ \sum_{k=1} N[\theta(\mu)]_{j,k} \tag{23}$$

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

$$C_{j\leftarrow}(\mu,d) = 100 \times \sum_{\substack{k=1 \\ k \neq j}}^{N} \left[\widetilde{\theta}(\mu,d)\right]_{j,k} \Big/ \sum_{j,k=1}^{N} \left[\widetilde{\theta}(\mu)\right]_{j,k} \tag{24}$$

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

$$C_{j\rightarrow}(\mu,d) = 100 \times \sum_{\substack{k=1 \\ k \neq j}}^{N} \left[\widetilde{\theta}(\mu,d)\right]_{k,j} \Big/ \sum_{k,j=1}^{N} \left[\widetilde{\theta}(\mu)\right]_{k,j} \tag{25}$$

Following Kang *et al*. (2019), we estimate that the temporary-, medium-, and persistent-term (1 month–6 months, 6 months–12 months, and more than 12 months, respectively) returns connectedness networks.

6. Empirical results

6.1 Average interconnectedness results

We report the average negative, symmetric, and positive interdependencies results in Table 4 [1] The average connectedness results indicate that the returns have symmetric interdependencies of an average of 25.45%. The largest transmitters of return shocks are FFR and BCI (44.1 and 41.47, respectively), while the largest recipients are CCI and BCI (41.49 and 40.41, respectively) on average. BCI, GPR, 102YrsSpr, and FFR are the net transmitters of shocks, whereas the rest of the returns are the net receivers.

The remaining portion of Table 4 details the average connectedness outcomes concerning positive and negative returns. Notably, TCI for negative returns stands slightly higher at 33.67% compared to 33.59% for positive returns. It’s noteworthy that the primary transmitters for both positive and negative returns are 102YrsSpr and FFR. Additionally, 102YrsSpr exhibits a relatively higher propagation of negative spillovers to other variables compared to FFR.

Regarding the net transmitting and receiving roles of returns, BCI, WTI, GPR, and AAA exhibit shifts between transmitting and receiving negative and positive spillovers, while the roles of the other nodes remain consistent. The observation regarding WTI is expected, given the study period is marked by significant oil price fluctuations during 2008–2009, 2014–2016, and 2021–2022. Notably, asymmetry is evident in the spillover results for GPR, which corroborates the findings of Long *et al*. (2022).

Table 4. Average connectedness results

	BCI	CCI	NG	WTI	SIR	GPR	102YrsSpr	FFR	AAA	FROM
BCI	59.59	18.24	0.9	5.2	2.98	1.4	3.54	4.93	3.22	40.41
CCI	24.76	58.51	3.36	1.99	3.1	0.64	3.94	2.71	0.99	41.49
NG	0.82	0.64	86.34	4.1	1.29	2.09	2.58	1.28	0.86	13.66
WTI	5.57	1.72	3.04	71.31	3.57	1.38	2.72	6.22	4.49	28.69
SIR	1.35	1.19	0.4	3.01	63.71	0.87	0.38	24.76	4.32	36.29
GPR	0.83	0.14	0.81	0.16	0.61	93.95	0.76	0.37	2.36	6.05
102YrsSpr	1.1	0.05	0.37	0.68	0.13	0.21	96.39	0.16	0.9	3.61
FFR	3.58	0.73	0.23	5.35	18.45	0.66	0.38	69.51	1.1	30.49
AAA	3.46	0.63	1.16	7.01	5.49	3.67	3.21	3.69	71.67	28.33
TO	41.47	23.34	10.27	27.51	35.62	10.93	17.52	44.1	18.25	229.02
NET	1.06	−18.15	−3.38	−1.18	−0.67	4.88	13.91	13.61	−10.08	TCI = 25.45

