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Oil price shocks and the connectedness of US state-level financial markets☆

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ABSTRACT

This paper investigates the impact of oil supply, demand, and risk shocks on U.S. state-level stock and bond returns, utilizing daily data from February 1994 to March 2024. It examines the individual effects of oil price shocks on each state's stock and bond returns and explores how fluctuations in oil prices influence the interdependence between state-level stock and bond markets. The findings reveal that oil demand shocks have a significant positive impact, while oil supply shocks have a significant negative impact on state-level stock returns. Although state-level bond returns also react to these supply and demand shocks, their response is statistically less significant than that of stock returns, indicating that cross-asset diversification is possible during periods of oil supply and demand shocks. However, both stock and bond returns are significantly and negatively affected by oil risk shocks, which implies limited opportunities for cross-asset diversification when oil price fluctuations are driven by risk factors. Additionally, the interdependence between U.S. equity and bond markets is more significantly influenced by oil risk shocks than by supply or demand shocks, suggesting an increase in the interconnectedness of stock and bond returns following an oil risk shock. Further analysis, using a reverse-MIDAS model to relate high-frequency connectedness measures to monthly oil price shocks, indicates that oil supply shocks positively and significantly impact stock market connectedness, while oil inventory demand shocks negatively affect bond market connectedness. Implications of our findings are discussed.

1. Introduction

Oil price shocks significantly affect key economic and financial variables, such as economic activity (Hamilton, 1983, 1996, 2003; Kilian, 2008, 2009), inflation rates (Kilian and Zhou, 2022), stock market returns (Huang et al., 1996; Jones and Kaul, 1996; Sadorsky, 1999; Kilian and Park, 2009; Salisu and Isah, 2018) or bond returns (Kang et al., 2014; Demirer et al., 2020). However, evidence indicates that the underlying source of oil price fluctuations—specifically supply versus demand shocks—impact these variables in distinct ways, underscoring the necessity to differentiate between these types of shocks (Kilian and Park, 2009; Kilian, 2009; Ready, 2018; Herrera et al., 2019; Baumeister and Hamilton, 2019). In fact, as explained by Kilian (2009) and Kilian and Park (2009), the studies that overlook this distinction are likely to be biased, leading to the identification of insignificant results. Similarly, Ready (2018) suggests a methodology to separate oil price changes into components driven by supply, demand, and risk, which are derived from the prices of daily traded assets, which allows to examine the relationship between daily oil price shocks and stock and bond market returns. In this context, while oil supply and demand shocks could be attributable to the shortfalls in oil production and to the expansion of the world economy, oil risk shocks will be related to an unstable financial market environment (Demirer et al., 2020; Wen et al., 2022).

Two are the main goals of this paper. It aims to investigate the impact of oil supply, oil demand and oil risk shocks on US state-level stock and bond returns, and to analyze how each of those shocks influence the interdependence among state-level stock and bond markets.

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Empirical literature finds that oil price shocks have diverse effects across industries (Lee and Ni, 2002; Elyasini et al., 2011; Jo et al., 2019) and that the macroeconomic and financial effects of oil shocks also depend on factors such as the size of the economy, labor market characteristics, monetary policy regimes, and the role of oil and other forms of energy in the economy (Baumeister et al., 2010; Peersman and van Robays, 2012). Given the regional heterogeneity in these variables, a state-level disaggregated analysis of the relationship between disentangled oil price shocks and stock and bond returns will shed more light on the underlying relationship between these variables. In this context, a key objective of this paper is to conduct an empirical exploration of how oil supply, demand, and risk shocks differentially impact US state-level stock and bond returns using daily data from February1994 to February 2024, and May 2006 to March 2024, respectively. This analysis will allow us to understand the vulnerability of each US state to oil price shocks. Although intuitively, US state-level stock and bond returns of oil-producing states will be more sensitive to oil price increases, the direction and size of the impact will differ depending on whether those increases are driven by supply, demand, or risk factors. At the same time, this analysis will shed more light on whether stock returns are more sensitive to oil price shocks than bond returns (Kang et al., 2014; Chiang et al., 2015). From a theoretical point of view, oil prices could affect asset returns through different transmission mechanisms (Degiannakis et al., 2018; Smyth and Narayan, 2018). First, oil price rises will decrease (increase) an oil-user (oil producer) firm's future cash flows, changing the affected firm's values (stock valuation channel). Second, fluctuations in oil prices can influence asset returns via inflation and interest rate changes (the monetary channel), as these factors affect the expected discount rates of future cash flows. Third, through the output channel, increases in oil prices can deteriorate the terms-of-trade for oil-importing economies, leading to reduced income and a negative wealth effect on consumption, which in turn negatively affects stock markets. Additionally, higher oil prices amplify uncertainty in the real economy, causing firms to reduce their demand for irreversible investments and, as a result, lowering expected cash flows (uncertainty channel). The differential impact of oil price shocks on stock and bond markets is pertinent for portfolio managers, since investing in both assets augments investors ability to diversify risk.

Moreover, recent academic literature analyzing the level of financial market interconnectedness (Bekaert and Harvey, 2000; Baur and Lucey, 2010; Diebold and Yilmaz, 2012, 2014; Aloui et al., 2013) among stock or bond returns suggest that oil price increases lead to higher connectedness among stock returns, indicating a heightened transmission of shocks across markets. Understanding the linkages between asset returns might be crucial for assessing systemic risks, portfolio diversification benefits, and the transmission of shocks across markets (Zhang, 2017; Geng et al., 2021; Bouri et al., 2022; Umar et al., 2022; Polat, 2024). For example, previous literature finds that increased interconnectedness leads to lower diversification opportunities, as correlation among asset returns tends to increase in periods of financial stress (Diebold and Yilmaz, 2012, 2014). It also suggests that, in an international context, stock markets are more integrated and interconnected than bond markets (Bekaert and Harvey, 2000). While there is significant evidence of international connectedness, research on the level of equity and bond connectedness at US the state level remains limited. Within this context, a second objective of this paper is to analyze the impact of oil supply, demand and risk shocks on the degree of both US state stock and bond connectedness.

Based on the above discussion, the main contributions of the paper are the following. First, we decompose oil price innovations into supply, demand and risk shocks following the approach of Ready (2018) and analyze their impact on US stock and bond returns using daily data covering the period of February 1994 to February 2024, and May 2006 to March 2024, respectively, which include different episodes of oil price movements, the Global Financial Crisis or the COVID pandemic. Second, we analyze both the US stock and bond markets to determine the differential impact of oil price shocks on each of these two financial assets, which will result in important implications for investors' ability to diversify risk. Third, we use US state level data in order to explore how oil price innovations will differently impact stock and bond returns in each of the US states. Fourth, we estimate both the stock and bond market connectedness within US states using alternative measures of connectedness (Ghysels et al., 2006; Diebold and Yilmaz, 2012, 2014; Balli et al., 2023) and analyze the response of these measures to each of the oil price movements. In this regard, as a matter of robustness, we also utilize the role of monthly oil shocks, in determining the daily connectedness of the two markets across the sates using the reverse-mixed data sampling approach of Foroni et al. (2018), which avoids any loss of information from averaging the high-frequency information of spillovers to match the low-frequency oil shocks.

Overall, our main results point to a positive and significant impact of oil demand shocks and a negative and significant impact of oil supply shocks on state-level stock returns. Although state-level bond results also respond to these supply and demand shocks, their response is statistically less significant compared to stock returns, suggesting that cross-asset diversification is possible during periods of oil supply and demand shocks. However, our results suggest that both stock and bond returns are significantly and negatively affected by oil risk shocks, implying low cross-asset diversification possibilities when oil price shocks are driven by oil risk factors. This highlights the importance of disentangling oil price shocks into their three components. Similarly, our results indicate that the connectedness of both the US stock and bond markets responds significantly more to oil risk shocks than to supply or demand shocks, suggesting an amplification in the interconnection of both bond and stock returns after an oil risk shock. When a reverse-MIDAS model is estimated to relate high-frequency connectedness measures to monthly oil price shocks, the results show that oil supply shocks exert a positive and significant impact on stock connectedness, while oil inventory demand shocks negatively impact bond connectedness.

The remainder of the paper is organized as follows: Section 2 provides a brief overview of the dataset used in the study. Section 3 details the empirical methodologies employed in the analysis. Section 4 presents the findings and discusses the key arguments. Finally, Section 5 summarizes the main results, explores the policy implications, and offers concluding remarks.

2. Data

Building on the work of Kilian (2009), Ready (2018), and Demirer et al. (2020), we classify daily oil price shocks into demand, supply, and risk components. For this analysis, we gather daily data on global integrated oil and gas producer indexes, use the nearest-maturity NYMEX crude light sweet oil futures contract as a proxy for crude oil prices, and incorporate the Chicago Board Options Exchange (CBOE) volatility index (VIX). ARMA (1,1)-based innovations are used to capture changes in the market discount rate that reflect shifts in risk attitudes. All the associated variables to compute the shocks are obtained from the Bloomberg terminal. The reader is referred to the Appendix for the details of the model of Ready (2018). In addition, as stated earlier, we also analyze the role of the monthly oil shocks (Baumeister and Hamilton, 2019) on the daily total connectedness of the state-level stock and bond markets using a reverse-mixed data sampling (R-MIDAS) approach. These authors by formulating a less restrictive framework, than traditionally used in the literature (see, for example, Kilian (2009)), and that incorporates uncertainty about the identifying assumptions of the underlying structural vector autoregressive model derive four global oil shocks namely, oil supply, economic activity, oil consumption demand,

and oil inventory demand.[1]

The state-level stock market indexes, sourced from the Bloomberg terminal, are utilized to compute log returns. These indexes are based on the capitalization-weighted performance of equities domiciled in each state. At the same time, the municipal bond indexes, also converted to log returns and obtained from the Bloomberg terminal, reflect the market-value-weighted performance of bonds issued by state and local municipalities in the U.S. For broader market analysis, the stock market returns correspond to the S&P 500 Index, while the bond returns are associated with the S&P Municipal Bond Index. The S&P Municipal Bond Index is a comprehensive, market-value-weighted index that tracks the performance of the US municipal bond market, reflecting the investment-grade bonds issued by state and local governments. It serves as a key benchmark for investors seeking exposure to tax-exempt municipal debt.

Based on data availability at the time of writing this paper, our analysis involving stock returns and bond returns data, along with the daily and monthly oil shocks covers the periods of (2nd) February 1994 to (9th) February 2024 and (2nd) May 2006 to (8th) March 2004, respectively.

3. Methodology

This section summarizes the different connectedness measures (Diebold-Yilmaz and R^2 decomposed) The Diebold-Yilmaz and R^2 decomposed connectedness measures are employed for their ability to capture both the contemporaneous and lagged spillover effects between state-level stock and bond markets. These approaches provide a detailed understanding of how oil price shocks propagate through markets, identifying the direction and intensity of spillovers. Traditional econometric methods would not offer the same granularity or the ability to disentangle the immediate and delayed responses to shocks. The R^2 Decomposed approach, in particular, adds depth by distinguishing between contemporaneous and lagged spillovers, a critical factor in understanding how systemic risk evolves over time. These approaches are thus implemented for their capacity to deliver more nuanced and comprehensive insights into the relationship between oil price shocks and financial market movements.

