OIL SHOCKS AND MACROECONOMIC POLICY UNCERTAINTY IN SOUTH AFRICA

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ABSTRACT

The study reevaluates the connection between oil shocks and macroeconomic policy uncertainty in South Africa over the period of 1990M1 to 2022M6 using spillover connectedness frameworks and Quantile-on-quantile regression analysis. The link between oil shocks and macroeconomy rests on the Neoclassical theory following the Hamilton (2005) production function framework. The following findings are apparent from the analysis. First, the average-based connectedness framework shows a moderate connection between oil shocks and macroeconomic policy uncertainty parameters. Economic policy uncertainty and political uncertainty exhibit the most prominent bi-directional spillovers, while political uncertainty and oil consumption demand shocks function as net spillover transmitters. However, using the quantile approach, the level of connectedness between oil shocks and macroeconomic policy uncertainty parameters is stronger and much higher at both tails of the conditional distribution. Specifically, the study finds that macroeconomic policy uncertainty parameters act as net receivers at lower quantiles, while all the oil shocks and financial policy uncertainty act as net receivers at median quantiles, and economic activity shocks and oil inventory demand shocks act as net receivers at upper quantiles. Thus, the application of the average based framework of connectedness is inadequate and restrictive. Finally, using the Quantile-on-Quantile regression analysis, the results demonstrate a substantial positive (negative) relationship between the upper quantiles of oil shocks and the lower (upper) quantiles of macroeconomic policy uncertainty. These findings suggest that policymakers keep an eye on the repercussions of oil shocks on macroeconomic conditions and develop monitoring frameworks that will help to predict the likely effects of external shocks emanating from oil. Simultaneously, investors should contemplate modifying their investment strategy regarding the circumstances and keep an eye on oil prices, government policies, and economic indicators.

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1 CHAPTER 1

INTRODUCTION

1.1 Background

Over time, oil price shocks have proven to be the cause of economic recessions, leading to a significant decline in global economic activity, particularly in oil-dependent and oil-consuming countries. The first oil crisis occurred in 1973, followed by the second oil crisis in 1979, which led to a significant increase in oil prices and triggered global recessions (Salameh, 2004). The 1973 crisis caused a 4.7% decline in gross domestic product (GDP) in the United States, followed by a 2.5% decline in Europe and a 7% decline in Japan, while the 1979 oil crisis caused a 3% decline in global GDP (Salameh, 2004). More recently, climate security has been an issue, followed by the COVID -19 crisis and the measures taken to deal with it. Recent developments of another global energy shock in 2022 were fueled by the Russia-Ukraine war, which caused significant disruptions in the global energy supply chain due to the West's harsh sanctions against Russia (Wilkinson, 2022). In 2022, the European Union accelerated the ban on Russian oil, which, according to Wilkinson's report, led to higher energy prices and an inflation crisis that negatively impacted consumers in various countries such as South Africa. As a result, the situation has led to various uncertainties that underscore the need for global policy intervention to promote international cooperation.

Looking at the negative consequences of the global economic crisis of 2007-08, the COVID-19 crisis, and the 2022 energy crisis, we find that Africa as a continent lacks a defined regulatory framework, policies, and crisis response plans. As a result, Africa is highly vulnerable to global crises, leading to high unemployment, high inflation, high poverty, food shortages, lack of commodities, economic depression, and low Foreign Direct Investment (FDIs) inflows (World Bank, 2022). Finally, the 2022 oil shock, with simultaneous high inflation and unemployment rates, has challenged monetary policymakers to control inflation without exacerbating unemployment (World Bank, 2022). This shows how uncertainty is increasing due to political uncertainty, low to stagnant economic growth, and weak institutions, indicating poor political structures in many developing countries, including South Africa.

Rising oil and gas prices have negatively impacted Africa, particularly in the electricity and food markets. Since many African countries rely on oil for electricity generation, fuel prices have increased across the continent (Odakare, 2022). As an illustration, the Russia-Ukraine war has led to a global shortage of fertilizer, rising food prices, a global increase in oil and fuel prices, and higher food production costs (Sacko & Mayaki, 2022). This Russia-Ukraine war had indirect and direct impacts on South Africa's economic, financial, and political environment, although some of these impacts were limited compared to other countries. First, an increase in inflation, particularly food and fuel prices, was observed in 2022 due to supply and demand disparities (Simpson, 2022). In July 2022, South African fuel prices almost reached R27 for gasoline and R26 for diesel (Writer, 2022). The global increase in crude oil prices because of the Russian invasion of Ukraine in February 2022 exacerbated this increase in fuel prices. Second, due to the risk associated with the conflict, the invasion weakened foreign investor confidence in South Africa, resulting in slower economic growth, which could be a driving force behind economic policy uncertainty (EPU). In addition, the invasion also had a financial impact, as increased uncertainty in global markets led to declining commodity prices, which negatively impacted the country's revenues, trade balance, and ability to repay debt. Furthermore, increased global crude oil prices have led to exchange rate fluctuations and interest rate hikes to control inflation caused by supply disruptions (Gumede, 2022), potentially adding to economic and financial uncertainty. In addition, South Africa faced persistently poor service delivery, increasing corruption, and an unreliable government that did not address the issues at hand, coupled with the war-induced increase in food prices. While it is true that the invasion had the potential to cause public unrest among the country's poor citizens (Gumede, 2022), so political uncertainty could potentially increase.

Following the above, policy uncertainty in the economic, financial, and political spheres is seen as a critical drag on South Africa's macroeconomic stability, leading to macroeconomic policy uncertainty (MPU). Al-Thaqeb and Algharabali (2019) defined policy uncertainty as an economic risk associated with unspecified future government actions and regulatory frameworks that cause businesses, investors, and consumers to postpone spending and investment due to market uncertainty. As a result, in this study, MPU is categorized as economic, financial, and political risks associated with inadequate regulatory systems, resulting in uncertainty. Various events have contributed to MPU in South Africa over time. For example, political pressure within the ruling party increased uncertainty during the democratic transition (Hlatshwayo & Saxeguard, 2016). Second, ongoing xenophobic attacks that have led to the deaths of many foreigners have contributed to increased MPU overtime. Third, political tensions in South Africa since 2008, when Thabo Mbeki resigned and Jacob Zuma was elected president, have led to an economic recession. Finally, these political conflicts within the African National Congress (ANC) as well as the resignation of Jacob Zuma have exacerbated MPU in the country. This implies that MPU has a negative impact on national economies because it discourages Foreign Direct Investments (FDIs), leading to, among other things, an increase in unemployment. Investor uncertainty in South Africa continues to increase due to the ESKOM power outages, which will lead to a decrease in FDI and consequently low economic growth. Looking more closely at the financial sector, financial uncertainty may have increased because the country has been downgraded to junk status several times. For example, following the cabinet reshuffle during Zuma's tenure, the country was downgraded to junk status by Fitch Ratings (Fitch) and Standard & Poor's Global (S&P) in 2017. Such a downgrade was consistent with the continuous depreciation of the exchange rate during Zuma's tenure, which has created some degree of uncertainty. In addition, Moody's downgraded South Africa's investment grade to "junk" status in the wake of the COVID-19 crisis (Bloomberg, 2020). These downgrades were caused by deteriorating financial strength and weak economic growth. According to Moody's, the slowdown in the economy was caused by ongoing power outages, low business and investor confidence, and labor market constraints (Bloomberg, 2020). Interest rate hikes, the devaluation of the rand, and higher inflation are the consequences of junk status. These effects exacerbate economic and financial policy uncertainty (FPU).

The relationship between oil shocks and MPU is determined by the response of economic agents to the nature and magnitude of the shock, and thus affects the degree of uncertainty that policymakers must consider, as noted by Haddow *et al*. (2013). Oil demand shocks lead to a decline in consumption and investment, while oil supply disruptions increase output uncertainty and lead to higher unemployment rates, as reported by Al-Thaqeb & Algharabali (2019). These economic challenges pose a dilemma for policymakers in terms of how to respond. Haddow *et* *al.* (2013) recommend that policymakers identify the source of uncertainty to make effective decisions.

In summary, the combination of inflation, unemployment, fuel price increases, interest rate hikes, weak growth, and currency devaluation resulting from oil shocks in South Africa leads to MPU, which is exacerbated by poor regulatory frameworks and corrupt government practices. The study of the relationship between oil price shocks and MPU has attracted considerable interest, and this paper aims to contribute to this literature by focusing on the South African context.

1.2 Problem Statement

Oil shocks can generate MPU through various channels, as they trigger second-round effects on the economy. For instance, rising oil prices can increase production costs in oil-importing countries, leading to reduced output, inflation, low profits, low investments, unemployment, and reduced wages. As a result, policymakers may adopt tight monetary policies to mitigate inflation, but this action fails to address other macroeconomic issues, leading to EPU (Aimer & Lusta, 2022). Oil shocks can also affect the prices of financial assets, including stocks, bonds, and exchange rates, destabilizing financial markets, and increasing risk and uncertainty. Financial institutions may reduce lending activities, tightening credit conditions, and causing FPU. Furthermore, oil shocks can stimulate speculation on interest rates, inflation, exchange rate volatility, and monetary policy behaviors, leading to increased FPU. Additionally, oil shocks can change the political landscape, as governments and political leaders try to respond to the economic and financial impacts of the shock. For example, governments may increase subsidies for energy products or implement price controls, leading to political uncertainty and further economic disruption. Geopolitical tensions and conflicts can also arise, further increasing economic, financial, and political uncertainty. These impacts can be particularly severe in countries heavily reliant on oil exports, facing increased pressure to maintain production levels and safeguard their economic interests.

It is true that there exists a link between oil price shocks and MPU. Oil supply shocks are often associated with external political events or geopolitical uncertainty (as noted by Hamilton, 2003), which can lead to significant disruptions in oil supply and give rise to macroeconomic problems like inflation, leading to an increase in economic uncertainty. According to Cunado *et al.* (2020), oil demand shocks are associated with excess demand for industrial commodities or oil due to uncertainty arising from oil supply shortages. For instance, in 2007-2008, there was a surge in global demand for oil, while the supply remained stagnant. The resulting excess demand for energy from countries like China and India led to skyrocketing oil prices, which contributed to the 2007 financial crisis by causing a massive influx of funds into the commodities market, generating uncertainty (Hamilton, 2009). This period witnessed a rise in financial uncertainty as stock markets and financial institutions plummeted, while the economic recession exacerbated economic uncertainty.

In essence, there is a clear spillover relationship between oil shocks and policy uncertainty, as noted by Antonakakis *et al*. (2014), who suggest a spillover effect between oil price shocks and EPU. As oil shocks can lead to negative effects on aggregate demand, including inflation and current account deficits, this can result in heightened EPU as policymakers are faced with difficult decisions. Furthermore, political divisions within ruling parties can add to the uncertainty. For example, in the case of a country like South Africa, an oil-consuming country facing interest rate hikes, exchange rate devaluation, and a junk status, this can contribute to increased FPU for regulators. Conversely, MPU can also spill over to oil shocks, as government policies and their impact on production can influence the demand for and price of oil. Factors such as political pressures, consumption levels, oil reserves, global exchange rates, environmental issues, and speculation in the financial market all contribute to the demand and supply of oil, emphasizing the dynamic nature of spillover effects between oil shocks and MPU. Therefore, it is important to examine this connection.