	BCI	CCI	NG	WTI	SIR	GPR	102YrsSpr	FFR	AAA	FROM
Positive										
BCI	53.79	7.8	5.56	4.48	5.08	4.09	9.31	4.93	4.97	46.21
CCI	7.17	63.4	2.09	3.15	3.89	3.66	4.91	6.15	5.58	36.6
NG	5.38	0.79	65.21	6.02	2.52	3.44	6.39	4.03	6.21	34.79
WTI	3.39	1.24	5.66	62.12	4.27	1.94	8	6.41	6.97	37.88
SIR	3.72	0.51	2.44	1.76	57.31	1.8	2.58	20.86	9.02	42.69
GPR	4.77	0.39	1.6	1.32	1.7	82.16	1.28	2.36	4.42	17.84
102YrsSpr	0.1	0.11	0.24	0.35	0.23	0.55	97.98	0.22	0.22	2.02
FFR	4.39	1.19	2.86	2.97	18.9	1.86	1.87	58.98	6.99	41.02
AAA	5.44	1.21	5.1	4.76	8.02	6.19	5.51	7.05	56.72	43.28
TO	34.36	13.24	25.55	24.8	44.62	23.53	39.84	52.01	44.38	302.33
NET	−11.85	−23.35	−9.25	−13.09	1.93	5.7	37.83	10.99	1.09	TCI = 33.59
Negative										
BCI	54.78	14.91	1	6.94	4.07	0.39	3.08	12.9	1.92	45.22
CCI	15.9	62.08	0.7	3.01	4.32	0.38	2.73	9.68	1.19	37.92

(*continued*)

Table 4. Continued

	BCI	CCI	NG	WTI	SIR	GPR	102YrsSpr	FFR	AAA	FROM
NG	1.28	0.69	75.98	4.34	3.35	1.04	9.34	3.16	0.83	24.02
WTI	8.13	2.71	4.37	59.12	3.96	0.73	2.55	12.31	6.13	40.88
SIR	7.9	2.83	0.68	7.47	46.31	0.14	3.3	27.43	3.94	53.69
GPR	0.73	0.5	1.33	0.99	0.99	87.61	5.88	0.99	0.97	12.39
102YrsSpr	0.1	0.2	0.14	0.19	0.28	0.07	98.6	0.24	0.19	1.4
FFR	11.88	4.24	0.54	10.82	19.39	0.12	1.99	48.33	2.7	51.67
AAA	3.67	1.83	0.76	10.97	6.06	1.27	3.24	8.05	64.15	35.85
TO	49.6	27.91	9.52	44.73	42.44	4.13	32.11	74.75	17.86	303.05
NET	4.38	−10.01	−14.5	3.84	−11.24	−8.26	30.71	23.08	−17.99	TCI = 33.67

Note(s): Results are estimated by TVP-VAR model with lag 1 (BIC) and a 10-step ahead forecast error variance decomposition (FEVD)
Source(s): Authors' own work

6.2 Time-varying asymmetric connectedness

We continue our analysis with asymmetric connectedness and illustrate them in Figure 2 [2].

The Symmetric TCI fluctuated between 18% and 60% throughout the period under examination, reaching its peak in May 2020 at 60.14%, shortly after the onset of the COVID-19 pandemic. This index demonstrated a gradual increase during periods of financial and geopolitical upheaval, such as the Dot-com crash of 2000–2001, the Global Financial Crisis (GFC) of 2007–2008, and the initial phase of the COVID-19 health crisis between late 2019 and early 2020. Both the TCIs for negative and positive returns indicated similar trends, with their highest points occurring in August 1998 (78.97%) and May 2020 (64.48%), respectively. Notably, the TCI for negative returns predominated throughout the study period, while the positive returns tended to be greater during specific intervals, notably from 1998:1 to 1999:1 and from 2012:1 to 2019:12.

6.3 Dynamic net directional connectedness (NDC)

The next phase of the study focuses on the NDC returns to determine their transmitter/receiver roles over the episode. Figure 3 depicts the findings for the NDC of returns [3].