3.1. Diebold-Yilmaz connectedness

Consider the following $VAR(p)$ model:

$$x_t = \sum_{i=1}^{p} \theta_i x_{t-1} + \varepsilon_t \tag{1}$$

where, $\varepsilon_t \sim (0, \Sigma)$ i.i.d. error terms with $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i.}$

Let's H-step-ahead forecast error variance decompositions by $\phi_{ij}^g(H)$, for $H = 1, 2, \dots$

$$\phi_{ij}^g(H) = \frac{\rho_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i\right)} \tag{2}$$

$\boldsymbol{\Sigma}$ represents the variance vector of ε, ρ_{ii} is the standard deviation of ε_t for the ith equation and e_i is the selection vector, with 1 as the ith element, 0 otherwise. The system is normalized as:

$$\widetilde{\phi}_{ij}^g(H) = \frac{\phi_{ij}^g(H)}{\sum_{j=1}^{N} \phi_{ij}^g(H)} \tag{3}$$

The total spillover:

$$S^g(H) = \frac{\sum_{i,j=1, i \neq j}^{N} \widetilde{\phi}_{ij}^g(H)}{\sum_{i,j=1}^{N} \widetilde{\phi}_{ij}^g(H)} \bullet 100 = \frac{\sum_{i,j=1, i \neq j}^{N} \widetilde{\phi}_{ij}^g(H)}{N} \bullet 100 \tag{4}$$

The directional spillovers retrieved by market i from all markets j:

$$S_{i.}^g(H) = \frac{\sum_{j=1, j \neq i}^{N} \widetilde{\phi}_{ij}^g(H)}{\sum_{i,j=1}^{N} \widetilde{\phi}_{ij}^g(H)} \bullet 100 = \frac{\sum_{j=1, j \neq i}^{N} \widetilde{\phi}_{ij}^g(H)}{N} \bullet 100 \tag{5}$$

The directional spillovers propagated by market i to all markets j:

$$S_{.i}^g(H) = \frac{\sum_{j=1, j \neq i}^{N} \widetilde{\phi}_{ji}^g(H)}{\sum_{i,j=1}^{N} \widetilde{\phi}_{ji}^g(H)} \bullet 100 = \frac{\sum_{j=1, j \neq i}^{N} \widetilde{\phi}_{ji}^g(H)}{N} \bullet 100 \tag{6}$$

The net spillover:

$$S_i^g(H) = S_{.i}^g(H) - S_{i.}^g(H) \tag{7}$$

The net pairwise spillover:

$$S_{ij}^g(H) = \frac{\widetilde{\phi}_{ji}^g(H) - \widetilde{\phi}_{ij}^g(H)}{N} \bullet 100 \tag{8}$$

3.2. R^2 decomposed connectedness approach

In this study, we employ the newly engineered R^2 interconnectedness approach introduced by Balli et al. (2023), which disentangles contemporaneous and lagged spillovers, tackling a limitation of prior studies that mainly focused on contemporaneous spillovers.

Consider the following $VAR(p)$ model with contemporaneous effects:

$$x_t = \sum_{i=0}^{p} A_i x_{t-i} + v_t v_t \sim N(0, \pi) \tag{9}$$

here x_t, x_{t-1}, and v_t are $N \times 1$ dimensional mean-adjusted vectors in time t, A_i, π are $N \times N$ dimensional matrices with $diag(A_0) = 0$.

In this methodology, it is essential to identify a transformation that converts the correlated series $x_{n,t}^1$ into orthogonal series. This transformation can be accomplished using the factor analysis. Therefore, the decomposition of R^2 of the multilinear regression model is given as follows:

$$R_{yy} = V \Lambda V' = CC' \tag{10}$$

$$C = V \Lambda^{1/2} V' = CC' \tag{11}$$

$$R^{2d} = C^2 \left(C^{-1} R_{xy}\right)^2 \tag{12}$$

where V, $\Lambda = diag(\lambda_1, \lambda_2, \dots, \lambda_{N(p+1)-1})$, and R_{yy} denotes $[N(p+1) - 1] \times [N(p+1) - 1]$ eigenvector, eigenvalue, and Pearson correlation terms, R_{xy} and R^{2d} represent $[N(p+1) - 1]$ Pearson correlation and R^2 contribution vectors. R_{yy}, and R_{xy} represent Pearson correlation coefficients.

IN this approach, $R_0^{2,d}$, $R_L^{2,d} = \left(R_1^{2,d} + \dots + R_i^{2,d} + \dots + R_q^{2,d}\right)$ denote the contemporaneous spillovers $\left(R_C^{2,d}\right)$, and the lagged spillovers, respectively.

[1] The oil shocks data are available for download from: https://sites.google.com/site/cjsbaumeister/datasets?authuser=0.

$R_C^{2,d}$ and $R_L^{2,d}$ replace the scaled GFEVD matrix.

The TCI is defined as:

$$TCI = \frac{1}{N}\sum_{n=1}^{N} R_n^2 \tag{13}$$

$$TCI = \left(\frac{1}{N}\sum_{n=1}^{N}\sum_{i-1}^{N} R_{C,n,i}^{2,d}\right) + \left(\frac{1}{N}\sum_{n=1}^{N}\sum_{i-1}^{N} R_{L,n,i}^{2,d}\right) \tag{14}$$

$$TCI = TCI^C + TCI^L \tag{15}$$

where TCI^C, and TCI^L correspond to the contemporaneous and lagged TCIs.

TO, FROM, and NET spillovers:

$$TO_i = \left(\frac{1}{N}\sum_{i-1}^{N} R_{C,n,i}^{2,d}\right) + \left(\frac{1}{N}\sum_{i-1}^{N} R_{L,n,i}^{2,d}\right) \tag{16}$$

$$TO_i = TO_i^C + TO_i^L \tag{17}$$

$$FROM_i = \left(\frac{1}{N}\sum_{i-1}^{N} R_{C,i,n}^{2,d}\right) + \left(\frac{1}{N}\sum_{i-1}^{N} R_{L,i,n}^{2,d}\right) \tag{18}$$

$$FROM_i = FROM_i^C + FROM_i^L \tag{19}$$

$$NET_i^C = TO_i^C - FROM_i^C \tag{20}$$

$$NET_i^L = TO_i^L - FROM_i^L \tag{21}$$

$$NET_i = TO_i - FROM_i \tag{22}$$

3.3. Reverse MIDAS model

We apply the reverse-MIDAS (R-MIDAS) model proposed by Foroni et al. (2018), which builds upon the mixed data sampling (MIDAS) framework introduced by Ghysels et al. (2006), to establish a connection between high-frequency TCI and low-frequency oil shock series. We implement the reverse-MIDAS model as it effectively combines high-frequency data (daily market returns) with lower-frequency data (monthly oil price shocks), preserving valuable information that might be lost in traditional data aggregation techniques. This is especially important when analyzing the timely effects of oil price fluctuations, as it allows for the analysis of both short- and long-term impacts in a unified framework. In this model, we consider the dependent variable x generated by an (p) process and variable y serves the exogenous predictor. Here, x is observed at high frequency every $t = 1/k$ periods, while y is only recorded at low frequency every k periods, the R-MIDAS model is formulated as follows:

$$x_t = \xi_i(L^{k+i})y_t + \rho_{1i}B_i(L,\theta_i)x_{t-1/k} + \varepsilon_t \tag{23}$$

$$t = 0 + \frac{i}{k}, 1 + \frac{i}{k+1}, 2 + \frac{i}{k+2}, i = 0, \dots, k-1 \tag{24}$$

where L represents the lag operator in high frequency and $B_i(L,\theta_i)$ is an exponential Almon lag polynomial.

$$B_i(L,\theta_i) = \sum_{j=1}^{\Theta} b_i(j,\theta_i)L^j, b_i(j,\theta_i) = \frac{exp\left(\theta_{i1}j + \theta_{i2}j^2\right)}{\sum_{j=0}^{K} exp\left(\theta_{i1}j + \theta_{i2}j^2\right)} \tag{25}$$

In this setting, the daily TCI, x_t represents latest month's oil price shocks (shocks related to oil supply, consumption demand, inventory demand and economic activity), y_t and x_t and their lags.

The choice of the reverse-MIDAS model and connectedness measures, such as the Diebold-Yilmaz and R2 Decomposed approaches, was driven by their distinct advantages in capturing the dynamic and interconnected nature of financial markets, particularly in the context of oil price shocks. The reverse-MIDAS model was selected because it effectively combines high-frequency data (daily market returns) with lower-frequency data (monthly oil price shocks), preserving valuable information that might be lost in traditional data aggregation techniques. This is especially important when analyzing the timely effects of oil price fluctuations, as it allows for the analysis of both short- and long-term impacts in a unified framework.

The Diebold-Yilmaz and R2 Decomposed connectedness measures were chosen for their ability to capture both the contemporaneous and lagged spillover effects between state-level stock and bond markets. These approaches provide a detailed understanding of how oil price shocks propagate through markets, identifying the direction and intensity of spillovers. Traditional econometric methods, such as standard VAR models, would not offer the same granularity or the ability to disentangle the immediate and delayed responses to shocks. The R^2 Decomposed approach, in particular, adds depth by distinguishing between contemporaneous and lagged spillovers, a critical factor in understanding how systemic risk evolves over time. These techniques were thus selected for their capacity to deliver more nuanced and comprehensive insights into the relationship between oil price shocks and financial market movements.

4. Empirical results

4.1. The impact of oil shocks on stock returns

We examine the influence of daily oil shocks (demand/supply) and VIX risk shock on the stock returns of US states, while controlling for stock market (SP500) returns as follows:

$$r_{i,t} = \beta_{0,i} + \beta_{d,i}d_t + \beta_{s,i}s_t + \beta_{VIX,i}\zeta_{VIX,t} + \beta_{SP500,i}r_{SP500,t} + \nu_t \tag{26}$$

where $r_{i,t}$ is the stock return in US state i for period t and d_t, s_t, and $\zeta_{VIX,t}$ are demand, supply and risk shocks, respectively. To control the US stock market movements, the return on the S&P 500 index, $r_{SP500,t}$, is also included in the model.

Table 1 displays the estimated coefficients for Eq. (26), utilized for the stock market returns of US states, with t-statistics provided in parentheses.

We note that fluctuations in oil demand exert a notable and favourable impact on stock returns in the US states. This finding aligns with the findings of Basher et al. (2018), Demirer et al. (2020), and Castro et al. (2023) and indicates that rises in oil prices resulting from positive shifts in global oil demand correspond to heightened stock market returns across various states. Unsurprisingly, the most significant impact of oil demand shocks is evident in Texas, a prominent energy-exporting state in the US, with an estimated coefficient of 0.575.

Supply shocks exhibit a strong adverse impact on equity returns in the majority of states (46 out of 50), aligning with the findings of Ewing et al. (2018) and Demirer et al. (2020). It is important to highlight those disruptions in oil production, resulting in negative shocks, particularly impact net oil-importing states. Given that most states in our sample fall into this category, it's unsurprising that supply-related shocks have adverse effects. Rising oil prices resulting from supply disruptions drive up production expenses for firms and reduce both discretionary income and household spending, and raises expectations of inflation, all of which negatively impact economic activity and, consequently, equity markets. Unsurprisingly, the exceptions oil producing states (Colorado, North Dakota, Oklahoma, and Texas), while stock returns in Alaska and New Mexico respond negatively to a positive oil supply shock.

Expectedly, the risk shock has a detrimental effect on stock returns in US states, whereas the influence of SP500 returns is insignificant for the majority of states.

Table 1
Effects of Oil Price Shocks on Stock Returns in U.S. States.

