North American Journal of Economics and Finance 68 (2023) 101989

Contents lists available at ScienceDirect

North American Journal of Economics and Finance

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

Oil price shocks and stock–bond correlation

Salem Adel Ziadat [a,b], Abdel Razzaq A. Al Rababa'a [c], Mobeen Rehman [d], David G. McMillan [b,*]

[a] Faculty of Business, Al-Ahliyya Amman University Jordan, Amman, Jordan
[b] Division of Accounting and Finance, University of Stirling, Stirling, UK
[c] Faculty of Economics and Administrative Sciences, Yarmouk University, Irbid, Jordan
[d] Shaheed Zulfikar Ali Bhutto Institute of Science and Technology (SZABIST), Islamabad, Pakistan

ARTICLE INFO

JEL classification:
C22
G12

Keywords:
Stocks
Bonds
Correlation
Oil
Shocks

ABSTRACT

This paper investigates the role of oil as a determinant of the US stock–bond correlation. The analysis uses monthly data over the period from February 1990 to July 2021. We examine the impact of oil shocks, using the Ready (2018) method, alongside a range of macroeconomic variables on the nature of stock–bond dynamic correlation. Our main findings demonstrate that during recessionary periods, the stock–bond correlation is adversely and statistically explained by oil supply shocks, and that correlation tends to statistically diverge from that of it is counterpart during expansionary periods. In addition, demand shocks are more pronounced in periods of pessimistic investor sentiment, whereas supply and risk shocks appear during optimistic periods. From a risk management standpoint, a backtesting exercise shows that the incorporation of supply and demand shocks generally improves the forecast of portfolio volatility under various portfolio weighting schemes and market conditions. A time-varying hedging exercise also reveals that accounting for both demand and supply shocks reduces the cost of hedging, mainly following major crisis periods. The contribution of shocks appears most with a long position in the bond market after the 2014 oil crisis period. Our main results remain the same after performing a set of the robustness checks.

1. Introduction

Crude oil is a key commodity that act as a driving force not only behind macroeconomic trends, consumer sentiment and corporate profitability but also the dynamic behaviour of other financial assets. From the late 1970s, a decline in US oil production is observed, however, innovations and new technologies in extraction methods have resulted in noticeable recent growth in US oil production.[1] This development is significant because an increase in US crude oil production directly enhances US income compared with an increase in a foreign crude oil production (Kang et al., 2016). Moreover, the increase in US oil production and the change from being a net importer to an exporter, may impact the economy and the relation between other assets. In the context of US financial markets, the existing literature dates to the seminal work of Hamilton (1983). According to Cologni and Manera (2008), an unexpected upward oil price shock prompts an increase in inflation and a decline in output growth. Expanding on this, Mohaddes and Pesaran (2017)

* Corresponding author at: Accounting and Finance Division, University of Stirling, FK9 4LA, UK.
E-mail addresses: salemfloyd@gmail.com (S.A. Ziadat), a.rababaa@yu.edu.jo (A.R.A. Al Rababa'a), Mobeenrehman@live.com (M. Rehman), david.mcmillan@stir.ac.uk (D.G. McMillan).

[1] Notably, this refers to the development of shale oil, or fracking, and is discussed by Kilian (2016).

https://doi.org/10.1016/j.najef.2023.101989
Received 6 January 2023; Received in revised form 13 June 2023; Accepted 14 August 2023
Available online 21 August 2023
1062-9408/

highlight that a fall in oil price lowers interest rates and inflation. The substantial fluctuation in oil prices from $150 (2007) to less than $15 (2020) is a clear expression of its volatility that can have consequences for global economic conditions.

Kilian (2009) proposes that a rise in the oil price can be decomposed according to its motivating source. Using a structural vector autoregressive (VAR) model, Kilian (2009) distinguishes between supply side shocks, attributable to the shortfalls in oil production, demand-side shocks, due to expansion of the world economy, and precautionary demand shocks, caused by expectations of future oil supply shortfalls. Oil price shocks have a significant impact on macroeconomic variables, trade and investments. From a theoretical standpoint, Smyth and Narayan (2018) identify multiple channels through which oil influences stocks. First, higher oil prices increase the cost of production therefore, dampening future cash flows and dividends. Second, higher oil prices insinuate higher expected inflation and higher nominal interest rates. This will increase the rate at which future earnings are discounted and reduce the current stock price. Third, heightened oil price volatility will affect the risk premium component of the discount rate, again leading to a lower present value of future earnings. Fourth, in oil-rich countries, oil prices influence government spending, aggregate wealth and demand (Bjørnland, 2009). Likewise, Filippidis et al. (2020) note that many of the same factors can impact upon government bond yields. Notably, this could be manifest in higher oil prices leading to higher consumer prices and resulting in higher inflation expectations, which increases government bond yields. Higher oil prices can dampen economic activity and affect both government spending and budget deficits leading towards higher government bond yields (Filippidis et al., 2020).

The stock–bond nexus is pertinent for portfolio managers. Since bonds provide investors with fixed income, while stocks compensate for higher risks, investing in both asset classes enhances investor ability to diversify risk. According to McMillan (2018), the stock–bond nexus also conveys essential information about the economy where a negative stock–bond return correlation indicates increasing economic and market risk and can predict recessions. However, the role of oil price shocks, as risk indicators, are not explored as potential drivers of the stock–bond correlation.

Based on the above discussion, our work contributes to the existing literature in the following ways. We argue that oil price shocks can be utilised as a measure of risk in the economy and therefore, have the ability to influence stock–bond correlations. Accordingly, we decompose oil price innovations into their constituent shocks following the approach of Ready (2018). These shocks are used to explain US stock–bond correlations, which are obtained using the Asymmetric Dynamic Conditional Correlation (ADCC GARCH) of Cappiello et al. (2006). Therefore, our work covers a gap in establishing the role of oil price shocks on the the interaction between US stock and bond markets. We also examine the impact of shocks according to investor sentiment and the sign of the shock itself. Oil price shocks can alter investor expectations of future cash flows and discount rates, who thereby adjust their positions in stock and bond holdings. Furthermore, given that stocks and bonds are the two most important asset classes, understanding their dynamics conveys important information for asset allocation and risk management (d'Addona & Kind, 2006; Kim, Moshirian, & Wu, 2006). A further contribution is the application of a robust modelling strategy that accounts for market states and investor sentiments. To address potential omitted variable bias, we perform the analysis while controlling for relevant risk measures and macroeconomic variables including Economic Policy Uncertainty (EPU), stock and bond volatility, industrial production, interest rates and inflation.

Our results highlight the importance of decomposing oil shocks into their respective sources as well as identifying market regimes. Our key findings show that oil supply shocks negatively and statistically explain the stock–bond connection during recessionary periods, and that tends to statistically deviate from it is counterpart during expansionary periods. Additionally, during pessimistic investment conditions, demand shocks are positive and significant in the stock–bond correlation equation, while supply shocks are positive amid optimistic regimes. Furthermore, our backtesting exercise confirms the role of both types of shock in improving the one-step ahead portfolio return forecasts. Considering the risk management context, accounting for the effect of demand shocks also notably reduces the probability of VaR (value-at-risk) failure at the 95 % confidence level across market states. Further, of notable importance, a time-varying hedging exercise demonstrates that accounting for both demand and supply shocks reduces hedging costs primarily after the main crisis periods.

Given that the stock–bond correlation provides important insights about future economic conditions (Asgharian and Christiansen, 2016; McMillan, 2018), our results provide policymakers with information about oil-economy links via asset prices and the correlation channel. Furthermore, given spillovers effects from financial markets to the economy and that financial markets crashes can have severe economic consequences (Bernanke & Gertler, 1999), our results provide policymakers with leading indicator information. Indeed, as Hamilton (1983) documents, there is a strong link between oil shocks and economic recessions. Given greater global stock market integration[2] and reduced cross-market diversification,[3] cross-asset diversification becomes more important. This paper presents oil as a factor in stock–bond risk diversification.

The remainder of this paper is organised as follows. Section 2 presents a short literature review, followed by Section 3 which describes the empirical strategy. Section 4 presents the data and the descriptive statistics. Section 5 presents the empirical results. Section 6 reports the results from the additional analyses. Section 7 concerns the robustness checks while Section 8 concludes the paper and describes the implications of the research.

2. Literature review

Few studies among the existing literature examine the determinants of stock and bond comovement. For example, Li (2002) and Ilmanen (2003) highlight the key role of business cycle variables including inflation. Guidolin and Timmermann (2006) discuss the

[2] See Forbes and Rigobon (2002); Kim, Moshirian, and Wu (2005); Longin and Solnik (1995); Morana and Beltratti (2008).

[3] Beine et al. (2010).

importance of the macro-economy in determining correlation regimes. Baele et al. (2010) attribute changes in stock–bond correlations to different levels of liquidity. Aslanidis and Christiansen (2012) elaborate on the importance of stock market uncertainty (VIX) for the stock–bond co-movement (also see Bansal et al., 2010). According to Aslanidis and Christiansen (2012), positive stock–bond correlation is likely to be accompanied by a larger yield spread.

Among a recent strand of literature, Li et al. (2015) and Fang et al. (2017) find that the economic policy uncertainty (EPU) measure exhibits a negative effect on the correlation between stocks and bonds. Gupta et al. (2018) establish a link between the stock–bond correlation and the news-implied volatility index (NVIX) of Manela and Moreira (2017).

While linking oil with stock and bond markets, Kang, Ratti, and Yoon (2014) examine the relation between oil shocks and bond returns and report a negative impact between oil demand shocks and US bond index returns. Christoffersen and Pan (2018) report an increasing role for oil volatility in predicting stock returns and volatility. According to Chiang et al. (2015), because of their common exposure to the macroeconomic fundamentals, the correlation between stock and bond returns is expected to be positive. However, when stock market uncertainty is heightened, the risk premiums of stocks and bonds diverge as investors become increasingly risk-averse. Consequently, bonds become more attractive, and investors reallocate capital from stocks to bonds, creating a flight-to-safety phenomenon (Asgharian et al., 2015; Dimic et al., 2016). In contrast, during booming market conditions, investors become less risk-averse and seek high returns, leading to a flight-from-safety behaviour.[4] Thus, the correlation between stock and bond returns can become negative due to these phenomena. More recently, Alquist et al. (2020) report that financial markets react to oil price fluctuations before being reflected in the real economy. Within the oil-bond nexus, Alquist et al. (2020) show that bond and oil returns exhibited a positive correlation before 2008 but turn negative afterwards. Balcilar et al. (2020) find that oil uncertainty predicts US bond returns and volatility. Similarly, Nazlioglu et al. (2020) show that oil prices tend to predict bond prices in Canada, Mexico, Norway, Russia, Venezuela China, and India. However, the authors provide limited evidence of volatility spillovers from oil to bonds.

Therefore, despite its important economic implications, the question of the influence of oil shocks on stock and bond co-movement remains unaddressed in the existing literature. This study seeks to address this gap in light of the abovementioned studies to examine the impact of oil shocks on stock–bond correlation.