Policymakers and investors may inquire about the effects of oil shocks and MPU, depending on the size and severity of the shocks and how MPU reacts to them. Severe oil shocks can lead to a considerable increase in MPU as policymakers may be uncertain about the appropriate response to the shock, such as implementing fiscal and monetary measures to mitigate its impact. Conversely, mild, or low oil shocks may have a lesser or even nonexistent impact on MPU, as policymakers may have more time to respond or may not feel the need to act. Given this consideration, the study explores the quantile effects of oil shocks on MPU to reveal how the severity of oil shocks affects MPU at a certain level.

1.3 Research Questions

This paper examines the oil shocks-MPU nexus in South Africa. The research questions to be addressed in this study are as follows:

i. What forms of spillovers exist between oil shocks and macroeconomic policy uncertainty?

ii. What relationship exists between oil shocks and macroeconomic policy uncertainty across different quantiles?

1.4 Research Objectives

To answer these questions proposed above, the study seeks to examine the impact of oil shocks on macroeconomic policy uncertainty. The specific goals are as follows:

i. Examine the spillovers between oil shocks and macroeconomic policy uncertainty.

ii. Analyze the quantile relationship between oil shocks and macroeconomic policy uncertainty.

1.5 Contribution of the Study

Oil prices have a substantial impact on the macroeconomic system. High energy prices, for example, have an undesirable consequence on real GDP and economic performance. This implies that a rise in the price of oil will induce changes in spending and production, giving rise to slower economic growth. Due to "higher oil prices," market participants face higher transportation and manufacturing costs. Rising oil prices have contributed to low GDP, a current account deficit, reduced domestic consumption and investment demand, import reduction, and reduced domestic production in oil-importing countries such as South Africa (Fofana *et al*., 2009). Furthermore, because of the rise in oil prices, households are facing an inflationary crisis. Oil price increases caused by disruptions in oil supply triggered by external events typically cause a reduction in growth and inflation in oil-importing countries such as South Africa, whereas oil price increases driven by higher demand result in an economic boom in oil-exporting countries. Sudden changes in oil prices can increase the cost of energy products, which can then lead to higher inflation and create uncertainty about the future direction of monetary policy. Second, oil price shocks can affect the financial sector, leading to increased volatility and uncertainty in financial markets. This can create risk for investors and make it difficult for policymakers to manage financial stability. All things considered, oil shocks, depending on the duration of the shock, could potentially trigger macroeconomic uncertainties as the government fails to address the escalating issues, causing businesses, investors, and consumers to prolong spending, investment, and production. In short, the significance of oil price shocks lies in their ability to create uncertainty and affect a wide range of economic and political factors.

Most of the literature on oil shocks has utilized Ready's (2018) categorization of oil shocks as oil supply shocks, oil-demand shocks, and exogenous shocks. However, other studies have followed Killian's (2009) disentangled shocks model, including Chisadza *et al.*'s (2016) work on the impact of shocks on the South African economy. Despite the importance of oil inventories in shaping investor expectations of future supply and demand, previous studies have overlooked their impact on oil shocks. Fueki *et al*. (2018) argue that speculative demand can also contribute to oil shocks. This study aims to enhance our understanding of oil shocks by categorizing them into four types: oil supply shocks, oil consumption demand shocks, oil inventory demand shocks (speculative demand shocks), and economic activity shocks. This approach follows Baumeister and Hamilton's (2019) framework and will lead to a more comprehensive analysis of the effects of oil shocks on MPU in South Africa. Baumeister and Hamilton (2019) find that oil inventory demand shocks play a significant role in oil price fluctuations. This implies that when oil inventory increases, demand for oil drops, causing traders to sell positions and triggering a price decline in financial markets. This study will evaluate the association between oil shocks and FPU, while accounting for the impact of oil inventories on oil shocks.

Moreover, the study contributes to the existing literature on the oil shock-MPU nexus, by using the average based spillovers, quantile spillovers and quantile-on-quantile (QQ) methodology. Previous studies have used different econometric approaches, for instance, You *et al*. (2017) used a quantile regression (QR) model, while others have employed mean regression methods such as OLS. The QQ approach was chosen for this study to provide distinct features in the nexus between oil shocks and MPU that are not observable when the QR and OLS regression methods are used. One limitation of the quantile regression model is that it does not capture complete dependence (Sim & Zhou, 2015); that is, while it can estimate different relationships between variables, it ignores the possibility that the nature of one variable (for instance, oil shocks) may also influence the way oil shocks and the MPU indices are related in this case. The

QQ approach was then developed to relax this limitation. 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 indices (Sim & Zhou, 2015). This methodology is appropriate for examining the effect of oil shocks on the performance of all macroeconomic entities, with a focus on the magnitude of the shocks. The approach is pertinent to this topic because MPU responds differently to oil shocks depending on the shock's magnitude. Large oil shocks have different effects on the macroeconomy, and the resulting MPU differs from the effects of smaller oil shocks. Moreover, the influence of oil price shocks during an economic boom and how policymakers and investors react to them differs from the effect of oil shocks during an economic downturn.

1.6 Scope of the Study

The research concentrates on global structural oil shocks and the corresponding MPU in South Africa from January 1990 to June 2022. While the endpoint for all the structural oil shocks and FPU is June 2022, the study has limited data availability for EPU and political uncertainty (PU), and hence the end date for these variables is July 2018.

1.7 Organization of the Study

The following is the structure of the paper's remaining sections. The review of theoretical and empirical literature of the study is presented in chapter two. Chapter three describes the theoretical framework and data while also providing a detailed explanation of the methodology used in this study. Furthermore, chapter four presents and discusses the empirical findings, while chapter five wraps up the paper and makes some policy recommendations.

2 CHAPTER TWO

LITERATURE REVIEW

The literature review is divided into two sections. Firstly, it examines the theoretical literature on the relationship between oil shocks and MPU. Secondly, it provides an overview of the empirical literature, including the methodologies employed and the findings obtained, that illustrates the link between oil shocks and MPU behavior.

2.1 Theoretical Review

Oil price shocks have had a significant impact on the economy through various mechanisms such as inflation, recessions, and economic growth. The relationship between oil shocks and macroeconomic conditions can be explained by Neoclassical models using production functions that include energy inputs (see, for example, Rasche & Tatom, 1977; Kim & Loungani, 1992; Hamilton, 2005), which imply that an increase in resource prices affects long-term production and average costs, which in turn affect supply and output. Increases or decreases in energy prices can cause a reduction or rise in energy use, which can result in a recession or boom. Rasche and Tatom (1977) documented that a drastic increase in the price of oil in 1974 resulted in a substantial decrease in productive capacity in the US.

Moreover, following a production function, oil price shocks, according to Bohi (1991), have both direct and indirect effects on economic performance. The direct effects occur because of the additional resources required for intermediate energy inputs, resulting in a decrease in net output. The substitution relationships between oil and capital determine the indirect effects. Short-term disruptions in oil supply can amplify indirect effects rather than reduce direct effects, making even minor price increases significant. Sticky price levels and capital obsolescence are two hypotheses that arise from the possibility of negative substitution relationships. Sticky prices can reduce employment and raise uncertainty, while capital obsolescence can reduce output and raise uncertainty. On the other hand, Hamilton's (1988) model states that output reacts similarly regardless of whether oil prices rise or fall. Bernanke (1983) added that oil shocks decrease value addition, causing firms to defer investment to determine the shock's duration and creating uncertainty. This has increased uncertainty since Bernanke's work. According to the study, if uncertainty is a significant mechanism triggering economic recession from oil shocks, sales of energy-intensive goods such as cars should decrease as oil prices fluctuate. This was observed in the drop in automobile sales following the oil shocks of 1974, 1979, and 1990 (see Bursky & Killian, 2004).

Another model which could possibly explain the linkage between oil shocks and MPU is the Monetary model. The model implies that money supply is an important determinant of the price level or inflation, so that in the case of oil price shocks, changes in the money supply can affect output and hence inflation (Copeland, 2005). This could possibly result in increased policy uncertainty, which can further complicate the response of the central bank to oil price shocks, leading to additional uncertainty in the economy. On the other hand, the Dutch Disease Model suggests that oil discovery can negatively affect manufacturing and agriculture, leading to a decline in the economy (Brahmbhatt *et al*., 2010). This implies that higher oil prices can cause a rise in a country's currency, reducing export competitiveness and causing a decline in other sectors like manufacturing. This impact on international trade may be worsened by policy uncertainty.

In the models presented above, they primarily focus on the direct and indirect effects of oil shocks on the macroeconomy. Nevertheless, the direct and indirect effects on the macroeconomy do not provide a complete picture of the second-round effects of oil shocks on the macroeconomy, which leads to policy uncertainty. As a result, this study follows Hamilton's Neoclassical model to examine the oil shocks-macroeconomy nexus, concluding that oil shocks lead to recession, which leads to uncertainty.

2.2 Empirical Review

The literature on the relationship between oil price shocks and EPU has been analyzed over time for different countries, resulting in disparate findings due to the use of different techniques. Looking at the relationship between oil price shocks and EPU on a multiscale basis, Chen *et al*. (2020) conclude that oil price shocks and EPU are positively related at the initial level, while positive time-varying effects are observed in the short and long run and negative effects in the medium run. Moreover, Antonakakis *et al*. (2014) explored this relationship for eight (8) countries namely Canada, China, India, the UK, Germany, France, Italy, and Spain. The findings highlighted that oil shocks and EPU are inversely related, whilst after reclassifying the shocks, aggregate oil demand shocks are negatively related to EPU, but oil-specific shocks and supply side shocks are inversely transformed by changes in EPU. On the other hand, Rehman (2022) highlighted that EPU for Spain, Japan, and India, reciprocates with oil price shocks, but aggregate demand shocks don't bring any changes. Furthermore, the author pointed out that the nature of the country also determines the sensitivity levels of oil shocks.

Many researchers have applied the Structural VAR model to derive answers on this nexus, but contradictory results have been drawn. For example, Kang *et al*. (2017) pointed out that EPU responds directly to U.S oil supply shocks, whilst an inverse reaction is identified towards non-U.S oil supply shocks. Contrastingly, Kang *et al*. (2019) came to conclude that oil shocks' effects on gasoline prices are interlinked with EPU, whilst Kang and Ratti (2013a) reported that positive oil aggregate demand shocks heavily affect EPU negatively, whilst structural oil shocks appeared to have long-term effects on EPU.

