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Disentangled oil shocks and macroeconomic policy uncertainty in South Africa

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ABSTRACT

This study examines the spillovers among oil shocks and macroeconomic policy uncertainty in South Africa between January 1990 to July 2022. The study arrives at some important findings.From the Diebold and Yılmaz (2012) connectedness analysis, which measures average connectedness, we find a moderate connection between oil shocks and macroeconomic policy uncertainty phenomena. Conversely, the connections among oil shocks and macroeconomic policy uncertainty are greatest at the low and upper quantiles. That is, when these phenomena are experiencing extreme values, the connectedness among them is formidable. Moreover, the study finds that over the period of assessment, macroeconomic policy uncertainty phenomena are net receivers at lower quantiles. Meanwhile, unlike financial policy uncertainty, economic policy uncertainty and political uncertainty become net transmitters at the middle and upper quantiles. On the other hand, the disaggregated oil shocks are net transmitters (receivers) at the low (median) quantiles. Interestingly, their receiver/transmitter roles are mixed at the upper quantile.Finally, using the Quantile-on-Quantile regression analysis, we find that oil shocks generally increase (reduce) macroeconomic policy uncertainty when this uncertainty is already low (high).

1. Introduction

The 2022 energy crisis caused by the Russia-Ukraine war has led to global disruptions in the energy supply chain, resulting in inflation in many countries including South Africa. Correspondingly, due to the lack of defined regulatory frameworks and poor crisis response plans, Africa is especially vulnerable to crises (World Bank, 2022). The recent energy crisis has negatively affected South Africa's economy, financial system, and political environment, resulting in a decline in investor confidence, low economic growth, and high inflation (Writer, 2022). Additionally, the country's persistently poor service delivery, increasing corruption, and poor governance have contributed to political uncertainty and hampered macroeconomic stability. Political tensions within South Africa's ruling party, xenophobic attacks, economic recession, and downgrades to junk status by rating agencies have contributed towards policy uncertainty (see, Hlatshwayo and Saxegaard, 2016; Bloomberg, 2020). The consequences of junk status include interest rate hikes, devaluation of the rand, and higher inflation, which exacerbate economic policy uncertainty and financial policy uncertainty.

At the same time, oil shocks birthed by global disturbances can generate macroeconomic policy uncertainty by triggering second-round effects on the economy, affecting financial markets, stimulating speculation, and changing the political landscape (Aimer and Lusta, 2022). Financial institutions may reduce lending activities, leading to financial policy uncertainty, and speculation on interest rates, inflation, and exchange rate volatility may increase, resulting in economic policy uncertainty. Moreover, governments may respond by implementing subsidies or price controls, causing economic disruptions and political uncertainty. In essence, there is a clear spillover relationship, which has been noted by previous studies (see, Antonakakis et al., 2014). Oil shocks may also negatively impact aggregate demand and cause current account deficits. Meanwhile, because shifts in monetary policy (a pillar of macroeconomic policy) can lead to changes in interest rates, it can diminish/raise demand for oil through its effect on firms. As an extension, uncertainty on future macroeconomic policies may lead to preemptive responses from firms. In the case of contractionary monetary policy, firms may not invest in new productive capacity or even reduce current production. This occurrence would expectedly lower demand for oil, leading to shocks in crude oil commodity prices.

In recognition of the importance of macroeconomic policy uncertainty and its relationship with oil markets, there has been a growing body of literature looking at this area of research (see, Antonakakis

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et al., 2014; You et al., 2017; Mokni et al., 2020; Lyu et al., 2021; Wang et al., 2022; Cao et al., 2023). However, to the best of our knowledge, few or no studies have focused on the relationships among macroeconomic policy uncertainty phenomena and oil shocks in a South African context. For example, with a focus on the U.S., Cao et al. (2023) examined economic policy uncertainty, fiscal policy uncertainty and trade policy uncertainty in relation to food and oil. However, as is evident from the preceding discussion, South Africa's socio-political and economic reality differs from that of the developed world which has enjoyed much of the attention on the subject. To fill this gap, we explore the relationship between disentangled oil shocks and South African macroeconomic policy uncertainty using the Diebold and Yılmaz (2012) spillover technique, Quantile connectedness, and the Quantile-on-Quantile (QQ) regression approach of Sim and Zhou (2015). This framework is particularly serviceable given the complexity of the associations among these variables. Specifically, the study disentangles oil price shocks into four types: oil supply shocks, oil consumption demand shocks, oil inventory demand shocks, and economic activity shocks following Baumeister and Hamilton's (2019) work. Meanwhile, we consider three types of macroeconomic policy uncertainty (MPU): economic policy uncertainty (EPU), financial policy uncertainty (FPU), and political uncertainty (PU). Foreshadowing our main result, the study uncovers a moderate relationship between macroeconomic uncertainty and disaggregated oil shocks using the Diebold and Yılmaz (2012) connectedness methodology. However, the quantile spillover approach shows a strong connection among oil shocks and macroeconomic policy uncertainty at the extreme quantiles. Moreover, we obtain crucial information from the quantile regression analysis. Specifically, we find that the direct effects among the variables are heterogeneous across each of the distributions.

The next section discusses relevant empirical literature on the subject. Following this, section three describes the data while also providing a detailed explanation of the methodology used in this study. Thereafter, section four presents and discusses the empirical findings. Lastly, section five concludes the paper and makes some policy recommendations.

2. Brief review of the literature

The extant literature on the relationship between oil prices and macroeconomic policy has differed in methods employed and in the scope. For example, Dash and Maitra (2021) used wavelet coherence and wavelet angle tests and uncovered that EPU and oil future price returns were inversely related. However, they concluded that, in comparison to oil spot prices, oil price futures had no more information to explain EPU beyond this. Meanwhile, from time domain connectedness analysis, Yang (2019) found that crude oil prices were receivers of spillovers from EPU across time scales and that the intensity of these spillovers increased as the time scales became longer. Interestingly, Wang et al. (2022) found that global economic policy uncertainty has an influence on international oil prices, both in the short and long run. Similarly, focusing on the U.S. and China, Huang et al. (2022) found that there were strong spillovers among EPU, crude oil, and gold markets. Moreover, they observed that these spillovers increased during times of financial upheaval. In addition to this revelation, Lin and Bai (2021) found that the impact of oil prices on EPU changed depending on whether the country was an oil importer or exporter. The EPUs of oil exporters were more affected than those of oil importers.

Looking at BRIC countries (excluding South Africa), Wang et al. (2022) uncovered that oil prices had a heterogeneous effect on the EPUs of the different countries. Moreover, this effect was nonlinear and asymmetric. They also found that the EPUs of oil importers (China and India) had a significantly negative effect global oil prices in the long run. Meanwhile, they found that oil prices negatively impacted Brazil's EPU in the high fluctuation regime (of oil prices). Whereas Russia (an oil exporter) has its EPU negatively impacted in the low fluctuation regime. Meanwhile, Ren et al. (2022), using QQ regression, found that EPU's effect on the spillovers among commodities market (including crude oil) was heterogeneous. Moreover, EPU had a positive effect on the highest quantiles of the spillovers (meaning greatest intensity). Also looking at the BRICS countries, Su et al. (2021) concluded that the influence of oil price shocks on a country's EPU changed depending on whether the country was oil importing or oil exporting. Moreover, the significance of oil prices varies across BRICS countries (which was related to oil demand). Interestingly, Cao et al. (2023) assessed the effect of several policy uncertainty measures on oil-food connectedness. They found that economic policy uncertainty and fiscal policy uncertainty had a significantly positive impact on oil-food spillovers while monetary policy uncertainty's effect was negative. Meanwhile, trade policy uncertainty had a weak effect on these spillovers.

Pertinently, empirical evidence suggests that EPU reciprocates with United States (U.S.) oil supply shocks (Kang et al., 2017), whilst an inverse reaction is identified towards non-U.S. oil supply shocks. In contrast, Kang et al. (2019) concluded that oil shocks' effects on gasoline prices are interlinked with EPU, whilst Kang and Ratti (2013a) reported that positive oil demand shocks heavily affect EPU negatively, whilst structural oil shocks appeared to have long-term effects on EPU. Wang and Lee (2020) employed a time domain (TVP-VAR) connectedness framework to evaluate the dynamic spillovers and connectedness between oil returns and policy uncertainty. The study found that EPU is the primary transmitter of shocks while fiscal policy uncertainty having the most significant impact on oil returns. Meanwhile, the effects of uncertainty stemming from exchange rate, monetary policy, and trade policy was not far behind in severity. Additionally, Fasanya et al. (2021) utilized the Diebold- Yılmaz spillover framework to examine the impact of U.S. EPU on the interconnectedness of oil and global foreign exchange markets. The study revealed that crude oil and currency markets are closely intertwined, with oil being the primary recipient of shocks.

Moreover, Kang and Ratti (2013b) confirm that the association between oil specific demand shocks and EPU is positive, whereas oil shocks and stock returns are inversely related. Beyond this, they observed that rising EPU negatively affects stock returns. On the other side, Wei (2019) extended the literature by evaluating the impact of oil shocks and EPU on China's trade. The study proposes that oil supply shocks and EPU cause exports to fall, whilst demand side shocks affect exports positively. Furthermore, the study highlighted that oil shocks arising from demand and supply lead to an increase in imports, whereas oil demand shocks enhance the terms of trade. The study also highlighted the crucial role played by EPU in improving China's terms of trade. A study by Rehman (2018) found that oil price volatility determined global EPU, while Hoque et al. (2019) uncovered that the effects of oil demand shocks were fostered by EPU, and geopolitical uncertainty contributed to oil supply shocks. The study emphasized that global EPU and oil demand shocks can be utilized to predict future stock market returns. In opposition, Antonakakis et al. (2017) concluded that geopolitical uncertainty and oil returns are negatively related.

Another line of research explored the quantile relationship between oil shocks, policy uncertainty, and other financial markets such as green bonds and stocks using QR. The work of Lee et al. (2021) highlighted that for upper quantiles, a one-way granger causality linkage from political uncertainty to oil exists, whereas at lower quantiles a bi-directional link between oil prices and green bonds exists and a linkage from geopolitical risk to green bond index also exists. Meanwhile, You et al. (2017) reported that oil price hikes significantly affect stock returns negatively at higher quantiles. The study highlighted that there is an asymmetric dependence between oil price and EPU, which is strongly correlated with stock returns (see also, Aimer and Lusta, 2022, who reported a long-term asymmetric linkage).

Despite the length and breadth of previous research on oil shocks and macroeconomic policy uncertainty, to the best of our knowledge, no study has yet assessed the direction and strength of spillovers among disentangled macroeconomic policy uncertainty and oil shocks in a South African context. Given this apparent gap in knowledge, the present study applies the Diebold and Yılmaz (2012) spillover approach, and Quantile connectedness. To supplement this, we use the Quantile-on-Quantile connectedness method to assess any possible heterogeneity across the distribution of each of the variables under a bivariate setting.