3. Methodology

In order to examine the determinants of the stock–bond correlation, we employ a set of explanatory variables in the following regression:

$$\rho_{ij,t} = \alpha_0 + \Sigma_k \beta_k x_{k,t} + \rho_{ij,t-1} + \varepsilon_t, \tag{1}$$

where $\rho_{ij,t}$ refers to the correlation between assets i and j at time period t, $x_{k,t}$ are the explanatory variables and ε_t is the random error term. We include the lagged correlation ($\rho_{ij,t-1}$) to account for possible serial correlation.

3.1. Asymmetric dynamic conditional correlation model (ADCC)

Following Engle (1982) and Bollerslev (1986), our analysis is based on the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. Correlations obtained using this approach are preferred to traditional correlation coefficients as they account for heteroscedasticity. As noted by Forbes and Rigobon (2002), the presence of heteroscedasticity creates bias in correlations, notably, during high stress periods. We use the Dynamic Conditional Correlation (DCC) GARCH class of models introduced by Engle (2002), which extends the constant conditional correlation (CCC) model of Bollerslev (1990) by allowing for time-variation in conditional correlations. The ADCC-GARCH model developed by Cappiello et al. (2006) further extends the DCC-GARCH model by allowing for asymmetric movement in correlations in response to positive and negative news. The DCC-GARCH models the time-varying correlation between each market pair with the conditional covariance matrix expressed in terms of the following decomposition:

$$\Omega_t = D_t \Gamma_t D_t, \tag{2}$$

Where D_t refers to the diagonal matrix of the conditional standard deviations and Γ_t is the matrix of conditional correlations. To estimate the model, individual GJR-GARCH(1,1) (Glosten et al., 1993) processes are estimated for each series. We implement the GJR-GARCH model to allow for an asymmetric effect within the conditional variance as such:

$$h_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-i}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1}, \tag{3}$$

where $I_t[\cdot]$ is and indicator function which takes the value of one when the lagged shock is negative ($\varepsilon_{t-1} < 0$) and zero for positive shocks. The asymmetry is captured by γ, with negative news having a greater impact on volatility when $\gamma > 0$, i.e., the effect of a negative shock on conditional variance is given by $(\alpha + \gamma)$ and positive shock by α. The standardised residuals (ξ_t) are computed as:

$$\xi_t = D_t^{-1} \varepsilon_t, \tag{4}$$

with the correlations given by:

[4] See Baur and Lucey (2009).

$$\Gamma = \frac{1}{T}\sum_{t=1}^{T}\xi_t\xi_t^{'} \tag{5}$$

Time-variation in the conditional correlation is modelled in a similar manner to the GARCH(1,1) model. Specifically, conditional correlations fluctuate around their constant (unconditional) value as such:

$$Q_t = (1-\alpha-\beta)\Gamma + \alpha\xi_{t-1}\xi_{t-1}^{'} + \beta Q_{t-1}, \tag{6}$$

Where Q is the time-varying correlation matrix. The estimated correlations are standardised, $\rho_{ij,t} = \Gamma_{t,ij} = Q_{t,ij}/\sqrt{Q_{ii}}\sqrt{Q_{jj}}$, to ensure they lie between −1 and 1. This also ensures both a positive definite matrix as well as readily interpretable correlations. Cappiello et al. (2006) introduce the ADCC model to allow for asymmetric effects in the correlation. Thus, equation (6) is extended as:

$$Q_{ij,t} = (1-\alpha-\beta)\Gamma + \alpha(\xi_{i,t-1}\xi_{j,t-1}^{'}) + \beta(Q_{ij,t-1}) + g(\varsigma_{t-1}\varsigma_{t-1}^{'}), \tag{7}$$

where $\varsigma_{it} = I[\overline{\xi}_{it} < 0]o\overline{\xi}_{it}$ the latter being the element-by-element Hadamard product of the residuals if shocks are negative, and $\overline{\zeta}_t =$ 0 otherwise. The term g captures asymmetric periods where both markets experience bad news (negative shocks). This study uses the diagonal version of the ADCC equation model, which is a special case of the Generalized ADCC (AG-DCC) model as the parameter matrices therein are replaced by scalars.[5]

3.2. Ready (2018) oil price decomposition

Ready (2018) introduces a methodology designed to decompose oil price changes into supply, demand and risk shocks. We use an index of oil-producing companies measuring changes in oil prices and expected returns. In order to cover the global oil industry, data for the World Integrated Oil and Gas Producer Index is extracted from DataStream. This index covers data for publicly traded large oil-producing companies like BP, Chevron, Exxon, Petrobras, and so forth, however, it does not include nationalized oil-producing firms like Aramco. Changes in oil prices are measured by taking one-month returns on the second nearest maturity NYMEX Crude-Light Sweet Oil contract. We also use US aggregate stock markets data covering CRSP stocks, while innovations to the VIX index as a proxy for changes in the discount rate. The VIX is calculated from options data and therefore, provides a measure of risk-neutral expectations of volatility.

First, we identify risk shocks by estimating an ARMA(1,1) model for the VIX. The residuals from this process are said to proxy for changes in market discount rates, which are driven by changes in attitudes to risk. Second, we estimate the following regression:

$$R_{t=\alpha+}\ \beta_{VIX}\ \xi_{VIX,t+}\ d_t \tag{8}$$

Where R_t are the returns to an oil producer stock index, $\xi_{VIX,t}$ is the VIX innovation obtained from above and d_t denotes the residual of this model, which is the demand shock. Thus, demand shocks are shocks to the oil producer index that are orthogonal to innovations in the VIX. That is, the returns to oil producers are affected by the level of oil demand and the market discount rate (proxied by VIX innovations). Third, oil supply shocks are the portion of change in oil prices that are orthogonal to both demand shocks and VIX innovations. This is given as:

$$\Delta p_t = \alpha + \beta_d d_t + \beta_{VIX}\xi_{VIX,t} + s_t, \tag{9}$$

Where Δp_t denotes oil price changes, d_t is obtained from equation (8), i.e., the demand shock, and $\xi_{VIX,t}$ is the VIX innovation. The residual from this regression, denoted as s_t, is the supply shock. By construction of equation (9), the demand shock, supply shock and innovation to VIX are normalised and constrained to sum to the total oil price change.

Our baseline equations are given by:

$$\rho_{ij,t} = \alpha_0 + \beta_1 Oilret_t + \beta_2 Oilvol_t + \beta_3 VIX_t + \beta_4 EPU_t + \beta_5 IND_t + \beta_6 Inf_t + \beta_7 Int_t + \beta_8 Bvol_t + \beta_9 Svol_t + \beta_{10}\ \rho_{ij,t-1} + \varepsilon_t, \tag{10}$$

Where *IND*, *Inf*, *Int*, *Bvol* and *Svol* denote the changes in the industrial production, the inflation rate, the interest rates, bond market volatility and stock market volatility respectively. We then expand this, in equation (11), to account for oil price shocks as follows:

$$\rho_{ij,t} = \alpha_0 + \beta_1 Sup_t + \beta_2 Dem_t + \beta_3 Risk_t + \beta_4 EPU_t + \beta_5 IND_t + \beta_6 Inf_t + \beta_7 Int_t + \beta_8 Bvol_t + \beta_9 Svol_t + \beta_{10}\ \rho_{ij,t-1} + \varepsilon_t, \tag{11}$$

Where *Sup, Dem* and *Risk* are the oil supply, demand and risk shocks. In order to estimate the incremental effect of the oil shocks in equation (11), we regress the correlations on the oil supply and demand shocks as the only predictors before running the regression again with all the predictors excluding the oil shocks.[6]

These baseline models are then further extended. We do this to account for non-linearities that correspond to different market states as:

[5] The estimation of the vector of parameters (θ) is carried out using the quasi-maximum likelihood estimation (QMLE) method that is robust to departures from normality of return series under regular conditions (see Bollerslev & Wooldridge, 1992).

[6] However, the resulted results from that analysis are reported in Table 3. These do not surprise us since finding incremental effect of shocks is not of our main concern here while we are interested in providing evidence for predictability in the scenarios coming after in the paper as well as the value at backtesting analysis.

$$\rho_{ijt} = \alpha_0 + \beta_1 rec^*Sup_t + \beta_2(1-rec)^*Sup_t + \beta_3 rec^*Dem_t + \beta_4(1-rec)^*Dem_t + \beta_5 rec^*Risk_t + \beta_6(1-rec)^*Risk_t + \beta_7 EPU_t + \beta_8 IND + \beta_9 Inf + \beta_{10} IR + \beta_{11} Bvol + \beta_{12}\ Svol + \beta_{13} Inf \beta_9(1-rec)^*\rho_{ijt-1} + \beta_{14}\ rec^*\rho_{ij,t-1} + \varepsilon_t \tag{12}$$

Where *rec* and *(1-rec)* are the recession and expansions periods respectively.

4. Data

To calculate the stock–bond correlation, we use S&P 500 and US 10-year bond yield.[7] The sample is from February 1990 to July 2021 on a monthly frequency and is obtained from DataStream. The sample covers important events including the Global Financial Crisis (GFC) of 2008, the oil price crash (2014–2016) and the COVID-19 pandemic. In considering the stock–bond correlation, it is important, for interpretation, to note that we follow Vácha et al. (2019) and use the log difference of bond yields.[8] This should ensure stationary bond data, which is then comparable with stock returns. Recalling that bond prices and yields exhibit an inverse relation, under normal conditions, we might expect a negative correlation in our analysis, while flight-to-safety will lead to a positive correlation. For example, a fall in interest rates, will typically lead to higher stock and bond prices and thus a positive correlation in returns. Where that fall in interest rates signals an oncoming recession, such that investors move from stocks to bonds, a negative correlation in returns will rise. For our stock return-bond yield correlation, the opposite relations will arise (for the same rationale).

As noted above, we include a range of control variables. Following Aslanidis and Christiansen (2012), we include innovations in the VIX.[9] However, instead of using the logarithmic change, we use the residual from an ARMA(1,1) process. To capture market volatility, we follow Chiang et al. (2015) and use a GARCH(1,1) process. We include industrial production growth, inflation (rate of change in CPI) and (short-term) interest rates as proxies for macroeconomic conditions and monetary policy stance, respectively.[10] We also include the Economic Policy Uncertainty (EPU) measure of Baker et al. (2016) in our analysis. Inclusion of EPU is motivated by the findings of Kang and Ratti (2013) who argue that oil price shocks and EPU are interlinked. In estimating the Ready (2018) oil price shocks, we also obtain monthly data on the world integrated oil and gas producer index, which represents the stock prices of global oil producer companies and the second nearest maturity of the NYMEX WTI futures contract.

Fig. 1 plots all the variable and indicates the impact of certain events on the dynamics. These events include the 2008 subprime crisis and the COVID-19 pandemic. Reflecting quantitative easing policies, interest rates display a sharp downward trajectory. Starting from late-1990 s/2000 s, the stock–bond correlation exhibits a noticeable increase compared with the early-1990 s. This pattern supports the earlier findings by Aslanidis and Christiansen (2012) and Chiang et al. (2015). Moreover, sharp changes in the correlation are noted during turbulent financial and economic periods like GFC (2008–09), oil crisis in 2016 and the most recent COVID-19 pandemic.