Over time, empirical studies evolved to the point where the spillover association between oil markets and policy uncertainty could be studied independently or collaboratively with other financial variables. 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, with fiscal policy uncertainty having the most significant impact on oil returns, followed by uncertainty stemming from exchange rate, monetary policy, and trade policy. According to Yang (2019), on the other hand, oil prices are net recipients of EPU shocks. Additionally, Fasanya *et al*. (2021) utilized the Diebold-Yilmaz spillover framework to examine the impact of United States (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. In addition, Mokni *et al*. (2020) evaluated the dynamic relationship between oil shocks and gold prices using the TVP-VAR and Diebold and Yilmaz (2014) connectedness framework. The study reports that oil supply shocks and oil risk shocks are net transmitters of shocks, while oil demand shocks are net receivers, with EPU having a substantial impact on the spillover link between oil shocks and gold.

Moreover, on the association between oil shocks, EPU and stock returns, Kang and Ratti (2013b) confirms the correlation between positive oil specific demand shock and EPU to be positive, whereas oil shocks and stock returns are inversely related and lastly rising EPU negatively affects stock returns (see also, Arouri *et al*., 2014). On the other side, Wei (2019) extended the literature by evaluating the impact of oil price shocks and EPU on China's trade. The study proposes that oil supply shocks and EPU causes exports to fall, whilst demand side shocks affect exports positively. Furthermore, the study highlighted that oil shocks arising from the 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.

Moving on to the relationship linking oil price shocks, global EPU, geopolitical risk, and financial markets. Rehman (2018) finds that oil price volatility determines global EPU, while Hoque *et al*. (2019) discover that the effects of oil demand shocks are fostered by EPU, and geopolitical uncertainty contributes to oil supply shocks. The study emphasizes that global EPU and oil demand shocks can be utilized to predict future stock market returns. On the contrary, Antonakakis *et al*. (2017) disclose that geopolitical uncertainty and oil returns are negatively related (see also Cunado *et al*., 2020). Moreover, high geopolitical uncertainty associated with oil supply shocks drives up oil prices (Cunado *et al*., 2020).

Another area of research explored the quantile relationship between oil price shocks, economic policy uncertainty, and other financial market factors such as green bonds and stock returns using quantile regression (QR) methodology. The work of Lee *et al*. (2021) highlighted that for upper quantiles, a one-way granger causality linkage from political uncertainty to oil prices exists, whereas at lower quantiles a bi-directional link between oil prices and green bond exists and a linkage from geopolitical risk to green bond index also exist. On the other hand, You and Tang (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 & Lusta, 2022), who reported a long-term asymmetric linkage.

Considering the preceding literature, numerous studies have examined the oil shocks-EPU nexus. Besides that, a few existing links have been found between oil shocks, EPU, and stock markets, whereas there is scarcity of literature analyzing the link between oil shocks and political uncertainty. Nonetheless, there are sizable gaps in the literature that have yet to be filled. First, recent studies have primarily focused on asymmetric linkage, structural relationships, dynamic effects, and time-varying effects (see, Antonakakis *et al*., 2014; Kang & Ratti, (2013a, 2013b, 2019); Aimer & Lusta, 2022), with little regard on quantile-based approaches hence the quantile dependence between oil shocks and MPU remains unexplored. Second, there is a big disparity between nexus of oil shocks and FPU. Choi and Shim (2019) evaluated the effects of FPU and EPU on real GDP growth in advanced markets such as Brazil, China, Chile, Korea, and Russia. Despite the exception of China, the study finds that shocks from FPU have a much greater impact on output than shocks from EPU. According to Hoque *et al*. (2019), political uncertainty amplifies EPU's influence.

Given the above issues, previous research has primarily centered on exploring the correlation between oil shocks and EPU. Nonetheless, EPU fails to provide a complete picture of a country's MPU tendencies. Therefore, it is crucial to incorporate FPU and political uncertainty, which have received inadequate attention so far. The aim of this study is to combine economic, financial, and political uncertainties into a single category known as "Macroeconomic Policy Uncertainty." The following issues are being evaluated as part of this research: (i) the spillovers between oil shocks and MPU (ii) the quantile dependence between oil shocks and MPU, with a focus on South Africa. Having noted prior studies, the linkage between oil shocks and MPU varies depending on the nature of the country; thus, this study aims at exploring the average-based spillover effects, quantile spillover effects, and the quantile relationship between oil shocks and MPU.

3 CHAPTER THREE

THEORETICAL FRAMEWORK, METHODOLOGY AND DATA

3.1. Theoretical Framework

According to the Neoclassical theory, the macroeconomic impact of oil prices can be explained by considering oil as a factor of production. When the price of this input, such as oil, increases, it results in a decrease in the level of output. Following the work by Hamilton (2005), the production function is then presented as follows:

$$Y = F(L, K, E) \tag{1}$$

Where Y denotes output, L symbolizes labour input Kdenotes capital input and E denotes energy as an input. Suppose the prices of output, labour, capital, and energy are represented as p (output price), w (wages), r (capital rent), and p_e (the price of energy) respectively. Equation 2 is presented as:

$$pY - wL - rK - p_e E \tag{2}$$

Hamilton (2005) went on to suggest that, in a perfect competition market structure, a firm would acquire energy up to a point where the real price of energy is equivalent to the marginal value of the product:

$$p_e = pF_e \tag{3}$$

Such that F_e signifies the partial derivative of F concerning E. Suppose, if both sides of equation 3 are multiplied by E, and divided by pY respectively, then equation 4 is then expressed as:

$$\frac{p_e E}{pY} = \frac{pF_e(L, K, E)}{pY} \tag{4}$$

Where the left-hand side measures the total production, and the right-hand side denotes the responsiveness of output considering energy use. Hamilton (2005) hypothesized that if the energy crisis is viewed as an externally caused price change, rather than a reduction in the amount of supply, therefore if fuel costs rise, consumers must continue consuming the same amount but at a higher price, whilst cutting down their spending on other goods. Following this hypothesis, the value of what the consumer lose, is expressed by $E(\Delta P_e)$, or by expressing it relative to its total income Py as:

$$\frac{E(\ \Delta P_e E)}{pY} = \frac{P_e E}{pY} \times \frac{\Delta P_e}{P_e} \tag{5}$$

Where the percentage change in oil prices is expressed by $\frac{\Delta P_e}{P_e}$, multiplied by the energy share value $\frac{P_e E}{pY}$. This is favourable in terms of how much the consumer loses, since consumers will prefer reducing energy than holding it fixed. If these energy shocks result in an economic downturn, it would be necessary to differentiate between changes in labor and capital movements and the value of lost energy as the cause. Given these assumptions, it supports that oil price shocks reduce consumption, cutting down output leading to recession hence uncertainty rises.

Given this, there are macroeconomic uncertainties that must not be overlooked because oil price shocks can have a significant influence on the macroeconomy, increasing uncertainty and volatility. There are several ways in which oil price shocks can be linked to macroeconomic uncertainty. Inflation, for example, can be caused by oil price shocks, which raise the cost of production and transportation of goods and services, as hypothesized by Hamilton (2005). This can result in an increase in consumer prices, increasing uncertainty about the future value of money, and higher inflation rates. Second, higher oil prices can be harmful to economic growth, especially in oil-importing countries. Higher energy costs can result in lower consumer spending, lower investment, and lower economic activity, as pointed out by Hamilton (2005). This can create uncertainty about the economy's future direction and growth prospects. Third, oil price fluctuations can have an impact on fiscal and monetary policy. In response to higher inflation, central banks may raise interest rates, tightening monetary policy. Governments may also need to adjust their fiscal policies in response to higher energy costs, potentially increasing uncertainty around government spending and taxation and thus exacerbating political uncertainty and EPU as the government and central banks face a dilemma in attempting to mitigate the problems at hand. Finally, higher oil prices can affect trade balances, particularly in oil-importing countries. The increased cost of oil imports may result in a larger trade deficit, potentially creating uncertainty about the future direction of trade balances and exchange rates. Overall, oil price shocks can have a range of macroeconomic effects, including increased uncertainty and volatility. The precise relationship between oil price shocks and macroeconomic uncertainty is determined by several factors, including the size and duration of the shock, the extent of the economy's dependence on oil, and the policy responses of governments and central banks.

3.2. Methodology

The methodology is organized in two parts. Firstly, the first objective is to explore the linkage between the oil shocks and MPU following the spillover framework. Secondly, the methodology presents the quantile dependence between oil shocks and MPU.

3.2.1. Diebold-Yilmaz Spillover Framework

The framework of Diebold and Yilmaz (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.

$$v_t = \Phi v_{t-1} + \varepsilon_{t\,;}\, \varepsilon_t \sim (0, \Sigma) \tag{6}$$

where $v_t = (v_{1t}, v_{2t} \dots, v_{Nt})'$ 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:

$$v_t = \sum_{i=0}^{\infty} A_i\, \varepsilon_{t-1} \tag{7}$$

where A_i adheres to recurrence $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}$, 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 indices. These indices includes 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 $i = 1,2 \dots N$. On the other hand, 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 $i, j = 1,2 \dots N$, 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:

$$\theta_{ij}^{g} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \sum A_h' e_i)} \tag{8}$$

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 Yilmaz (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 Yilmaz standardized each entry of the variance decomposition matrix by the row sum as follows:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{9}$$

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

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq 1}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq 1}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{10}$$

Equation 10 determines the total contribution of volatility shock spillovers across all oil shocks and uncertainty indices considered. In this study, the overall spillover index quantifies the impact of volatility spillovers across four (4) categories oil shocks and three (3) MPU parameters to the total forecast error variance.

The generalized VAR framework, using Diebold and Yilmaz (2012) methodology, enables the analysis of spillovers across three (3) MPU indices and four (4) categories 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:

$$S_{.i}^{g}(H) = \frac{\sum_{\substack{j=1\\ j\neq 1}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \times 100 = \frac{\sum_{\substack{j=1\\ j\neq 1}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} \times 100 \tag{11}$$

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

$$S_{i.}^{g}(H) = \frac{\sum_{\substack{j=1\\ j\neq 1}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{\substack{j=1\\ j\neq 1}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{12}$$

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

$$S_{i}^{g}(H) = S_{.i}^{g}(H) - S_{i.}^{g}(H) \tag{13}$$

Net spillovers are defined as the distinction between the total volatility shocks transmitted to and received from all shocks and uncertainty indices. Net spillovers, as shown in equation 13 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.