3. Methodology and data

3.1. Diebold- Yılmaz spillover framework

The framework of Diebold and Yılmaz (2012) is applied in this study to examine the dynamic spillover effects and linkages between oil shocks and MPU. This framework is based on the generalized autoregressive vector model (VAR), which leads to variance decompositions that are order invariant. A stationary covariance VAR (ρ) is considered when constructing a spillover index.

$$v_t = \Phi v_{t-1} + \varepsilon_t \,; \ \varepsilon_t \sim (0, \Sigma) \tag{1}$$

where $v_t = (v_{1t}, v_{2t}\ldots, v_{Nt})'$ denotes an $N \times 1$ vector of shock series, Φ signifies an $N \times N$ parameter matrix, while ε_t denotes a vector of independently and identically distributed errors and Σ symbolizes the variance matrix for the error vector ε. The moving average representation is then expressed as follows:

$$v_t = \sum\nolimits_{i=0}^{\infty} A_i \varepsilon_{t-1} \tag{2}$$

where A_i adheres to recurrence $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}$, whilst A_O denotes an identity matrix with dimension $N \times N$, and $A_i = 0$ for $i < 0$. The coefficients of the moving average in Equation (7) are utilized to compute the spillover indexes. These indices include variance shares, which consist of own and cross variances. The own variance represents the proportion of the H-step-ahead error variances in forecasting v_i that are attributed to shocks to v_i, for $i = 1,2\ldots N$. Conversely, the cross variance is the fraction of the H-step-ahead error variances in predicting v_i that are due to spillovers to v_j, for $i,j = 1,2\ldots N$, and i is not equal to j.

Using KPSS's generalized VAR framework, we can represent H-step-ahead forecast error variance decompositions as θ_{ij}^g where:

$$\theta_{ij}^g = \frac{\sigma_{jj}^{-1} \sum\limits_{h=0}^{H-1} \left(e_i' A_h \sum e_j\right)^2}{\sum\limits_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_i\right)} \tag{3}$$

Where σ_{jj} denotes the standard deviation of the error term for the j^{th} equation, whilst e_i is a selection vector with a value of one in its i^{th} element and zeros elsewhere. The error term variance matrix is denoted by $\sum$. According to Diebold and Yılmaz (2012), the sum of each row's elements in the variance decomposition table is not equal to one. Therefore, to use all the information in the variance decomposition matrix in calculating the spillover index, Diebold and Yılmaz standardized each entry of the variance decomposition matrix by the row sum as follows:

$$\widetilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum\limits_{j=1}^{N} \theta_{ij}^g(H)} \tag{4}$$

where $\sum_{j=1}^{N} \widetilde{\theta}_{ij}^g(H) = 1$ and $\sum_{i,j=1}^{N} \widetilde{\theta}_{ij}^g(H) = N$ by construction. Given the KPSS variance decomposition presented in equation (9), the total spillover index is expressed as follows:

$$S^g(H) = \frac{\sum\limits_{\substack{i,j=1 \\ i \neq 1}}^{N} \widetilde{\theta}_{ij}^g(H)}{\sum\limits_{i,j=1}^{N} \widetilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum\limits_{\substack{i,j=1 \\ i \neq 1}}^{N} \widetilde{\theta}_{ij}^g(H)}{N} \times 100 \tag{5}$$

Equation (5) determines the total contribution of volatility shock spillovers across all oil shocks and uncertainty indexes considered. In this study, the overall spillover index quantifies the impact of volatility spillovers across four categories oil shocks and three MPU parameters to the total forecast error variance.

The generalized VAR framework, using Diebold and Yılmaz (2012) methodology, enables the analysis of spillovers across three MPU indices and four types of oil shocks. This spillover approach distinguishes between "*Directional Spillover To*" and "*Directional Spillover From*." The term "*Directional Spillover To*" refers to the directional shock spillovers transmitted by market i to all other markets j, whereas "*Directional Spillover From*" refers to the directional shock spillovers received by market i from all other markets j. The "*Directional Spillover Index To*" is denoted by $S_{.i}^g$ as follows:

$$S_{.i}^g(H) = \frac{\sum\limits_{\substack{j=1 \\ j \neq 1}}^{N} \widetilde{\theta}_{ji}^g(H)}{\sum\limits_{i,j=1}^{N} \widetilde{\theta}_{ji}^g(H)} \times 100 = \frac{\sum\limits_{\substack{j=1 \\ j \neq 1}}^{N} \widetilde{\theta}_{ji}^g(H)}{N} \times 100 \tag{6}$$

Besides, the "*Directional Spillover Index From*" is denoted by $S_{i.}^g$ as follows:

$$S_{i.}^g(H) = \frac{\sum\limits_{\substack{j=1 \\ j \neq 1}}^{N} \widetilde{\theta}_{ij}^g(H)}{\sum\limits_{i,j=1}^{N} \widetilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum\limits_{\substack{j=1 \\ j \neq 1}}^{N} \widetilde{\theta}_{ij}^g(H)}{N} \times 100 \tag{7}$$

Given the above directional spillovers, the net spillovers can be computed as follows:

$$S_i^g(H) = S_{.i}^g(H) - S_{i.}^g(H) \tag{8}$$

Net spillovers, as shown in equation (8) above, provide information about each shock's or uncertainty index's contribution to the volatility of other shocks or uncertainty indices. The study involved the consideration of second-order VARs with seven variables, along with 10-step-ahead forecasts.

3.2. Quantile connectedness framework

The study also applies the quantile vector autoregressive model (QVAR). To begin with, quantile regression, as proposed by Koenker and Bassett (1978), permits us to measure the dependence of y_t on x_t at each quantile τ of the conditional distribution of $y_t/_{x_t}$. This quantile regression approach can be expressed as:

$$Q_t(y_t|x_t) = x_t \beta(\tau) \tag{9}$$

where Q_t denotes the τ^{th} conditional function of y_t; τ symbolizes the quantile which range between zero (0) and one (1); x_t signifies independent variables' vector, whilst $\beta(\tau)$ establishes the association of dependence between x_t and the τ^{th} quantile of y_t. $\beta(\tau)$ denotes the parameter vector estimated at the τ^{th} conditional quantile using the following expression:

$$\widehat{\beta}(\tau) = \underset{\beta(\tau)}{argmin} \sum_{t-1}^{T} \left(\tau - 1_{\{y_t < x_t\beta(\tau)\}}\right)\left|y_t - x_t\beta(\tau)\right) \quad (10)$$

As a result, the n-variable quantile VAR process of p^{th} order is as follows:

$$y_t = c(\tau) + \sum_{i=1}^{p} \beta_i(\tau) y_{t-i} + e_t(\tau), t = 1, \ldots, T \quad (11)$$

where y_t is an n-vector of dependent variables, $c(\tau)$ and $e_t(\tau)$ are the n-vectors of constants and residuals at quantile τ, respectively. $\beta_i(\tau)$ denotes the matrix of dependent variable lagged coefficients at quantile τ, where $i = 1, \ldots, p$. The computation of $\widehat{\beta}(\tau)$ and $\widehat{c}(\tau)$ is based on the assumption that residuals satisfy the population quantile restriction, $Q_t\left(e_t(\tau)\middle|y_{t-1}, \ldots\ldots, y_{t-p}\right) = 0$. Equation (17) provides the population's conditional quantile response of y, which can be estimated on an equation-by-equation basis for each quantile as:

$$Q_t\left(e_t(\tau)\middle|y_{t-1}, \ldots\ldots, y_{t-p}\right) = c(\tau) + \sum_{i=1}^{p} \widehat{\beta}_i(\tau) y_{t-i} \quad (12)$$

The study utilizes the quantile VAR model proposed by Ando et al. (2022) to evaluate the quantile connectedness between oil shocks and MPU indices. This model builds upon the mean-based spillover framework suggested by Diebold and Yılmaz (2012, 2014). A moving vector average of infinite order in a quantile VAR is used to calculate the quantile spillover measures. The infinite order moving average (M.A) is presented as:

$$y_t = \mu(q) + \sum\nolimits_j^p \Phi_j(q) y_{t-j} + u_t(q) = \mu(q) + \sum\nolimits_{i=0}^{\infty} \Omega_i(q) u_{t-i} \quad (13)$$

The study employs the generalized forecast error variance decomposition (GFEVD) that is invariant to ordering, as proposed by Koop et al. (1996) and Pesaran and Shin (1998). The GFEVD is calculated for a forecast horizon of H and can be represented as:

$$\theta_{ij}^{g} = \frac{\sum \left(\tau\right)_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Omega_h(q) \sum (q) e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Omega_h(q) \sum (q) \Omega_h(q)' e_i\right)'} \quad (14)$$

where e_i denotes a zero-length vector with a value of one at the i^{th} position. The following is the normalization of each element in the decomposition matrix:

$$\widetilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{k} \theta_{ij}^{g}(H)'}, \text{ with } \sum\nolimits_{j=1}^{k} \widetilde{\theta}_{ij}^{g} = 1 \text{ and } \sum\nolimits_{j=1}^{k} \widetilde{\theta}_{ij}^{g}(H) = 1 \quad (15)$$

Furthermore, according to Diebold and Yılmaz (2012, 2014), the GFEVD-based spillovers and connectedness measures are computed at each quantile as follows:

$$TSI_t = \frac{\sum_{i,j=1, i\neq 1}^{k} \widetilde{\theta}_{ij}^{g}(H)}{k-1} \quad (16)$$

$$TO_{j,t} = \sum\nolimits_{i=1, i\neq j}^{k} \widetilde{\theta}_{ij,t}^{g}(H) \quad (17)$$

$$FROM_{j,t} = \sum\nolimits_{i=1, i\neq j}^{k} \widetilde{\theta}_{ji,t}^{g}(H) \quad (18)$$

$$NET_{j,t} = TO_{j,t} - FROM_{j,t} \quad (19)$$

$$NPDC_{i,j,t} = \widetilde{\theta}_{ij,t}(H) - \widetilde{\theta}_{ji,t}(H) \quad (20)$$

TSI_t refers to the average level of total connectedness in the preceding equations. The notation $TO_{j,t}$ refers to the collective effect of a shock in variable j on all other variables, while $FROM_{j,t}$ represent the total impact of all other variables on variable j. Additionally, $NET_{j,t}$ indicate the distinction between "*TO*" and "*FROM*." A positive value indicates a net transmission effect, whereas a negative value suggests a net reception impact from other shocks and MPU parameters. Moreover, the expression $NPDC_{i,j,t}$ determines whether variable j is driving variable i or the other way around. If $NPDC_{i,j,t} > 0$ ($NPDC_{i,j,t} < 0$) variable j may be predominating (dominated by) variable i. The quantile spillover analyses employ a VAR lag order of 8 and a forecast horizon of 10. The study employs a 200-day rolling window to assess these quantile spillovers.

3.3. *Quantile-on-quantile regression*

The QQ method permits us to examine the effects of the different quantiles of one variable (oil shocks) on different quantiles of another variable (MPU). The QQ model is a hybrid of quantile regression and nonparametric estimation techniques (Sim and Zhou, 2015). To evaluate whether the impact of oil shocks on MPU are large or small, the nonparametric QR model is used as the point of origin. The model QR is expressed as follows:

$$MPU_t = \beta^{\sigma}(OIL_t) + u_t^{\sigma} \quad (21)$$

Where MPU_t represents macroeconomic policy uncertainty index in period t; OIL_t represents structural oil shocks decomposed into oil consumption demand shocks, oil inventory demand shocks, oil supply shocks and economic activity shocks in time t; $\beta^{\sigma}(.)$ symbolizes the parameter between the explanatory variable and the dependent variable with the conditional σ^{th} quantile; u_t^{σ} denotes a quantile disturbance error term with a zero value on the conditional σ^{th} quantile.