Consistent with our earlier findings, the interconnectedness of the system was primarily driven by negative returns. Furthermore, asymmetry, particularly notable in GPR, aligns with the observations of Zhang *et al.* (2023). Reflecting a shared pattern, negative spillovers originating from WTI, 102YrsSpr, SIR, and FFR surged due to the influence of GPR. Specifically, asymmetry in GPR was evident during the GFC. Similarly, negative spillovers from WTI, FFR, BCI, and CCI sharply increased in early 2020 with the onset of the pandemic. Notably, asymmetry became prominent during periods of financial or geopolitical turmoil throughout the episode. Lastly, the 102YrsSpr disseminated a significant volume of positive and negative spillovers at the episode's outset, triggered by a steep rise in bond yield volatility across major bond markets in 1994 (Borio and McCauley, 1996).

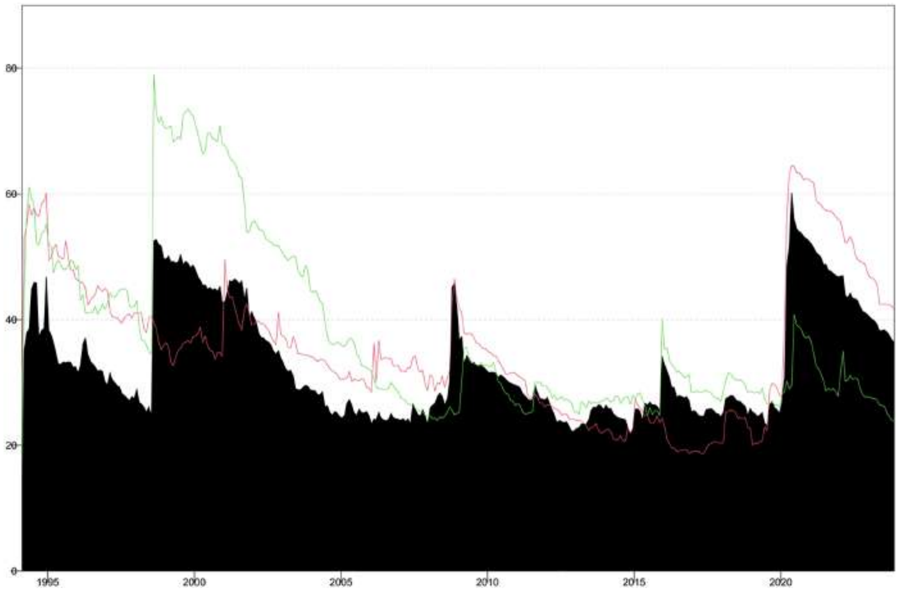

Figure 2. TCIs. **Notes:** The results are obtained by employing the TVP-VAR model application. **Source:** Authors' own work