3.2.2. Quantile Connectedness Framework

The study begins by looking at 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:

$$Q_t(\, y_t \mid x_t\,) = x_t\beta(\tau) \tag{14}$$

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:

$$\hat{\beta}(\tau) = \underset{\beta(\tau)}{argmin} \sum_{t-1}^{T} (\tau - 1_{\{y_t < x_t\beta(\tau)\}}) \mid y_t - x_t\beta(\tau) \mid \tag{15}$$

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

$$y_t = c(\tau) + \sum_{i=1}^{p} \beta_i(\tau) y_{t-i} + e_t(\tau), \qquad t = 1,,,,,,,,T \tag{16}$$

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 $i = 1,,,,,,,p$. The computation of $\hat{\beta}(\tau)$ and $\hat{c}(\tau)$ is based on the assumption that residuals satisfy the population quantile restriction, $Q_t\big(\, e_t(\tau) \mid y_{t-1},,,,,,,,,,,y_{t-p}\,\big) = 0$. 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:

$$Q_t\big(\, e_t(\tau) \mid y_{t-1},,,,,,,,,,,y_{t-p}\,\big) = c(\tau) + \sum_{i=1}^{p} \hat{\beta}_i(\tau) y_{t-i} \tag{17}$$

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 Yilmaz (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:

$$y_t = \mu(q) + \sum\nolimits_{j}^{p} \Phi_j(q) y_{t-j} + u_t(q) = \mu(q) + \sum\nolimits_{i=0}^{\infty} \Omega_i(q) u_{t-i} \tag{18}$$

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:

$$\theta_{ij}^{g} = \frac{\sum(\tau)_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Omega_h(q) \sum(q)\, e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Omega_h(q) \sum(q) \Omega_h(q)'\, e_i)'} \tag{19}$$

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:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{k} \theta_{ij}^{g}(H)'}, \text{ with } \sum_{j=1}^{k} \tilde{\theta}_{ij}^{g} = 1 \text{ and } \sum_{j=1}^{k} \tilde{\theta}_{ij}^{g}(H) = 1 \tag{20}$$

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

$$TSI_t = \frac{\sum_{i,j=1,i\neq 1}^{k} \tilde{\theta}_{ij}^{g}(H)}{k-1} \tag{21}$$

$$TO_{j,t} = \sum_{i=1,i\neq j}^{k} \tilde{\theta}_{ij,t}^{g}(H) \tag{22}$$

$$FROM_{j,t} = \sum_{i=1,i\neq j}^{k} \tilde{\theta}_{ji,t}^{g}(H) \tag{23}$$

$$NET_{j,t} = TO_{j,t} - FROM_{j,t} \tag{24}$$

$$NPDC_{i,j,t} = \tilde{\theta}_{ij,t}(H) - \tilde{\theta}_{ji,t}(H) \tag{25}$$

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 $FROM_{j,t}$ represents the total impact of all other variables on variable j. Additionally, $NET_{j,t}$ indicates 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

To answer the research questions about the quantile relationship, the study uses the quantile-on-quantile (QQ) methodology. The QQ method permits us to examine the effects of the different quantiles of one variable (in this case, oil price shocks) on different quantiles of another variable (MPU). The QQ model is a hybrid of quantile regression and nonparametric estimation techniques (Sim & Zhou, 2015). To evaluate whether the impact of oil price shocks on MPU are large or small, the nonparametric quantile regression (QR) model is used as the point of origin. The model QR is expressed as follows:

$$MPU_{\mathrm{t}} = \beta^{\sigma}(OIL_{\mathrm{t}}) + u_{\mathrm{t}}{}^{\sigma} \tag{26}$$

Where MPU_{t} represents macroeconomic policy uncertainty index disaggregated into economic policy uncertainty index (EPU), financial policy uncertainty index (EPU) and political uncertainty index (PU) in period t; OIL_{t} represents structural oil price 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; $u_{\mathrm{t}}{}^{\sigma}$ 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 price shocks, and since $\beta^{\sigma}(.)$ is not known, the first-order Taylor expansion approach around the quantile OIL^{τ} is then expressed as:

$$\beta^{\sigma}(OIL_{\mathrm{t}}) \approx \beta^{\sigma}(OIL^{\tau}) + \beta^{\sigma'}(OIL^{\tau})(OIL_{\mathrm{t}} - OIL^{\tau}) \tag{27}$$

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 28 is expressed as:

$$\beta^{\sigma}(OIL_{\mathrm{t}}) \approx \beta_0(\sigma, \tau) + \beta_1(\sigma, \tau)(OIL_{\mathrm{t}} - OIL^{\tau}) \tag{28}$$

Equation 28 characterizes the interdependence effect between the σ^{th} quantile of MPU index and the τ^{th} quantile of oil price shocks. To formulate equation 29, equation 28 is then substituted into equation 26 as:

$$MPU_{\mathrm{t}} = \beta_0(\sigma, \tau) + \beta_1(\sigma, \tau)(OIL_{\mathrm{t}} - OIL^{\tau}) \; + u_{\mathrm{t}}{}^{\sigma} \tag{29}$$

Backing up the work by Sim and Zhou (2015), the QQ approach was developed to provide a comprehensive view in terms of dependence, in which several quantiles of oil price shocks are chosen, in this case, 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 price shocks. This entails that the QQ methodology gives disaggregated results which fully explains the association between oil price shocks and MPU. This association is fundamentally expressed by, $\beta_0(\sigma, \tau)$, and $\beta_1(\sigma, \tau)$.

Equation 29 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:

$$min \sum\nolimits_{k=0}^{n} \rho_{\sigma}\left[MPU_{\mathrm{t}} - b^0 - b^1\left(\widehat{MPU}_{\mathrm{t}} - \widehat{OIL^{\tau}}\ \right)\right] K\left(\frac{F_{\mathrm{n}}(\widehat{OIL}_t - \tau)}{h}\right) \tag{30}$$

Where, ρ_{σ} denotes the quantile loss function, whilst $K(.)$ denotes a Gaussian kernel used to weight observations around OIL_{t}, whilst h symbolizes a bandwidth. Local linear regression is utilized to eliminate dimensionality issues (Sim & Zhou, 2015). Furthermore, it leads to large bias on computed estimates associated with low variances (Sim & Zhou, 2015). Following the work of Sim and Zhou (2015), a bandwidth of $h = 0.05$ is utilized in this paper.

3.4. Data Description

To achieve the research objectives, this study considers monthly data for the oil price shocks and MPU indices for the period from 1990M1 to 2022M6, with the endpoint for the EPU and PU being 2018M7 due to data limitations. The data for the FPU index determine the commencement date, while the EPU and PU determine the end date. The time frame chosen in this study is established on the basis that all series have the same time frame. Monthly data are available for the oil price shocks and the FPU, while data for the EPU and PU are quarterly, so they were extrapolated to a monthly frequency. Hlatshwayo and Saxegaard (2016) compiled data for the South African indicators PU and EPU. 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), following the work of Baumeister and Hamilton (2019). They reconstruct datasets from the work of Kilian (2009) and Kilian and Murphy (2012) and integrate oil supply and demand shocks using monthly measures of global oil production, the WTI oil price, and CPI. Baumeister and Hamilton (2019) use indices of industrial production for OECD (Organization for Economic Cooperation and Development) and BRICS (Brazil, Russia, India, China, and South Africa) countries and Indonesia to calculate shocks to economic activity.

Table 1: Description of Variables

Variable	**Source**
Oil consumption demand shocks are defined as oil shocks that result from consumption demand. These shocks are also referred to as oil-specific market demand shocks.	Christiane Baumeister Website: Baumeister and Hamilton (2019) https://sites.google.com/site/cjsbaumeister/datasets?pli=1
Oil inventory demand shocks are defined as oil shocks originating from speculative demand. These demand shocks are calculated by multiplying U.S. crude oil and petroleum stocks by the share of OECD stocks.	Christiane Baumeister Website: Baumeister and Hamilton (2019) https://sites.google.com/site/cjsbaumeister/datasets?pli=1
Oil supply shocks are oil shocks originating from production and caused by unforeseen events that disrupt the supply chain.	Christiane Baumeister Website: Baumeister and Hamilton (2019) https://sites.google.com/site/cjsbaumeister/datasets?pli=1
Economic activity shocks are shocks derived from aggregate demand. Shocks to economic activity are also referred to as shocks to aggregate demand.	Christiane Baumeister Website: Baumeister and Hamilton (2019) https://sites.google.com/site/cjsbaumeister/datasets?pli=1
Economic Policy Uncertainty is an economic risk resulting from the uncertainty surrounding government policies and regulatory frameworks. The EPU index is created using news-based information that focuses on phrases related to economics, policy, and uncertainty.	Hlatshwayo and Saxegaard (2016).

Financial Policy Uncertainty is then defined as a financial risk associated with undefined financial regulatory framework. The Financial Condition Index (FCI) is considered the best proxy for FPU index, serving as a predictor of monetary policy behavior during high volatility in financial markets. FCI is computed using real interest rates, yield curve, share earnings yields, excess money supply growth, and real effective exchange rate change, and FCI gives an analysis of financial factors affecting inflation expectations and economic performance.	Quantec Database: https://www.quantec.co.za/
Political Uncertainty is a political risk associated with political tensions or which is caused by uncertainty over electoral outcomes. The index for political uncertainty is derived from news-based information concentrating on phrases pertaining to uncertainty, politics, and government.	Hlatshwayo and Saxegaard (2016).

4. CHAPTER FOUR

PRESENTATION AND DISCUSSION OF RESULTS

4.1. Preliminary Analysis

The statistical properties of the variables are usually given in an empirical analysis. The statistical analysis for oil shocks and MPU indices is shown in Table 2. Compared to the uncertainty indices, the average value for oil shocks is relatively low, ranging from -0.1% to 0.13%. The average values for oil supply shocks (Oil_ss), oil inventory demand shocks (Oil_inv^d), and economic activity shocks (Oil_aggr^d) are all negative. Negative values for Oil_ss indicate reduced oil supply, negative values for Oil_inv^d indicate a sudden drop in oil demand, and negative values for Oil_aggr^d indicate a sudden drop-in economic activity, such as a recession. In contrast, the average values for oil consumption demand shocks (Oil_cons^d), EPU, FPU, and PU are all positive. Positive Oil_cons^d indicate increased oil demand, while positive MPU parameters indicate higher uncertainty about economic, financial, and political conditions, which may lead to a decline in growth and investment. In terms of volatility, the MPU indices have the maximum value of 17.48, which is more than four (4) times more volatile than the most volatile oil shock (Oil_cons^d), whose standard deviation is 3.5421.