State	Constant	d_t	s_t	$\zeta_{VIX,t}$	$r_{SP500,t}$	Adj. R^2
Alabama	0.000416***	0.375302***	−0.014246**	−2.89988***	0.00137	0.428
	(2.845)	(26.759)	(−2.203)	(−69.347)	(0.111)	
Alaska	0.000441***	0.188599***	−0.011188	−1.162350***	−0.00941***	0.059
	(2.103)	(9.370)	(−1.206)	(−19.369)	(−0.530)	
Arizona	0.000511***	0.334461***	−0.004974	−2.813537***	−0.010360***	0.382
	(3.299)	(22.511)	(−0.726)	(−63.514)	(−0.790)	
Arkansas	0.000528***	0.055673***	−0.068455***	−1.930730***	0.0127235***	0.207
	(3.385)	(3.717)	(−43.231)	(−43.231)	(0.962)	
California	0.000700***	0.118487***	−0.012893**	−2.951671***	−0.003674***	0.410
	(4.844)	(8.543)	(−2.016)	(−71.378)	(−0.300)	
Colorado	0.000236*	0.308324***	0.027909***	−2.404069***	−0.004929***	0.377
	(1.747)	(23.723)	(4.658)	(−62.040)	(−0.430)	
Connecticut	0.0005214***	0.261351***	−0.043528***	−2.877806***	0.009268***	0.470
	(4.045)	(21.136)	(−7.635)	(−78.060)	(0.849)	
Delaware	0.000372**	0.357079***	−0.037989***	−2.823415***	0.003969***	0.374
	(2.343)	(23.396)	(−5.399)	(−62.047)	(0.295)	
Florida	0.000369***	0.239667***	−0.030236***	−2.602752***	0.003444	0.545
	(3.686)	(24.922)	(−6.819)	(−90.777)	(0.406)	
Georgia	0.000438***	0.185670***	−0.049409***	−2.325500***	0.0070152	0.490
	(4.406)	(19.453)	(−11.228)	(−81.719)	(0.832)	
Hawaii	0.000272***	0.244602***	−0.039083***	−2.132588***	−0.0002331	0.321
	(2.032)	(19.051)	(−6.602)	(−55.709)	(−0.021)	
Idaho	0.000911***	0.3127122***	−0.039083***	0.017459	0.0637311	0.179
	(2.840)	(10.162)	(−6.602)	(1.231)	(2.346)	
Illinois	0.000039***	0.2290***	−0.03548***	−2.261***	−0.009378	0.585
	(4.843)	(29.377)	(−9.870)	(−97.258)	(−1.362)	
Indiana	0.000620***	0.218017***	¯0.051479***	−2.2993***	−0.011619	0.328
	(4.427)	(16.211)	(−8.302)	(−57.344)	(−0.979)	
Iowa	0.000503***	0.327472***	−0.02762***	−2.75256***	−0.010942	0.431
	(3.670)	(24.909)	(−4.557)	(−70.225)	(−0.943)	
Kansas	0.000069***	0.2817***	−0.01343***	−2.591***	−0.01952	0.261
	(0.371)	(15.704)	(−1.624)	(−48.435)	(−1.232)	
Kentucky	0.000451***	0.212391***	−0.027251***	−2.19690***	0.009123	0.366
	(3.693)	(18.115)	(−5.041)	(−62.845)	(0.881)	
Louisiana	0.000252***	0.389574***	0.002947***	−2.250844***	−0.014907	0.478
	(2.328)	(37.470)	(0.615)	(−72.612)	(−1.624)	
Maine	0.000982***	0.201524***	−0.001978***	−2.551670***	0.023840	0.126
	(3.506)	(7.497)	(−0.160)	(−31.838)	(1.004)	
Maryland	0.000414***	0.219845***	−0.026559***	−2.623620***	−0.002730	0.445
	(3.373)	(18.660)	(−4.889)	(−74.688)	(−0.263)	
Massachusetts	0.000553***	0.143016***	−0.035187***	−2.984412***	0.006137	0.438
	(4.000)	(10.771)	(−5.748)	(−75.389)	(0.524)	
Michigan	0.000297***	0.287951***	−0.037785***	−2.506627***	0.008940	0.436
	(2.423)	(24.438)	(−6.956)	(−71.353)	(0.859)	
Minnesota	0.000491***	0.2158***	−0.03942***	−2.325***	−0.01382	0.516
	(5.148)	(23.561)	(−9.336)	(−85.138)	(−1.709)	
Mississippi	0.000401***	0.238598***	−0.011584***	−2.365381***	−0.007889	0.334
	(2.827)	(17.525)	(−1.846)	(−58.271)	(−0.656)	
Missouri	0.000487***	0.3262***	−0.02671***	−2.432***	−0.001618	0.538
	(4.913)	(34.276)	(−6.088)	(−85.723)	(−1.926)	
Montana	0.000594***	0.447246***	−0.014665***	−2.729011***	0.017564	0.187
	(2.305)	(18.090)	(−1.287)	(−37.022)	(0.805)	
Nebraska	0.000444***	0.260150***	−0.021915***	−1.932226***	−0.015093	0.338
	(3.727)	(22.764)	(−4.159)	(−56.70)	(−1.496)	
Nevada	0.000469***	0.337675***	−0.015120***	−2.954177***	0.042196**	0.269
	(2.251)	(16.873)	(−1.639)	(−49.511)	(2.388)	
New Hampshire	0.000364**	0.247933***	−0.009598***	−2.503736***	0.005657	0.290
	(2.193)	(15.555)	(−1.306)	(−52.686)	(0.402)	
New Jersey	0.000433***	0.1874***	−0.005093***	−2.065***	0.01275	0.457
	(4.530)	(20.411)	(−12.030)	(−75.448)	(−1.573)	
New Mexico	0.000716***	0.12852***	−0.024928***	−2.35356***	−0.012555	0.084
	(2.245)	(4.199)	(−1.767)	(−25.791)	(−0.465)	
New York	0.000265***	0.23878***	−0.041883***	−2.72559***	−0.019003**	0.565
	(2.631)	(24.699)	(−9.396)	(−94.558)	(−2.226)	
North Carolina	0.000421***	0.276265***	−0.040247***	−2.89753***	−0.022669**	0.456
	(3.137)	(21.423)	(−6.769)	(−75.361)	(−1.991)	
North Dakota	0.000352***	0.398087***	0.005331	−2.081231***	−0.011913	0.287
	(2.279)	(26.829)	(0.779)	(−47.045)	(−0.909)	
Ohio	0.000405***	0.2054***	−0.03469***	−2.151***	−0.01157	0.536
	(4.779)	(25.224)	(−9.240)	(−88.581)	(−1.609)	
Oklahoma	0.000449***	0.827021***	0.13105***	−2.86841***	−0.03066**	0.519
	(2.917)	(55.948)	(19.230)	(−65.085)	(−2.350)	
Oregon	0.00057***	0.18332***	−0.02519***	−2.73841**	0.01188	0.339
	(3.633)	(12.097)	(−3.606)	(−60.606)	(0.888)	

(continued on next page)

Table 1 (*continued*)

State	Constant	d_t	s_t	$\zeta_{VIX,t}$	$r_{SP500,t}$	Adj. R^2
Pennsylvania	0.000334***	0.2790***	−0.02825***	−2.547***	−0.01387*	0.592
	(3.689)	(32.041)	(−7.036)	(−98.073)	(−1.803)	
Rhode Island	0.000463***	0.212811***	−0.052253***	−2.263525***	−0.03571***	0.296
	(3.105)	(14.858)	(−7.913)	(−53.005)	(−2.824)	
South Carolina	0.000269***	0.232254***	−0.02285***	−2.293814***	−0.011728	0.363
	(2.085)	(18.719)	(−3.996)	(−62.008)	(−1.071)	
South Dakota	0.000380***	0.27626***	−0.022086***	−2.142516***	−0.027359**	0.297
	(2.632)	(19.925)	(−3.455)	(−51.827)	(−2.235)	
Tennessee	0.000392***	0.254542***	−0.042396***	−2.568678***	0.007190*	0.490
	(3.520)	(23.811)	(−8.602)	(−80.593)	(0.762)	
Texas	0.000344***	0.5750***	0.04321***	−2.444***	−0.02485***	0.615
	(3.532)	(61.453)	(10.016)	(−87.599)	(−3.008)	
Utah	0.000289**	0.288524***	−0.015375***	−2.709457***	0.005274	0.423
	(2.141)	(22.250)	(−2.572)	(−70.081)	(0.461)	
Vermont	0.000908***	0.172231***	−0.011086	−1.766960***	−0.003733	0.072
	(3.397)	(6.715)	(−0.937)	(−23.106)	(−0.165)	
Virginia	0.000398***	0.247740***	−0.034989***	−2.235498***	−0.013602	0.477
	(3.952)	(25.611)	(−7.845)	(−77.512)	(−1.593)	
Washington	0.000875***	0.102841***	−0.020420***	−2.926445***	0.001714	0.351
	(5.405)	(6.616)	(−2.849)	(−63.140)	(0.125)	
West Virginia	0.000300*	0.261538***	−0.015831**	−2.380090***	−0.013207	0.288
	(1.869)	(16.983)	(−2.230)	(−51.838)	(−0.971)	
Wisconsin	0.000459***	0.278873***	−0.034202***	−2.657712***	0.011255	0.521
	(4.231)	(26.768)	(−7.121)	(−85.563)	(1.224)	
Wyoming	−0.0000730	0.4227***	0.1007***	−1.402***	0.01552	0.035
	(−0.170)	(10.286)	(5.313)	(−11.439)	(0.428)	

Note: This table presents the coefficient estimates of the impact of disentangled oil price shocks on stock returns of individual states in the framework of the multifactor linear regression model given in Eq. (26). d_t and s_t are oil demand and supply shocks, respectively, $\zeta_{Vix,t}$ represents risk shocks relied on the CBOE volatility VIX index and $r_{SP500,t}$ is the SP500 return. This table presents the estimates of Eq. (26). Significance levels are denoted by ***, **, and * for 1 %, 5 %, and 10 %, respectively.

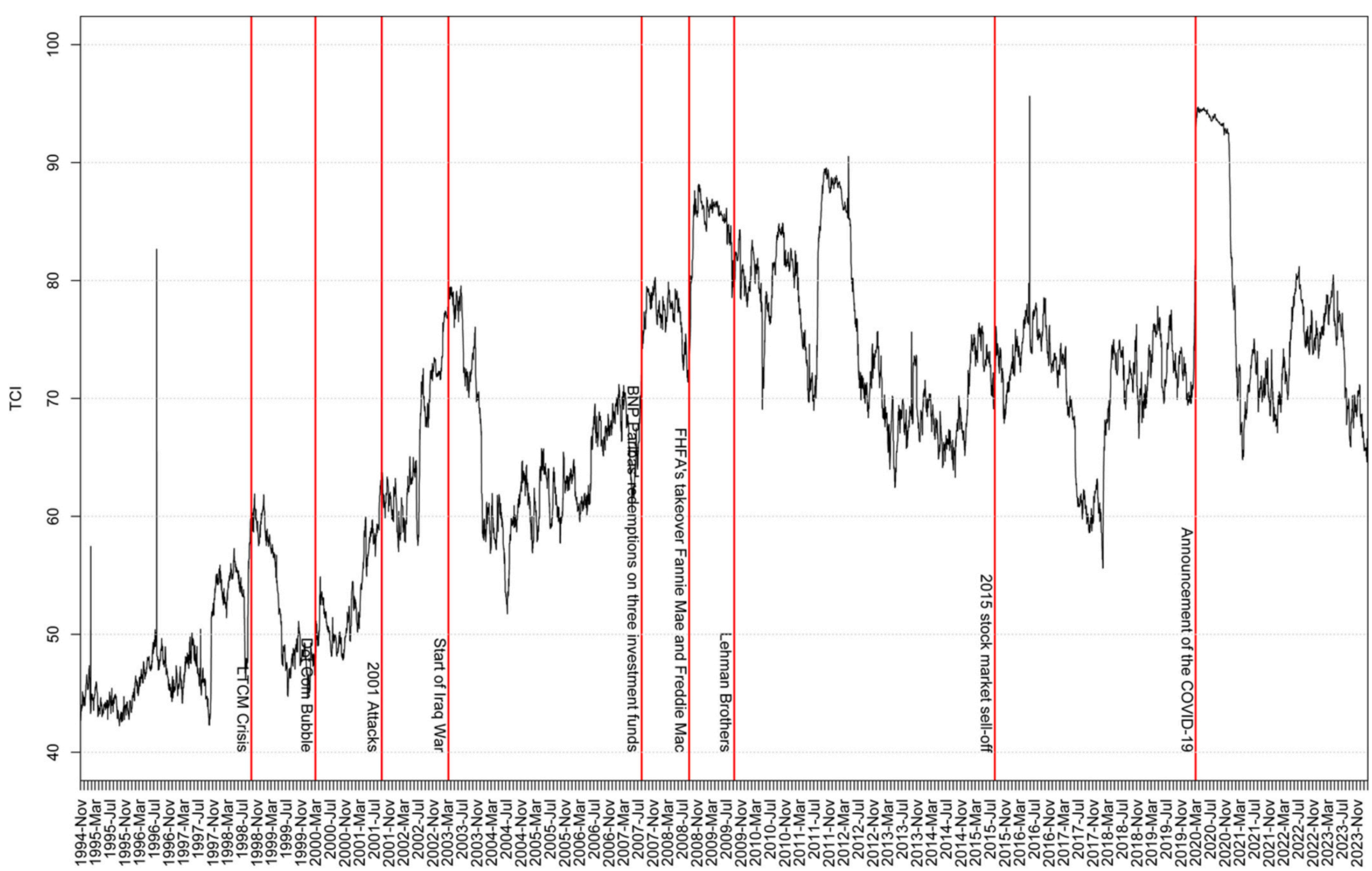

Fig. 1. DY Connectedness US States Stock Returns.
Note: This figure presents the total spillover of the system with window length (200) and forecast horizon (H = 10) trading days. Optimal lag is selected to be 1 by the Schwarz Information Criterion (SIC).

4.2. Connectedness among stock returns

Next, we compute the DY, overall, contemporaneous, and lagged connectedness among of US states stock returns and illustrate them alongside significant events in Figs. 1, 2, respectively.