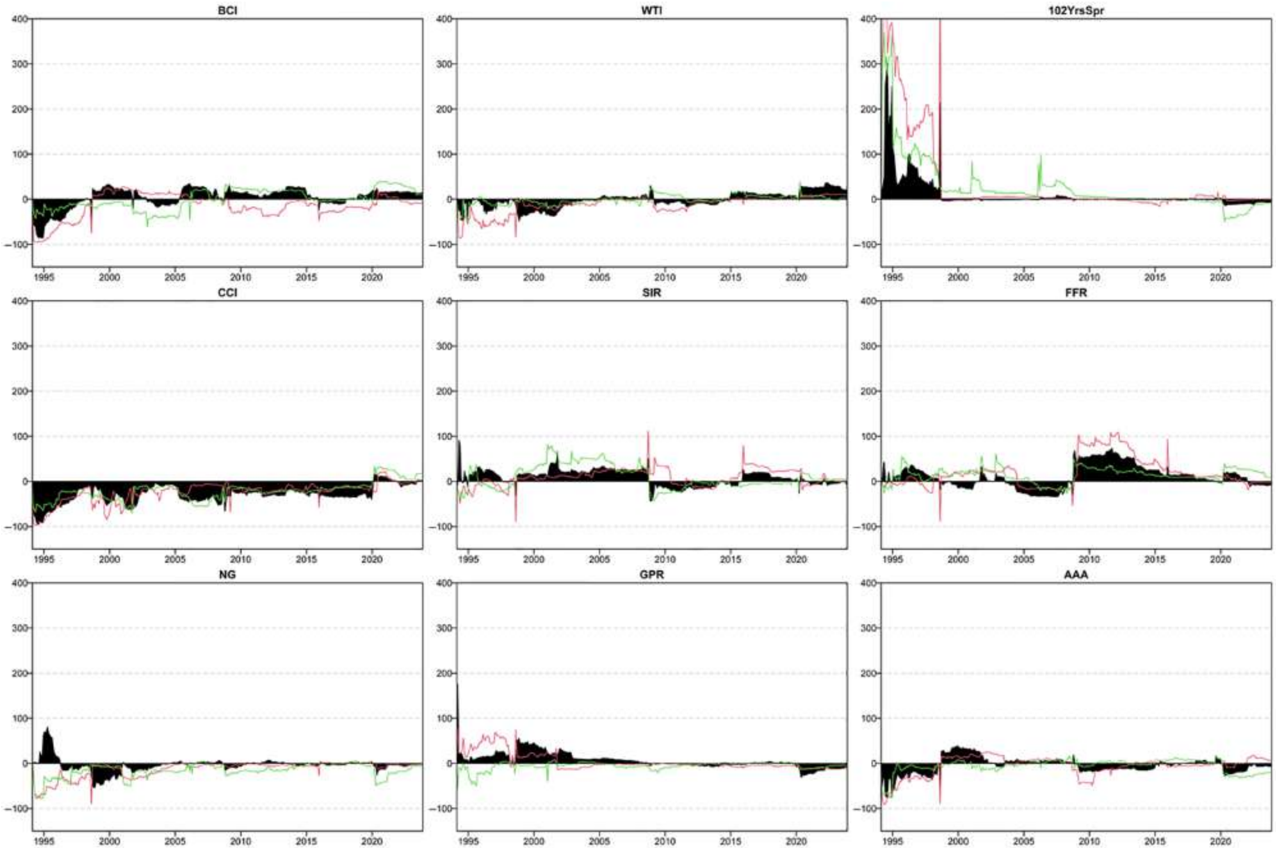

Figure 3. Time-varying NDC. **Notes:** Results are obtained by TVP-VAR model. **Source:** Authors' own work

6.4 Dynamic net pairwise connectedness (NPC)

Next, we calculate the time-varying NPC among the returns and visualize them in Figure 4. At a glance, we observe relatively robust connectedness among pairs such as BCI-CCI, BCI-FFR, WTI-FFR, SIR-FFR, BCI-WTI, and SIR-AAA consistently throughout the episode compared to other pairs. Additionally, pairwise spillovers experienced a dramatic increase during periods of financial or geopolitical turmoil, such as the Global Financial Crisis (GFC) and the COVID-19 pandemic. Notably, GPR exhibited a transmission of negative spillovers to other nodes in 2000–2001, attributed to heightened geopolitical tensions in the U.S.

6.5 Frequency-based dynamic interdependencies

Regarding the diverse economic entities and market players that exhibit interest in spillover effects at varying intervals, we aim to scrutinize interdependencies in different frequency domains. To achieve this, we employ a time-varying parameter vector autoregressive model (TVP-VAR) featuring a dynamic covariance form using the Quasi-Bayesian Local Likelihood (QBLL) technique. This approach dissects the overall interdependence into distinct frequency domains, imparting insights into the frequencies that predominantly contribute to system interconnectedness. These findings hold significance for investors shaping their short-term and long-term investment choices. Notably, participants, guided by distinct beliefs, preferences, aims, risk thresholds, and limitations, differ in their temporal outlooks. While day traders, oriented toward brief horizons, prioritize short-term interconnections, institutional investors with prolonged perspectives emphasize long-term interdependence. Consequently, this methodology offers meticulous insights beneficial to investors, computing network interconnectivity over short, medium, and extended periods while accounting for fluctuating coefficients and variance-covariance structures.