Table 2: 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

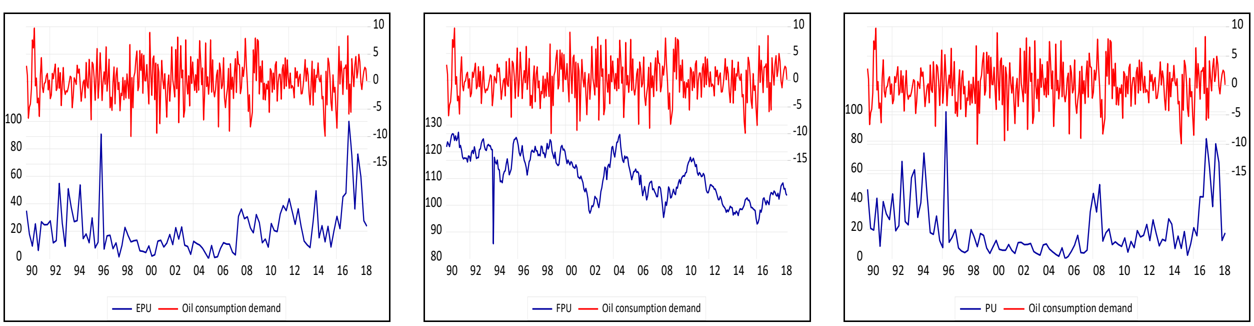
Source: Author's own compilation

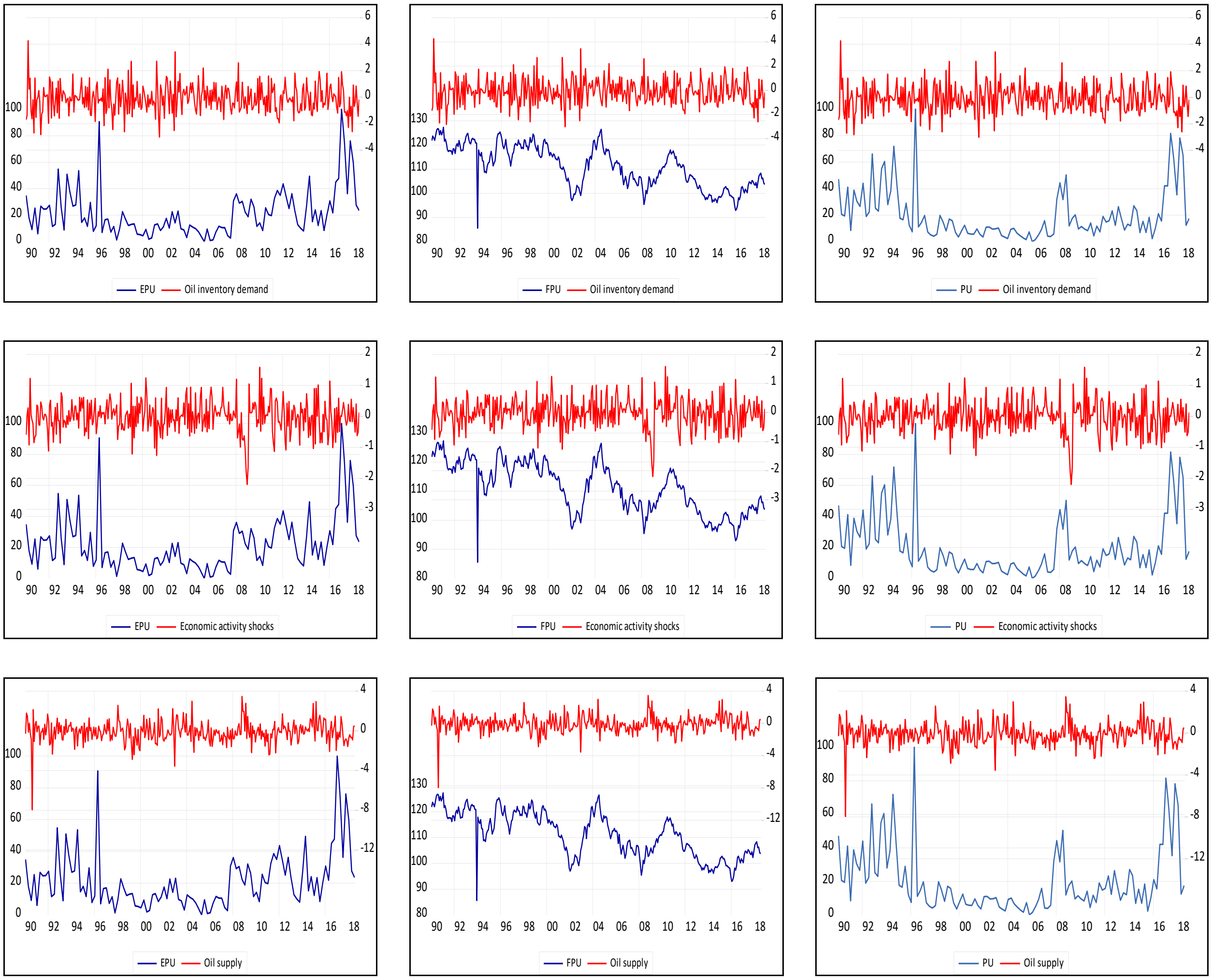
*Note: ADF represents Augmented Dickey-Fuller, whilst PP represents Phillips Perron unit root tests statistics. *; ** and *** signifies stationarity of a variable at 1%; 5% and 10% significance levels respectively, confirming that the null hypothesis of unit root is rejected, whilst the Schwarz Information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

The remaining variables, apart from EPU, PU, and Oil_inv^{d}, are skewed to the left. The kurtosis statistics show that all variables are leptokurtic. Except for 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. Considering that most variables are highly tailed and not normally distributed, the quantile-on-quantile regression approach is justified.

4.2. Unit Root Tests

Before performing the empirical analysis, all series must be examined for unit roots. To check the properties of the time series data, a graphical unit root test is first performed. As shown in Figure 1, all oil shocks exhibit consistent mean values over time. EPU and PU show no discernible trend over time, while FPU shows a decreasing trend, indicating a non-stationary series. Apart from the oil shocks, there may be signs of structural breaks in EPU, FPU, and PU, and this could be addressed by using quantile spillovers. In addition, stationarity is tested using the Phillips-Perron(PP) and Augmented Dickey Fuller (ADF) methods. These two (2) tests give the same results. As shown in Table 2, all the series are integrated of order zero at 1%, 5% and 10% significance levels, indicating that the variables are stationary in level form.





Source: Author's own compilation
Figure 1: Graphical illustration of trends for all oil shocks and macroeconomic policy uncertainty variables.

4.3. Diebold-Yilmaz Spillover Analysis

Considering the first research objective, the evaluation of dynamic spillover effects between oil shocks and MPU is crucial. These dynamic spillovers are as follows: "*Directional Spillovers To*"," labeled "*To others*"," and "*Directional Spillovers From*"," labeled "*From others*" As shown in Table 3, the spillover table depicts how shocks are retained and distributed. The table shows how a particular shock or MPU parameter contributes to the variance of the forecast error with respect to other shocks or indices. The net spillover is obtained by subtracting the total contribution to others from the total contribution from others. The net spillover can be positive or negative. Positive (negative) net spillover values indicate shock transmission (receiver). In addition, the total spillover or connectedness index (TCI) is determined by adding the "*contribution to others*" or the "*contribution from others*" as a percentage of the "*contribution including own*." This measure characterizes the total spillover effects transmitted between the oil market and the macroeconomy.

Table 3: Diebold - Yilmaz 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%**

Source: Authors' own compilation
Note: TCI signifies the total connectedness/spillover index. "To others" signifies contribution to others, whilst "From others" signifies contribution from others.

Starting with individual directional spillover effects for EPU, among the other oil shocks and MPU parameters, PU makes the largest contribution to its forecast variance at around 39%, followed far behind by Oil_aggr^d at 3.26%. This suggests that PU shocks have a strong impact on EPU shocks. On the other hand, EPU has the largest contribution to the variance of forecast errors in PU, about 34.17%, while Oil_aggr^d is far behind with 3.68%. This means that shocks to the EPU have a larger impact on PU shocks.

Oil_cons^d has the largest influence on the variance of Oil_ss forecast error, accounting for about 13.45%, while Oil_inv^d and Oil_aggr^d are close behind with 11.33% and 7.54%, respectively. This suggests that oil consumption demand shocks are more likely to affect the behavior of oil supply shocks than other types of shocks. Meanwhile, compared with other shocks and MPU parameters, Oil_aggr^d has the largest impact on the forecast error variance of Oil_ss, explaining about 6.05% of the forecast error variance of Oil_ss. PU contributes about 5.56% to the forecast error variance of Oil_aggr^d. FPU receives a small contribution from other shocks and MPU parameters, with Oil_inv^d accounting for about 5.99%, followed by Oil_ss with about 4.90%. At the same time, Oil_ss makes a small contribution to the variance of the forecast error of Oil_inv^d with about 5.45%, followed by FPU with 4.28%. There are bidirectional spillover effects between EPU and PU as well as between Oil_ss and Oil_cons^d, Oil_inv^d versus Oil_cons^d, EPU and Oil_aggr^d, and Oil_inv^d and FPU.

Moreover, the EPU is the largest recipient of spillover effects from associated oil shocks and uncertainty indices, with a value of 48.94%. It is followed by PU with 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 total directional spillover effects on EPU have a stronger influence on other shocks and uncertainty indices. Among them, after EPU, PU, Oil_cons^d, Oil_ss, Oil_inv^d and Oil_aggr^d have the largest influence on others, while FPU has a relatively small influence. On the other hand, PU, EPU, Oil_cons^d and Oil_ss remain among the most important shock transmitters to others. These results aligns with Mokni *et al*. (2020)'s work, which highlighted that Oil_ss are net transmitters of shocks. Basically, the oil price shocks and MPU parameters are prone to be influenced by the shocks of PU, EPU, Oil_cons^d and Oil_ss.

In terms of net spillovers, EPU receives more shocks than it provides, yielding a negative spillover value of -1.43%, while PU receives less than it provides, yielding a positive net spillover value of 10.13%. These results contradict the findings of Antonakakis *et al*. (2014), who reported that the EPU is the primary shock transmitter. Oil_aggr^d, Oil_inv^d, Oil_ss, and FPU are also net shock receivers. These findings aligns with Mokni *et* al. (2020) who reported Oil_aggr^d as net shock receivers. On the other hand, this result contradicts the findings of Antonakakis *et al*. (2014), who found that oil supply shocks are net spillover transmitters (see also, Mokni *et al*., 2020). Oil_cons^d and PU, on the other hand, are net spillover transmitters. This result is consistent with the work of Antonakakis *et al*. (2014), who found that oil-specific demand shocks are net spillover transmitters.

With a focus on the total connectedness index (TCI), the estimated value is 34.12%. This suggests that shocks across oil shocks and MPU parameters account for just under half of the total variation in forecast errors during the sample, while idiosyncratic shocks explain the remaining 65.88%, suggesting a moderate relationship between oil shocks and MPU.

4.4. Quantile Spillover Analysis

Table 4 compares the results with the average-based connectedness analysis of Diebold-Yilmaz (2012) and shows the spillover results using a quantile spillover methodology. The table is divided into three (3) sections. Panel A first assesses connectedness at the lowest quantile ($q = 0.05$), while Panel B assesses connectedness at the median quantile ($q = 0.5$). Finally, Panel C examines the spillover association between oil shocks and MPU parameters at the highest quantiles ($q = 0.95$).

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 ($q = 0.5$). The TCI at the lowest quantiles ($q = 0.05$) and TCI at the upper quantiles ($q = 0.95$) are 71.77% and 72.59%, respectively, as shown in Table 4. This signifies that the spillover indexes within the quantile framework are relatively higher than the conditional mean results. Furthermore, spillover effects to and from others have a greater influence. This clearly indicates that the overall contribution of specific shocks at the highest and lowest quantiles is significantly greater than the average and median contributions.