To capture the correlation between the σ^{th} quantile of MPU index and the τ^{th} quantile of oil shocks, and since $\beta^{\sigma}(.)$ is not known, the first-order Taylor expansion approach around the quantile OIL^{τ} is then expressed as:

$$\beta^{\sigma}(OIL_t) \approx \beta^{\sigma}(OIL^{\tau}) + \beta^{\sigma'}(OIL^{\tau})(OIL_t - OIL^{\tau}) \quad (22)$$

Where, $\beta^{\sigma'}$ symbolizes the partial derivative of $\beta^{\sigma}(OIL^{\tau})$. $\beta^{\sigma}(OIL^{\tau})$, and $\beta^{\sigma'}(OIL^{\tau})$ are functions of σ and τ respectively. Furthermore, $\beta^{\sigma}(OIL^{\tau})$ and $\beta^{\sigma'}(OIL^{\tau})$ are reformulated as $\beta_0(\sigma, \tau)$ and $\beta_1(\sigma, \tau)$ accordingly. Following this, equation (23) is expressed as:

$$\beta^{\sigma}(OIL_t) \approx \beta_0(\sigma, \tau) + \beta_1(\sigma, \tau)(OIL_t - OIL^{\tau}) \quad (23)$$

Equation (23) characterizes the interdependence effect between the σ^{th} quantile of MPU index and the τ^{th} quantile of oil shocks. To formulate equation (24), equation (23) is then substituted into equation (21) as:

$$MPU_t = \beta_0(\sigma, \tau) + \beta_1(\sigma, \tau)(OIL_t - OIL^{\tau}) + u_t^{\sigma} \quad (24)$$

Equation (24) shows how the QQ approach provides a comprehensive view in terms of dependence, in which several quantiles of oil shocks are chosen, and estimated based on the local effect that those quantiles may have on the quantiles of the MPU index. The QQ breaks down the computed estimates of the QR and run a regression of the σ^{th} quantile of MPU index on the τ^{th} quantile of oil shocks. This entails that the QQ methodology gives disaggregated results which fully explains the association between oil shocks and MPU. This association is fundamentally expressed by, $\beta_0(\sigma, \tau)$, and $\beta_1(\sigma, \tau)$.

Equation (24) is then estimated by substituting OIL_t and OIL^{τ} with their computed estimates $\widehat{OIL_t}$ and $\widehat{OIL^{\tau}}$ accordingly. The local linear estimates can be derived from the following:

$$\min_{b^0 b^1} \sum\nolimits_{k=0}^{n} \rho_{\sigma}\left[MPU_t - b^0 - b^1(\widehat{OIL_t} - \widehat{OIL^{\tau}})\right] K\left(\frac{F_n(\widehat{OIL_t}) - \tau}{h}\right) \quad (25)$$

Where, ρ_{σ} denotes the quantile loss function, whilst $K(.)$ denotes a Gaussian kernel which is used to weight observations around OIL_t, whilst h symbolizes a bandwidth. Moreover, we have:

$$F_n(\widehat{OIL}_t) = \frac{1}{n} \sum_{k=1}^{n} (\widehat{OIL}_k < \widehat{OIL}_t) \tag{26}$$

Local linear regression is utilized to eliminate dimensionality issues (Sim and Zhou, 2015). Furthermore, it leads to large bias on computed estimates associated with low variances (Sim and Zhou, 2015). Following the work of Sim and Zhou (2015), a bandwidth of $h = 0.05$ is utilized in this paper.

4. Empirical results

4.1. Data and preliminary analysis

The study accommodates monthly data for oil shocks and MPU indices spanning from January 1990 to June 2022. However, due to data constraints, the end point for EPU and PU is July 2018. Data for FPU index determines the commencement date, while EPU and PU controls the end point. The variables follow a common timeline. Monthly data are available for oil shocks and FPU, while data for EPU and PU are quarterly, so they have been extrapolated to a monthly frequency. Hlatshwayo and Saxegaard (2016) compiled data for South Africa's PU and EPU indicators. EPU and PU are news-based indices that measure economic and political uncertainty, respectively, and are constructed using phrases related to economics, policy, politics, government, and uncertainty. FPU is a financial risk that arises from an undefined financial regulatory framework. The Financial Condition Index (FCI) is the best proxy for the FPU index and predicts monetary policy behavior during high volatility in financial markets (Quantec Database, 2022). The FCI is computed using real interest rates, yield curves, share earnings yields, excess money supply growth, and real effective exchange rate change, and it analyzes financial factors affecting inflation expectations and economic performance. Oil shocks are categorized into oil consumption demand shocks (Oil_cons^d), oil inventory demand shocks (Oil_inv^d), oil supply shocks (Oil_ss), and economic activity shocks also known as aggregate demand shocks (Oil_aggr^d). These shocks are retrieved from a structural vector autoregressive (SVAR) in Baumeister and Hamilton (2019). The data for these oil shocks are freely available at https://sites.google.com/site/cjsbaumeister/. The data used in the SVAR by Baumeister and Hamilton (2019) were retrieved from various sources. Specifically, the world oil production data was obtained from the Energy Information Administration (EIA) and nominal oil prices were sourced from the Federal Reserve Economic Data (FRED) which is maintained by St. Louis Federal Reserve. Meanwhile, global economic activity was constructed as a summation of industrial production of OECD countries as well as six other countries (which include South Africa and China, among others). Lastly, they modified U.S. crude oil stocks to arrive at global stocks. Data for these oil stocks were obtained from the EIA. For contrast, we also consider how South Africa's MPU responds to the trade and economic policy uncertainty of China and the U.S., two of South Africa's foremost trading partners. These data are sourced from http://www.policyuncertainty.com.

The summary statistics for oil shocks and MPU indices are presented in Table 1. When compared to uncertainty indices, the average value for oil shocks is lower, ranging from −0.1% to 0.13%. The average values for Oil_ss, Oil_inv^d, and Oil_aggr^d are all negative. Negative values for Oil_ss suggest reduced oil supply, negative values for Oil_inv^d suggest sudden drop in oil demand, and negative values for Oil_aggr^d imply sudden economic activity decrease, such as a recession. While the average values for Oil_cons^d, EPU, FPU, and PU are all positive. Positive Oil_cons^d mean increased oil demand, while positive MPU parameters indicate higher uncertainty in economic, financial, and political conditions, potentially leading to reduced investment. In terms of volatility, MPU indices have the maximum value of 17.48, being more than four times as volatile as the most volatile oil shock (Oil_cons^d), whose standard deviation is 3.5421.

The remaining variables, apart from EPU, PU, and Oil_inv^d, are skewed to the left. Kurtosis statistics show that all variables are leptokurtic. Apart from Oil_cons^d, the Jarque-Bera statistics and associated probabilities show that most variables are not normally distributed, confirming that the null hypothesis of normal distribution has been rejected. Given that most of the variables are heavily tailed and not normally distributed, the QQ regression approach is justified. Furthermore, to verify the properties of time series data, a graphical unit root test is initially conducted. As depicted in Fig. 1, all the oil shocks exhibit consistent mean averages over time. EPU and PU do not show any discernible trend as they evolve over time, while FPU displays a declining trend, indicating a non-stationary series. Additionally, stationarity is tested using the Phillips-Perron and Augmented Dickey Fuller methods. All series are integrated of order zero at 1%, 5% and 10% significance levels, indicating that variables are stationary in level form (see, Table 1).

4.2. Diebold- Yılmaz spillover analysis

Considering the objectives of the study, evaluating the dynamic spillovers between oil shocks and MPU is crucial. These dynamic spillovers are as follows: "*Directional Spillovers To*," which is denoted by "*To others*," and "*Directional Spillovers From*," which is denoted by "*From others*." As shown in Table 2, the spillover table depicts how shocks are received and transmitted. The table shows how a particular shock or MPU parameter contributes to the forecast error variance in relation to other shocks or indices. The net spillover is determined by subtracting the total contribution "From others" from the total contribution "To others". The net spillover can be positive or negative. Positive (negative)

Table 1
Summary statistics.

Statistics	Oil_cons^d	Oil_inv^d	Oil_ss	Oil_aggr^d	EPU	FPU	PU
Mean	0.1314	−0.1055	−0.1015	−0.0206	21.5494	111.1786	19.9964
Median	0.1167	−0.1633	−0.0853	0.0037	17.0621	111.7154	13.8479
Maximum	9.7381	4.2552	3.4498	1.5821	100.0000	127.3027	100.0000
Minimum	−9.9589	−3.0077	−7.9486	−2.1970	0.0000	85.6065	0.0000
Std.Dev	3.5421	1.0606	1.0769	0.5254	16.3629	8.6346	17.4800
Skewness	−0.1020	0.3079	−0.9061	−0.2506	1.7540	−0.1483	1.6189
Kurtosis	3.2207	3.6813	11.2077	3.9082	7.1039	1.9726	5.4280
Jarque-Bera	1.2908	12.0519	1009.718	15.3776	416.5870	16.3411	234.0679
Probability	0.5244	0.0024	0.0000	0.0005	0.0000	0.0003	0.0000
UNIT ROOT TESTS							
ADF	−18.6736*	−20.9545*	−17.7091*	−11.2766*	−3.5319*	−2.7155***	−3.4117**
PP	−18.6830*	−21.5478*	−17.8401*	−18.8766*	−3.4280**	−2.8945**	−3.5380*
Observations	343	343	343	343	343	343	343

Note: ADF represents Augmented Dickey-Fuller, whilst PP represents Phillips Perron unit root tests statistics. *; ** and *** signifies stationarity of a variable at 1%; 5% and 10% significance levels respectively, confirming that the null hypothesis of unit root is rejected, whilst the Schwarz Information Criterion (SIC) decides the exogenous lags.