Overall and contemporaneous TCIs exhibit similar patterns in line with Balli et al. (2023). Additionally, we observe that contemporaneous connectedness surpasses that of their lagged counterparts. TCIs notably elevate around financial/geopolitical stress incidents (LTCM-Long Term Capital Management crisis in September 9, 1998, Dot-Com bubble in March 10, 2002, the 9/11 attacks on September 11, 2001, the start of Iraq war on March 19, 2003, BNP Paribas' redemptions on three investment funds on August 9, 2007, FHFA's takeover Fannie Mae and Freddie Mac on September 6, 2008, Lehman Brothers' collapse on September 15, 2008, the 2015 stock market sell-off on August 18, 2015, and the proclamation of the pandemic on March 11, 2020).

Examining dynamic net total connectedness of returns, we depict them in Fig. 2.

The net connectedness findings illustrated in Fig. 3 reveal significant spillovers of stock returns occurring around notable incidents of the episode. Among the states, Alaska, Arkansas, Maine, Montana, Nebraska, New Mexico, Kansas, Rhode Island, Vermont, and Wyoming primarily receive shocks, while the remaining states mainly act as transmitters. Notably, Alaska, Vermont, and Wyoming consistently experience significant spillovers from other states, indicating a shared trend.

4.3. Oil price shocks and stocks connectedness

We analyze the impact of daily oil price shocks (demand/supply) on the overall connectedness of the stock returns, controlling for the Aruoba-Diebold-Scotti (Aruoba et al., 2009) business conditions index (ADSBCI),[2] and a common metric of unconventional and conventional monetary policies, via the shadow short rate (SSR) developed by Krippner (2013, 2015) based on a two-factor term-structure model of interest rates,[3] in the following multifactor linear model:

$$TCI_t = \alpha_{0,i} + \alpha_{d,i}d_t + \alpha_{s,i}s_t + \alpha_{VIX,i}\zeta_{VIX.t} + \alpha_{SSR,i}SSR_t + \alpha_{ADSBCI,i}ADSBCI_t + u_t \tag{27}$$

where TCI_t is TCI (DY TCI and overall, contemporaneous, and lagged TCI) for period t, d_t, s_t, $\zeta_{Vix.t}$ are oil supply, demand, and risk shocks, respectively. *SSR* and *ADSBCI* are included in the model to control monetary policy shocks and real business conditions, respectively.

Table 2 presents the estimated coefficients for Eq. (27), by controlling monetary policy (*SSR*), real business cycles (*ADSBCI*) shocks, with t-statistics provided in parentheses.

In summary, except for the lagged TCI, risk shocks are observed to exert a substantial positive impact on the interconnectedness of stocks. This indicates that oil price surges triggered by heightened risk attitude leading increased interconnectedness among stocks. This trend might arise from heightened uncertainty in financial markets, growing risk aversion, fostering a more synchronized trading attitude across stocks, which in turn leads to amplified interlinkages among stocks (Demirer et al., 2018: Naeem et al., 2020; Youssef et al., 2021; Hussain and Rehman, 2023).

Moreover, a common trend emerges where business cycle shocks negatively affect interconnectedness, while their influence on the DY TCI is considered negligible. It's crucial to emphasize that the ADSBCI mirrors real business conditions in the US, and any decline in these conditions signifies a tightening of equity return interconnections, as supported by abound studies (Gong et al., 2019; Youssef et al., 2021; Costa et al., 2022; Naeem et al., 2023). Similarly, monetary policy shocks demonstrate a significant adverse effect on both overall and contemporaneous interconnectedness. However, their influence turns positive for lagged counterparts, although their impact on the DY TCI remains insignificant.

Upon further examination of the results outlined in Table 2, it is evident that oil supply shocks exert a pronounced detrimental effect on equity market interconnectedness, sharing a common characteristic. This discovery suggests that when oil prices rise due to supply-driven shocks, there is a tendency for the level of interconnectedness among the relevant stock markets to decrease. Conversely, the effects of demand-driven shocks on the connectedness emerge as insignificant in the regression models.

4.4. The effect of monthly oil shocks on connectedness

Table 3 provides the estimated coefficients for Eq. (23), including the TCIs for US states stocks, shocks related to oil supply (*s*), consumption demand (*cd*), inventory demand (*id*) and economic activity (*ea*), with t-statistics provided in parentheses.

Examining the estimates outlined in Table 3, it is evident that the monthly oil supply shock exerts a notable and favourable influence on overall interconnectedness, except for the lagged TCI. This finding aligns with the research conducted by Naeem et al. (2020) and suggests that a positive oil supply shock relates to an upsurge in global oil prices. It is important to highlight that such a positive supply shock triggers an escalation in product prices, ultimately leading to inflationary pressures that may unsettle the stock market, consequently fostering heightened interconnectedness.

We proceed our analysis by estimating the results pertaining to municipal bonds in the US States.

4.5. The effect of oil specific shocks on US States' municipal bond returns

Table 4 shows the results for Eq. (28), implemented to the returns of municipal bonds in US states, with t-statistics reported in parentheses.

$$R_{i,t} = \beta_{0,i} + \beta_{d,i}d_t + \beta_{s,i}s_t + \beta_{VIX,i}\zeta_{VIX.t} + \beta_{SP500,i}r_{BUSMBI,t} + \nu_t \tag{28}$$

where $R_{i,t}$ is the bond return in US state *i* for period *t* and d_t, s_t, and $\zeta_{Vix.t}$ are demand, supply and risk shocks, respectively. Bloomberg U.S. Municipal Bond Index returns, $r_{BUSMBI,t}$ are control variables.

Findings in Table 4 reveal that the Bloomberg U.S. Municipal Bond Index exerts a positive and significant effect on US states municipal bonds. We note that fluctuations in oil demand and supply predominantly influence bond returns in the United States, particularly in states 26 and 27 out of 50, with a significant and favourable effect, albeit less statistically significant compared to stock returns. Conversely, the VIX has a negative impact on bond returns, with significance observed only in 22 states. It is interesting to note that, while the state-level heterogeneity on the response of stock market returns could be easily explained by the oil-importing or oil-exporting status of each of the states, this is not the case for the bond market returns.

4.6. Connectedness among bond returns

Subsequently, we compute the DY, overall, contemporaneous, and lagged connectedness among US municipal bond returns. We present these findings, alongside significant events, in Figs. 4, and 5, respectively.

The overall and contemporaneous connectedness measures exhibit similar trends, aligning with findings by Balli et al. (2023), indicating that immediate relationships among bond returns drive the market's general connectedness. Throughout the period, contemporaneous connectedness consistently exceeds lagged connectedness, reflecting the

[2] The data can be accessed at: https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/ads.

[3] The data can be downloaded from: https://www.ljkmfa.com/visitors/.

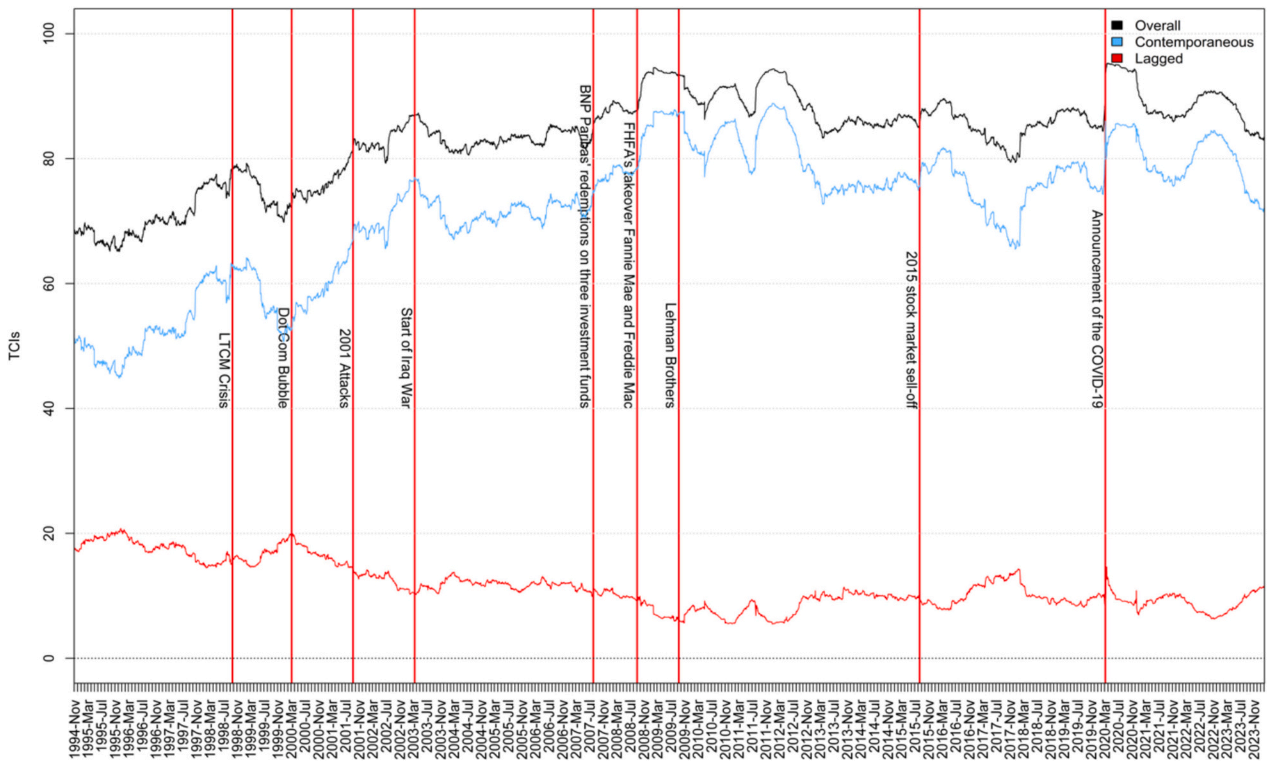

Fig. 2. Overall contemporaneous, and lagged connectedness of US States Stock Returns.
Note: The estimations are based on a 200 window length and forecast horizon equal to 10. Optimal lag is selected to be 1 by the SIC. The black lines represent net total directional connectedness, while net contemporaneous and net lagged directional connectedness are shown in blue and red, respectively.

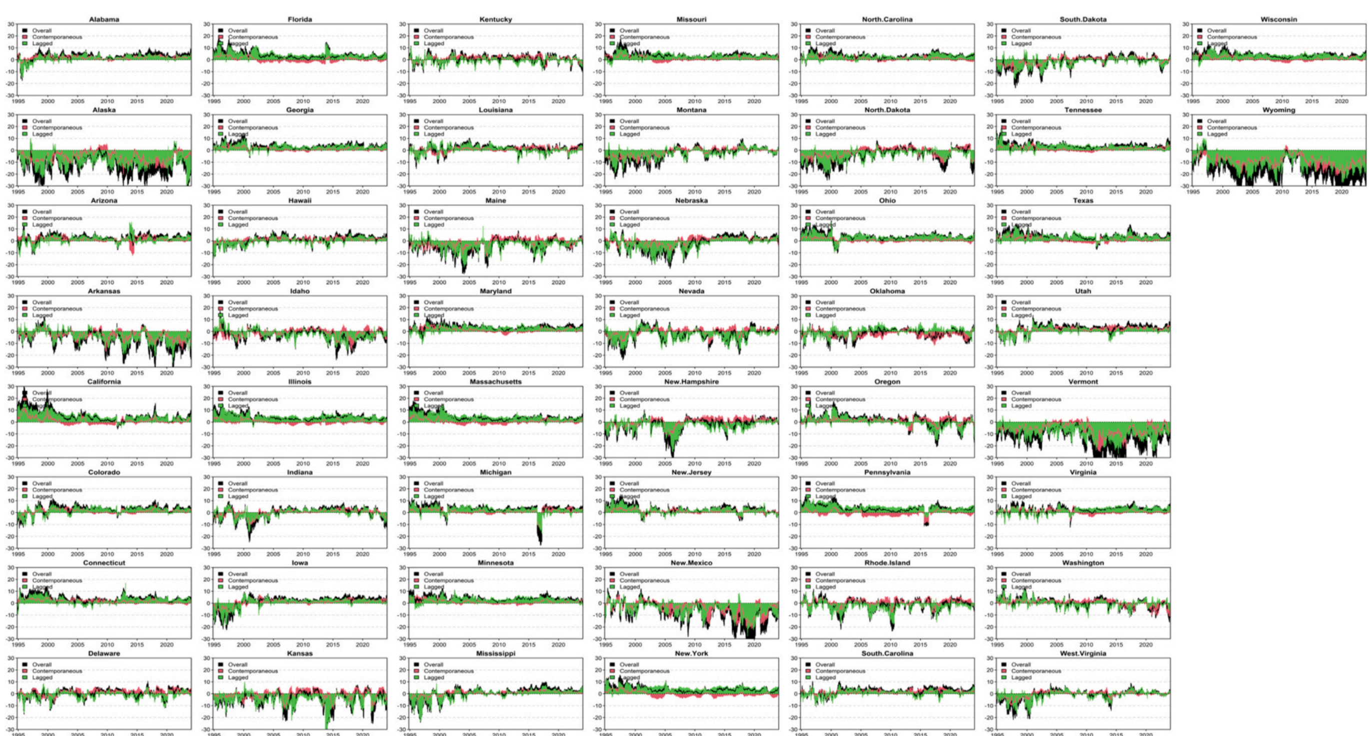

Fig. 3. Net Total Connectedness for US Stocks.
Note: The black shades represent net overall directional connectedness, while net contemporaneous and net lagged directional connectedness are represented in red and green, respectively.