We adopt the approach of Kang *et al.* (2019) to compute connectedness networks for short-term (1–6 months), medium-term (6–12 months), and long-term (more than 12 months) returns. We visualize these networks alongside notable geopolitical or financial events in Figure 5.

Frequency-based interdependency networks reveal that transitory interconnections are more pronounced than medium- and persistent interdependencies, a trend supported by prior research (Kang *et al.*, 2019; Maghyereh and Abdoh, 2022; Umar *et al.*, 2022a). Additionally, frequency-based connectedness indices effectively highlight significant stress events, showing noticeable surges during periods of financial or geopolitical turmoil. Interestingly, medium- and persistent connectedness indices display similar patterns consistent with existing literature (Umar *et al.*, 2022b). Notably, medium- and long-term connectedness indices better capture the Global Financial Crisis (GFC), diverging from transitory connectedness, a finding consistent with Barunik and Ellington (2024).

7. Robustness check

To check the sensitivity of our results, we carried out a series of sensitivity analyses that varied some key parameters of the TVP-VAR connectedness model. Specifically, we studied three alternative specifications: (1) one with a shorter forecast horizon (10-step ahead instead of the baseline 20-step), (2) a larger rolling window size (250 observations instead of 200), and (3) an increased lag order (lag $= 2$ instead of 1). As shown in Figure 6, the total connectedness index (TCI) for each return type is very similar across specifications.

While there are some differences between specifications, especially during periods of high volatility, the overall shape, trajectory, and timing of peaks (high connectedness) and troughs (low connectedness) of TCI are the same. This provides evidence that our main results are not too sensitive to different parameterizations and gives further evidence of empirical stability.