Table 1 provides summary statistics of all our variables. Of notable interest, the average correlation is marginally positive. For all series, we observe the usual pattern in financial data of a relatively larger standard deviation to mean and non-normality. We also ensure that our data is stationary in order to generate reliable results.

5. Empirical results

5.1. Baseline analysis: Linear regressions

We first consider the baseline linear regression models as described in equations (10) and (11) to examine the impact of oil shocks on the stock–bond correlation. Table 2 presents the results from equation (10), regressing the US stock–bond correlation on oil return and volatility together with the other macroeconomic variables with statistical significance based on Newey and West (1987) t-statistics. While oil returns and volatility have negative coefficients, they are both statistically insignificant. Among the macroeconomic variables, VIX and EPU are also statistically insignificant. This insensitivity of the stock–bond correlation to these variables contradicts the findings of Li et al. (2015) who report a positive impact of EPU on the US stock–bond correlation. It equally contradicts the early results of Connolly et al. (2009) and Skintzi (2019) for the US and Eurozone respectively. Stock and bond volatility are also statistically insignificant.

Industrial production growth and inflation are significant (with interest rates marginally so). Output growth exhibits a negative relation with the stock–bond correlation. This suggest that a decrease in economic activity leads to an increase in the correlation that is consistent with a flight-to-safety effect. This finding is consistent with Asgharian et al. (2016) who document such flight-to-safety

[7] We also used the US 2-year bond yields in our analysis. The results tend to be qualitatively and quantitatively similar.
[8] Their study examined the co-movements between the 10-year bond yields data in the Euro area.
[9] Also see Connolly, Stivers, and Sun (2005); Andersson et al. (2008).
[10] See Yang et al. (2009).

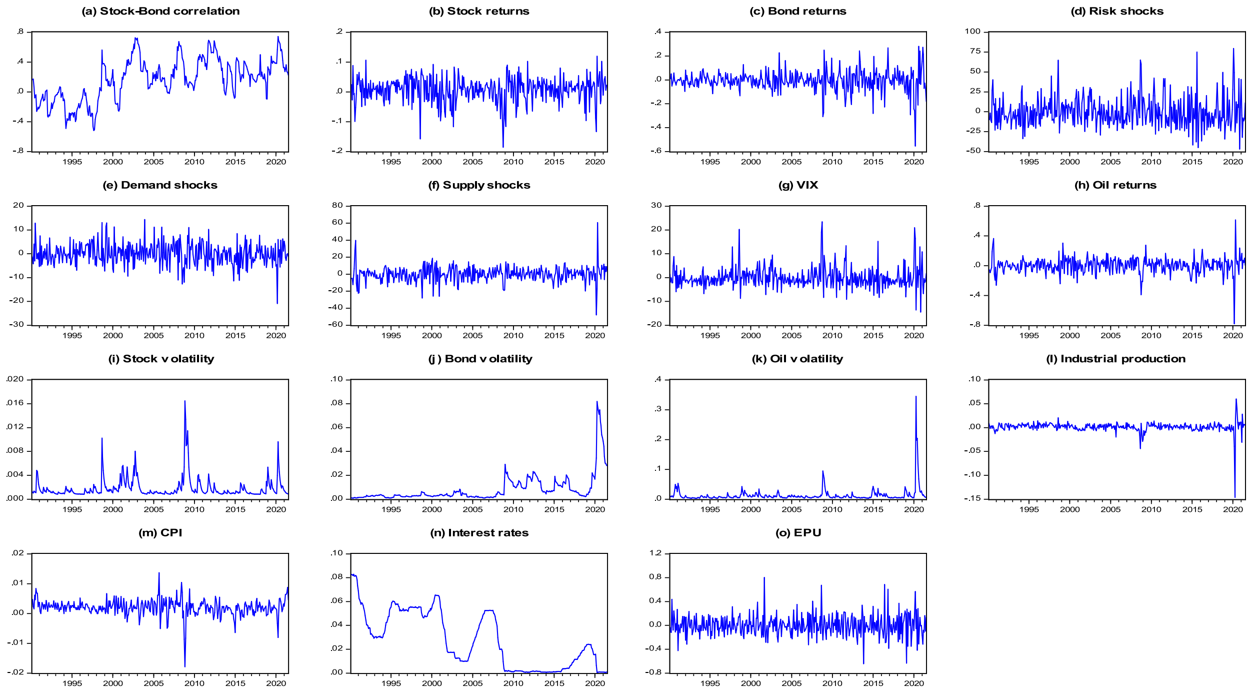


Fig. 1. Plots of the variables.

under weak economic conditions. The positive coefficient on inflation likewise suggests that periods of economic stress lead to an increase in the stock–bond correlation and is consistent with Li (2002) and is similar to that of Perego and Vermeulen (2016). Albeit only marginally significant, the negative coefficient on interest rates supports the view that higher rates lead to lower stock prices. This arises as an increase in interest rates dampens business activities and consumer spending and reduces expected cash flows and reduce company valuations.

The results in Table 2 appear to indicate that the US stock–bond correlation is numb to oil price changes. This may arise either because there is indeed no relation between these variables or that the relation is more nuanced such that the use of broad variables across all types of shock and regimes fail to capture it. The first consideration therefore is to examine the separate oil shocks using the approach of Ready (2018). The results of equation (11) are reported in Table 3. Again, however, we find an insignificant relation between oil shocks and the stock–bond correlation. This contradicts Demirer et al. (2020) who argue that oil shocks are a major driver for the linkages between financial markets. Again, there is a significant relation with output growth, inflation and interest rates, although the changing coefficient sign suggests instability in the relation.

Table 1
Summary Statistics.

Variable	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	PP test	ADF
Stock returns	0.007	0.042	−0.7811	4.765	87.506***	0.000	0.000
Bond returns	−0.005	0.086	−0.7084	8.951	589.406***	0.000	0.000
Stock volatility	0.008	0.012	3.6726	19.094	4929.252***	0.000	0.000
Bond volatility	0.162	0.27	−0.1676	2.390	7.639***	0.052	0.042
ADCC Correlation	0.002	0.002	4.0298	24.319	8181.786***	0.014	0.015
Industrial production	0.001	0.010	−6.4368	93.212	130787.900**	0.000	0.000
Interest rates	0.028	0.024	0.3801	1.853	29.818***	0.017	0.012
Inflation rates	0.002	0.003	−1.3474	13.978	2012.634***	0.000	0.000
EPU	0.001	0.176	0.4556	5.483	110.165***	0.000	0.000
Demand shock	0.000	8.915	0.3486	11.218	1071.225***	0.000	0.000
Supply shock	−0.007	4.369	1.5312	9.043	722.963***	0.000	0.000
VIX	0.000	4.587	−0.0186	4.160	21.207***	0.000	0.000
Risk shock	−0.171	18.554	0.9060	4.837	104.874***	0.000	0.000
Oil returns	0.013	0.025	8.8252	99.801	152489.800***	0.000	0.000
Oil volatility	0.003	0.107	−0.6463	13.310	1700.623***	0.000	0.000

Notes: The first difference is applied to the correlation. Stock return, bond return oil, VIX, and EPU are calculated using the first logarithmic difference. As for stock and bond volatilities, the GJR-GARCH model is applied. Figures below the PP and ADF columns represent the p-values. ***, ** and * denote statistically significant at the 1 %, 5 % and 10 % significance levels respectively.

Table 2
Baseline model: excluding the impact of shocks.

	Stock-bond correlation	
	Coefficient	t-Statistic
C	0.0110	0.7564
Oil Returns	−0.0133	−0.1967
Oil Volatility	−0.1273	−0.3569
VIX	0.0002	0.1552
EPU	0.0041	0.1155
Industrial production	−1.0951	−3.1469***
Inflation rate	4.2249	2.2264**
Interest rate	−0.6040	−1.6858*
Bond volatility	0.2303	0.2788
Stock volatility	0.8258	0.9932
Lagged correlation	0.8957***	32.8074
Adjusted R^2	0.8926	

Notes: ***, ** and * denote statistical significant at 1 %, 5 % and 10 % significant levels respectively.

Table 3
Baseline models: the effects of oil shocks.

	Impacts of oil shocks		Exc. impacts of oil shocks		Shocks and controllers	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Constant	0.0498***	2.7292	0.0103**	1.9957	0.0123	0.9168
Supply shocks	−0.0004	−0.7214			−0.0008	−1.2503
Demand shocks	0.0010	−1.2154			0.0018	1.3548
Risk Shocks			0.0001	0.7878	0.0001	0.3249
EPU			−0.0075	−1.2091	0.0084	0.2295
Industrial production			0.2514***	2.8425	4.3360**	2.1481
Inflation rate			1.3840**	2.2277	−0.9146***	−3.0300
Interest rate			−0.0338	−0.4440	−0.6631**	−2.0031
Bond volatility			−0.0947	−1.6475	0.0764	0.1680
Stock volatility			−2.5719**	−1.8126	0.0765	1.0659
Lagged correlation			0.8957	39.0630	0.8994	32.9596
Adjusted R^2	0.0140		0.8919		0.8940	

Notes: see notes on Table 1.

5.2. *The impact of oil shocks across the market states*

Having not revealed any significant relation between oil shocks and the stock–bond correlation, the second consideration is to examine the relation across market states. An asymmetric relation is motivated by the findings of Clements et al. (2019) and Alquist et al. (2020) who argue that the role of oil shocks in the equity markets has changed after the GFC.[11] This also builds on the recent work of Jiang et al. (2021) who investigate the dependency of oil shocks on stock returns according to credit conditions. Table 4 reports effect of oil shocks on the stock–bond correlation under market conditions represented by the NBER recession and expansion indicators.

In Table 4, we begin to see a pattern of behaviour where oil price shocks do affect the correlation. Notably, both demand and supply shocks as well as EPU are significant during recessionary periods. The impact of shocks in recessions reflects similar results in Antonakakis et al. (2017) and Hwang and Kim (2021). The former notes that supply shocks influence stock returns when economies are facing geopolitical turbulence, while the later finds evidence for state-dependent impact of shocks on stock returns.

Running the regressions with and without control variables (as seen in Table 3), our results illustrate a significant negative supply shock suggesting a fall in stock prices and rising bond yields, perhaps due to an increase in expected inflation. The results confirms the importance of ascribing oil price fluctuations to their underlying causes (see, for example, Kilian, 2014; Baumeister & Kilian, 2016; Gronwald, 2016; Caldara et al., 2019), where an oil price increase due to demand side factors differs from an oil price increase arising from supply side disruptions. The former conveys positive news about the economy (e.g., Kilian, 2009; Cunado et al., 2015; Gbatu et al., 2017) while the latter hints at higher risks facing the economy (Kilian, 2005, 2008). Of note, the adverse impact of oil supply shocks may create inflationary pressure triggering a monetary response. This can be in the form of higher interest rates that impact bonds directly, leaving a stronger, negative, impact on bond prices.