Table 2
Effects of oil shocks on US states stocks connectedness.

Constant	d_t	s_t	$\zeta_{VIX,t}$	SSR_t	$ADSBCI_t$	**Adj. R^2**
Panel A: DY TCI						
0.00001458	0.0007923	−0.00243	0.0683***			0.00538
(0.393)	(0.224)	(−1.477)	(6.418)			
0.00003084	−0.000148	−0.002021	0.07689***	0.000939		0.00743
(1.106)	(−0.052)	(−1.502)	(8.919)	(0.710)		
0.00002850	−0.0001576	−0.002011	0.07687***	0.001021	−0.00001347	0.00748
(1.017)	(−0.055)	(−1.495)	(8.917)	(0.770)	(−0.857)	
Panel B: Overall TCI						
0.00002415	0.0005271	−0.00185*	0.083680***			0.0210
(1.056)	(0.241)	(−1.818)	(12.721)			
0.0000555***	−0.0000919	−0.002196**	0.090780***	−0.003942***		0.0294
(3.064)	(−0.049)	(−2.513)	(16.212)	(−4.585)		
0.0000468***	−0.0001269	−0.002161**	0.090710***	−0.003640***	−0.000049***	0.0314
(2.579)	(−0.068)	(−1.495)	(16.216)	(−4.227)	(−4.853)	
Panel C: Contemporaneous TCI						
0.0000416	0.00387	−0.000880	0.1447***			0.02038
(1.050)	(1.019)	(−0.499)	(12.673)			
0.0000877***	0.00171	−0.001207	0.15410***	−0.00562***		0.02662
(2.796)	(0.530)	(−0.798)	(15.89)	(−3.780)		
0.0000820***	0.001687	−0.001184	0.15400***	−0.005429***	−0.000032***	0.02684
(2.605)	(0.523)	(−0.783)	(15.887)	(−3.638)	(−1.831)	
Panel D: Lagged TCI						
−0.0000452	−0.01168	-0.008956	-0.3959***			0.01296
(−0.331)	(0.241)	(−1.474)	(−10.078)			
−0.0000672	−0.003358	-0.008928*	-0.3851***	0.008564***		0.0127
(−0.609)	(−0.049)	(−1.677)	(−11.287)	(1.635)		
−0.0001077	-0.0035227	-0.008761*	−0.385406***	0.009984*	−0.000233***	0.01391
(−0.972)	(−0.311)	(−1.646)	(−11.304)	(1.903)	(−3.747)	

Note: The presented table showcases coefficient estimates, along with their corresponding t-statistics in parentheses, derived from the regression model outlined in Eq. (27). This model aims to elucidate the impact of various oil price shocks on the total connectedness observed across stocks throughout the entire sample period. The assessment employs the overall return spillover index formulated by Diebold and Yilmaz (2012) and Balli et al. (2023) as a metric for evaluating the interconnectedness among markets. Within the model, d_t,s_t, $\delta_{vix,t}$ denote oil demand, supply, and risk shocks, respectively. $\vartheta_{SSR,t}$, and $\mu_{ADSBCI,t}$ represent monetary policy shock and real business cycle, respectively. Significance levels are denoted by ***, **, and * for 1 %, 5 %, and 10 %, respectively.

Table 3
Effects of monthly oil price shocks on US states stocks connectedness.

Constant	s_t	cd_t	id_t	ea_t
Panel A: DY TCI				
-0.0000085	0.0000051	0.0000014	0.0000029	−0.0000273
(−0.840)	(0.382)	(0.113)	(1.015)	(−2.808)
Panel B: Overall TCI				
0.000276**	0.00020**	0.000106	-0.000027	−0.000055
(2.478)	(1.969)	(−3.138)	(−0.977)	(−0.571)
Panel C: Contemporaneous TCI				
0.0004029**	0.0004078**	0.0001525	0.00000681	−0.00002816
(1.967)	(2.048)	(1.073)	(0.140)	(−0.160)
Panel D: Lagged TCI				
−0.0003282	−0.0006297	−0.0002298	−0.0002162	−0.0006291
(−0.683)	(−1.161)	(−0.417)	(−1.526)	(−1.186)

Note: This table presents coefficient estimates, along with their corresponding t-statistics in parentheses, derived from the regression model outlined in Eq. (23). This model aims to elucidate the impact of disentangled oil price shocks on the total connectedness for stocks. The assessment employs the overall return spillover index formulated by Diebold and Yilmaz (2012) and Balli et al. (2023) as a metric for evaluating the interconnectedness among markets. In this model, cd_t, s_t, $id_t$and ea_t denote oil supply, consumption demand, inventory demand and economic activity shocks, respectively. Significance levels are denoted by ***, **, and * for 1 %, 5 %, and 10 %, respectively.

stronger impact of immediate market interactions. Notably, significant spikes in both overall and contemporaneous connectedness are observed during periods of financial and economic stress, such as BNP Paribas' redemption freeze in August 2007, the FHFA's takeover of Fannie Mae and Freddie Mac in 2008:9, Lehman Brothers' collapse in September 2008, and the COVID-19 pandemic announcement in 2020:3. These spikes suggest that the U.S. municipal bond market becomes more interconnected during crises, reflecting heightened systemic risk and synchronized market reactions to shared information or conditions.

The net connectedness findings illustrated in Fig. 6 reveal notable spillovers of municipal bond returns across different states. Among the states, Alaska, Hawaii, Idaho, Iowa, Kansas, Mississippi, New Hampshire, New Mexico, North Dakota, South Dakota, Vermont, and Wyoming primarily receive shocks, indicating that these states are more influenced by external factors. In contrast, states like California, Florida, Illinois, Kentucky, Louisiana, New Jersey, and Texas primarily act as transmitters of shocks, suggesting that their municipal bond markets are more influential in the broader network.

Notably, states such as Vermont, Wyoming, and Montana consistently experience significant spillovers from other states, indicating that their bond markets are particularly sensitive to external economic or financial conditions. This pattern suggests that the municipal bond markets in these states are more vulnerable to systemic risks, possibly due to their smaller market sizes or less diversified economic bases. On the other hand, more economically robust or diversified states like California and Texas appear to be key drivers of market movements, impacting other states through their economic and financial activities.

Table 4
Effects of oil price shocks on US municipal bond returns.

State	Constant	d_t	s_t	$\zeta_{VIX,t}$	$r_{BUSMBI,t}$	Adj. R^2
Alabama	0.000020**	0.001127*	−0.000340	−0.001091	0.903791***	0.938
	(2.771291)	(1.731352)	(−1.0565)	(−0.60824)	(260.0377)	
Alaska	0.000003	0.001137*	0.000840***	−0.001242	0.855711***	0.935
	(0.468913)	(1.797146)	(2.683767)	(−0.71251)	(253.2273)	
Arizona	0.000001	0.001360***	0.000283	−0.000922	0.994987***	0.971
	(0.115358)	(2.811176)	(1.183211)	(−0.69173)	(385.158)	
Arkansas	0.000003	−0.000309	0.000959**	−0.000780	0.883701***	0.876
	(0.330292)	(−0.33108)	(2.074988)	(−0.30301)	(177.1894)	
California	−0.000036***	−0.002425***	0.000234	0.001793	1.310521***	0.964
	(−4.65481)	(−3.42215)	(0.666981)	(0.918219)	(346.3361)	
Colorado	0.000006	0.00000036	−0.000178	−0.004237***	1.046786***	0.963
	(0.989943)	(0.000639)	(−0.62602)	(−2.66994)	(340.3304)	
Connecticut	0.000016***	0.000683	−0.000301	0.002276	0.805938***	0.948
	(2.747257)	(1.291077)	(−1.15177)	(1.561791)	(285.2949)	
Delaware	0.000007	0.001747**	−0.001044***	−0.010952***	0.834044***	0.908
	(0.820661)	(2.34917)	(−2.83757)	(−5.34662)	(210.0561)	
Florida	−0.000001	−0.000624***	0.000674***	−0.003867***	1.025410***	0.979
	(−0.30696)	(−1.50879)	(3.29388)	(−3.39349)	(464.2693)	
Georgia	0.000001***	0.001517**	−0.000513***	−0.004990***	0.932384***	0.962
	(0.193672)	(2.945231)	(−2.01376)	(−3.51656)	(339.0198)	
Hawaii	0.000013	0.000551**	−0.000365	0.003252**	0.856027***	0.951
	(2.217311)	(1.01568)	(−1.35974)	(2.174318)	(295.3266)	
Idaho	0.000009	−0.001546**	0.001004	−0.004394	0.994973***	0.883
	(0.772119)	(−1.52167)	(1.997897)	(−1.56965)	(183.3727)	
Illinois	0.000011***	0.003003***	−0.001187***	0.011888***	1.072241***	0.934
	(1.191094)	(3.747823)	(−2.99398)	(5.38453)	(250.5564)	
Indiana	0.000015**	0.000520	0.000742***	0.005677***	0.957583***	0.960
	(2.406233)	(0.944427)	(2.726639)	(3.743895)	(325.8235)	
Iowa	−0.000016	0.001097	0.000195	−0.000237	0.952603***	0.738
	(−0.91609)	(0.687628)	(0.24667)	(−0.05383)	(111.7815)	
Kansas	0.000020***	−0.000963	0.000002	0.013598***	0.889422***	0.932
	(2.630991)	(−1.42728)	(0.006361)	(7.318538)	(246.9624)	
Kentucky	0.000018*	−0.001843**	0.000905**	−0.009427***	0.928548***	0.911
	(1.956858)	(−2.26381)	(2.248296)	(−4.20385)	(213.622)	
Louisiana	0.000019*	0.001472*	0.001036**	−0.001015	0.970460***	0.904
	(1.947859)	(1.657084)	(2.358815)	(−0.41469)	(204.5998)	
Maine	0.000018	−0.000524*	−0.000790*	−0.007040***	0.896968***	0.881
	(1.756528)	(−0.565)	(−1.72231)	(−2.75511)	(181.1137)	
Maryland	0.000001	0.000947	−0.000347*	−0.000737	0.880871***	0.973
	(0.284701)	(2.307919)	(−1.70727)	(−0.65119)	(401.8109)	
Massachusetts	−0.000003	−0.000642	−0.000365*	−0.000807	0.993101***	0.977
	(−0.532)	(−1.49878)	(−1.72487)	(−0.68366)	(434.3321)	
Michigan	0.000010*	0.000288	−0.000581**	0.000382	0.945300***	0.957
	(1.679035)	(0.511172)	(−2.08277)	(0.245941)	(313.8351)	
Minnesota	0.000008	0.000173	−0.000638**	0.002301	0.874877***	0.959
	(1.398435)	(0.339198)	(−2.5334)	(1.63939)	(321.581)	
Mississippi	0.000020***	0.000820	−0.000110	0.002710	0.868667***	0.923
	(2.624861)	(1.160655)	(−0.31417)	(1.391875)	(230.2204)	
Missouri	−0.000003	−0.001845***	−0.000685**	0.000906	1.028466***	0.963
	(−0.47955)	(−3.27913)	(−2.46193)	(0.584435)	(342.297)	
Montana	0.000004	−0.003110	0.000147	0.011964**	1.065082***	0.703
	(0.18925)	(−1.59452)	(0.152538)	(2.226141)	(102.2459)	
Nevada	0.000006	0.000079	−0.000972***	0.002135	0.916463***	0.946
	(0.839574)	(0.128744)	(−3.18485)	(1.256273)	(278.2397)	
New Hampshire	−0.000033	0.006282***	−0.004493***	−0.011536**	1.161901***	0.751
	(−1.60539)	(3.330115)	(−4.81447)	(−2.21942)	(115.3278)	
New Jersey	0.000012	−0.004122***	0.001661***	−0.002090	1.032136***	0.900
	(1.128864)	(−4.27653)	(3.483173)	(−0.78694)	(200.4848)	
New Mexico	0.000026***	−0.000090	−0.000265	0.000280	0.696646***	0.921
	(4.072485)	(−0.15742)	(−0.93601)	(0.177916)	(228.0608)	
New York	−0.000044***	−0.002379***	0.000241	0.002291	1.317776***	0.969
	(−6.06008)	(−3.58503)	(0.734631)	(1.252777)	(371.8226)	
North Carolina	0.000002	−0.001228***	0.00000004	0.002926***	0.900286***	0.975
	(0.405636)	(−3.07012)	(0.000223)	(2.654356)	(421.3043)	
North Dakota	0.000010	0.005581***	−0.004289***	−0.012867***	0.954014***	0.721
	(0.523596)	(3.333293)	(−5.17811)	(−2.78893)	(106.6838)	
Ohio	−0.000006	0.000489	−0.000046	−0.001324	0.980000***	0.950
	(−0.83076)	(0.776129)	(−0.14712)	(−0.76322)	(291.4619)	
Oklahoma	0.000012	−0.000230	−0.000466	−0.008982***	0.913975***	0.930
	(1.565863)	(−0.32604)	(−1.33528)	(−4.61938)	(242.5145)	
Oregon	0.000005	−0.000546	−0.000318	0.003359**	0.986087***	0.971
	(0.917739)	(−1.14933)	(−1.3505)	(2.564743)	(388.4381)	
Pennsylvania	0.000013***	0.000257	−0.000309	−0.000731	0.964193***	0.978
	(2.948397)	(0.641063)	(−1.55725)	(−0.66144)	(450.3038)	