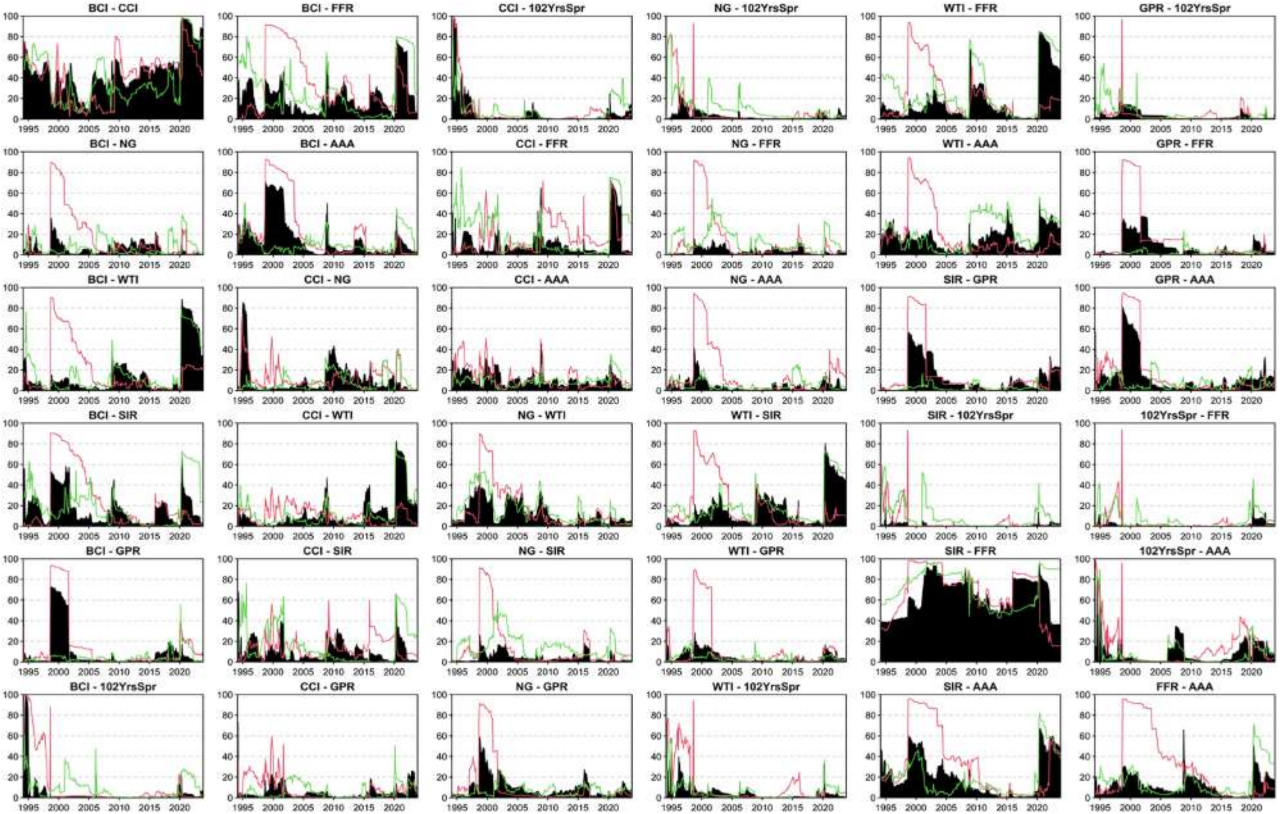

Figure 4. Time-varying pairwise spillovers. **Source:** Authors' own work

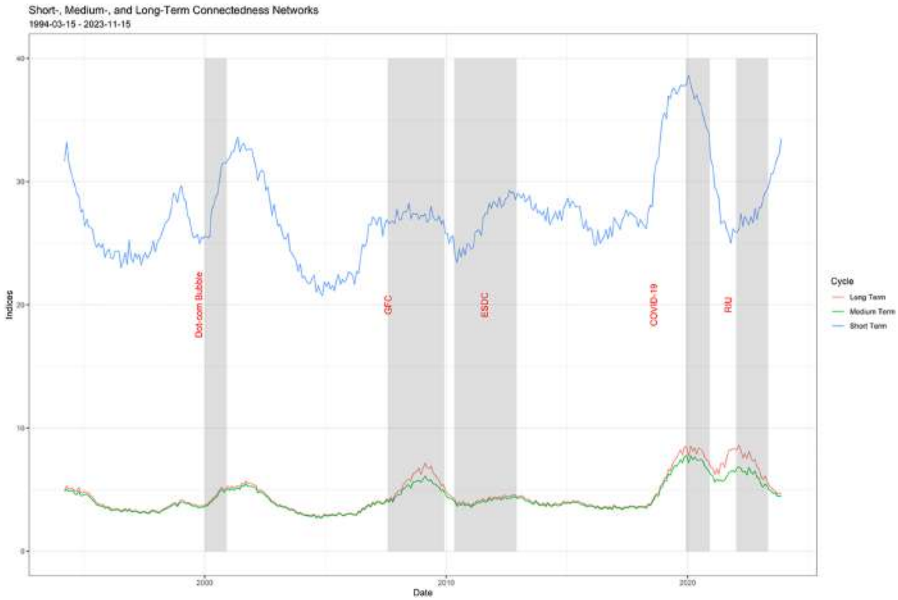

Figure 5. Frequency-based connectedness networks. **Source:** Authors' own work

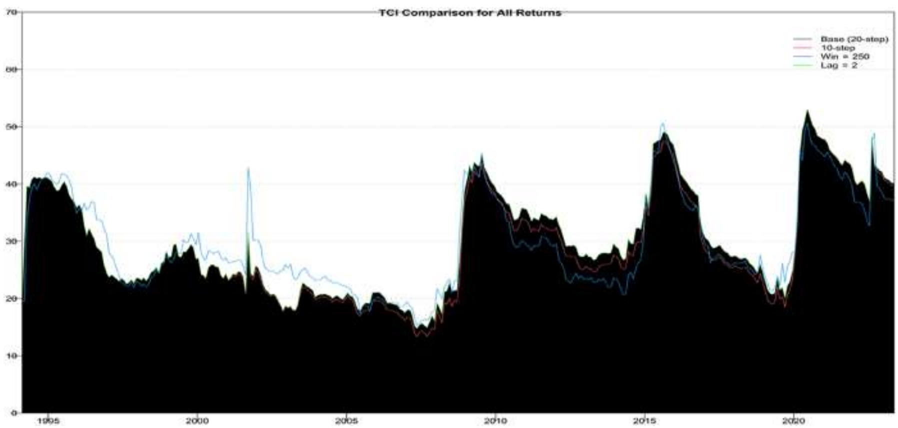

Figure 6. Robustness of Total Connectedness Index (TCI) under alternative model specifications for all returns. **Source:** Authors' own work

To evaluate the sensitivity of our results regarding the frequency band cutoffs, two alternative band specifications were constructed based on a recombination of the original short-, medium-, and long-term connectedness indices. An alternative medium-range band, for example, was specified as the average of the short- and medium-term connectedness, representing a 3–12-month horizon, and an alternative long-range band capturing periods longer than five months is the average of the medium- and long-term connectedness. As illustrated in Figure 7, the connectedness patterns resulting from these alternative specifications indicate connectedness is largely characterized by similar patterns (in terms of trend, timing of peaks, and responses to major economic events) as the original bands. The findings indicate that

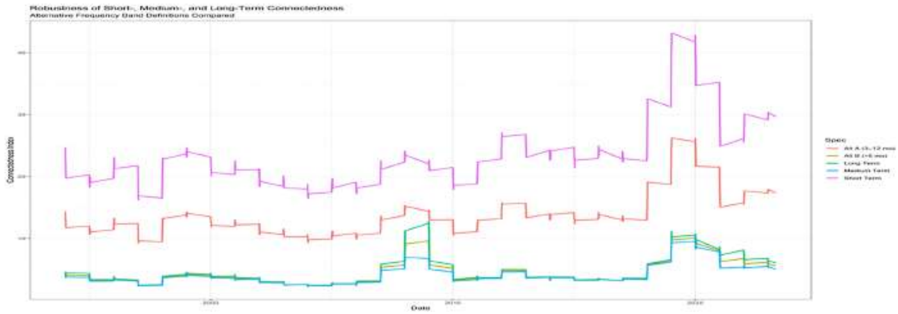

Figure 7. Robustness of frequency-based connectedness indices under alternative band definitions. **Source:** Authors' own work

our key findings are not overly sensitive to the precise cutoff frequency points, which enhances the robustness, stability, and reliability of the frequency-domain connectedness analysis.

A closer exploration of the essential macro-financial variables further enhances our empirical insights. The difference between the 10-year and 2-year Treasury yields, a commonly accepted indicator of yield curve inversion, stands out as a key channel for both positive and negative spillovers, particularly during times characterized by expectations of recession and tightening monetary policy. Its increased interconnectivity aligns with the recent volatility in the bond market and reinforces its role in forecasting macroeconomic downturns. Geopolitical risk, measured by the Caldara-Iacoviello index, reveals significant asymmetries in spillover dynamics, particularly during major crises such as the Global Financial Crisis and the COVID-19 pandemic, highlighting its role as an amplifier of shocks sensitive to sentiment. Finally, Moody's Seasoned AAA Corporate Bond Yield (AAA) serves a dual purpose, acting both as a recipient and transmitter of spillovers. In times of credit stress or tightening financial conditions, changes in AAA yields notably influence confidence levels, especially among companies that are sensitive to borrowing expenses. The evolving and nonlinear effects of these variables, especially across different economic conditions emphasize the importance of our TVP-VAR framework in capturing the asymmetric, time-dependent interconnectedness.