Observing that oil supply shocks are significant in the recessionary regime, lends itself to the important role played by oil in the

[11] Tsai (2015) argue that prior to 2008, US stock returns were negatively affected by oil prices while the post 2008 period demonstrate a positive link.

Table 4
The impact of shocks across the market states.

	Stock-bond correlation	
	Coefficient	t-Statistic
Constant	0.0071***	2.1691
Supply shocks * recession	**−0.0008*** **	**2.7991**
Supply shocks * expansion	0.0001	−0.1496
Demand shocks * recession	**0.0010**	1.6089
Demand shocks * expansion	−0.0001	−0.4739
Risk shocks * recession	−0.0001	−0.3179
Risk shocks * expansion	0.0001	1.3352
EPU	−0.0047	−0.6693
IP	0.2010*	1.7130
Inflation	0.8465	1.6112
Interest rate	0.0318	0.5150
Bond volatility	0.0432***	0.3482
Stock volatility	−2.3005***	−2.8923
Lagged correlation * recession	0.9836	29.6065
Lagged correlation * expansion	0.8862	39.2610
Adjusted R^2	0.8950	

Notes: Figures in bold indicate the statistical rejection in the equality of the predictor's effect across the market states according to the Wald test. ***, ** and * denote statistical significant at 1 %, 5 % and 10 % significant levels respectively.

global economy. This partially mirrors the recent finding of Ziadat et al. (2022) and Naeem et al. (2022) where spillover effects to stock market returns are more significant during the down-market states. Abid et al. (2019) also confirm that a significant increase in contagion between stock markets during periods of market turmoil can be attributed to variations in oil returns. Additionally, our analysis seems to complete the early finding of Kang et al. (2014) that demand shocks negatively impact the US bond returns.

We also report a significant positive effect of EPU on the stock–bond correlation during recessionary periods. This result is consistent with Fang et al. (2017) as well as studies that examine the impact of other uncertainty proxies on correlations (e.g., Connolly et al., 2005; Dimic et al., 2016). This also replicates the result of Chiang et al. (2015) who observe a negative and significant impact of financial market uncertainty on the US stock–bond correlation in the aftermath of the GFC but not before.

The positive effect of bond market uncertainty on the stock–bond correlation might stem from the fact that when the equity risk premium is fairly stable, heightened uncertainty in the bond market affects the expected future discount rates for both stocks and bonds in the same direction. This leads to a positive correlation between returns on outstanding stocks and long-term bonds. A decrease in uncertainty in the bond market is likely to moderate the bond yield, pushing up bond prices. However, the decline in bond yields may not drive-up stock prices because the equity risk premium works in the opposite direction. Bansal et al. (2010), Connolly et al. (2007), Connolly et al. (2005), Aslanidis and Christiansen (2012) and Andersson et al. (2008) highlight the significance of stock market uncertainty (VIX) for the comovements of bonds and stocks. Parallel to that, Fang et al. (2017) and Li et al. (2015) find that Economic Policy Uncertainty (EPU) has a negative influence on stock–bond correlation. The negative impact highlights the asymmetric impact these variables exert on stocks and bonds, pushing them in different directions.

6. Additional analysis

6.1. Examining the role of investor sentiment

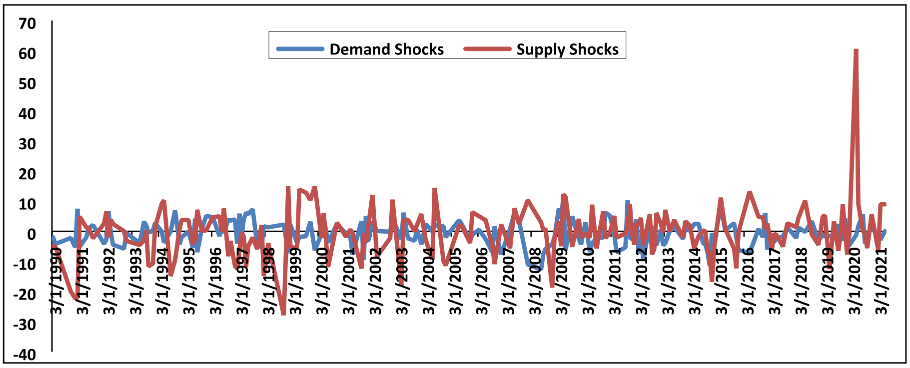
We now consider whether the response of the correlation to shocks depend upon investor sentiment by categorising the data into positive and negative changes. To proxy for sentiment, we follow Baele et al. (2010) and employ the monthly sentiment index of the University of Michigan.[12] Accounting for the effect of investor sentiment is motivated by recent studies (e.g., Qadan & Nama, 2018; Chen et al., 2021, among others) who find that swings in sentiment predict the variations in energy markets.

Fig. 2 plots oil demand and supply shocks under increasing (Panel A) and decreasing (Panel B) sentiment. From Panel A, we can see greater volatility in supply shocks compared to demand shocks. This adds to the recent finding of Shahzad et al. (2017) as it reveals a specific relation between sentiment and oil shocks, although they could not find a clear statistical difference of the impact of sentiment on oil volatility across the market regimes. In Panel B, we can see greater volatility of both shocks during falling sentiment periods.

In Table 5, we observe that during pessimistic states, demand shocks exhibit a positive and statistically significant effect on the stock–bond correlation. In contrast, during optimistic periods, supply and risk shocks have a positive and significant affect on the stock–bond correlation. Thus, with each of these shocks, stock prices and bond yields move in the same direction. EPU also has a significant effect during optimistic periods, while interest rates are significantly negative in both periods. This latter result is similar to

[12] For more details, see Surveys of Consumers (umich.edu). The index is also employed by Lemmon and Portniaguina (2006).

Panel A. the effects throughout the increasing sentiment state



Panel B. the effects throughout the decreasing sentiment state

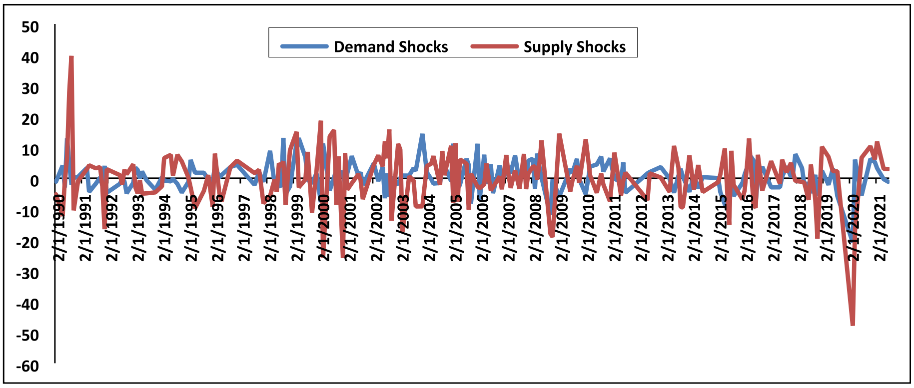


Fig. 2. The impacts of oil shocks across the sentiment states.

Table 5
Impact of shocks across sentiment states.

	Pessimist investors		Optimist investors	
	Coefficient	t-Statistic	Coefficient	t-Statistic
Constant	0.0343	1.5548	0.0413	1.4983
Supply shocks	−0.0007	−0.5053	0.0029***	3.7052
Demand shocks	0.0048**	2.1572	−0.0013	−0.6343
Risk Shocks	−0.0006	−1.1941	0.0011**	2.0303
EPU	0.1015	1.6341	−0.1286*	−1.6679
Industrial production	4.3883	1.0153	3.8583	1.1327
Inflation rate	−1.2145	−2.0947	−0.0224	−0.0174
Interest rate	−1.2955***	−2.3618	−1.1686**	−2.0365
Bond volatility	−0.7266	−0.9180	−0.1573	−0.1765
Stock volatility	0.1477	1.3359	0.8236	0.6937
Lagged correlation	0.8108***	16.4116	0.8035***	15.5079
Adjusted R^2	0.8236	0.8179		

Notes: Pessimist investors represent the case where the changes of the current level of sentiment is negative compared to its previous value. Positive and negative values are then replaced with 1 and 0 dummies. ***, ** and * denote statistical significant at 1 %, 5 % and 10 % significant levels respectively.

that of Gokmenoglu and Hadood (2020). Overall, these results, follow the general finding of Nadal et al. (2017), who also note the impact of oil shocks cross sentiment states, albeit for the oil-stock markets correlation, while more general results are reported by Wang et al. (2022).[13]

6.2. Rolling regression analysis

This results in Tables 4–6 suggest time-variation in the nature of the relation between oil shocks and the stock–bond correlation. In this section, we consider this further by examining rolling regressions. Such variation supports the view that the impact of oil shocks varies across regimes (e.g., Ewing et al., 2018; Qin, 2020; Escobari & Sharma, 2020; Sadeghi & Roudari, 2022). Moreover, fixed-parameter estimation can be misleading and lead to biased coefficients estimates. Therefore, we undertake rolling regression using a window size of 60 months.

Panel A of Fig. 3 present results for rolling-based regression coefficients whereas Panel B presents the associated p values. Examining the results in detail, we observe an increase in the effect of demand and supply shocks during the 2001 dotcom crash. During this period, there is a noticeable decrease from EPU and increase from output growth and interest rates. For the 2008 financial crisis period, we see a fall in the coefficient of supply and risk shocks (albeit with an initial increase), but a rise for demand shocks. Both stock and bond volatility effects are at their highest during this period. During the COVID-19 period, both supply and demand shocks fall, while risk shocks are largely unchanged. The difference in the reaction to oil shocks across the crises periods is consistent with the analysis of Boufateh and Saadaoui (2021) in credit markets. A further point of interest is that the sign of the oil shocks coefficients switches between negative and positive across the sample period.