(continued on next page)

Table 4 (*continued*)

State	Constant	d_t	s_t	$\zeta_{VIX,t}$	$r_{BUSMBI,t}$	Adj. R^2
Rhode Island	−0.000008	−0.000529***	0.001849	−0.000579	0.929325***	0.801
	(−0.58485)	(−0.40728)	(2.874642)	(−0.16165)	(133.8558)	
South Carolina	0.000013*	−0.002852***	0.000628*	0.001646	0.939582***	0.929
	(1.662482)	(−3.89941)	(1.735785)	(0.816849)	(240.536)	
South Dakota	0.000016	0.002941	−0.000733	−0.006653	1.037063***	0.711
	(0.796348)	(1.582981)	(−0.79773)	(−1.29949)	(104.5064)	
Tennessee	0.000013	0.002873***	−0.001311***	−0.008736***	0.871456***	0.906
	(1.467084)	(3.654691)	(−3.37049)	(−4.03276)	(207.5362)	
Texas	0.000002	−0.000809**	0.000037	0.001126	1.015020***	0.985
	(0.551642)	(−2.3174)	(0.211437)	(1.170683)	(544.4431)	
Utah	0.000008	−0.001050	−0.000946***	0.001088	0.881337***	0.936
	(1.131131)	(−1.62044)	(−2.95304)	(0.609281)	(254.7515)	
Vermont	−0.000005	−0.001358	0.000285	0.003973	1.111963***	0.801
	(−0.29989)	(−0.8699)	(0.369359)	(0.923317)	(133.3333)	
Virginia	−0.000002	0.001630***	0.000251	−0.003797***	0.938362***	0.976
	(−0.33304)	(3.984227)	(1.237604)	(−3.3683)	(429.5158)	
Washington	0.000008*	0.000266	0.000079	0.004217***	0.929973***	0.977
	(1.745112)	(0.667239)	(0.403225)	(3.845312)	(437.471)	
West Virginia	0.000012	0.001871	−0.000292**	−0.006967***	0.996096***	0.891
	(1.069521)	(1.914202)	(−0.60348)	(−2.58741)	(190.8497)	
Wisconsin	0.000016**	−0.001326**	0.000944***	0.005000***	0.861246***	0.944
	(2.414944)	(−2.25626)	(3.246019)	(3.086811)	(274.3355)	
Wyoming	−0.000047	−0.002571	0.009572***	−0.030787***	1.275572***	0.525
	(−1.259)	(−0.756)	(5.692)	(−3.287)	(70.258)	

Note: This table presents coefficient estimates, along with their corresponding t-statistics in parentheses, derived from the regression model outlined in Eq. (23). This model aims to elucidate the impact of disentangled oil price shocks on the total connectedness for stocks. The assessment employs the overall return spillover index formulated by Diebold and Yilmaz (2012) and Balli et al. (2023) as a metric for evaluating the interconnectedness among markets. In this model, cd_t, s_t, $id_t$and ea_t denote oil supply, consumption demand, inventory demand and economic activity shocks, respectively. This table presents the estimates of Eq. (28). Significance levels are denoted by ***, **, and * for 1 %, 5 %, and 10 %, respectively.

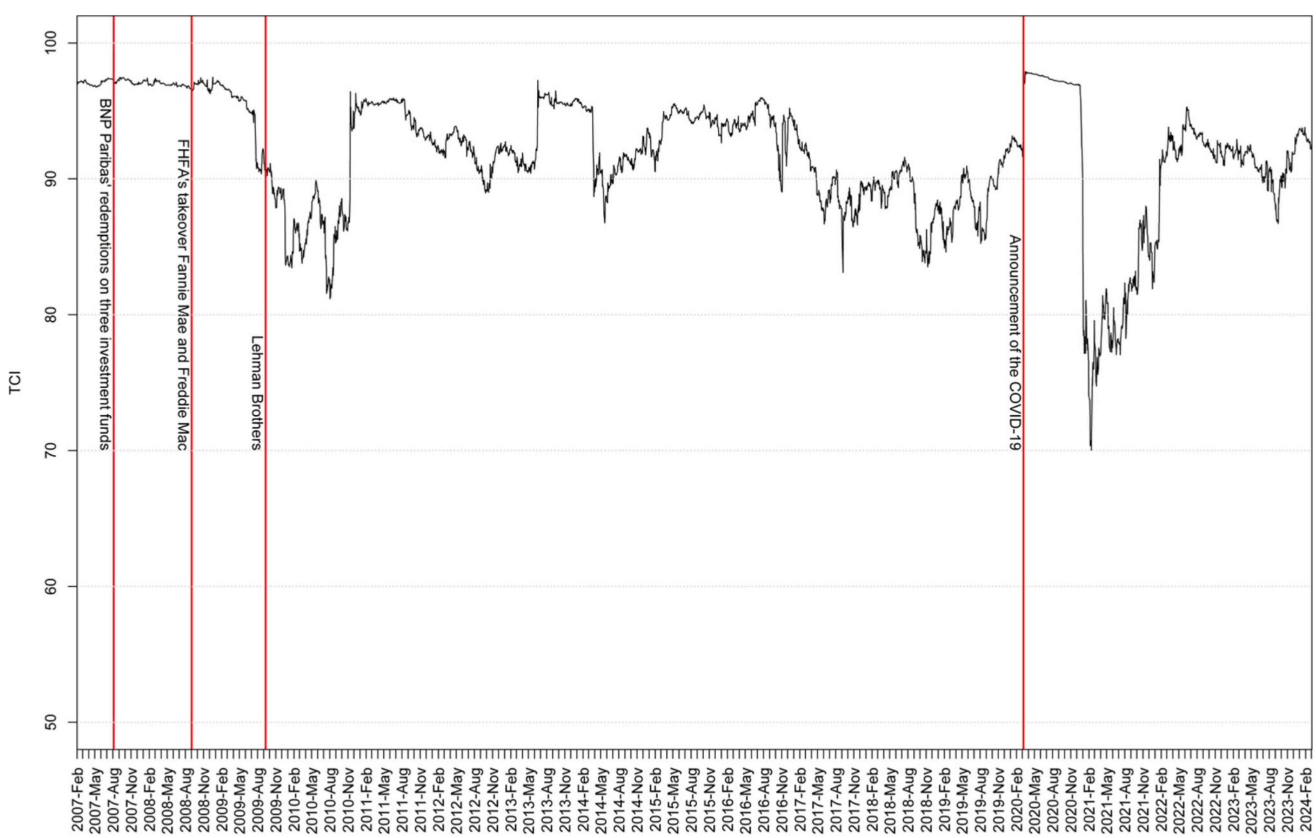

Fig. 4. DY Connectedness US Municipal Bond Returns.
Note: This figure presents the total spillover of the system with window length (200) and forecast horizon (H = 10) trading days. Optimal lag is selected to be 1 by the SIC.

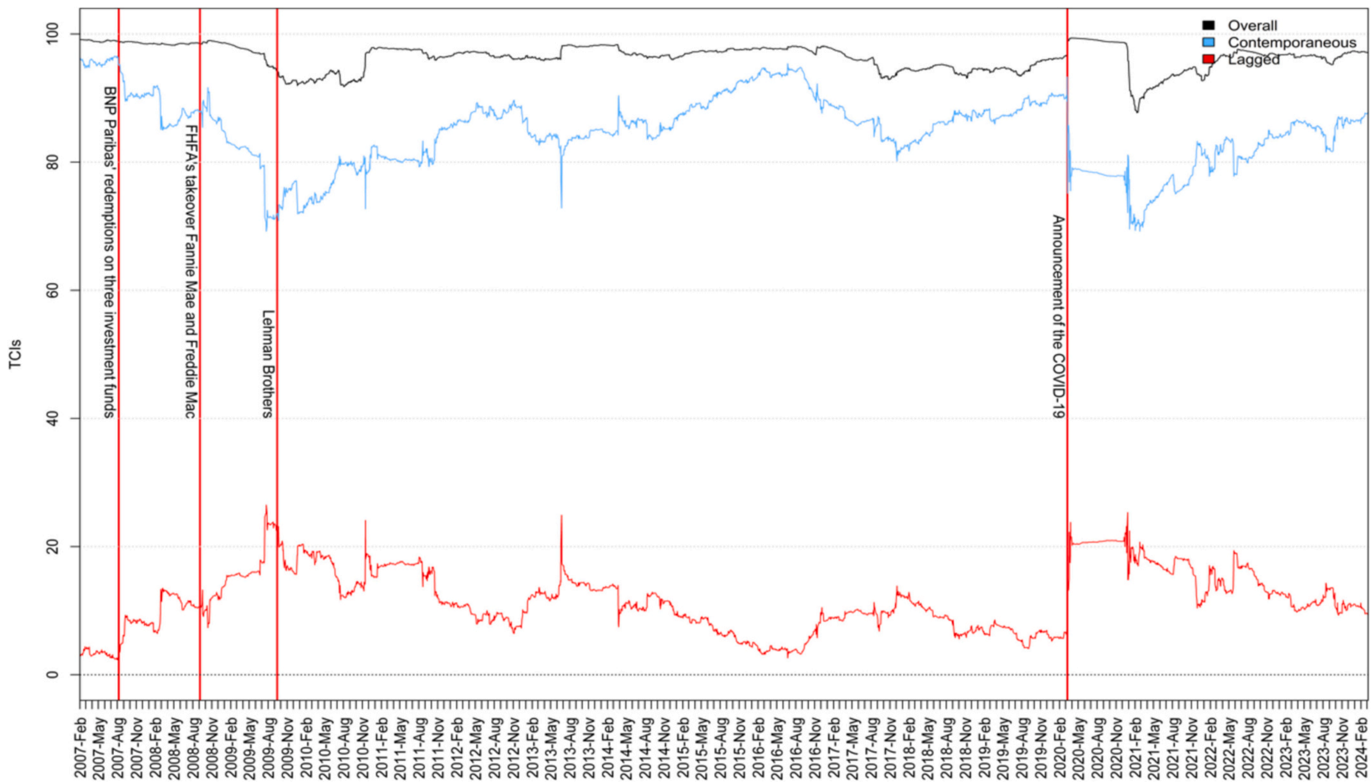

Fig. 5. Overall contemporaneous, and lagged connectedness of US Municipal Bond Returns.
Note: The estimations are based on a 200 window length and 10 forecast horizon. Optimal lag is selected 1 by the SIC The black lines represent net total directional connectedness, while net contemporaneous and net lagged directional connectedness are shown in blue and red, respectively. Optimal lag is selected to be 1 by the SIC.