Our findings on asymmetric spillovers, particularly the stronger impact of negative shocks, align with studies emphasizing the vulnerability of economic confidence to adverse macroeconomic events. Edelstein and Kilian (2009) show that higher gasoline prices erode consumer confidence, consistent with our result that oil and gas shocks exert stronger negative spillovers. Bildirici and Badur (2019) identify bidirectional causality between oil prices and business confidence, supporting our observation that business sentiment acts both as a transmitter and a receiver of shocks. Unlike earlier works such as Lahiri and Zhao (2016) and Kilic and Cankaya (2016), which use static models, our TVP-VAR framework captures time-varying and reciprocal effects, revealing the Federal Fund Rate and short-term interest rates as persistent spillover sources—extending Dees and Brinca's (2013) insights. We also confirm that geopolitical risk (GPR) intensifies negative spillovers during crises, in line with Zhang *et al.* (2023) and Antonakakis *et al.* (2017). Compared to Arzova *et al.* (2023), our results show more stable negative effects from energy prices in the U.S. context. Integrating both consumer and business confidence indices, our study offers a more holistic view than Apergis *et al.* (2018) or Kabiri *et al.* (2023). Finally, consistent with Kang *et al.* (2019) and Barunik and Ellington (2024), our frequency-domain analysis reveals the dominance of short-term spillovers during turbulent periods.

8. Conclusion

The body of economic confidence research primarily investigates the efficiency of consumer and business indices. Nonetheless, the factors influencing economic confidence have gained significant attention recently. Exploring these determinants not only gauges economic stability but also offers insights for shaping forthcoming policies. Our connectedness model examines the drivers of both consumer and business indices within the U.S..

Empirical findings reveal that negative return spillovers dominate throughout the study period, with the Federal Fund Rate and short-term interest rates identified as the most influential transmitters. The symmetric Total Connectedness Index (TCI) peaked in January 2020, aligning with the onset of the COVID-19 pandemic, and showed similar surges during other major crises, such as the Dot-com crash and the Global Financial Crisis. Frequency-based analysis indicates that short-term (transitory) linkages are stronger than medium- and long-term ones, which nonetheless follow similar patterns especially during periods of financial or geopolitical stress confirming trends observed in the existing literature.

Our findings present implications for governments and businesses. Governments can shape economic confidence through policy decisions and targeted interventions, particularly in response to energy price volatility. Measures such as subsidies for oil and gas, strategic reserves, price controls, and incentives for sustainable energy practices can help stabilize sentiment and mitigate inflationary pressures. Educational campaigns on energy conservation may further enhance public awareness. On the business side, firms can reinforce confidence and resilience by optimizing debt structures, diversifying funding sources and energy inputs, improving supply chain efficiency, and employing hedging strategies against energy price risks.

The asymmetry in spillover dynamics where negative shocks exert stronger and more persistent effects on economic confidence carries key policy implications. During periods of geopolitical or financial stress, proactive monetary and fiscal measures may be more effective in mitigating adverse sentiment. Early implementation of rate cuts or targeted fiscal support can help cushion the impact of negative shocks. The findings also suggest a need for differentiated policy responses: monetary tools may reduce market anxiety, while fiscal interventions can directly support household and business confidence. Effective communication strategies are also essential to anchor expectations. Overall, the results call for a flexible, context-sensitive policy approach that accounts for the nonlinear nature of confidence responses.

This study has some limitations. Since monthly data are used, some financial and non-financial data are not included in the analysis. Future studies may examine these variables. In addition, The Connectedness model can also be applied for another important economic center as the European Union.

Notes

1. The off-diagonal values in Table 4 denote the shocks from the ith to the jth component in the network.
2. The black-shaded area illustrates the asymmetric TCI, while the green and red lines depict the dynamics of TCIs for positive and negative returns, respectively.
3. Negative/positive values depict the recipients/transmitters.

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