6.3. Does isolating the impact of shocks reduce the value-at-risk of the portfolio?

As additional analysis, we rely, in this section, on well-documented evidence that oil shocks play a major role in risk management (see, for example, Ouyang et al., 2022, among others). Specifically, we aim to examine whether accounting for oil shocks improves value-at-risk (hereafter, VaR) estimates of the stock–bond portfolio. VaR is a commonly used measurement for risk in portfolios and shows the maximum amount of loss the portfolio can produce at a pre-determined confidence level over a specific time period. Specifically, four VaR estimates are obtained over the full sample period and NBER-based recessions and expansions market states. As a first step in the analysis, the VaR of a portfolio p encompassing one stock and one government bond at the $(1-\alpha)$ confidence level can be calculated as follows:

$$VaR = I_0\phi^{-1}(1-\alpha)\sigma_P \tag{13}$$

Where I_0 is the \$1 portfolio value. $\phi(.)$ is the standard normal cumulative distribution function and σ_P is the standard deviation of the designed portfolio. Additionally, α reflects the 1 % (5 %) risk threshold complying with Basel risk requirements. To measure the variance of the portfolio we apply the following equation:

$$h_p^2 = W_x h_x^2 + W_y h_y^2 + 2\cdot W_x W_y h_{xy}^2 \tag{14}$$

Where W_x and W_y are the weights of the stock and bond investments respectively, h_x^2 and h_y^2 their corresponding estimated variances and $h_{xy_t}^2$ the covariance between their returns. To illustrate the effect of oil shocks in estimating the VaR, we obtain portfolio returns for three scenarios namely 40 % stock/60 % bond, 50 %/50 % and 60 % stock/40 % bond. Additionally, we follow Kroner and Ng (1998) and estimate the dynamic portfolio weights based on the conditional variances from the ADCC-GARCH model such as:

$$W_{x_t} = \frac{h_{y_t}^2 - h_{xy_t}^2}{h_{x_t}^2 - 2h_{xy_t}^2 + h_{y_t}^2} \tag{15}$$

Here, W_{x_t} denotes the weight of stock investment while 1-W_{x_t} is the weight of the bond in the portfolio at time t. The estimated conditional variances in equations (14) and (15) are extracted for stocks and bonds returns using either of following four models in order. First, Model 1 employs a ARMA (1,1) process to model the portfolio returns, together with the EGARCH model of Nelson (1991) to estimate the conditional volatilities. The obtained conditional variances of stock and government bond from that model are then used in equation (14) to yield the conditional variance of the benchmark portfolio h_{p1}^2. Next, Model 2 instead employs the same specification as Model 1 but accounts for the simultaneous impact of supply shocks in both mean and variance parts of the EGARCH model. Estimating this model twice on stock and government bond produce the conditional variance of the first competing portfolio denoted by h_{pSup}^2 Model 3 replaces the supply shocks with demand shocks and provides the third estimate of the portfolio variance h_{pDem}^2. Model 4 includes both supply and demand shocks and generates the comprehensive oil shocks portfolio variance-based estimate of $h_{pS,D}^2$. One-step ahead forecasts are then obtained before calculating the corresponding 1 % and 5 % VaR values of Model 1 (i.e. VaR_{P1}), Model 2 (VaR_{PSup}), Model 3 (VaR_{PDem}) and Model 4 ($VaR_{PS,D}$). For the ease of the mathematical representation, we use the term VaR_{Pj}

[13] However, the documented consistency between the sentiment and EPU-based regressions (Tables 4 and 5) is surprising and seems to be in line with the result of Guo et al. (2022) that the ability of sentiment to drive the market state is very hard to observe under rationality assumption. In our setting, switching between stocks and government bonds assumes rational behaviour.

Table 6
Backtesting results.

Scenario 1: 40 % stocks/ 60 % bonds								
	Full sample period							
	95 %VaR				99 %VaR			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
CC	0.3740	0.2760	0.2874	0.2166	0.0216	0.0216	0.0072	0.0216
POF	6.6138	6.8783	6.0847	6.6138	2.6455	2.6455	2.9101	2.6455
TUFF	0.3740	0.2760	0.2874	0.2166	63	63	92	102
	Recessions							
CC	0.1423	0.1423	0.1423	0.1423	0.4003	0.1442	0.4003	0.4003
POF	11.3333	11.1111	8.3333	8.3333	5.5556	5.5556	5.5556	5.5556
TUFF	16	1	16	16	26	26	26	26
	Expansions							
CC	0.4684	0.4781	0.5920	0.4335	0.0870	0.0870	0.0328	0.0870
POF	6.4327	6.4327	5.8480	6.4327	2.3361	2.3392	2.6316	2.3392
TUFF	4	11	55	11	55	55	84	94
Scenario 2: 50 % stocks/ 50 % bonds								
	Full sample period							
CC	0.1963	0.1895	0.1895	0.1394	0.0072	0.0022	0.0022	0.0072
POF	7.1429	6.8783	6.8783	7.1429	2.9101	3.1746	3.1746	2.9101
TUFF	7	63	63	7	7	92	92	92
	Recessions							
CC	0.2048	0.5290	0.5290	0.2048	0.0165	0.1423	0.1423	0.1423
POF	11.1111	8.3333	8.3333	11.1111	8.3333	5.5556	5.5556	5.5556
TUFF	1	16	16	1	1	26	26	26
	Expansions							
CC	0.3422	0.3532	0.3532	0.3445	0.0870	0.0109	0.0109	0.0328
POF	6.7251	6.7251	6.7251	6.7251	2.3392	2.9240	2.9240	2.6316
TUFF	11	55	55	11	94	84	84	84
Scenario 3: 60 % stocks/40 % bonds								
	Full sample period							
CC	0.2661	0.0837	0.1895	0.0837	0.1387	0.0061	0.1387	0.1387
POF	6.3492	6.8783	6.8783	6.8783	2.5641	2.9101	2.1164	2.1164
TUFF	6	6	6	6	6	6	92	6
	Recessions							
CC	0.1056	0.0062	0.0657	0.0365	0.1423	0.0012	0.6589	0.6788
POF	13.8890	19.4444	13.8889	16.6667	5.5556	11.1111	2.7778	2.7778
TUFF	2	5	15	3	26	2	34	2
	Expansions							
CC	0.8964	0.8964	0.5328	0.5920	0.4025	0.2020	0.2020	0.2020
POF	5.5556	5.5556	6.1404	5.4480	1.7544	2.0468	2.0468	2.0468
TUFF	84	84	84	84	94	94	84	84
Scenario 4: time-varying portfolio weighting								
Full sample period								
CC	0.5997	0.4554	0.4740	0.4740	0.2895	0.0582	0.0216	0.0582
POF	6.0847	6.3492	6.3492	6.3492	2.4400	2.3810	2.6455	2.3810
TUFF	6	6	6	6	102	6	6	6
Recessions								
CC	0.2347	0.0657	0.2347	0.2347	0.1423	0.0182	0.0182	0.0182
POF	11.1111	13.8889	11.1111	11.1111	5.5556	6.0000	8.3333	8.3333
TUFF	5	4	4	2	1	6	6	7
Expansions								
CC	0.2925	0.2925	0.7701	0.7701	0.6723	0.4025	0.2020	0.4025
POF	5.5556	5.5556	5.8480	5.8480	1.4620	1.7544	2.0468	1.7544
TUFF	84	69	69	69	94	94	94	94

Notes: Model 1 employs the ARMA (1,1) process to model the portfolio returns and the EGARCH model of Nelson (1991) to estimate the volatility. This model then represents a benchmark where neither types of the shocks are inserted in the model's mean and variance equations. Model 2 accounts for simultaneous impact of the supply shocks in both parts of the EGARCH model. CC entries are the p-values of the conditional coverage test, while POF and TUFF are the probability of failure and time until first failure respectively. Lastly, the supply shocks in model 2 are then replaced with the demand and both types of shocks to formulate the models 3 and 4 respectively.

where j denotes the portfolio under consideration.

We check the adequacy of each of the VaR_{Pj} using the conditional coverage approach of Christoffersen (1998; henceforth, CC). This approach is based on interval forecasts, which in turn need to be sufficiently wide during volatile times to prevent the clustering of observations outside the interval. Considering the VaR predictions for y at time t calculated from time $t-1$, $\{y_{t,t-1}\}_{t=1}^{T}$, with T being the sample size and r is the portfolio return series, the indicator sequence is given as follows:

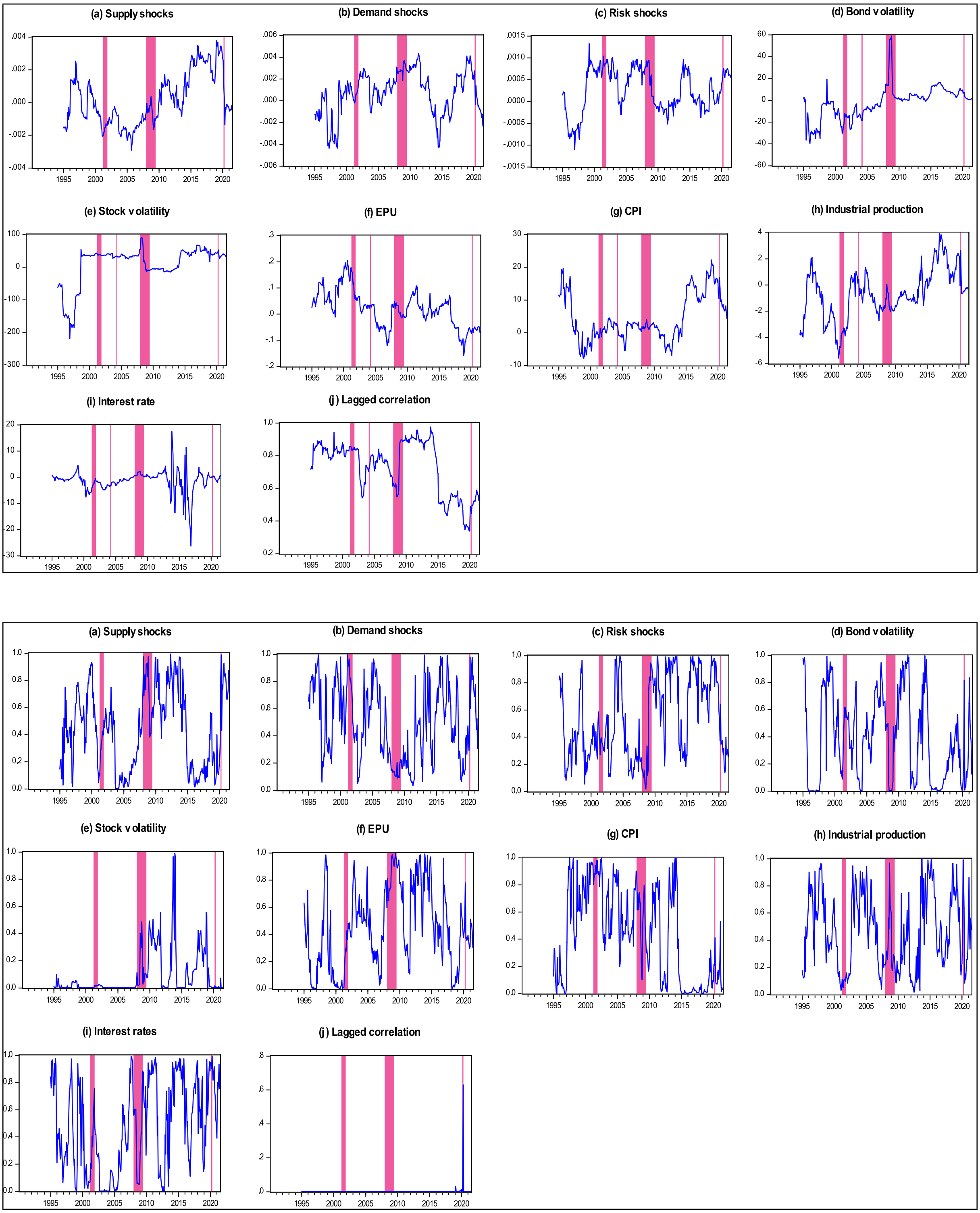


Fig. 3. Rolling regression exercise on the analysis in Table 3. **Notes:** the analysis is performed on a window size of 60 months and 1 step ahead. Shaded areas represent the NBER recession periods.

$$I_t = \left\{ \begin{array}{l} 1, r_t < y_t \\ 0, r_t \geqslant y_t \end{array} \right\} \tag{16}$$

Here, the indicator function will either be 0 or 1, depending on how the realized returns and ex-post forecasts compare. The construction of this interval forecast is said to be efficient at time t relevant to the information set at time $t-1$ (i.e.,Ψ_{t-1}) if it provides the correct conditional coverage p, that is, $E(I_t|\Psi_{t-1}) = p$ where $\Psi_{t-1} = \{I_{t-1}, I_{t-2}, ..., I_1\}$. Christoffersen (1998) develops a backtesting methodology utilizing the likelihood ratio framework from this broad hypothesis.