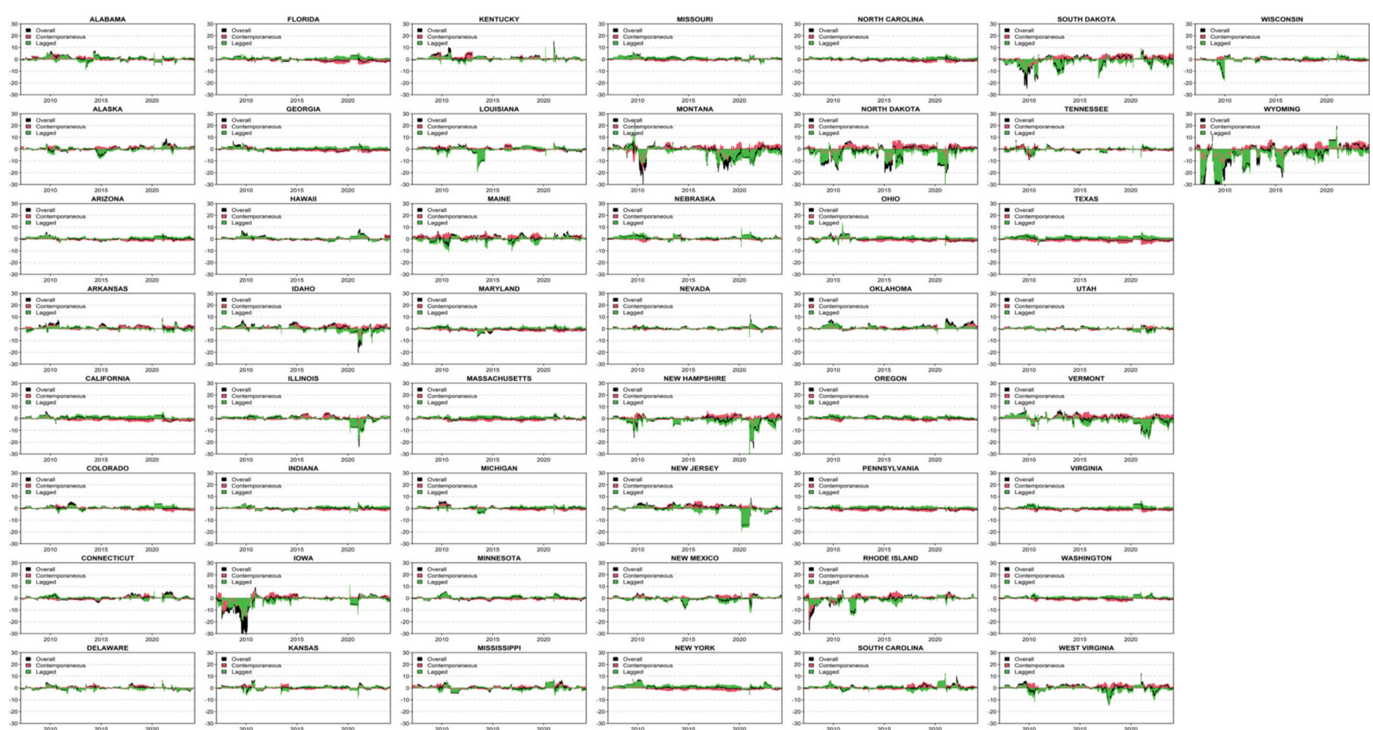

Fig. 6. Net Total Connectedness for the US Municipal Bonds.
Note: The black shades represent net overall directional connectedness, while net contemporaneous and net lagged directional connectedness are represented in red and green, respectively.

Table 5
: Effects of Oil Price Shocks on Bonds Connectedness.

Constant	d_t	s_t	$\zeta_{VIX,t}$	SSR_t	$ADSBCI_t$	Adj. R^2
Panel A: DY TCI						
−0.00000037	−0.0000249	−0.0002711*	0.003025***			0.00270
(−0.102)	(−0.075)	(−1.652)	(3.316)			
−0.0000054*	−0.0001891	-0.0002109	0.002805***	0.0002518*		0.00217
(−1.825)	(−0.648)	(−1.441)	(3.482)	(1.786)		
−0.0000057*	-0.0001917	-0.0002093	0.002805***	0.0002601*	−0.00000098	0.00210
(−1.911)	(−0.617)	(−1.430)	(1.839)	(−0.014)	(−0.747)	
Panel B: Overall TCI						
−0.0000048	−0.002672*	−0.000301	0.0063680*			0.00107
(−0.318)	(−1.953)	(−0.446)	(1.694)			
−0.0000145	−0.003035**	0.0000031	0.0065340**	0.002051		0.00261
(−1.185)	(−2.543)	(−0.446)	(1.984)	(3.560)		
-0.0000190	-0.0030750***	0.0000263	0.006538**	0.002175***	−0.0000148***	0.00366
(−1.541)	(−2.577)	(0.044)	(1.986)	(3.766)	(−2.745)	
Panel C: Contemporaneous TCI						
−0.000018	0.02166**	0.00688	-0.1813***			0.0149
(−0.185)	(2.438)	(1.567)	(−7.431)			
0.000022	0.01877**	0.006382*	−0.1288***	0.008034**		0.0101
(0.290)	(2.492)	(1.691)	(−6.199)	(2.210)		
0.000025	0.018790**	0.00637*	-0.1288***	0.007971**	0.0000074***	0.0099
(0.316)	(2.494)	(1.687)	(−6.199)	(2.186)	(0.219)	
Panel D: Lagged TCI						
0.0002462	−0.2170918	−0.052367*	1.2384921***			0.0201
(−0.331)	(−3.887)	(−1.898)	(8.075)			
−0.0002523	−0.2014747***	−0.047061**	-0.92905***	-0.0534970***		0.0158
(−0.527)	(−4.316)	(−2.012)	(7.213)	(−2.374)		
−0.0003405	-0.2022436***	-0.04660**	0.9291344***	-0.0510712**	−0.0002885	0.0159
(−0.706)	(−4.332)	(−1.992)	(7.214)	(−2.260)	(−1.371)	

Note: The presented table showcases coefficient estimates, along with their corresponding t-statistics in parentheses, derived from the regression model outlined in Eq. (27). This model aims to elucidate the impact of various oil price shocks on the total connectedness observed across bonds throughout the entire sample period. The assessment employs the overall return spillover index formulated by Diebold and Yilmaz (2012) and Balli et al. (2023) as a metric for evaluating the interconnectedness among markets. Within the model, d_t,s_t, $\delta_{vix,t}$ denote oil demand, supply, and risk shocks, respectively. $\vartheta_{SSR,t}$, and $\mu_{ADSBCI,t}$ represent monetary policy shock and real business cycle, respectively. Significance levels are denoted by ***, **, and * for 1 %, 5 %, and 10 %, respectively.

4.7. Oil price shocks and bonds connectedness

Table 5 displays the estimated coefficients for Eq. (27), incorporating bonds connectedness, while controlling for monetary policy (SSR) and shocks from real business cycles (ADSBCI), with t-statistics included in parentheses.

Upon scrutinizing the results presented in Table 5, we observe that risk shocks stemming from oil prices exert a notable and positive impact on TCI across most panels (excluding lagged TCI). This implies that during periods of heightened risk aversion in the market, there is a discernible amplification in the interconnection of bonds as oil prices surge. This phenomenon may be attributed to escalated uncertainty prompting synchronized trading activities, thereby fortifying the interconnectedness among bonds. Moreover, our findings also highlight the negative influence of real business cycle shocks (ADSBCI) on bond connectedness, with a negligible effect on the DY TCI. This finding resonates with previous studies indicating that deteriorating economic conditions, as manifested by a decline in ADSBCI, foster stronger connections among bond returns. Likewise, monetary policy shocks exhibit a negative influence on both overall and contemporaneous TCI, possibly indicative of a constricting effect on financial markets. However, their influence turns positive for lagged TCI, indicating a nuanced relationship that merits deeper exploration.

4.8. The effect of monthly oil shocks on bond connectedness

Table 6 presents the estimated coefficients for Eq. (23), encompassing TCIs for US municipal bonds along with shocks associated with oil

Table 6
Impact of monthly oil price shocks on US municipal bonds connectedness.

Constant	s_t	cd_t	id_t	ea_t
Panel A: DY TCI				
-0.0000085	0.0000051	0.0000029	-0.0000273***	0.0000014
(−0.840)	(0.382)	(1.015)	(−2.808)	(0.113)
Panel B: Overall TCI				
−0.0000932*	0.0000273	-0.0000049	-0.0000685**	-0.0000672*
(−1.928)	(0.747)	(−0.379)	(−2.503)	(−1.660)
Panel C: Contemporaneous TCI				
0.000057	-0.0000372	0.0000207	0.000384***	-0.000080
(0.244)	(−0.235)	(0.384)	(2.652)	(−0.404)
Panel D: Lagged TCI				
-0.0004883	0.0009982	-0.0003621	-0.0042637***	0.0006475
(−0.263)	(0.675)	(−0.785)	(−3.440)	(0.415)

Note: This table presents coefficient estimates, along with their corresponding t-statistics in parentheses, derived from the regression model outlined in Eq. (23). This model aims to elucidate the impact of disentangled oil price shocks on the total connectedness for US municipal bonds. The assessment employs the overall return spillover index formulated by Diebold and Yilmaz (2012) and Balli et al. (2023) as a metric for evaluating the interconnectedness among markets. In this model, cd_t, s_t, $id_t$and ea_t denote oil supply, consumption demand, inventory demand and economic activity shocks, respectively. Significance levels are denoted by ***, **, and * for 1 %, 5 %, and 10 %, respectively.

supply, consumption demand, inventory demand, and economic activity, with t-statistics given in parentheses:

Upon examining the estimates presented in Table 6, we determine that the monthly oil inventory demand shock significantly impacts overall interconnectedness, except for contemporaneous TCI. This observation implies that a positive shock in oil inventory demand relates with a decline in global oil prices. It is crucial to note that such a positive shock in oil inventory demand precipitates a decrease in product prices, consequently generating deflationary pressures that could unsettle the US municipal bond market, thereby contributing to decreased interconnectedness.

5. Conclusions

This paper examines the effects of oil price shocks on stock and bond returns at the state level in the US, utilizing daily data from February 1994 to March 2024. It achieves this by separating oil price shocks into components of oil supply, oil demand, and shocks stemming from financial market-related risks, following the methodology proposed by Ready (2018). Following the literature, we assume that oil supply and demand shocks could be attributable to the shortfalls in oil production and to the expansion of the world economy, while oil risk shocks are linked to an unstable financial market environment. Our preliminary results suggest that, after adjusting for stock market returns, oil supply shocks have a negative impact on stock returns in the majority of states, particularly in those that rely on oil imports. This observation aligns with conclusions drawn in prior research (Ewing et al., 2018; Demirer et al., 2020). On the contrary, oil demand shocks have a positive and significant effect on stock returns, especially in energy-exporting states (i.e., Texas), which is again in line with the previous literature (Basher et al., 2018; Demirer et al., 2020; Castro et al., 2023). Although US state-level bond returns also respond to these supply and demand shocks, their response is statistically less significant compared to stock returns, in line with Kang et al. (2014). These results seem to suggest that cross-asset diversification is possible during periods of oil supply and demand shocks since stock and bond returns are not equally affected by these oil price movements. However, these diversification opportunities disappear when oil price movements are driven by oil risk shocks, as both U.S. state-level stock and bond returns are significantly and negatively impacted across all states, regardless of whether they are oil-importing or oil-producing. Overall, our results highlight the importance of disentangling oil price shocks into their three components.

The paper also analyzes the degree of connection among both the US stock returns and the US bond returns over time, using different measures of connectedness (Ghysels et al., 2006; Diebold and Yilmaz, 2012, 2014; Balli et al., 2023). These estimations show that financial connectedness have increased around financial or geopolitical stress incidents, as the LTCM crisis in 1998, the Dot.com bubble in 2002, the GFC in 2008 or the COVID-19 pandemic in 2020. Furthermore, the paper investigates the distinct effects of oil supply, oil demand, and oil risk components on US stock returns connectedness. We find a positive and significant impact of oil risk shocks on connectedness. This suggests that an increase in oil prices leads to heightened interlinkages among US stock returns, thereby reducing diversification opportunities. However, this positive impact is not found when oil price movements are driven by oil supply or demand components. As before, our results highlight the importance of disentangling the supply, demand and risk component of oil price movements to better understand their impact on stock and bond markets. When a reverse-MIDAS model is estimated to relate high-frequency connectedness measures on monthly oil price shocks, the results show that oil supply shocks exert a positive and significant impact on stock connectedness, while oil inventory demand shocks negatively impact bond connectedness.