At the lower quantiles, the largest proportion to the forecast error variance of FPU is recorded by Oil_inv^d at approximately 16.85%, followed by Oil_cons^d at around 14.85%. On the other hand, Oil_cons^d accounts for the highest contribution to Oil_aggr^d at about 14.41%, followed by FPU at 12.80%. Additionally, there is a bi-directional spillover effect between Oil_ss and Oil_inv^d at the lower quantile. Moreover, at the lower quantiles, the oil shocks, and MPU parameters with the greatest influence on other variables are EPU, followed by PU, FPU, Oil_inv^d, Oil_ss, and Oil_cons^d, with Oil_aggr^d having the lowest impact. While, at the median quantiles, Oil_cons^d has a greater impact on other shocks, followed by PU, EPU, Oil_aggr^d, Oil_inv^d, FPU, with Oil_ss having the least impact. At the upper quantiles, Oil_inv^d has the greatest impact on other shocks, followed by Oil_aggr^d, EPU, Oil_ss, Oil_cons^d, while PU has the least effect on others.

Additionally, at the median quantiles, shocks to FPU are primarily driven by shocks from EPU at approximately 11.57%. The behavior of FPU is more vulnerable to be affected by shocks to EPU and PU at around 11.57% and 8.27%, respectively, than by other shocks and MPU parameters. Furthermore, at the upper quantiles, the highest contribution to the forecast error variance of Oil_aggr^d is recorded by Oil_cons^d and Oil_inv^d at approximately 14.65% and 13.73%, respectively. Conversely, Oil_ss and Oil_aggr^d report the highest contribution to Oil_inv^d at about 14.95% and 14.04%, respectively. Similarly, to the Diebold-Yilmaz framework, shocks that affect EPU are predominantly driven by PU across the lower (16.28%), median (39.99%), and upper quantiles (22.88%). At the same time, shocks to PU are also heavily influenced by EPU across all quantiles (19.35%; 40,85% and 20.22%) , resulting in a mutual flow of spillover effects across the full range of quantiles.

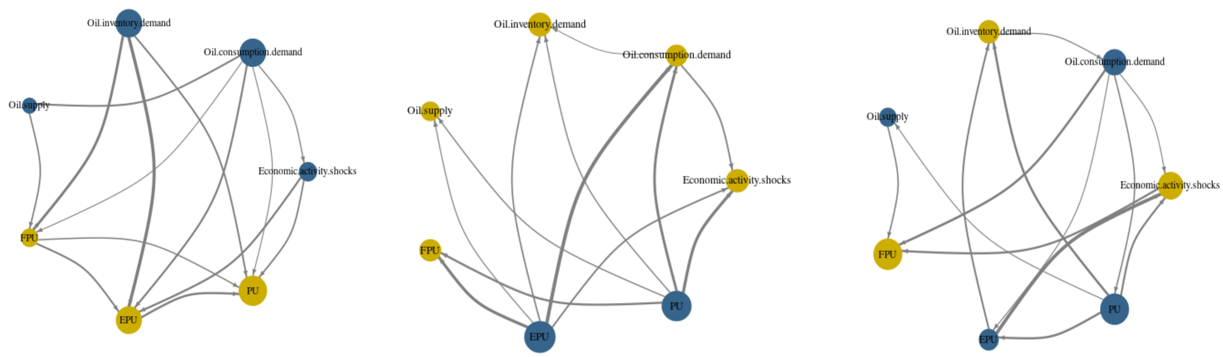
Furthermore, shock net receivers and transmitters vary from those shown in Table 3. First, all the structural oil shocks are net transmitters at the lowest quantiles, while EPU, FPU, and PU are net receivers of spillovers. This is consistent with the findings of Antonakakis *et al*., (2014), who concluded that Oil_ss and Oil_cons^d are net shock transmitters. Alternatively, all oil shocks and FPU are net receivers at the median quantiles, except for EPU and PU, which are net transmitters. These results are in accordance with Wang and Lee (2020) who highlighted that EPU is a net transmitter. 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 aggregate demand shocks 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 conditional mean and across lower quantiles. These findings are in accordance with the results of Antonakakis *et al*. (2014), who discovered that in the presence of oil supply shocks, economic activity shocks, and oil consumption demand shocks, EPU is the net recipient of spillover in the cases of Spain and Germany. According to the findings in Table 4, there are stronger upper-quantile spillovers compared to the rest of the quantiles.

Table 4: 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%**

Source: Authors' own compilation
Note: TCI signifies the total connectedness/spillover index. "To others" signifies contribution to others, whilst "From others" signifies contribution to others.



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

Source: Authors' own compilation
Figure 2: 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.

Figure 2 shows the network plot lines of the oil shocks and MPU indices at the lower, median, and upper quantiles. The network of oil shocks and MPU interconnectivity at the median quantiles demonstrates a moderate connection for oil shocks and MPU spillovers, although at the highest and lowest quantiles they exemplify a much greater connection. The graphical network spillover plots are compatible with the results in Table 4. The quantile spillover technique reveals that the lower and upper quantiles are more connected than the median quantiles.

4.5. Quantile on Quantile Results

Upon examining the quantile association between oil shocks and MPU, Figure 3 illustrates the beta estimates of the slope coefficient $\beta_1(\theta, \tau)$ which captures the effect of the τ^{th} quantile of oil shocks on the θ^{th} quantile of MPU. Similar effects have emerged across different MPU components and different oil shocks, as shown in the graphs in Figure 3. First, there is a significant positive relationship between oil shocks and MPU. Second, there is a noticeable negative correlation between oil shocks and MPU.

As presented in Figure 3 (i), there is an overall positive relationship between EPU and oil supply shocks. This implies that the median to upper quantiles of oil supply shocks ($\tau = 0.5 - 0.95$) have a positive effect on EPU in the median quantiles ($\theta = 0.4 - 0.6$), except for lower and upper quantiles of EPU. These results are in accordance with the works of Su *et al*. (2019) who reported that oil supply shocks have a positive effect on China, India, and Brazil's EPU, whilst Sheng *et al*. (2020), discovered that oil supply shocks have a long-term and positive impact on EPU. Conversely, a negative association is observed across all quantiles of oil supply shocks when EPU is lowest ($\theta = 0.05 - 0.2$). A substantial negative response is discovered between oil supply shocks' upper quantiles ($\tau = 0.95$) and EPU's upper quantiles ($\theta = 0.8 - 0.95$). Noticeably, the effect of oil supply shocks on EPU is almost identical to FPU and PU. This negative relationship between oil supply shocks and EPU corresponds to the work by Antonakakis *et al*. (2014). As shown in Figure 3 (i), (v) and (ix), all these three (3) variables show a significantly high positive effect from the median to upper quantiles of oil supply shocks when MPU (EPU, FPU and PU) is slightly low and normal.

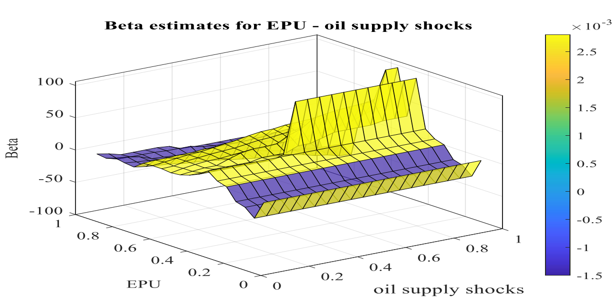
Positive and inverse relationship between oil consumption demand shocks and EPU is observed in Figure 3 (ii) with significant changes in the upper quantiles of oil consumption demand shocks. Oil consumption demand shocks' upper quantiles ($\tau = 0.75 - 0.95$) are positively correlated with EPU's lower to median quantiles ($\theta = 0.2 - 0.5$). This positive effect is in accordance with the works of Kang and Ratti (2013b) who highlighted a positive relationship between oil specific demand shocks (oil consumption demand shocks) and EPU. Contrastingly, a negative reaction is identified when upper quantiles ($\tau = 0.75 - 0.95$) of oil consumption demand shocks negatively affects EPU's upper quantiles ($\theta = 0.75 - 95$). The negative relationship observed above aligns with the work by Antonakakis *et al*. (2014) who highlighted that oil specific demand shocks (oil consumption demand shocks) inversely determine changes in the EPU index. Moreso, the impact of oil consumption demand shocks on EPU is almost like FPU and PU respectively. All the three series shows a positive link between the upper quantiles of oil consumption demand shocks and the lower quantiles of MPU (EPU, FPU and PU), whilst a negative relationship between the upper quantiles of oil consumption demand shocks and upper quantiles of MPU is observed as shown in Figure 3 (ii), (vi) and (x).

From Figure 3 (iii), (vii) and (xi), a significant positive link between economic activity shocks' upper quantiles ($\tau = 0.75 - 0.95$) and lower quantiles of EPU, FPU and PU ($\theta = 0.1 - 04$) is evident. On the other hand, MPU's upper quantiles ($\theta = 0.75 - 0.95$) is highly affected negatively by the upper quantiles of economic activity shocks ($\tau = 0.8 - 0.95$). This study's findings are consistent with the results of Kang and Ratti (2013a) and Sheng *et al*. (2020), who discovered that economic activity shocks have a negative impact on EPU.

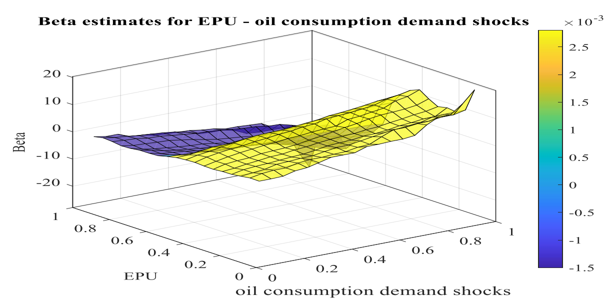
Results for MPU and oil inventory demand shocks are presented in Figure 3 (iv), (viii) and (xii). The impact oil inventory demand shocks exerted on FPU has a greater positive effect, however the positive and negative effects are almost similar on EPU and PU. A substantial positive correlation is observed between the upper quantiles of oil inventory demand shocks ($\tau = 0.7 - 0.95$) and lower quantiles of EPU, FPU and PU respectively ($\theta = 0.1 = 0.4$). On the other hand, except for lower and median quantiles, a noticeable negative linkage between upper quantiles of oil inventory demand shocks ($\tau = 0.8 - 0.95$) and upper quantiles of EPU, FPU and PU respectively ($\theta = 0.6 - 0.9$) is observed. These findings are supported by Sheng *et al*. (2020), who discovered that oil inventory demand shocks have a negative influence on EPU.