The CC test considers how well the forecast provides accurate conditional coverage. This test combines both unconditional coverage and a test of independence, is asymptotically distributed χ^2 with two degrees of freedom and is given by:

$$LR_{cc} = -2\log[(1-p)^{n_0}p^{n_1}/L(\widehat{\Pi}_1; I_1, I_2, ..., I_T)] \sim \chi^2 \tag{17}$$

Where $\widehat{\Pi}_1 = \begin{matrix} \frac{n_{00}}{n_{00}+n_{01}} & \frac{n_{01}}{n_{00}+n_{01}} \\ \frac{n_{10}}{n_{10}+n_{11}} & \frac{n_{11}}{n_{10}+n_{11}} \end{matrix}$ and n_0 and n_1 are the total number of zeros and ones in the indicator function respectively.

For a more comprehensive evaluation of the forecasting performance, we estimate the probability of failure (POF) and the time until first failure (TUFF) of Kupiec (1995). The POF investigates whether the proportion of failures (number of failures divided by number of observations) is compatible with the VaR confidence level. The TUFF determines whether the number of periods before the first failure is consistent with the VaR confidence level.

Statistically, the p-value of the POF test is the probability that a χ^2 distribution with 1 degree of freedom exceeds the likelihood ratio LRatioPOF such as:

$$p - valuePOF = 1 - F(LRatioPOF) \tag{18}$$

The *LRatioPOF* can be calculated either as $LRatioPOF = -2N\log(1-pVaR)$ if $x = 0$ or as $LRatioPOF = -2N\log(pVaR)$ when $x = N$, where N is the number of observations and × is the number of failures, and pVaR = 1 - VaRLevel.

Similarly, the p-value under the TUFF test can be calculated as follows:

$$p - valueTUFF = 1 - F(LRatioTUFF) \tag{19}$$

Where $LRatioTUFF = -2\log(pVaR)$.

Fig. 4 depicts the time-varying stock–bond portfolio weights over the full sample period. It can be noted that underweighting in the stock market is more evidenced during the 1998 Asian and the GFC crises. Another drop in the weight of stocks is also clear in the latter part of 2018 reflecting flight-to-safety during the oil crash. Taken as a whole, this demonstrates notable variation in the stock–bond weighting, which can impact portfolio risk.

Table 6 reports the backtesting results from the CC, POF and TUFF tests. Of note, incorporating the impact of demand shocks in Model 3 provides the lowest POF regardless of the market state. That evidence is stronger at the 5 % significance level. At the 1 %, Model 4 is the best performer with the minimum (maximum) POF (TUFF) in both the full and expansion samples. Interestingly, all models are able to pass the CC test, with Model 2 preferred as it is associated with the lowest p-value of 0.0072. For the analysis combining recessions and the 99 % VaR, the findings are inconclusive, with none of the models able to outperform the others.

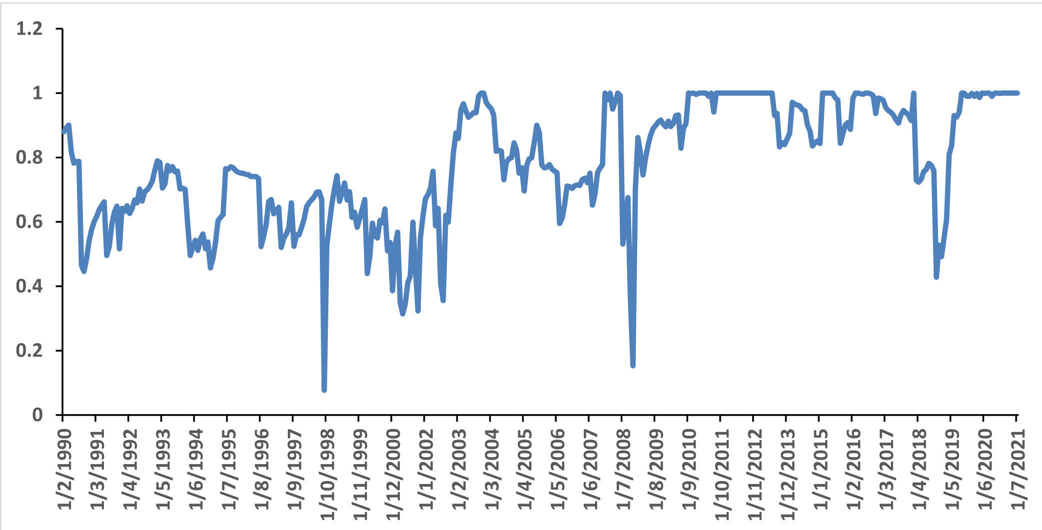


Fig. 4. Time-varying stock–bond portfolio weights.

The estimates from the equally weighted portfolios over the full sample and recession states reveal the difficulty in differentiating between the impact demand and supply shocks. This observation applies mostly in the 95 % VaR exercise where, with respect to POF and TUFF, Models 2 and 3 are preferred. Across alternative risk management scenarios, either of the oil shocks-based models provide the same POF and TUFF values. Further, observing i the 50/50 panel under expansions, this also confirms the superiority of Models 2–4. Here, a model accounting for the impact of shocks statistically passes the CC test at the 5 % significance level or below.

The third panel in Table 6 suggests superior CC-related estimates for Model 2 over the entire sample period. Using the same test, Model 4 is also among the best performers. Furthermore, models accounting for demand shocks are clearly preferred for all tests under recessionary periods when the stock investment is over-weighed in the portfolio. This later observation exists the most under the 95 % VaR condition. Another interesting observation in this panel is the ability of Model 2 to pass the CC in full and recessionary samples. Concerning the expansionary period, the last panel in table notes the benchmark model as the best with the POF analysis only.

The last panel in the table shows that the performance of all the competing models can outperform the benchmark model during the full and recessionary periods. This evidence applies most notably when the conditional coverage test is employed. The same conclusion is also reached with the TUFF proxy while the POF measure only confirms the superiority of Models 2 and 4 under the full sample and 99 % VaR. Conversely, the expansionary-based analysis fails to find clear evidence on the superiority of Models 2–4 at both the 1 % and 5 % levels.

Generally, the results in Table 6 stress that incorporating oil shocks into the model improves the forecasts across markets states and portfolio weighting scenarios. Among the obtained results and from the 95 % VaR exercise, we observe that the model considering the impact of demand shocks and overweighting the bond investment produces the lowest POF under all market states. This suggests that accounting for demand shocks is important in improving the stock–bond portfolio performance.

Our mixed results regarding the superiority of only one model over others appear consistent with several studies that consider a risk management exercise in the oil market (e.g., Patra, 2021). Additionally, we provide supporting evidence to Ma et al. (2021) that oil demand shocks reduce risk at the short-term investment horizon, and acknowledge the role of shocks in the risk management context.

6.4. Dynamic hedging

The purpose of the analysis in this section is to investigate whether accounting for oil shocks helps in reducing the cost of hedging. To do so, we use the conditional volatility estimates to calculate a hedge ratio. A long position in the stock market (x) can be hedged with a short position in the bond market (y). According to Kroner and Sultan (1993), the hedge ratio for a long position in the stock market can be calculated as follows:

$$\beta = h^2_{xy_t} / h^2_{yy_t} \tag{20}$$

Fig. 5 depicts the estimated time-varying hedge ratio to show how the cost of hedging varies over time.[14] In our analysis, we derive the hedge ratio twice, both before and after isolating the effects of oil demand and supply shocks. Estimates are made for long/short investment combinations in the stock/bond pair, with the results plotted in panels A and B of Fig. 5. Overall, the plots show a significant increase in the bond-to-stock hedging ratio following the dotcom crash. Following the Asian crisis, this upturn may be seen in the stock–bond strategy before it peaks in the middle of 2002 (see, panel B). However, during the 2008 financial crisis, the cost of hedging fell before returning to a positive level in the same panel. During the COVID-19 pandemic, the cost of hedging using stocks increased again. Taking bond/stock hedges into account reveals significant shifts in the ratio over the 2001, 2014, and the pandemic period. Surprisingly, the mid-2014 oil crisis coincides with the highest fall in the bond/stock hedge ratio, making the hedge the least expensive throughout the whole sample period. At that point, the ratio is around −0.5, compared to the −0.1 gained from the stock/bond hedging. This finding supports the significance of switching between stocks and bonds during the oil crisis.

Turning our attention to the differences between the oil shocks-included and excluded estimates. More variation is observed over the full sample period, notably, in Panel A. Interestingly, the cost of hedging becomes less expensive in 2015 at the end of oil crisis period after isolating the impact of oil shocks on stock and bond returns. This finding only applies when the bond investment is in the long position. This observation can also be noted over the period 1994–1996 in both panels of the figure. Another contribution in isolating the impacts of shocks is observed in the stock/bond hedge exercise following the dotcom crisis and the GFC.

Overall, the results in these figures indicate that accounting for oil shocks reduces the cost of hedging following the major crises period. Although this depends on the hedging position for which asset is to be considered as the input for the long position.

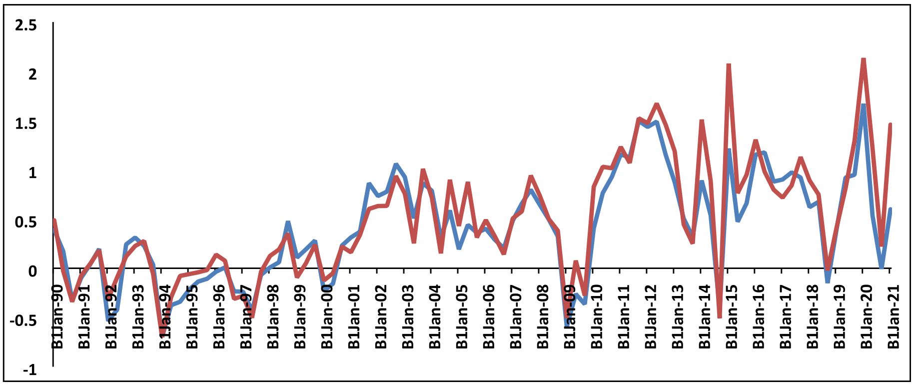
7. Robustness checks

To ensure the robustness of our results, we consider a set of alternative specifications. This includes using alternate stock and bond series and correlation estimation.

Table 7 presents three sets of results, where we replace the S&P 500 with the DJIA, where we replace the 10-year bond yield with a 2-year bond yield and where we replace the ADCC estimated correlation with a DCC (Engle, 2002) estimated correlation. The results

[14] On average, the estimated hedge ratio before isolating the impacts of shocks is found to be higher relative to its counterpart before accounting for the oil shocks (i.e., 0.42 against 0.35). However, depicting the time-varying ratio is essential to examine how specific events impact the hedging exercise more than others.