Our analysis highlights that oil-exporting states, such as Texas, Oklahoma, and North Dakota, tend to benefit from positive oil demand shocks, as higher oil prices increase the revenue and profitability of their energy sectors, leading to positive stock market reactions. Conversely, oil-importing states like California, New York, and Illinois experience negative impacts from oil supply shocks, which increase production costs for businesses and reduce consumer spending power, thereby adversely affecting their stock market performance. This heterogeneity is further influenced by the industrial composition of each state, where states heavily reliant on energy production are more sensitive to oil price increases, while states with more diversified economies or those heavily dependent on energy imports are more vulnerable to supply disruptions.

The results of this study carry important implications for policy, affecting both market participants and policymakers. For market participants, especially investors and portfolio managers, the results suggest that municipal bonds could serve as a viable hedging instrument during periods of oil price increases, depending on the nature of the oil price shock. For example, bonds tend to provide better diversification benefits when oil price surges are driven by supply and demand factors rather than by risk factors. However, when oil price movements are driven by risk shocks, the potential for diversification diminishes, highlighting the importance of a nuanced approach to portfolio management that considers the underlying drivers of oil price fluctuations.

For policymakers, the study underscores the need for robust risk management frameworks that can alleviate the negative effects of oil risk shocks on both equity and bond markets. This is particularly relevant for state and local governments, which may rely on municipal bonds for financing public projects. Understanding the dynamics between oil price shocks and municipal bond returns can help in formulating policies that stabilize local economies and ensure the smooth functioning of capital markets. Additionally, policymakers should consider the interconnectedness of financial markets when crafting regulations, as heightened connectedness during periods of financial stress can amplify systemic risks.

For academic researchers, this paper contributes to the academic literature in several ways. First, it adds a regional perspective to the literature on financial market connectedness. Furthermore, it highlights the importance of disentangling oil price shocks into their three components. From a methodological point of view, the paper demonstrates the value of applying advanced econometric techniques, such as the Diebold-Yilmaz connectedness framework and the R^2 Decomposed Connectedness approach, to better understand the spillover effects of oil price shocks on financial markets. These methodologies provide a nuanced view of how contemporaneous and lagged effects influence market dynamics, offering a more comprehensive understanding of both immediate and delayed market reactions. Additionally, the use of the reverse-MIDAS model showcases the benefit of incorporating high-frequency data to link oil price movements with financial market responses more accurately. This methodological contribution paves the way for future research to refine these approaches and apply them to other asset classes or geographic regions, further enhancing our understanding of market behavior in response to external shocks.

While this study offers important insights into the effects of oil price shocks on U.S. state-level stock and bond markets, several limitations must be considered. First, data constraints, particularly for smaller or less economically active states, may affect the precision of the bond market analysis. Additionally, the methodologies used, including the decomposition of oil price shocks, rely on structural assumptions that may not fully capture the complexities of the oil market or its interactions with other macroeconomic variables, potentially introducing bias. Finally, the generalizability of the findings is limited to U.S. markets, and the results may not directly apply to other countries or regions with different economic structures and energy dependencies. Future research should address these limitations by exploring alternative data sources, refining the econometric models, and extending the analysis to other markets and regions.

This study provides several future research directions. One potential area of exploration is the impact of oil price shocks on the connectedness of other financial markets, such as corporate bonds or real estate. It could also be extended to commodity markets. Additionally, further research could examine the effects of oil price shocks on the interconnectedness of financial markets over various time scales, exploring how short-term versus long-term impacts differ. Another important avenue of research would be to evaluate the long-term effects of oil price shocks on economic growth, fiscal stability or labour market variables, with a particular focus on the interaction between stock and bond markets. We include Table A.1 in the Appendix, which outlines potential areas for future research, including concrete research questions and suggested methodologies. One specific avenue we propose is to analyze the correlation between state-level stock and bond returns in response to oil price shocks, leveraging both the Generalized Autoregressive Score (GAS) model and the Dynamic Conditional Correlation (DCC-GARCH) model to capture the dynamic relationships between these asset classes. Additionally, future studies could investigate the daily correlations of bond and stock returns with daily shocks, utilizing data from various sources such as Känzig (2021), Degasperi (2023), and Ready (2018). We suggest applying inverse MIDAS monthly shocks from Känzig (2021) and Degasperi (2023), along with monthly shocks identified by Baumeister and Hamilton (2019), to enrich the analysis. By presenting preliminary results using aggregate US S&P 500 returns and 10-year Government Bond returns data and various types of oil shocks in a single table, we aim to highlight the correlation between state stock and bond returns and their responsiveness to oil price shocks, paving the way for more nuanced future research in this area. Understanding these dynamics could help investors and policymakers improve risk management strategies and enhance economic resilience, especially since the relationship, when significant, is negative between oil shocks and correlations.

CRediT authorship contribution statement

Onur Polat: Writing – original draft, Software, Methodology, Formal analysis. **Juncal Cunado:** Writing – review & editing, Writing – original draft, Supervision, Project administration. **Oguzhan Cepni:** Writing – review & editing, Software, Methodology, Formal analysis, Data curation. **Rangan Gupta:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Appendix A. Daily oil price shocks

The oil price model of Ready (2018) can be represented as follows:

$$W_t = BX_t \tag{A1}$$

where $W_t = \left[\Delta oil_t, R_t^{Prod}, \xi_{VIX,t}\right]'$ is a 3×1 vector, Δoil_t- oil price change in period t, R_t^{Prod} global stock index return of oil producing firms, and $\zeta_{VIX,t}$ represents innovation to the VIX, based on an ARMA(1,1) specification. Our focus is $X_t = [s_t, d_t, v_t]'$. Finally, B is a 3×3 matrix of coefficients defined as:

$$B = \begin{bmatrix} 1 & 1 & 1 \\ 0 & b_{22} & b_{23} \\ 0 & 0 & b_{33} \end{bmatrix} \tag{A2}$$

Ready (2018) imposes the following condition to achieve orthogonality among the three types of shocks:

$$B^{-1}\Sigma_W\left(B^{-1}\right)^T = \begin{bmatrix} \sigma_s^2 & 0 & 0 \\ 0 & \sigma_d^2 & 0 \\ 0 & 0 & \sigma_v^2 \end{bmatrix} \tag{A3}$$

where Σ_W is the covariance matrix of the variables in W_t, while σ_s^2, σ_d^2 and σ_v^2 are the variance of the supply, demand and risk shocks, respectively. The specification in Eq. (A3) reflects a re-normalization of the orthogonalization implemented to create structural shocks in a structural VAR.

Table A.1
Results on Correlation between Aggregate US Stock and Bond Returns in Response to Oil Shocks.

Panel A: DCC-GARCH Correlations					
Daily OSSS (Känzig, 2021)	**Constant**	**Correlation**	**Daily OSSS (Känzig, 2021)**	**Constant**	**Correlation**
Front	−0.016168***	0.016729*	7-M	−0.016206***	0.013945
	(−4.524)	(1.784)		(−4.534)	(1.121)
1-M	−0.016181***	0.015527	8-M	−0.016209***	0.013964
	(−4.527)	(1.512)		(−4.535)	(1.099)
2-M	−0.016188***	0.014430	9-M	−0.016211***	0.013944
	(−4.529)	(1.348)		(−4.536)	(1.076)
3-M	−0.016194***	0.014598	10-M	−0.016211***	0.013556
	(−4.531)	(1.314)		(−4.536)	(1.029)
4-M	−0.016199***	0.014746	11-M	−0.016196***	0.007525
	(−4.532)	(1.285)		(−4.531)	(0.482)
5-M	−0.016201***	0.014450	12-M	−0.016195***	0.004841
	(−4.533)	(1.221)		(−4.531)	(0.302)
6-M	−0.016203***	0.013833	PC	−0.016220***	0.013434
	(−4.533)	(1.140)		(−4.538)	(1.087)
Daily OSNS based on the S&P 500 Movements (Degasperi, 2023)	**Constant**	**Correlation**	**Daily Oil Risk, Demand, and Supply Shocks (Ready, 2018)**	**Constant**	**Correlation**

(continued on next page)

Table A.1 (*continued*)

Panel A: DCC-GARCH Correlations					
Daily OSSS (Känzig, 2021)	**Constant**	**Correlation**	**Daily OSSS (Känzig, 2021)**	**Constant**	**Correlation**
S&P 500 Positive	−0.015933*** (−4.404)	0.015741 (0.947)	Oil Risk Shock	−0.088484*** (−23.832)	−2.156936*** (−1.988)
S&P 500 Negative	−0.015915*** (−4.399)	0.010032 (0.531)	Oil Demand Shock	−0.088488*** (−23.828)	0.111419 (0.303)
			Oil Supply Shock	−0.088486*** (−23.829)	−0.173985 (−1.094)
Monthly OSSS and OSSN (Känzig, 2021)	**Constant**	**Correlation**	**Monthly Oil Shocks (Baumeister and Hamilton, 2019)**	**Constant**	**Correlation**
OSSS	−0.018692 (−0.202)	0.009114 (0.998)	**EAS**	−0.01829 (−0.203)	0.03556 (1.386)
OSNS	−0.018686 (−0.200)	−0.007062 (−0.232)	**OIDS**	−0.018807 (−0.201)	−0.001144 (−0.082)
			OCDS	−0.018740 (−0.200)	0.0000971 (0.019)

Panel B: GAS Correlations					
Daily OSSS(Känzig, 2021)	**Constant**	**Correlation**	**Daily OSSS (Känzig, 2021)**	**Constant**	**Correlation**
Front	−0.006993*** (−2.703)	0.002343 (0.345)	7-M	−0.006999*** (−2.705)	0.002572 (0.286)
1-M	−0.006995*** (−2.703)	0.002404 (0.323)	8-M	−0.007000*** (−2.705)	0.002221 (0.273)
2-M	−0.006996*** (−2.704)	0.002296 (0.296)	9-M	−0.007000*** (−2.705)	0.013944 (0.237)
3-M	−0.006997*** (−2.704)	0.002542 (0.316)	10-M	−0.006999*** (−2.705)	0.001773 (0.186)
4-M	−0.006998*** (−2.705)	0.002753 (0.331)	11-M	−0.006996*** (−2.704)	−0.004435 (−0.392)
5-M	−0.006999*** (−2.705)	0.002734 (0.319)	12-M	−0.006996*** (−2.704)	−0.006239 (−0.538)
6-M	−0.006999*** (−2.705)	0.002419 (0.275)	PC	−0.007001*** (−2.706)	0.001791 (0.200)
Daily OSNS based on the S&P 500 Movements (Degasperi, 2023)	**Constant**	**Correlation**	**Daily Oil Risk, Demand, and Supply Shocks (Ready, 2018)**	**Constant**	**Correlation**
S&P 500 Positive	−0.006627*** (−2.532)	−0.003421 (−0.284)	Oil Risk Shock	−0.04750*** (−17.270)	−0.21435*** (−0.266)
S&P 500 Negative	−0.006636*** (−2.535)	0.007059 (0.516)	Oil Demand Shock	−0.04750*** (−17.270)	0.15126 (0.555)
			Oil Supply Shock	−0.04750*** (−17.271)	−0.12048 (−1.022)
Monthly OSSS and OSSN (Känzig, 2021)	**Constant**	**Correlation**	**Monthly Oil Shocks (Baumeister and Hamilton, 2019)**	**Constant**	**Correlation**
OSSS	0.016023 (0.828)	0.004168 (0.607)	**EAS**	0.015584 (0.800)	0.007432 (0.421)
OSNS	0.016024 (0.838)	0.007382 (0.396)	**OIDS**	0.015456 (0.801)	0.003793 (0.433)
			OCDS	0.015335 (0.794)	−0.001507 (−0.541)

Note: OSNS: Oil Supply News Shock; OSSS: Oil Supply Surprise Shock; EAS: Economic Activity Shock; OIDS: Oil Inventory Demand Shock; OCDS: Oil Consumption Demand Shock. The R package "GAS" (Ardia et al., 2019) was used to estimate correlations within a multivariate Generalized Autoregressive Score (GAS) model, and the R package "rmgarch" (Galanos, 2022) was utilized to obtain DCC-GARCH(1,1) correlations. Statistical significance is denoted by *** for 1 %.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.108128.

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