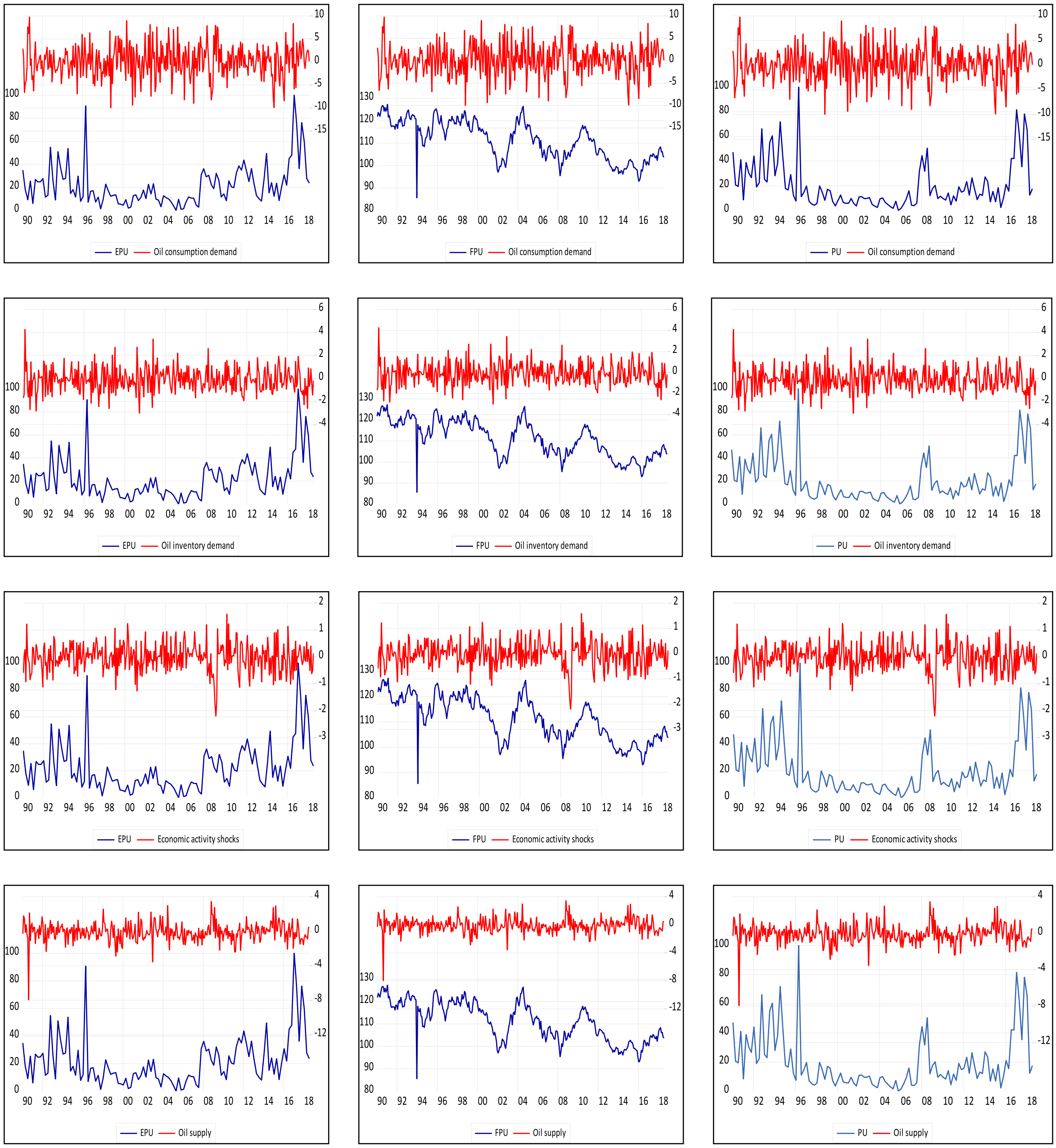


Fig. 1. Graphical illustration of trends for all oil shocks and MPU variables.

Table 2
Diebold - Yılmaz spillover results.

	FROM							
TO	Oil_aggr^{d}	Oil_cons^{d}	Oil_inv^{d}	Oil_ss	FPU	EPU	PU	From others
Oil_aggr^{d}	**71.55**	7.54	2.77	5.54	3.37	3.68	5.56	28.45
Oil_cons^{d}	3.10	**65.69**	9.48	12.29	3.49	3.06	2.89	34.31
Oil_inv^{d}	3.42	11.33	**70.05**	5.45	4.28	2.48	2.99	29.95
Oil_ss	6.05	13.45	4.75	**67.31**	3.47	2.15	2.82	32.69
FPU	2.79	1.79	5.99	4.90	**80.58**	1.96	1.99	19.42
EPU	3.26	1.63	1.94	1.74	1.38	**51.06**	*39.00*	48.94
PU	1.68	2.13	2.48	2.07	2.57	*34.17*	**54.90**	45.10
To others	20.30	37.87	27.42	31.99	18.55	47.50	55.23	**238.87**
Including own	91.84	103.55	97.47	99.30	99.14	98.57	110.13	
Net_spillovers	−8.15	3.56	−2.53	−0.70	−0.87	−1.44	10.13	**TCI=34.12%**

Note: TCI signifies the total connectedness/spillover index. "To others" signifies contribution to others, whilst "From others" signifies contribution to others.

net spillover values indicate shock net outbound (inbound) spillover transmission. In addition, the total spillover or connectedness index (TCI) is obtained by adding up the "contribution to others" or the "contribution from others" as a percentage of the "contribution including own". This measure characterizes the total spillovers transmitted among the oil market and the macroeconomy.

EPU, with total spillovers received summing up to 48.94%, is the highest recipient of spillovers from the associated oil shocks and MPU indices. It is followed by PU, which has a value of 45.10%, followed by Oil_cons^d with about 34.31%, and FPU is the lowest recipient of shocks from others with about 19.42%. This suggests that the overall directional spillovers to EPU exert a stronger impact on other shocks and MPU indices. Nevertheless, PU, EPU, Oil_cons^d, and Oil_ss continue to be among the top shock transmitters to others. These increased EPU and PU spillover effects may be influenced by political conflicts, a weakening in economic fundamentals, and corruption in South Africa. political issues (the fall of former president Zuma) between 2013 and 2017 also resulted in declining investor confidence, culminating in sluggish growth, and can be viewed as an element that has driven high shock transmission.

Meanwhile, EPU receives more shocks than it transmits, yielding a negative spillover value of −1.43%, whereas PU receives less than it gives, yielding a positive net spillover value of 10.13%. This could be explained by the fact that South Africa is an oil-consuming country, hence if an Oil_ss emerges, global oil prices will increase, resulting in inflation and interest rate hikes. This results in EPU as the major recipient of shocks, as the government might fail to address the macroeconomic problems at hand. These findings contradict the findings of Antonakakis et al. (2014), who reported that the EPU is the primary shock transmitter. Moreover, Oil_aggr^d, Oil_inv^d, Oil_ss, and FPU are also net shock receivers which also contradicts the findings of Antonakakis et al. (2014), who found that Oil_ss are net spillover transmitter. Consequently, Oil_cons^d and PU are net spillover transmitters. This result aligns with the work of Antonakakis et al. (2014), who discovered that Oil_cons^d are net spillover transmitters. This could possibly be due to consumer demand imbalances and political pressures within the ANC, such that when an oil shock occurs, the government fails to contain both internal party pressures and external shock pressures, resulting in spillovers being transmitted to other parts of the economy. Interestingly, like Huang et al. (2022) who uncover that the Chinese EPU is a net transmitter of shocks to oil prices, we observe that South African EPU transmits more spillovers to the oil shocks than it receives.

Meanwhile, the total connectedness index (TCI) is 34.12%. This indicates that spillovers among oil shocks and MPU parameters account for a third of the overall variation in forecast errors during the sample, with the remaining 65.88% explained by idiosyncratic shocks. This means there is a moderate connection between oil shocks and policy uncertainty.

Moreover, we also observe, in Fig. 2, that the connectedness among the variables has hovered between 20% and 30%. We find that the total dynamic connectedness was lowest around 2014. We also see in Fig. 2 that the connectedness among these variables has been increasing steadily from around 2014. This means that the variables within the network have, on average, become more vulnerable to the influences of other variables. Meanwhile, from Fig. 3, we also find that oil consumption demand shocks were a net transmitter of spillovers over the entire period of assessment, but oil supply shocks were net receivers of spillovers. Furthermore, aggregate demand shocks were net transmitters for almost the entire period of assessment but was a net receiver of spillovers in the 1990's. Interestingly, we observe, from Fig. 4, that there was greater connectedness among oil shocks and among MPU variables than across these.

Strikingly, we see a strong connection between economic policy uncertainty and political uncertainty in Fig. 4. The observation that there may be spillover effects between these two phenomena is not surprising given the economic disparities created during the Apartheid era. Certainly, many in the political domain have long advocated for economic solutions to ameliorate the impact of Apartheid. However, the strictly net transmitter role for political uncertainty post 2014 we see in Fig. 3 shows that political dysfunction has serious consequences on the economy. This is because, after 2014, political uncertainty has spilled over to economic policy uncertainty. This economic policy uncertainty is reasonably expected to weigh heavily on businesses and those holding capital.

Beyond this, it is also apparent that the bivariate spillovers between the different oil shocks and macroeconomic policy uncertainty phenomena are heterogeneous. These differences primarily reflect the level of concern apportioned to the source of oil shocks by consumers and firms as well as their attitude to these oil shocks. For example, in Fig. 4, FPU is especially susceptible to oil inventory shocks. It is apparent, therefore, that fluctuations in current levels of oil inventories may lead to elevated concern among firms. Similarly, PU has a strong connection with oil consumption shocks, which entail that changes in oil consumption are acutely felt in the political arena. This observation may arise on account that oil consumption, more than other oil shocks, better reflects the current state of the economy, in terms of production and employment.

4.3. Quantile spillover analysis

Comparing the results to the average-based connectedness analysis of Diebold and Yılmaz (2012), Table 3 displays the spillover results using a quantile spillover methodology. The table is divided into three sections. Panel A first assesses connectedness at the lowest quantile (0.05), while Panel B assesses connectedness at the median quantile

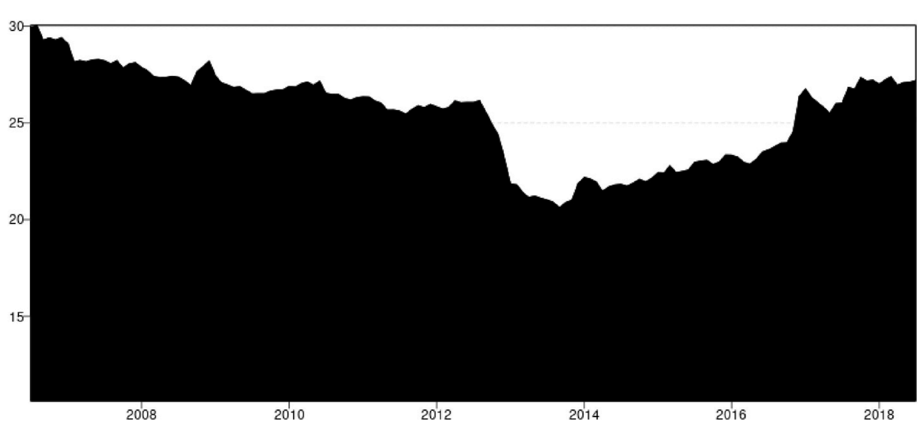


Fig. 2. Dynamic total connectedness
Note: Dynamic total connectedness among oil shocks and macroeconomic policy uncertainty between 01/1990 and 06/2022.

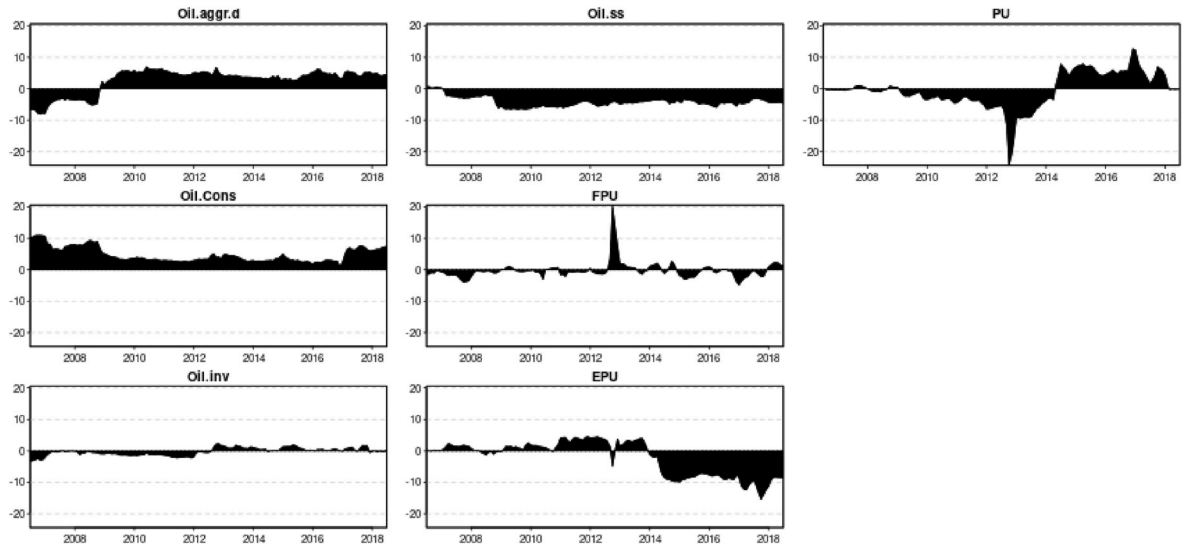


Fig. 3. Net total directional connectedness.