Panel A: Hedge of bond with stock



Panel B: Hedge of stock with bond

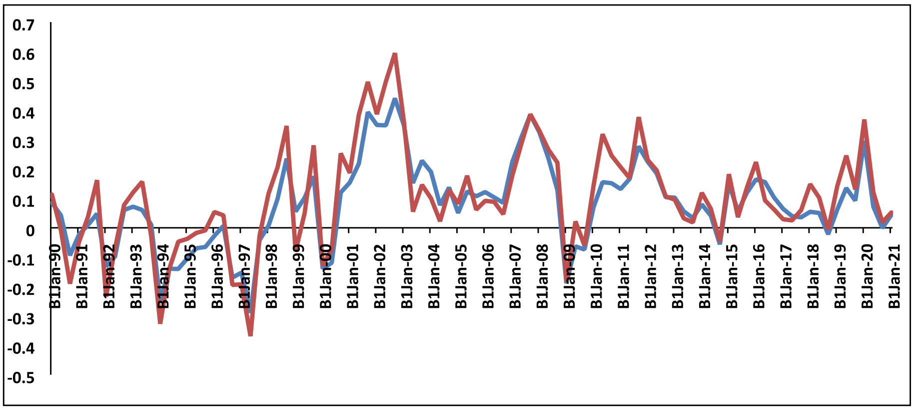


Fig. 5. Time-varying hedge ratio. **Notes:** the blue line depicts the hedge estimates after isolating the impacts of oil shocks.

Table 7
The results from the robustness checks.

	With DJIA returns		With DCC-GARCH		With 2-year bond data	
	Coeff.	t-Stat.	Coeff.	t-Stat.	Coeff.	t-Stat.
Constant	0.0402***	2.6364	0.0136	1.0222	0.0081	0.8593
Supply shocks * recession	**−0.0030****	−2.3063	**−0.0025*****	−2.4839	**−0.0015****	−1.9412
Supply shocks * expansion	−0.0001	−0.0919	−0.0002	−0.2602	−0.0001	−0.2583
Demand shocks * recession	**−0.0012**	−0.5566	0.0021	1.0648	0.0007	0.3797
Demand shocks * expansion	0.0004	0.3436	0.0018	1.2299	0.0012	1.0313
Risk shocks * recession	−0.0006	−0.7696	−0.0004	−0.7263	**0.0007****	2.3082
Risk shocks * expansion	−0.0001	−0.4002	0.0002	0.7137	0.0004*	1.8036
EPU	0.0038	0.1212	0.0037	0.0987	0.0035	0.1536
IP	−1.0064**	−2.0412	−0.6865**	−2.0040	−0.7355***	−3.1188
Inflation	2.5621	1.0163	5.6981***	2.9432	1.8870	1.4517
Interest rate	−0.2440	−1.0481	−0.7391**	−2.3499	−0.3196*	−1.7235
Bond volatility	0.0646	0.1323	−0.1219	−0.3060	−0.1755	−0.6899
Stock volatility	9.3663	1.1551	6.0236	0.9522	7.7189	1.3897
Lagged correlation * recession	0.7784***	10.4782	0.9140***	19.7277	0.8610***	10.8929
Lagged correlation * expansion	0.8107***	24.8484	0.9012***	34.6399	0.9048***	35.0105
Adjusted R^2	0.7274		0.8946		0.8934	

Notes: Figures in bold indicate the statistical rejection the equality of the predictor's effect across the market states according to the Wald test. ***, ** and * denote statistical significant at 1 %, 5 % and 10 % significant levels respectively.

for this robustness analysis continue to support our earlier findings. Specifically, both supply and demand shocks affect the stock–bond correlation only during recessionary periods, with a negative coefficient for the supply shock and a positive coefficient for the demand shock. There is evidence that risk shocks also exhibit a positive effect during a recession for the 2-year bond, while EPU continues to largely exhibit a positive coefficient during a recessionary period.

8. Summary and conclusion

This paper examines the effect of oil shocks on the US bond-stock correlation. Demand, supply and risk shocks are extracted from oil prices following the approach of Ready (2018). The stock–bond correlation is estimated using S&P 500 returns and 10-year Treasury bond yields and the asymmetric-DCC model. Our modelling framework allows for regimes of behaviour according to economic expansion and contraction and changes in investor sentiment. A range of control variables, including economic policy uncertainty, stock and bond volatility, output growth, inflation and interest rates are also utilised.

Results show that oil supply shocks negatively and statistically explain the stock–bond correlation during recessionary periods and this differs statistically to it is counterpart during the expansionary periods. This general result holds even after performing a series of robustness checks. In addition, demand shocks are more prominent in periods of pessimistic investor sentiment, while supply and risk shocks appear during optimistic periods. Our main results are robust to changing the correlation estimation technique and using alternative measures for the stock and bond series.

Overall, our results indicate the importance of identifying the constituent parts of oil shocks. Notably, while the oil return itself did not indicate any significant results, we see that both oil demand and supply shocks separately do exhibit such an effect. Moreover, these significant results only manifest themselves if we equally identify regimes of behaviour based around economic conditions or market sentiment. From a portfolio perspective, our results also indicate that demand and supply shocks may exhibit different influences on the stock–bond correlation. Here, demand shocks suggest stock returns and bonds yields move together during recessions, while supply shocks indicate the opposite movement. More significantly, the outcome of a backtesting exercise shows that both kinds of oil shock may enhance the forecast for portfolio volatility under various weighting schemes and market conditions. Market conditions and the degree of conservatism used in the risk management exercise are also found to be key in providing supportive evidence for the inclusion of shocks. Of note, accounting for oil demand shocks is reported to be important in improving failure rates across market states. A time-varying hedging exercise also demonstrates that isolating the impact of demand and supply shocks on stock and bond returns reduces the cost of hedging, especially after crisis periods.

In sum, our results provide implications for both investors and risk managers. Notably, to improve portfolio performance, investors who rebalance their stock–bond portfolios should take account of oil shocks, which impact the correlation. To make the best choice when moving between stocks and bonds, it is crucial to disentangle the effects of demand and supply shocks. In doing so, investors will be better able to examine the potential impact that oil shocks can have on the returns on their portfolios. Moreover, the outcomes of the sentiment-based research imply that the attitude of US investors may also impact the effects of oil shocks. Accounting for these different factors will allow investors the potential to reap greater benefits from diversification.

CRediT authorship contribution statement

Salem Adel Ziadat: Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft. **Abdel Razzaq A. Al Rababa'a:** Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft. **Mobeen Rehman:** Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft. **David G. McMillan:** Conceptualization, Methodology, Writing – review & editing.

Declaration of Competing Interest

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

Data availability

The authors do not have permission to share data.

References

Abid, I., Goutte, S., Guesmi, K., & Jamali, I. (2019). Transmission of shocks and contagion from US to MENA equity markets: The role of oil and gas markets. *Energy Policy, 134*, Article 110953.
Alquist, R., Ellwanger, R., & Jin, J. (2020). The effect of oil price shocks on asset markets: Evidence from oil inventory news. *Journal of Futures Markets, 40*, 1212–1230.
Andersson, M., Krylova, E., & Vähämaa, S. (2008). Why does the correlation between stock and bond returns vary over time? *Applied Financial Economics, 18*, 139–151.
Antonakakis, N., Chatziantoniou, I., & Filis, G. (2017). Oil shocks and stock markets: Dynamic connectedness under the prism of recent geopolitical and economic unrest. *International Review of Financial Analysis, 50*, 1–26.
Asgharian, H., Christiansen, C., & Hou, A. J. (2015). Effects of macroeconomic uncertainty on the stock and bond markets. *Finance Research Letters, 13*, 10–16.

Asgharian, H., Christiansen, C., & Hou, A. J. (2016). Macro-finance determinants of the long-run stock–bond correlation: The DCC-MIDAS specification. *Journal of Financial Econometrics, 14*, 617–642.

Aslanidis, N., & Christiansen, C. (2012). Smooth transition patterns in the realized stock–bond correlation. *Journal of Empirical Finance, 19*, 454–464.

Baele, L., Bekaert, G., & Inghelbrecht, K. (2010). The determinants of stock and bond return comovements. *Review of Financial Studies, 23*, 2374–2428.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics, 131*(4), 1593–1636.

Balcilar, M., Gupta, R., Wang, S., & Wohar, M. E. (2020). Oil price uncertainty and movements in the US government bond risk premia. *North American Journal of Economics and Finance, 52*, Article 101147.

Bansal, N., Connolly, R. A., & Stivers, C. (2010). Regime-switching in stock index and Treasury futures returns and measures of stock market stress. *Journal of Futures Markets, 30*, 753–779.

Baumeister, C., & Kilian, L. (2016). Forty years of oil price fluctuations: Why the price of oil may still surprise us. *Journal of Economic Perspectives, 30*, 139–160.

Baur, D. G., & Lucey, B. M. (2009). Flights and contagion—An empirical analysis of stock–bond correlations. *Journal of Financial stability, 5*, 339–352.

Beine, M., Cosma, A., & Vermeulen, R. (2010). The dark side of global integration: Increasing tail dependence. *Journal of Banking & Finance, 34*, 184–192.

Ben Bernanke & Mark Gertler (1999). *Monetary policy and asset price volatility*. Proceedings (pp. 77–128). Federal Reserve Bank of Kansas City.

Bjørnland, H. C. (2009). Oil price shocks and stock market booms in an oil exporting country. *Scottish Journal of Political Economy, 56*, 232–254.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*, 307–327.

Bollerslev, T. (1990). Modelling the coherence in short-run nominal exchange rates: A multivariate generalized arch model. *The Review of Economics and Statistics, 72*(3), 498–505.

Bollerslev, T., & Wooldridge, J. M. (1992). Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances. *Econometric Reviews, 11*, 143–172.

Boufateh, T., & Saadaoui, Z. (2021). The time-varying responses of financial intermediation and inflation to oil supply and demand shocks in the US: Evidence from Bayesian TVP-SVAR-SV approach. *Energy Economics, 102*, Article 105535.

Cappiello, L., Engle, R. F., & Sheppard, K. (2006). Asymmetric dynamics in the correlations of global equity and bond returns. *Journal of Financial Econometrics, 4*, 537–572.

Chen, R., Bao, W., & Jin, C. (2021). Investor sentiment and predictability for volatility on energy futures Markets: Evidence from China. *International Review of Economics & Finance, 75*, 112–129.

Chiang, T. C., Li, J., & Yang, S. Y. (2015). Dynamic stock–bond return correlations and financial market uncertainty. *Review of Quantitative Finance and Accounting, 45*, 59–88.

Christoffersen, P. (1998). Evaluating interval forecasts. *International Economic Review, 39*, 841–862.

Christoffersen, P., & Pan, X. N. (2018). Oil volatility risk and expected stock returns. *Journal of Banking & Finance, 95*, 5–26.