To summarize the above, a substantial positive correlation exists between oil shocks' upper quantiles and MPU's lower quantiles, and a significant negative correlation is observed between oil shocks' upper quantiles and MPU's upper quantiles for a case in South Africa.

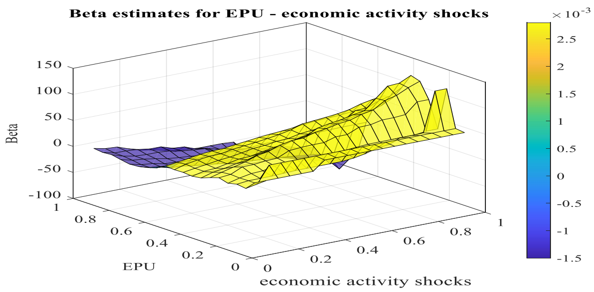
i) EPU & Oil Supply Shocks



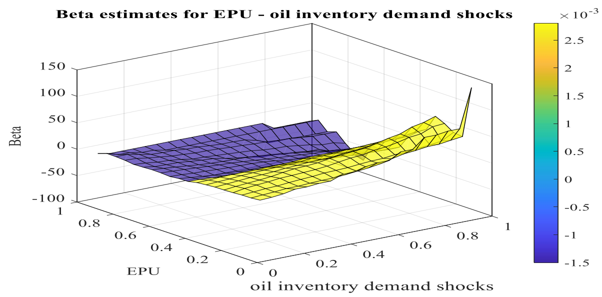
ii) EPU & Oil Consumption Demand Shocks



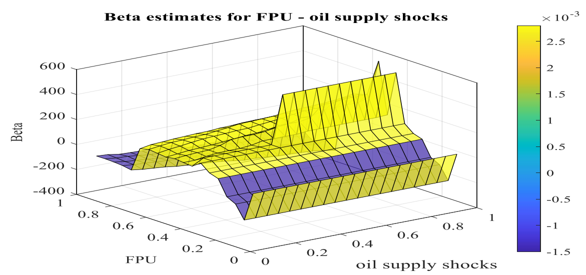
iii) EPU & Economic Activity Shocks



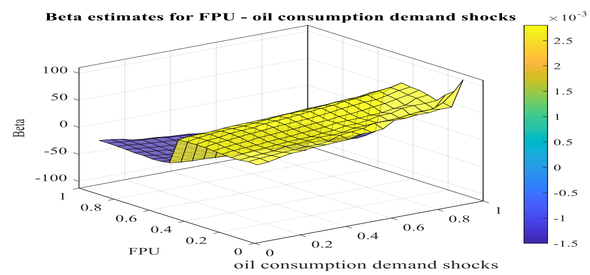
vi) EPU & Oil Inventory Demand Shocks



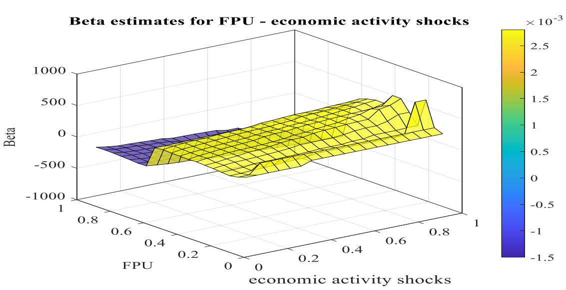
v) FPU & Oil Supply Shocks



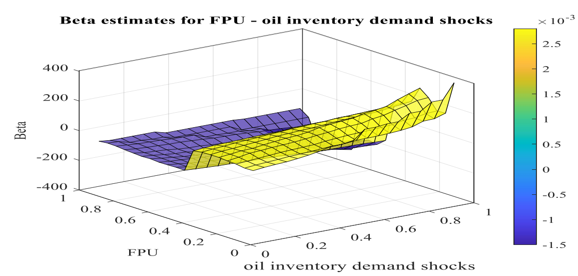
vi) FPU & Oil Consumption Demand Shocks



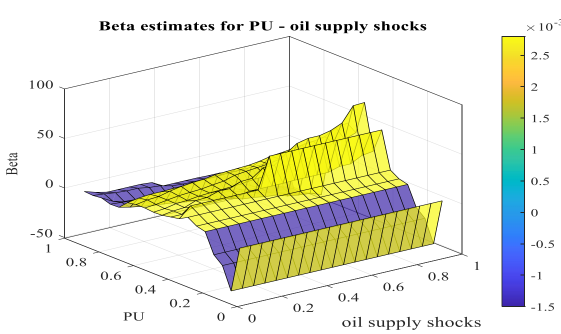
vii) FPU & Economic Activity Shocks



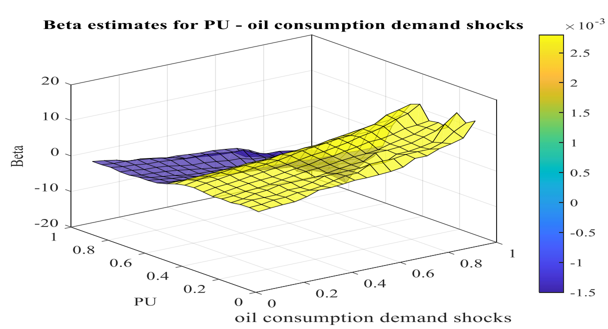
viii) FPU & Oil Inventory Demand Shocks



ix) PU & Oil Supply Shocks

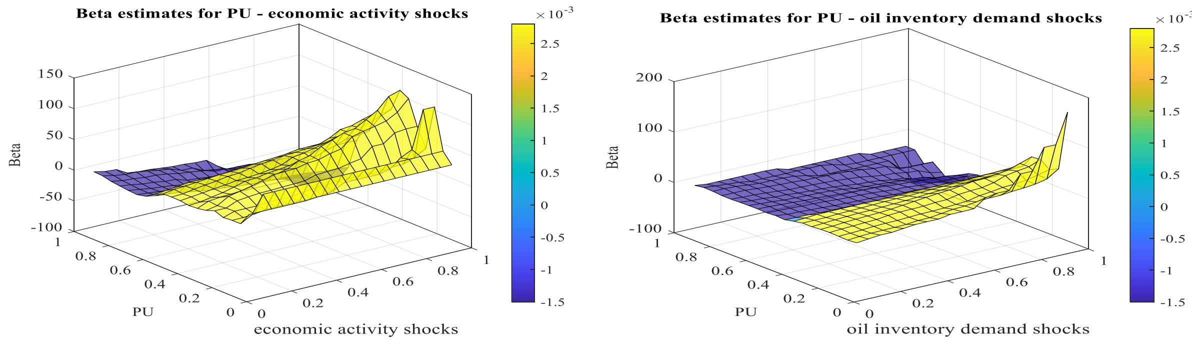


x) PU & Oil Consumption Demand Shocks



xi) PU & Economic Activity Shocks

xii) PU & Oil Inventory Demand Shocks



Source: Authors' own compilation
Figure 3: Quantile on Quantile Regression Plots

4.6.Discussion of Results

Analyzing the spillovers between oil shocks and MPU as the first objective, the study concludes that, among other uncertainty parameters, EPU is the highest recipient of spillovers, followed by PU, oil consumption demand shocks and FPU being the lowest recipient of shocks from others, using the Diebold-Yilmaz framework. The increased EPU and PU spillover effects may be influenced by political conflicts, economic collapse, and corrupt practices in South Africa. High EPU spillovers may be strongly associated with the highest degree of power outages in the country, which have directly impacted key economic activities such as FDIs. Rising political issues (the fall of 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. Similarly, according to the quantile spillover framework, EPU and PU have a bi-directional spillover effect across all quantiles. Any shocks to the economic environment that result in a negative outlook for the economy cause EPU to rise, which eventually causes PU to rise. Likewise, shocks to the political environment that results in bad economic outlook results in rising EPU. The strong relationship between the political environment and the economy can justify these PU and EPU spillovers. This can be described by the volatility in the Rand against the US dollar caused by political events. For example, following the dawn of democracy, the rand appreciated; however, during Zuma's tenure, the rand devalued following the dismissal of Finance Minister Nhlanhla Nene in December 2015 and the demoting of Finance Minister Pravin Gordhan in April (United Nations International Children's' Emergency Fund-UNICEF, 2017).

Ultimately, EPU is the primary receiver of shocks from others at the conditional mean and across lower quantiles. This implies that South Africa receives more shocks from its trading partners hence resulting in spillovers. Even though South Africa does not rely on oil imports, South Africa's trading partners are major contributors to receiving the most shocks from others. This could be explained by the fact that South Africa imports oil from other countries such as Saudi Arabia, Nigeria, Ghana, and the United Arab Emirates, among others. If an oil supply shock emerges, world prices of oil will rise, and fuel prices will also skyrocket, 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. Contrastingly, oil consumption demand shocks are reported as net spillover transmitter at conditional mean, and across lower and upper quantiles, while PU is reported as a net spillover transmitter at conditional mean, and across median and upper quantiles. This is possibly explained by consumer demand imbalances combined with recurring political pressures within the ruling party 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.

At median quantiles, oil consumption demand has the greatest influence, whilst oil inventory demand has the greatest impact at upper quantiles. This implies that when oil inventory demand shocks are high, this results in high EPU, rising from increased demand which might be associated with macroeconomic factors such as economic downturn or inflationary pressures. While EPU, FPU and PU are net spillovers recipients, oil shocks act as net transmitters at the lowest quantiles. This may suggest that in periods of low oil shocks and uncertainty, oil shocks receive net spillovers from both the demand and supply sides. The reason for the EPU, FPU and PU receiving net spillovers is due to economic issues such as inflation and currency devaluation experienced in South Africa resulting from these oil shocks. At the upper quantiles, shocks in oil inventory demand are the highest net receivers. This is because oil inventories impact investor expectations regarding future oil demand and supply, as stated by Fueki *et al*. (2018).

Along the same lines, the quantile relationship between oil shocks and MPU is explored. To begin with, a positive quantile relationship between the upper quantiles of oil supply shocks and median quantiles of EPU exist. One possible explanation for this result could be that a positive oil shock resulting from a sudden increase in oil supply, leading to lower oil prices and lower prices for oil derivatives, can have a positive impact on oil-consuming countries like South Africa. On the other hand, a negative association is observed across all quantiles of oil supply shocks when EPU is low, and this result is identical to the effect of oil supply on FPU and PU. These findings could be explained by the fact that negative oil supply shocks, associated with oil prices and its derivatives price hikes because of oil supply disruptions portrays a negative picture of the economy, intensifying EPU, FPU and PU.

Second, the positive quantile relationship between oil consumption demand shocks and MPU. This positive association can be described by the 2007-08 oil demand shock, caused by increased demand for oil due to a shortfall of oil, with China being the biggest exporter of crude oil. Given that China is among South Africa's major import partners, there exists a direct adverse effect in which oil shocks impacting the Chinese economy influence the South African economy. Moreover, during the same time of the oil demand shock, South Africa was faced with mass strikes all over the country and Zuma being elected as the Chairman of the ruling party, followed by the resignation of Thabo Mbeki causing slow economic growth in the republic. This might have increased both economic and political uncertainty due to corruption within the ANC, hence the positive correlation between oil consumption demand shocks and MPU. Conversely, there is a negative quantile relationship between oil consumption demand and MPU.