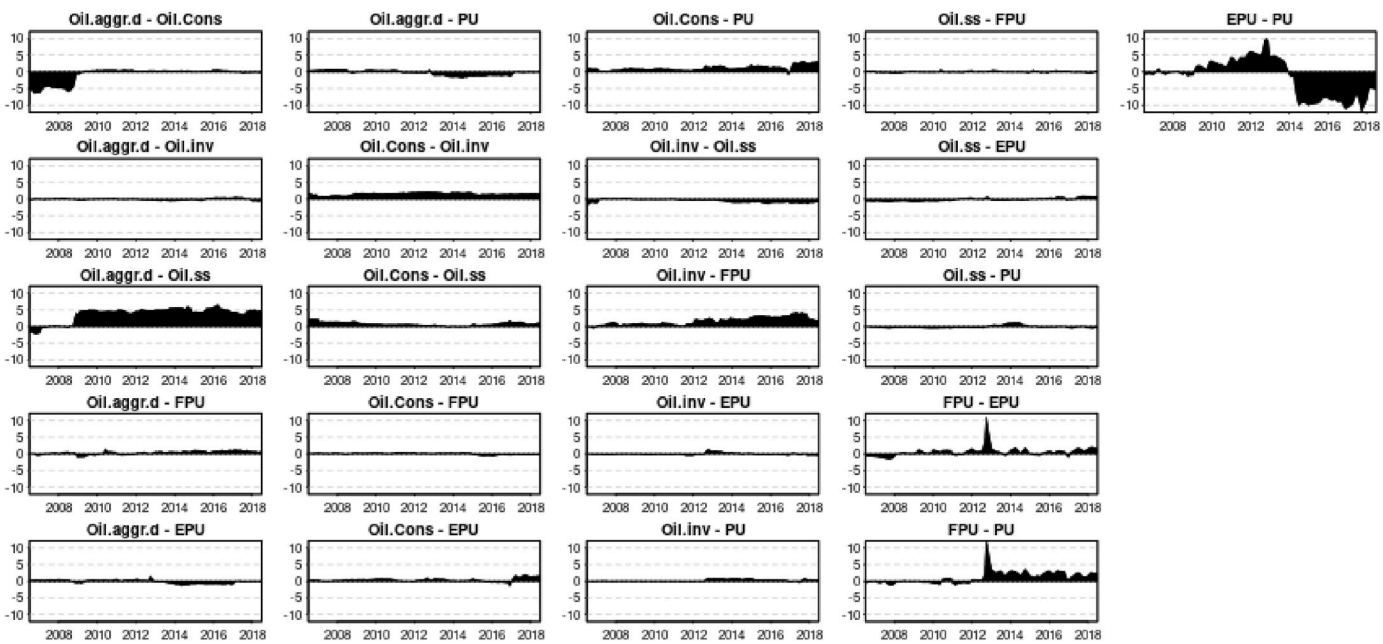


Fig. 4. Net pairwise directional connectedness.

(0.5). Finally, Panel C examines the spillover linkage between oil shocks and MPU parameters at the highest quantiles (0.95). For context, the median quantiles entail average levels in the various macroeconomic policy uncertainty phenomena and oil shocks. Meanwhile, the lower (upper) quantile corresponds to oil shocks of small (large) magnitude. Similarly, these extreme quantiles (lower and upper) would entail very low and high macroeconomic uncertainty.

There is evidence of shared ground between spillover findings estimated at the mean and estimates at the median quantiles. The TCI at the average and median ranges are 34.12% and 40.89%, respectively, indicating that the mean spillover result is significantly lower than the median quantile result (0.5). The TCI at the lowest quantiles and TCI at the upper quantiles are 71.77% and 72.59%, respectively, as shown in Table 3. Overall, this shows that these phenomena are more susceptible to spillovers when they are relatively very high or low. That is, during extreme periods, there is a stronger connection between macroeconomic policy uncertainty and oil shocks. This is an indication that, during these periods, when there are large oil shocks, firms and other market participants are especially vigilant of future policies. Meanwhile, given the magnitude of the oil shocks, policymakers are compelled to act through macroeconomic policy. These actions may themselves translate into movements in the economy that lead to shocks in oil markets.

Like the Diebold and Yılmaz (2012) framework, shocks that affect EPU are predominantly driven by PU across the lower (16.28%), median (39.99%), and upper (22.88%) quantiles. At the same time, shocks to PU are also heavily influenced by EPU across all quantiles, resulting in a bi-directional spillover effect across the full range of quantiles. These results are consistent with what we observed in Fig. 4 (net pairwise directional connectedness). The dominance political uncertainty has on economic policy uncertainty across all three quantiles is a serious concern. This is because dysfunction emanating from the political arena creates unnecessary stumbling blocks for market participants.

Furthermore, shock net receivers and transmitters vary from those shown in Table 3. First, all the structural oil shocks are net transmitters

Table 3
Quantile spillover results.

PANEL A: LOWER QUANTILES (Q) = 0.05								
Variable	Oil_aggr^d	Oil_cons^d	Oil_inv^d	Oil_ss	FPU	EPU	PU	From others
Oil_aggr^d	**31.00**	14.41	12.25	11.43	12.80	9.42	8.70	69.00
Oil_cons^d	12.69	**30.50**	12.62	10.01	13.45	10.07	10.67	69.50
Oil_inv^d	12.35	13.06	**29.06**	14.12	13.00	8.82	9.60	70.94
Oil_ss	11.40	12.60	13.99	**29.62**	11.65	10.67	10.07	70.38
FPU	12.40	14.85	16.85	13.87	**27.48**	8.07	6.49	72.52
EPU	12.33	12.89	13.50	10.64	10.70	**23.66**	16.28	76.34
PU	11.04	12.10	12.14	10.76	8.35	19.35	**26.27**	73.73
To others	72.22	79.90	81.34	70.82	69.95	66.40	61.80	**502.42**
Including own	103.21	110.40	110.40	100.44	97.43	90.05	88.07	
Net spillovers	3.21	10.40	10.40	0.44	−2.57	−9.95	−11.93	**TCI=71.77%**
PANEL B: MEDIAN QUANTILES (Q) = 0.5								
Variable	Oil_aggr^d	Oil_cons^d	Oil_inv^d	Oil_ss	FPU	EPU	PU	From others
Oil_aggr^d	**59.06**	10.24	3.44	5.14	3.45	6.90	11.77	40.94
Oil_cons^d	4.01	**50.75**	7.11	9.12	5.26	13.55	10.20	49.25
Oil_inv^d	5.85	10.50	**59.95**	6.35	5.44	6.53	5.38	40.05
Oil_ss	5.47	9.41	4.38	**65.19**	6.03	4.53	4.99	34.81
FPU	5.64	3.73	3.10	4.65	**63.05**	11.57	8.27	36.95
EPU	0.39	0.08	0.68	0.34	0.30	**58.21**	39.99	41.79
PU	0.41	0.14	0.65	0.25	0.11	40.85	**57.59**	42.41
To others	21.78	34.09	19.37	25.85	20.58	83.93	80.60	**286.20**
Including own	80.84	84.84	79.32	91.04	83.63	142.14	138.19	
Net spillovers	−19.16	−15.16	−20.68	−8.96	−16.37	42.14	38.19	**TCI=40.89%**
PANEL C: UPPER QUANTILES (Q) = 0.95								
Variable	Oil_aggr^d	Oil_cons^d	Oil_inv^d	Oil_ss	FPU	EPU	PU	From others
Oil_aggr^d	**25.88**	14.65	13.73	13.69	9.78	11.63	10.65	74.12
Oil_cons^d	13.40	**28.22**	11.63	13.95	9.75	11.68	11.37	71.78
Oil_inv^d	14.04	10.29	**25.23**	14.95	11.98	12.44	11.08	74.77
Oil_ss	13.06	13.05	15.06	**26.56**	10.89	10.83	10.54	73.44
FPU	12.34	12.63	12.44	12.71	**29.55**	9.55	10.78	70.45
EPU	7.51	12.94	10.16	10.33	9.79	**26.40**	22.88	73.60
PU	8.21	13.13	8.17	9.31	10.96	20.22	**30.01**	69.99
To others	68.55	76.69	71.19	74.94	63.15	76.34	77.31	**508.16**
Including own	94.43	104.90	96.42	101.50	92.69	102.73	107.33	
Net spillovers	−5.57	4.90	−3.58	1.50	−7.31	2.73	7.33	**TCI=72.59%**

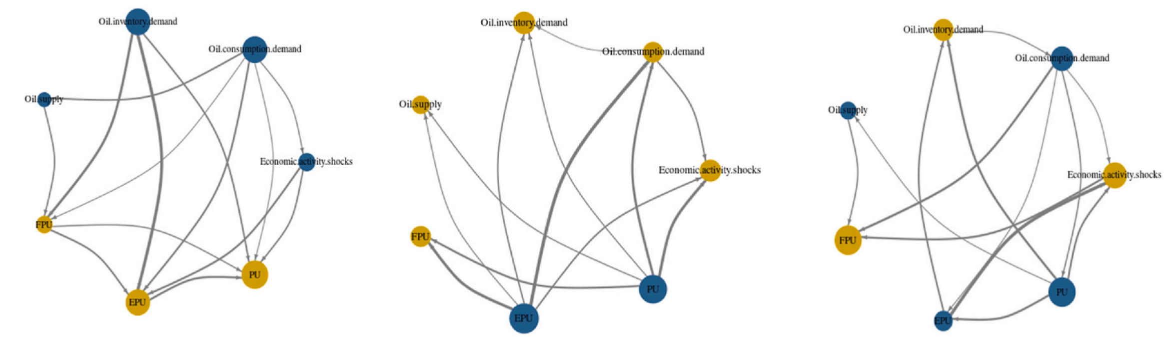
Note: TCI signifies the total connectedness/spillover index. “To others” signifies contribution to others, whilst “From others” signifies contribution to others.

at the lowest quantiles, while MPU parameters are net receivers of spillovers. This observation entails that small oil shocks are not affected by macroeconomic policy uncertainty. In turn, this is evidence that the response of policymakers to small oil shocks does not impact macroeconomic policy uncertainty enough to affect demand for oil. These results are consistent with the findings of Antonakakis et al. (2014), who concluded that Oil_ss and Oil_cons^d are net shock transmitters. The net spillovers of MPU parameters in South Africa are due to economic issues such as inflation and currency devaluation resulting from oil shocks. Meanwhile, all oil shocks and FPU are net receivers at the median quantiles, except for EPU and PU, which are net transmitters. Finally, PU, EPU, FPU, Oil_cons^d and Oil_ss are net shock transmitters, while Oil_aggr^d and Oil_inv^d are net shock receivers at the highest quantiles. These findings contradict the findings of Antonakakis et al. (2014) who reported that Oil_aggr^d are net spillover transmitters. Looking at the lower quantiles, EPU (76.34%), PU (73.73%), and FPU (72.52%) are the most affected by shocks, while at the median quantiles, Oil_cons^d (49.25%), PU (42.41%), and EPU (41.79%) are the most affected. Furthermore, at the upper quantiles, Oil_inv^d (74.77%), Oil_aggr^d (74.12%), and EPU (73.60%) are all noticeable receivers of spillovers. Ultimately, EPU is the primary receiver of shocks from others at the median and lower quantiles.