Clements, A., Shield, C., & Thiele, S. (2019). Which oil shocks really matter in equity markets? *Energy Economics, 81*, 134–141.

Cologni, A., & Manera, M. (2008). Oil prices, inflation and interest rates in a structural cointegrated VAR model for the G-7 countries. *Energy Economics, 30*, 856–888.

Connolly, R., Stivers, C., & Sun, L. (2005). Stock market uncertainty and the stock-bond return relation. *Journal of Financial and Quantitative Analysis, 40*, 161–194.

Connolly, R. A., Stivers, C., & Sun, L. (2009). Commonality in the time-variation of stock–stock and stock–bond return comovements. *Journal of Financial Markets, 10*, 192–218.

Cunado, J., Jo, S., & de Gracia, F. P. (2015). Macroeconomic impacts of oil price shocks in Asian economies. *Energy Policy, 86*, 867–879.

d'Addona, S., & Kind, A. H. (2006). International stock–bond correlations in a simple affine asset pricing model. *Journal of Banking & Finance, 30*, 2747–2765.

Demirer, R., Ferrer, R., & Shahzad, S. J. H. (2020). Oil price shocks, global financial markets and their connectedness. *Energy Economics, 88*, Article 104771.

Dimic, N., Kiviaho, J., Piljak, V., & Äijö, J. (2016). Impact of financial market uncertainty and macroeconomic factors on stock–bond correlation in emerging markets. *Research in International Business and Finance, 36*, 41–51.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica, 50*, 987–1007.

Escobari, D., & Sharma, S. (2020). Explaining the nonlinear response of stock markets to oil price shocks. *Energy, 213*, Article 118778.

Ewing, B. T., Kang, W., & Ratti, R. A. (2018). The dynamic effects of oil supply shocks on the US stock market returns of upstream oil and gas companies. *Energy Economics, 72*, 505–516.

Fang, L., Yu, H., & Li, L. (2017). The effect of economic policy uncertainty on the long-term correlation between US stock and bond markets. *Economic Modelling, 66*, 139–145.

Filippidis, M., Filis, G., & Kizys, R. (2020). Oil price shocks and EMU sovereign yield spreads. *Energy Economics, 86*, Article 104656.

Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market comovements. *Journal of Finance, 57*, 2223–2261.

Gbatu, A. P., Wang, Z., Wesseh, P. K., Jr, & Tutdel, I. Y. R. (2017). The impacts of oil price shocks on small oil-importing economies: Time series evidence for Liberia. *Energy, 139*, 975–990.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance, 48*, 1779–1801.

Gokmenoglu, K. K., & Hadood, A. A. A. (2020). Impact of US unconventional monetary policy on dynamic stock-bond correlations: Portfolio rebalancing and signalling channel effects. *Finance Research Letters, 33*, Article 101185.

Gronwald, M. (2016). Explosive oil prices. *Energy Economics, 60*, 1–5.

Guidolin, M., & Timmermann, A. (2006). An econometric model of nonlinear dynamics in the joint distribution of stock and bond returns. *Journal of Applied Econometrics, 21*, 1–22.

Guo, H., Hung, C. H. D., & Kontonikas, A. (2022). The Fed and the stock market: A tale of sentiment states. *Journal of International Money and Finance, 128*, Article 102707.

Gupta, R., Kollias, C., Papadamou, S., & Wohar, M. E. (2018). News implied volatility and the stock-bond nexus: Evidence from historical data for the USA and the UK markets. *Journal of Multinational Financial Management, 47*, 76–90.

Hamilton, J. D. (1983). Oil and the macroeconomy since World War II. *Journal of Political Economy, 91*, 228–248.

Hwang, I., & Kim, J. (2021). Oil price shocks and the US stock market: A nonlinear approach. *Journal of Empirical Finance, 64*, 23–36.

Ilmanen, A. (2003). Stock-bond correlations. *Journal of Fixed Income, 13*, 55–66.

Jiang, Y., Wang, G. J., Ma, C., & Yang, X. (2021). Do credit conditions matter for the impact of oil price shocks on stock returns? Evidence from a structural threshold VAR model. *International Review of Economics & Finance, 72*, 1–15.

Kang, W., & Ratti, R. A. (2013). Oil shocks, policy uncertainty and stock market return. *Journal of International Financial Markets, Institutions and Money, 26*, 305–318.

Kang, W., Ratti, R. A., & Vespignani, J. (2016). The impact of oil price shocks on the US stock market: A note on the roles of US and non-US oil production. *Economics Letters, 145*, 176–181.

Kang, W., Ratti, R. A., & Yoon, K. H. (2014). The impact of oil price shocks on US bond market returns. *Energy Economics, 44*, 248–258.

Kilian, L. (2005). The effects of exogenous oil supply shocks on output and inflation: Evidence from the G7 countries. *Journal of the European Economic Association, 6*, 78–121.

Kilian, L. (2008). Exogenous oil supply shocks: How big are they and how much do they matter for the US economy? *Review of Economics and Statistics, 90*, 216–240.

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review, 99*, 1053–1069.

Kilian, L. (2014). Oil price shocks: Causes and consequences. *Annual Review of Resources Economics., 6*(1), 133–154.

Kilian, L. (2016). The impact of the shale oil revolution on US oil and gasoline prices. *Review of Environmental Economics and Policy, 10*, 185–205.

Kim, S. J., Moshirian, F., & Wu, E. (2005). Dynamic stock market integration driven by the European Monetary Union: An empirical analysis. *Journal of Banking & Finance, 29*, 2475–2502.

Kim, S. J., Moshirian, F., & Wu, E. (2006). Evolution of international stock and bond market integration: Influence of the European Monetary Union. *Journal of Banking & Finance, 30*, 1507–1534.

Kroner, K. F., & Ng, V. K. (1998). Modeling asymmetric comovements of asset returns. *Review of Financial Studies, 11*, 817–844.
Kroner, K. F., & Sultan, J. (1993). Time-varying distributions and dynamic hedging with foreign currency futures. *Journal of Financial and Quantitative Analysis, 28*, 535–551.
Kupiec, P. (1995). Techniques for Verifying the Accuracy of Risk Management Models. *Journal of Derivatives, 3*, 73–84.
Lemmon, M., & Portniaguina, E. (2006). Consumer confidence and asset prices: Some empirical evidence. *Review of Financial Studies, 19*, 1499–1529.
Li, X. M., Zhang, B., & Gao, R. (2015). Economic policy uncertainty shocks and stock–bond correlations: Evidence from the US market. *Economics Letters, 132*, 91–96.
Li, L., 2002. Macroeconomic factors and the correlation of stock and bond returns. Available at SSRN 363641. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=363641.
Longin, F., & Solnik, B. (1995). Is the correlation in international equity returns constant: 1960–1990? *Journal of International Money and Finance, 14*, 3–26.
Ma, Y., Zhang, Y., & Ji, Q. (2021). Do oil shocks affect Chinese bank risk? *Energy Economics, 96*, Article 105166.
Manela, A., & Moreira, A. (2017). News implied volatility and disaster concerns. *Journal of Financial Economics, 123*, 137–162.
McMillan, D. G. (2018). The information content of the stock and bond return correlation. *Quantitative Finance and Economics, 2*, 757–775.
Mohaddes, K., & Pesaran, M. H. (2017). Oil prices and the global economy: Is it different this time around? *Energy Economics, 65*, 315–325.
Morana, C., & Beltratti, A. (2008). Comovements in international stock markets. *Journal of International Financial Markets, Institutions and Money, 18*, 31–45.
Nadal, R., Szklo, A., & Lucena, A. (2017). Time-varying impacts of demand and supply oil shocks on correlations between crude oil prices and stock markets indices. *Research in International Business and Finance, 42*, 1011–1020.
Naeem, M. A., Pham, L., Senthilkumar, A., & Karim, S. (2022). Oil shocks and BRIC markets: Evidence from extreme quantile approach. *Energy Economics, 108*, Article 105932.
Nazlioglu, S., Gupta, R., & Bouri, E. (2020). Movements in international bond markets: The role of oil prices. *International Review of Economics & Finance, 68*, 47–58.
Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the econometric society, 59*, 347–370.
Ouyang, Z. S., Liu, M. T., Huang, S. S., & Yao, T. (2022). Does the source of oil price shocks matter for the systemic risk? *Energy Economics, 109*, Article 105958.
Patra, S. (2021). Revisiting value-at-risk and expected shortfall in oil markets under structural breaks: The role of fat-tailed distributions. *Energy Economics, 101*, Article 105452.
Perego, E. R., & Vermeulen, W. N. (2016). Macro-economic determinants of European stock and government bond correlations: A tale of two regions. *Journal of Empirical Finance, 37*, 214–232.
Qadan, M., & Nama, H. (2018). Investor sentiment and the price of oil. *Energy Economics, 69*, 42–58.
Qin, X. (2020). Oil shocks and financial systemic stress: International evidence. *Energy Economics, 92*, Article 104945.
Ready, R. C. (2018). Oil prices and the stock market. *Review of Finance, 22*, 155–176.
Sadeghi, A., & Roudari, S. (2022). Heterogeneous effects of oil structure and oil shocks on stock prices in different regimes: Evidence from oil-exporting and oil-importing countries. *Resources Policy, 76*, Article 102596.
Shahzad, S. J. H., Raza, N., Balcilar, M., Ali, S., & Shahbaz, M. (2017). Can economic policy uncertainty and investors sentiment predict commodities returns and volatility? *Resources Policy, 53*, 208–218.
Skintzi, V. D. (2019). Determinants of stock-bond market comovement in the Eurozone under model uncertainty. *International Review of Financial Analysis, 61*, 20–28.
Smyth, R., & Narayan, P. K. (2018). What do we know about oil prices and stock returns? *International Review of Financial Analysis, 57*, 148–156.
Tsai, C. L. (2015). How do US stock returns respond differently to oil price shocks pre-crisis, within the financial crisis, and post-crisis? *Energy Economics, 50*, 47–62.
Vácha, L., Šmolík, F., & Baxa, J. (2019). Comovement and disintegration of EU sovereign bond markets during the crisis. *International Review of Economics & Finance, 64*, 541–556.
Wang, W., Su, C., & Duxbury, D. (2022). The conditional impact of investor sentiment in global stock markets: A two-channel examination. *Journal of Banking & Finance*, Article 106458.
Yang, J., Zhou, Y., & Wang, Z. (2009). The stock–bond correlation and macroeconomic conditions: One and a half centuries of evidence. *Journal of Banking & Finance, 33*, 670–680.
Ziadat, S. A., McMillan, D. G., & Herbst, P. (2022). Oil shocks and equity returns during bull and bear markets: The case of oil importing and exporting nations. *Resources Policy, 75*, Article 102461.
Engle, R. (2002). Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business and Economic Statistics, 20*, 339–350.
Caldara, D., Cavallo, M., & Iacoviello, M. (2019). Oil price elasticities and oil price fluctuations. *Journal of Monetary Economics, 103*, 1–20.
Connolly, R., Stivers, C., & Sun, L. (2007). Commonality in the time variation of stock–bond and stock–stock return comovements. *Journal of Financial Markets, 10*, 192–218.