Interestingly, Su et al. (2021) find that, among the BRICS countries, when the EPUs are high, only the EPUs of Brazil, India and China affect the crude oil market. This is in stark contradiction to our observation that high South African economic policy uncertainty has a formidable impact on oil markets (in terms of shocks to supply, consumption, inventory demand, and aggregate demand). See the bivariate relationship between EPU and oil shocks in the upper quantile.

Recalling that the quantiles entail different magnitudes of each variable, Fig. 5 shows the network plot lines of the oil shocks and uncertainty indices across three quantiles. The low, median, and upper quantiles account for small, average, and large observations of each of the variables. Consistent with what we found in Table 3, we observe that FPU, EPU, and PU are all net receivers of spillovers at the lower quantile. That is, when these macroeconomic policy uncertainty phenomena are already low, their effects are overwhelmed by other MPU and oil shocks. We also find that among the three types of macroeconomic policy uncertainty, FPU is the only consistent receiver of spillovers across all three quantiles. Moreover, the extent to which it is affected increases across quantiles. That is, while FPU experiences no reversals in its association with the other MPUs and oils shocks, as it rises, its susceptibility to other adverse phenomena only increases. Meanwhile, both EPU and PU take the role of net-transmitter at median and upper quantiles. This is an indication that when economic and political uncertainty are already in their average state or historically high, rather than being affected by other phenomena, these uncertainties spill over to oil shocks and the other macroeconomic policy uncertainty phenomena.

On the other hand, the roles of the oil shocks at the extreme quantiles differ from that at the median quantile. While all the oil shocks are net receivers at the median quantile, they take the role of net transmitter at the lower quantile. We however see a more complex situation among the oil shocks in the upper quantiles, with some becoming net transmitters and others becoming net receivers. This is evidence that changes in macroeconomic policy uncertainty and other oil shocks may increase/reduce the severity of oil shocks in their various forms depending on



Lower Quantile (q = 0.05) **Median Quantile (q = 0.5)** **Upper Quantile (q = 0.95)**

Fig. 5. Network plots spillovers between oil shocks and MPU
Note: The net shock transmitter (receiver) is highlighted by the blue (yellow) nodes. Averaged net pairwise directional connectedness measures are used to weight vertices. The weighted average net total directional connectedness of nodes is represented by their size.

whether the oil shocks being experienced are small or large. As an extension of what we uncovered in our discussion around Table 3, Fig. 5 reveals a clearer picture than what is found in numbers. These results show that policymakers must take care to adapt their solutions to the various states of the macroeconomic policy uncertainties and oil shocks.

4.4. Quantile-on-quantile results

Supplementing the spillover analysis which provided crucial insight on the inter-phenomena relationships, we assess the quantile associations among these phenomena. We do this to analyze the direct impacts of movements among the variables in their various states. These quantile relationships among oil shocks and macroeconomic policy uncertainty are presented in Fig. 6. An overall positive relationship between EPU and Oil_ss exist as shown in Fig. 6 (i). That is, the median to upper quantiles of Oil_ss (0.5 to 0.95) have a positive effect on EPU in its median quantiles (0.4 to 0.6), except for lower and upper quantiles of EPU. This implies that large oil supply shocks increase economic policy uncertainty when this uncertainty is not particularly high or low. These results are in accordance with the works of Su et al. (2021) and Sheng et al. (2020), who discovered that Oil_ss have a positive impact on EPU. Conversely, a negative association is observed across all quantiles of Oil_ss when EPU is lowest (0.05 to 0.2). A substantial negative response is also evident between oil supply shocks' upper quantiles (0.95) and EPU's upper quantiles (0.8 to 0.95). These reversals in the association between EPU and oil supply shocks must be seriously considered because it implies that EPU responds differently when its already very high or very low (at least historically). Moreover, the observation that oil supply shocks reduce economic policy uncertainty when this uncertainty is very low is an indication that such news is generally viewed by market participants as providing greater clarity about future policies. Noticeably, the effect of Oil_ss on EPU is almost identical to FPU and PU. As shown in Fig. 6 (i), (v) and (ix), all these three variables show a highly positive effect from the median to upper quantiles of Oil_ss when MPU is slightly low and normal. Given the effect of oil shocks on expected inflation, it is not surprising that all the macroeconomic policy uncertainty variables are similarly affected. That is, the inevitable response from policymakers to changes in inflation likely leads to greater macroeconomic policy uncertainty. However, a special note must be made for political uncertainty. While policy responses may adversely/favorably affect unemployment and the prices of goods and services, we submit that oil shocks are taken as signals of future events in the political arena.

Oil consumption demand shocks' upper quantiles (0.75 to 0.95) are positively correlated with EPU's lower and median quantiles (0.2 to 0.5) as shown in Fig. 6 (ii). The global financial crisis of 2007/2008 is a quintessential example of the effect of oil shocks on the macroeconomy. These shocks arose from a fall in demand during the crisis. Compounding this state of affairs, during the same period, South Africa was experiencing mass strikes, political turmoil, and slow economic growth. Certainly, in this environment, EPU, FPU and PU increased. Conversely, a negative reaction is identified when upper quantiles (0.75 to 0.95) of Oil_cons^d negatively affect EPU's upper quantiles (0.75 to 0.95). The negative relationship observed aligns with the work by Antonakakis et al. (2014) who highlighted that Oil_cons^d inversely determine changes in the EPU index. Moreso, the impact of Oil_cons^d on EPU is similar to its effect on FPU and PU. All the three MPUs show a positive link between the upper quantiles of Oil_cons^d and the lower quantiles of MPU, whilst a negative relationship between the upper quantiles of Oil_cons^d and upper quantiles of MPU is observed as shown in Fig. 6 (ii), (vi) and (x). This general nexus shows that if macroeconomic policy uncertainty is already historically high (low), oil consumption demand shocks will decrease (increase) uncertainty.

From Fig. 6 (iii), (vii) and (xi), a significant positive link between aggregate demand shocks' upper quantiles (0.75 to 0.95) and lower quantiles of MPU parameters (0.1 to 0.4) is evident. These results are counter to those we observed for the relationships among macroeconomic policy uncertainty and oil supply shocks. That is, in this case, large aggregate demand shocks generally increase MPU when it is currently low. This positive effect might be explained by increased economic activity, which further causes inflation. Given that monetary authorities are compelled to respond in some way, this results in higher MPU. However, when macroeconomic policy uncertainty is already high, large aggregate demand shocks reduce uncertainty. This is evident from the negative effect when aggregate demand shocks and the MPU's are in their upper-most quantiles. We may infer that the expected response from policymakers seems to provide clarity to market participants. These results are consistent with the results of Sheng et al. (2020) and Kang and Ratti (2013a), who discovered that Oil_aggr^d have a negative impact on EPU.

The associations among macroeconomic policy uncertainty and oil inventory shocks are presented in Fig. 6 (iv), (viii) and (xii). The effects of oil inventory shocks on EPU, FPU and PU are almost identical. Strikingly, what matters most for the associations among oil inventory shocks and macroeconomic policy uncertainty is whether these uncertainties (EPU, FPU and PU) are low or high. Generally, any oil inventory shocks reduce macroeconomic policy uncertainty among firms and other market participants when this uncertainty is already high. Conversely, when this uncertainty is low, oil inventory shocks increase macroeconomic uncertainty. Like the effect we observed for the aggregate demand shocks, we infer that the occurrence of shocks that affect inflation leads to greater clarity among economic actors of expected policies from policymakers. These findings are supported by Sheng et al. (2020), who discovered that Oil_inv^d have a negative influence on EPU.

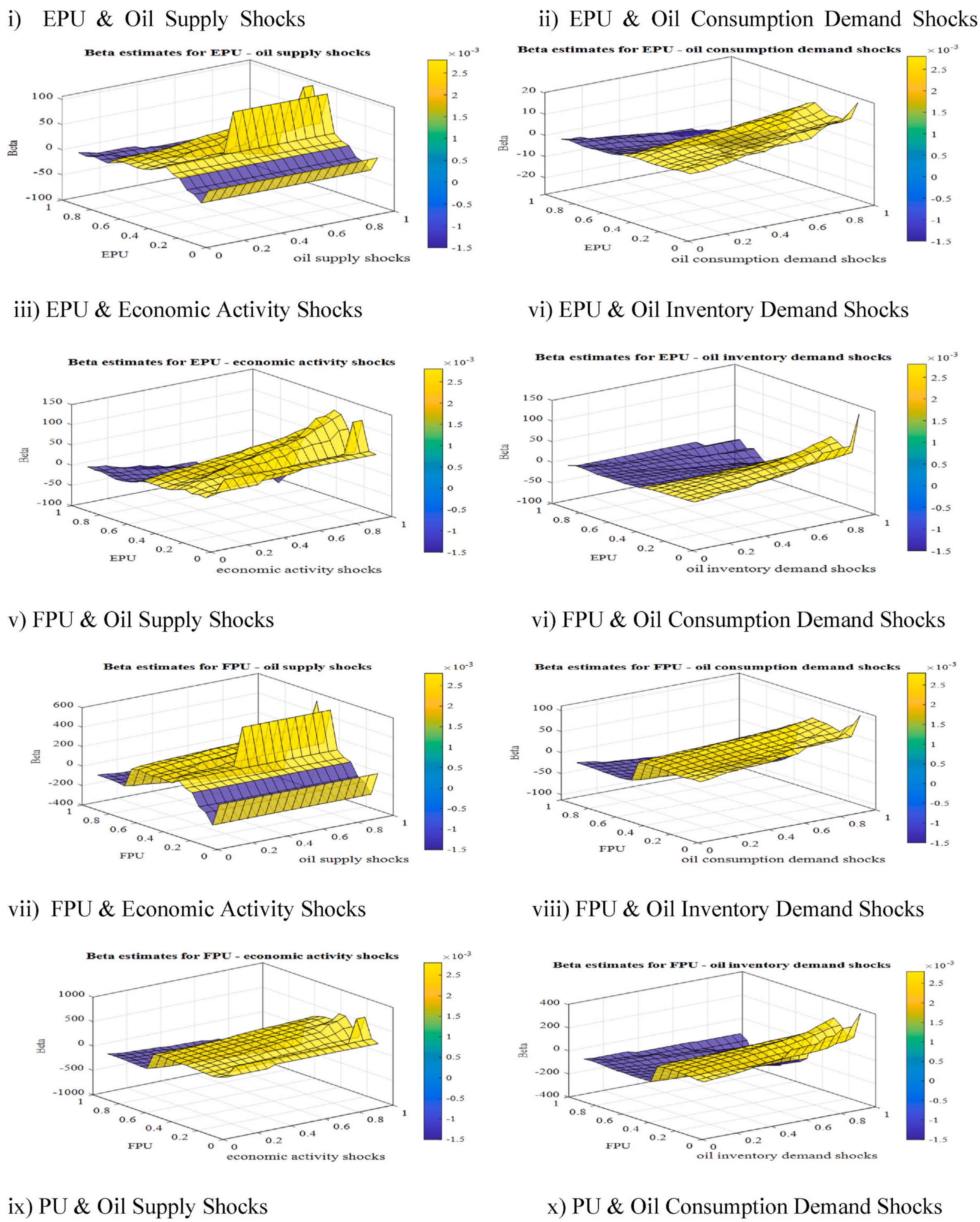
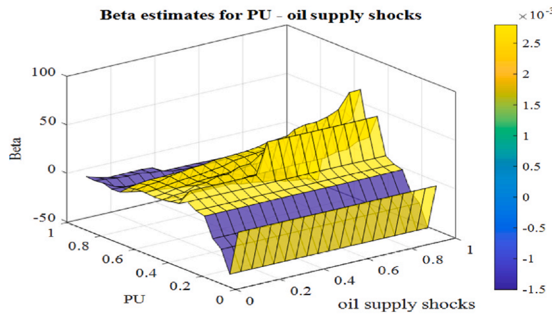


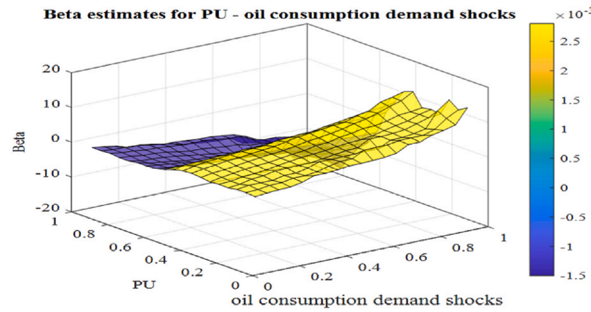
Fig. 6. Quantile-on-quantile Regression Plots

The negative association between Oil_inv^d and economic growth poses a challenge for policymakers as they must balance the need for economic growth with controlling inflation and stabilizing the financial sector. This uncertainty can make decision-making difficult, exacerbating the negative effects of Oil_inv^d and causing prolonged deleterious effects on the economy.

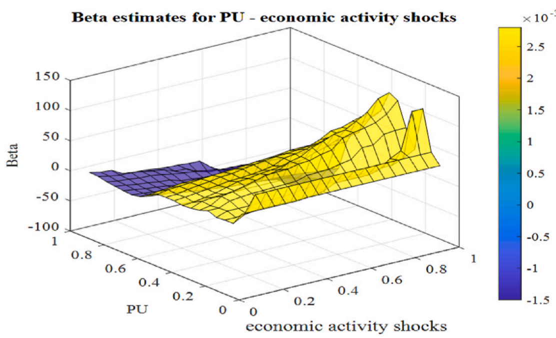
These results are similar to those observed in studies that focused on other BRICS countries. For example, Wang et al. (2022) found that greater oil prices led to a decrease in the EPUs of Brazil, Russia, China, and India in the short run. Interestingly, as Wang et al. (2022) note, this association was observed for both oil exporters (Russia) and oil importers (China and India). Of course, in our analyses, we find that the negative effect from oil shocks to South Africa's EPU is observed in the higher quantiles when this macroeconomic uncertainty is very high.

Overall, we find that there is heterogeneity in the associations between South African macroeconomic uncertainty phenomena and oil shocks. However, the most salient observation is that the state of macroeconomic policy uncertainty phenomena is what matters most in these





xi) PU & Economic Activity Shocks



xii) PU & Oil Inventory Demand Shocks

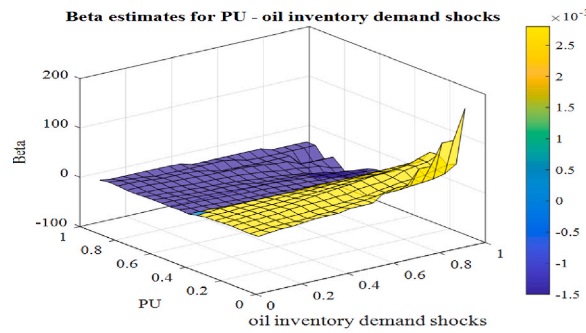


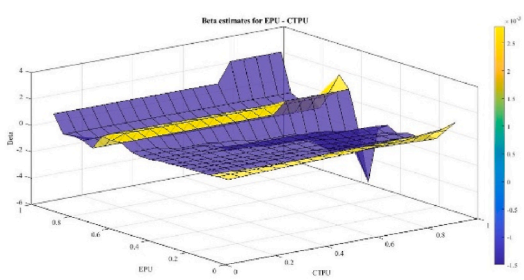
Fig. 6. (*continued*).

associations. Although the quantile spillover analysis in section 4.3 and a cursory look at Fig. 6 clearly show that low levels of macroeconomic policy uncertainty generally make it more susceptible to oil shocks, caution must be taken. That is, policymakers should strive to reduce uncertainty in pursuit of allaying fears among market participants. This is because high macroeconomic policy uncertainty is reasonably expected to disincentivize investment and employment.

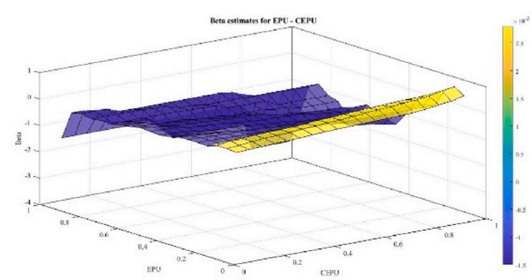
4.5. The impact of China and U.S. Trade and economic policy on South Africa MPU

To supplement and provide contrast to the main analysis of this paper, which looked at disentangled oil shocks, we also sought to assess how trade and economic policy uncertainty (TPU and EPU) indices for China and the U.S. may affect South Africa's macroeconomic policy

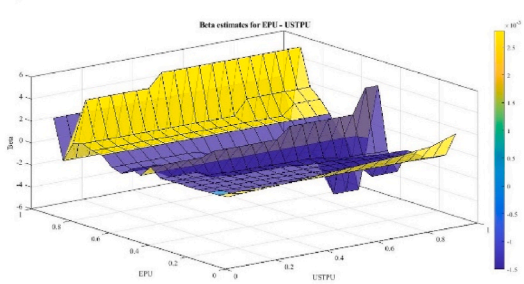
i) EPU & CTPU



ii) EPU & CEPU



iii) EPU & USTPU



iv) EPU & USEPU

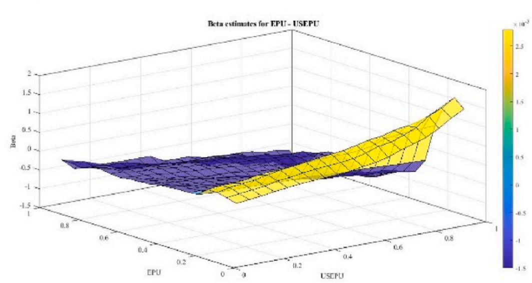


Fig. 7. South Africa Macroeconomic Policy Uncertainty & China/U.S. TPU and EPU
Source: Authors' compilation

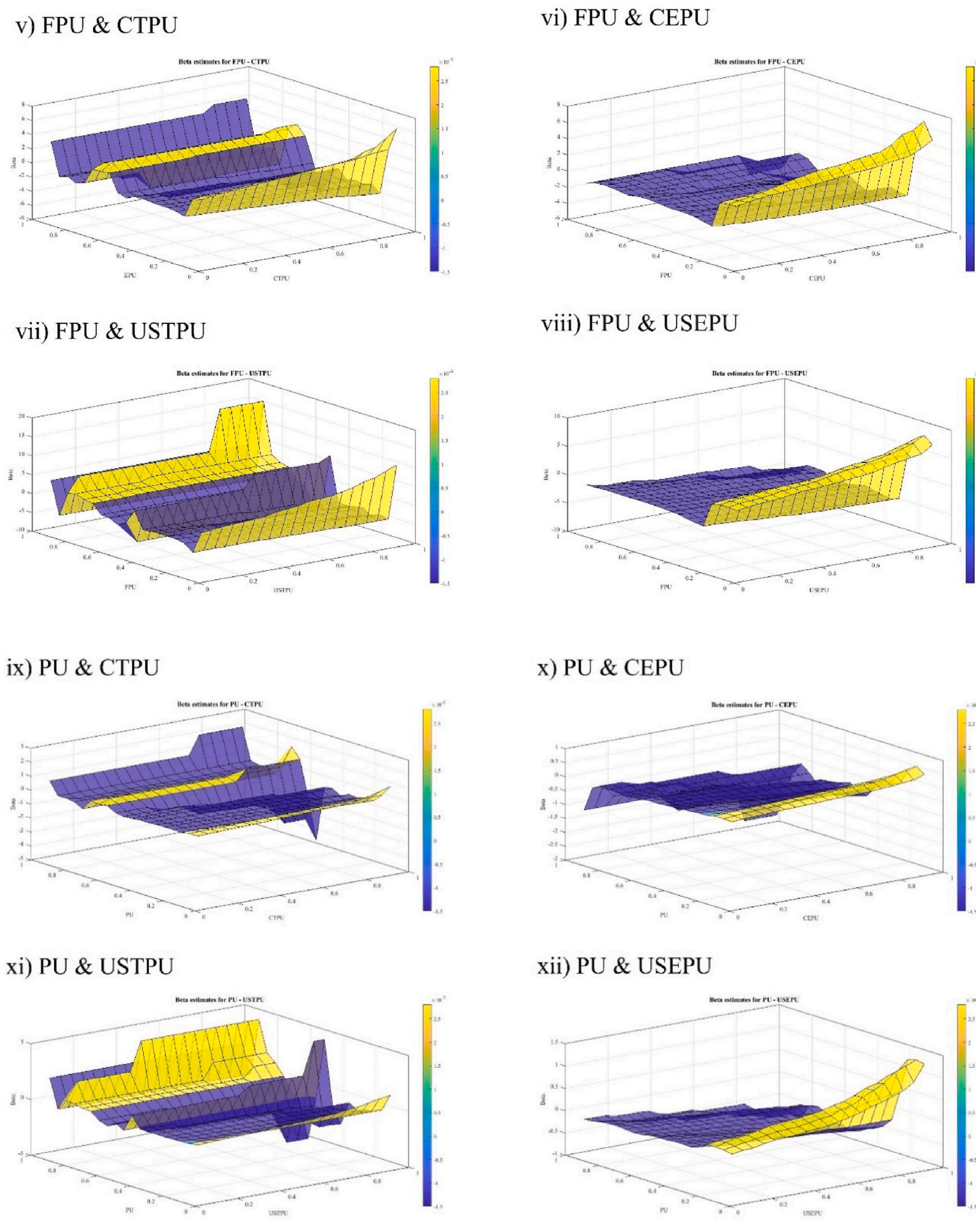


Fig. 7. (*continued*).

uncertainty. Unlike shocks to oil prices, which have direct effects on production costs and the concomitant inflation, pressures from both within and outside the country may lead to increases in political uncertainty and necessitate macroeconomic responses from policymakers. Specifically, we have focused on the U.S. and China on account that these two countries are South Africa's biggest trading partners. Together they accounted 22.59% of South Africa's exports and 27.62% of imports in 2021 (WITS World Bank, n.d.). Therefore, any shifts in policy in these two countries, whether advantageous or disadvantageous, will expectedly be impactful on South Africa's macroeconomy. It is on this basis that we apply the Quantile-on-Quantile regression approach to assess the effect of these economic and trade policy uncertainty indices on South Africa's macroeconomic policy uncertainty. From Fig. 7, we observe that the salient factor in the association between South Africa's macroeconomic policy uncertainty (EPU, FPU and PU) and CTPU, CEPU, USTPU as well as USEPU is whether MPU is low, average, or high (which coincides with low, middle, and high quantiles of MPUs). Although there is heterogeneity in the way South Africa's EPU, FPU and PU are affected by the Trade policy and economic policy uncertainties of the nation's largest trading partners, there are many similarities. For example, China and U.S. EPU increases South Africa's EPU, FPU and PU when these MPU's are low (that is, the lowest quantiles). Expectedly, we observe that, among South Africa's MPUs, EPU was particularly affected by China and US TPU. The trade policy uncertainty emanating from these two countries increased South Africa's EPU when it was low. These relationships are informative for understanding how such events as trade wars among large economies and trading blocs may affect a smaller economy like South Africa.

4.6. Robustness

We extend our findings by considering the quantile regression (QR) technique to test the robustness and reliability of the QQ results. Fig. 8 indicates that the results of the QR plots tend to be similar across the quantiles of the MPU parameters, but notable exceptions are observed following QR, which shows that the lower quantiles of the MPU

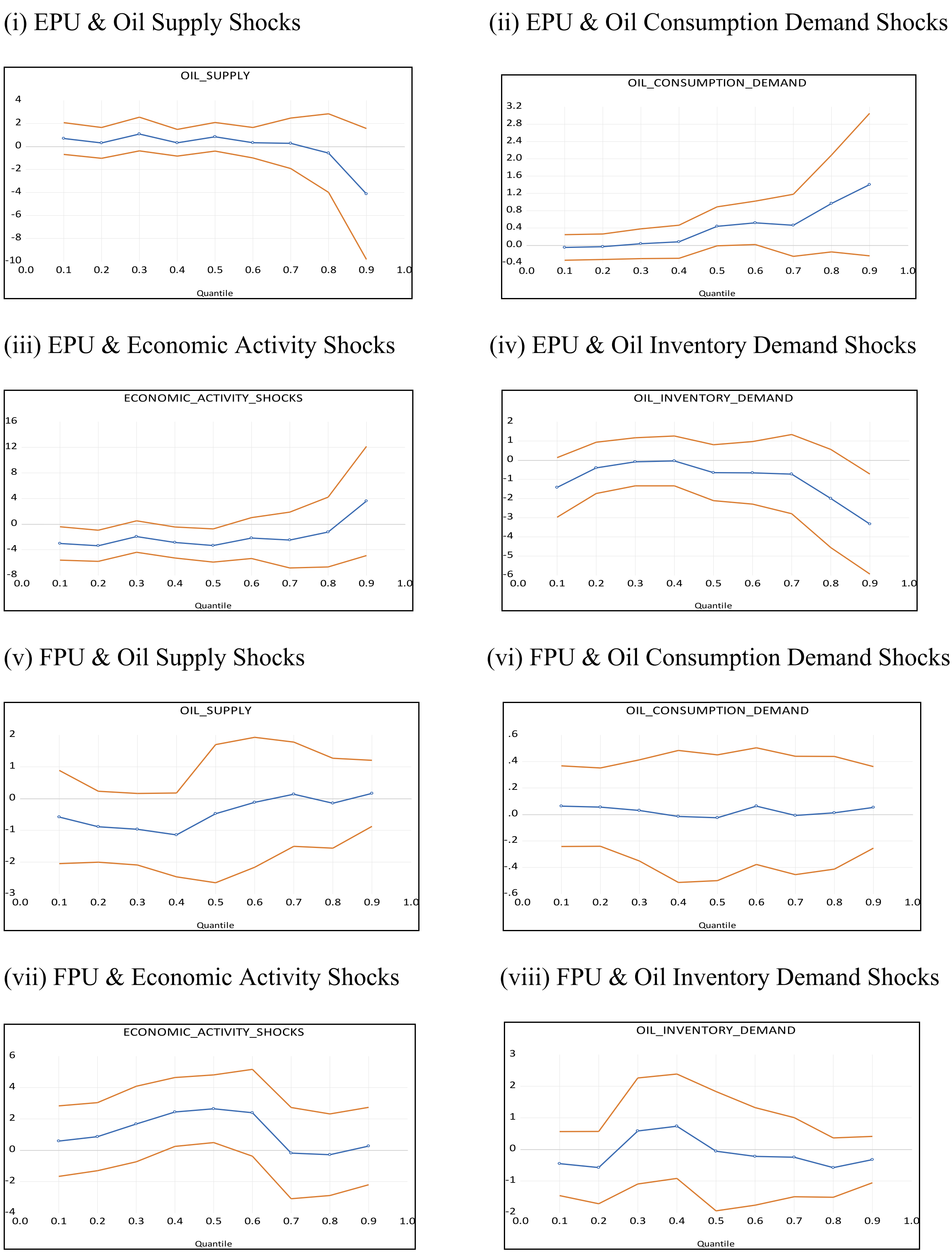


Fig. 8. Quantile Regression Plots
Source: Authors' own compilation

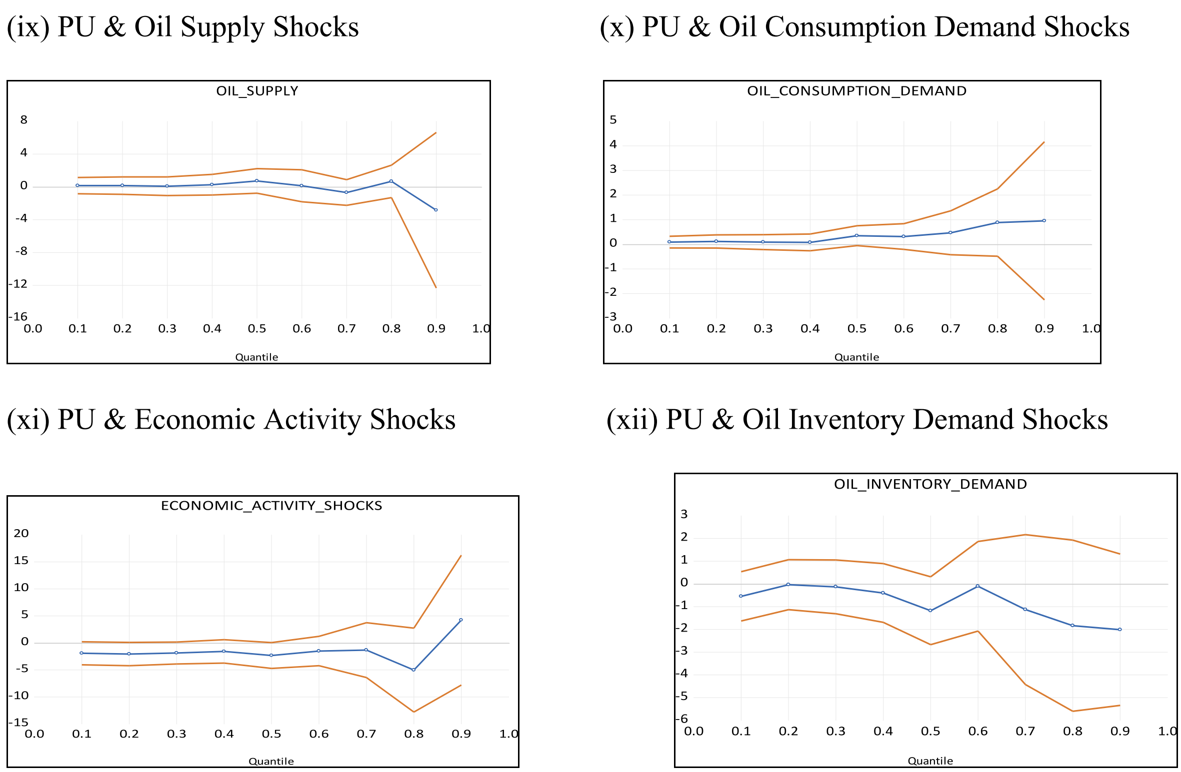


Fig. 8. (*continued*).

phenomena are negatively associated with the oil consumption demand shocks. Compared to the QQ estimates, there is a positive relationship between economic activity shocks and EPU around the upper quantile, but the reverse is the case at the lower to median quantiles of EPU. In addition, we observe a negative relationship between oil supply shocks and upper quantiles of EPU. Above all, these results show that, while the QQ is generally consistent with the QR, it provides a fuller picture of the associations among relevant variables. Consequently, the effect of oil price shocks on monetary policy uncertainty may be heterogeneous, varying when economic and market conditions, and the nature of the oil price shocks differ.

5. Conclusion

The study sought to evaluate the spillover connectedness among macroeconomic policy uncertainty and disaggregated oil shocks in a South African context. Using the Diebold and Yılmaz (2012) framework, the study found a moderate degree of connectedness among oil shocks and MPU. Moreover, from the quantile connectedness analysis, we uncovered that the net receiver/transmitter roles among oil shocks and MPU indices varied across quantiles. That is, whether these phenomena were historically low, average, or high. Pertinently, the results of the quantile connectedness framework showed that, while the average and median connectedness was relatively weak, the network explained the greater part of the movements among macroeconomic policy uncertainty phenomena and oil shocks during extreme conditions.

Interestingly, we uncovered that there has been a significant relationship between economic policy uncertainty and political uncertainty in South Africa. Strikingly, fears and uncertainty concerning South Africa's political arena have consistently sent shockwaves to economic policy uncertainty. This has serious consequences for investment and employment. The paper also applied the Quantile-on-Quantile regression analysis to analyze the associations among the variables. The study uncovered that the key determinant in the MPU - Oil shock nexus was the state of the MPU indices. That is, whether the indices were high or low.

Overall, the findings of this study are relevant to South African policy makers and other economic actors. By considering what has been uncovered in this study, policy makers will be better informed about the relationships among oil shocks and South African macroeconomic policy uncertainty. This is especially important given the effect oil shocks and macroeconomic policy uncertainty are expected to have on the economy. Notwithstanding these findings, the study has several limitations. The most salient of these is the lack of data to examine other variables, beyond those we have included, that are theoretically expected to affect South African macroeconomic policy uncertainty. Future research could assess the spillovers among MPU and precious metals and how they are affected by geopolitical risk. This would be particularly serviceable to investors and business analysts.

CRediT authorship contribution statement

Ismail Fasanya: Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization. **Samantha Makanda:** Writing – original draft, Formal analysis, Data curation.

Declaration of competing interest

This research paper authored by us is an original and genuine research work. It does not infringe on the right of others and does not contain any libelous or unlawful statements. It has not neither been submitted for publication nor published elsewhere in any print/electronic form. There are no competing interests between the authors.

Data availability

Data will be made available on request.

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