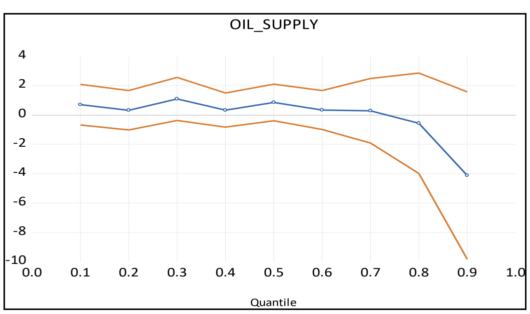
Third, there is a positive quantile association between upper quantiles of economic activity shocks and lower quantiles of EPU, FPU and PU. This positive effect might be explained by increased economic activity, which further causes inflationary pressure and triggers consumers to import more, resulting in an increase in EPU. For instance, South Africa’s economic agents quickly change their spending patterns hence when inflation is looming, more is imported than exported. An alternative explanation arises from economic activities such as technological advancements, which can lead to increased economic activity and growth, thereby reducing MPU. On the other hand, a negative quantile relationship exist between upper quantiles of economic and upper quantiles of MPU. This negative effect can be explained by increasing economic activity, which indicates good economic performance, so that policymakers and investors do not face a decision-making dilemma in formulating their policies, thus reducing MPU. On the other hand, shocks in economic activity caused by natural events such as floods, hurricanes, earthquakes, or financial crises can cause the economy to contract, which in turn triggers MPU. For example, the floods that have occurred in South Africa in recent years, leading to an economic contraction, could be a contributing factor to an MPU within the government, economic, and financial regulators.

Last, oil inventory demand shocks exerts positive effects on FPU, EPU and PU. This implies that positive oil inventory demand shocks may reduce MPU in some cases. Since oil inventory demand emanates from speculation. For example, if a positive oil inventory demand shock leads to higher oil prices, it can increase uncertainty in oil-importing countries such as South Africa. Contrastingly, oil inventory demand shocks have a negative influence on EPU, FPU, and PU. Policymakers may be unsure how to respond to a negative oil inventory demand shock, as they must balance the need to support economic growth with the need to control inflation and stabilize the financial sector. For example, they may be uncertain about the best monetary or fiscal policy to pursue because the South African Reserve Bank (SARB) may be uncertain on whether to raise the repo rate or to use the exchange rate policy to support growth in the economy or the government, may be uncertain about the impact of their policy choices on the economy. This uncertainty can make it difficult for policymakers to make sound decisions, exacerbating the effects of the negative oil inventory demand shock. For example, if MPU causes a delay in making effective policy initiatives, the deleterious effects on the economy can be prolonged, leading to even more uncertainty.

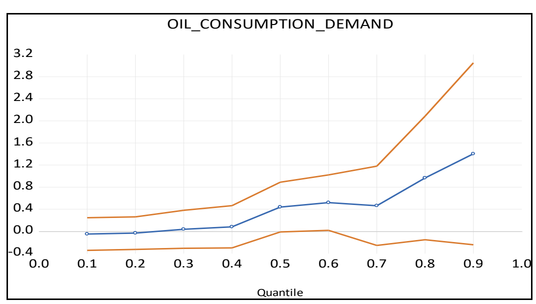
Overall, since oil shocks are exogenous, the impact of oil shocks on the South African MPU could be explained by several factors, including economic conditions, natural events, the consequences of the shock, the involvement in international trade, political tensions, and the reactions of the business and financial communities and policymakers, which explains the degree of uncertainty in the South African economy.

4.7. Robustness Check

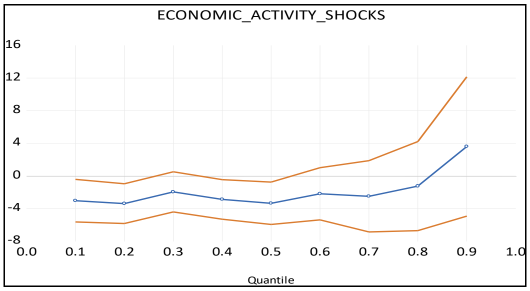
(i) EPU & Oil Supply Shocks



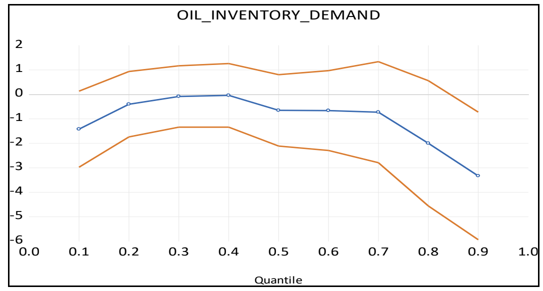
(ii) EPU & Oil Consumption Demand Shocks



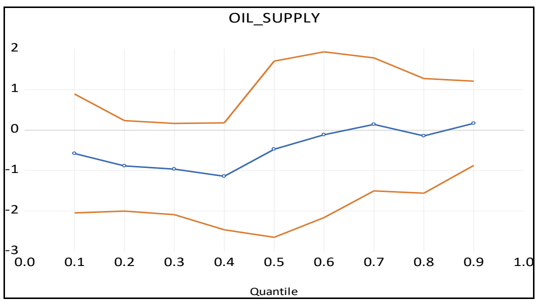
(iii) EPU & Economic Activity Shocks



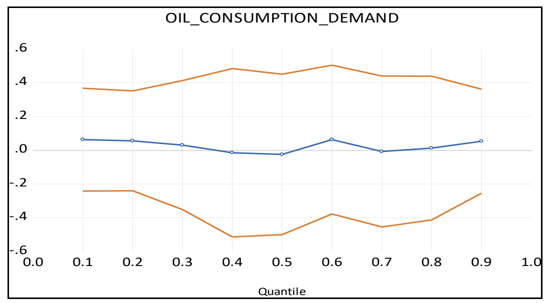
(iv) EPU & Oil Inventory Demand Shocks



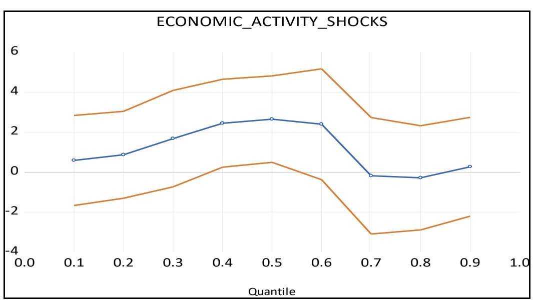
(v) FPU & Oil Supply Shocks



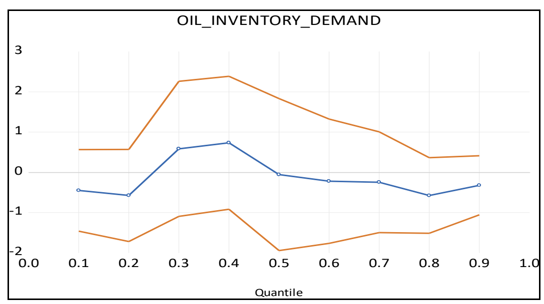
(vi) FPU & Oil Consumption Demand Shocks



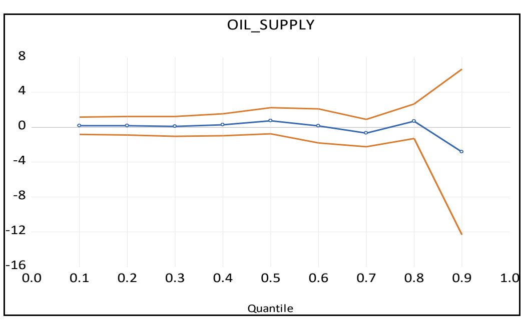
(vii) FPU & Economic Activity Shocks



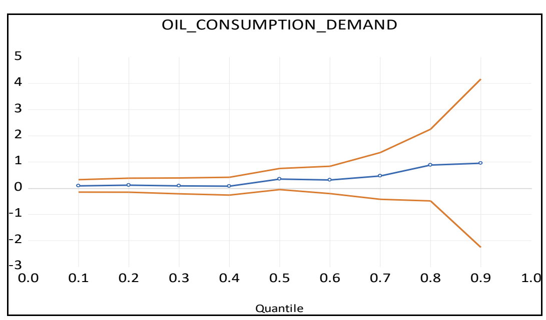
(viii) FPU & Oil Inventory Demand Shocks



(ix) PU & Oil Supply Shocks

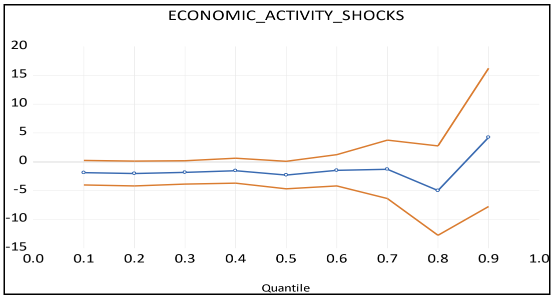


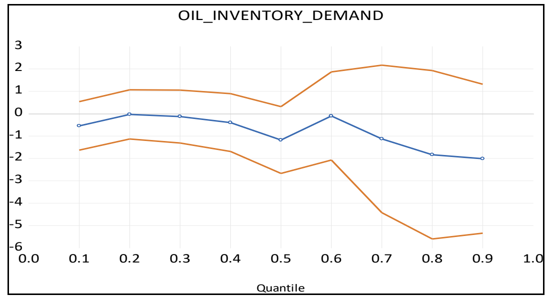
(x) PU & Oil Consumption Demand Shocks



(xi) PU & Economic Activity Shocks

(xii) PU & Oil Inventory Demand Shocks





Source: Authors' own compilation
Figure 4: Quantile Regression Plots

The quantile regression (QR) methodology is used in this study to test the robustness and validity of the QQ results. Figure 4 indicates that the results of the QR plots tend to be similar across the quantiles of the MPU parameters as in Figure 5, but notable exceptions are observed following QR, which shows that the lower quantiles of the MPU parameters are negatively associated with the oil consumption demand shocks, so that the results of QR differ from those of the QQ. Compared to the QQ estimates, there is a positive relationship between economic activity shocks and upper quantiles of EPU, while there is a negative relationship between economic activity shocks and lower to median quantiles of EPU. There is also a negative relationship between oil supply shocks and upper quantiles of EPU. In summary, the comparison of the results from QR, shows that the QQ has a positive relationship between the upper quantiles of oil shocks and the lower quantiles of the MPU, while there is a negative relationship between the upper quantiles of oil shocks and the lower quantiles of the MPU. These results suggest that the QQ is more informative than the QR, because the QQ coefficients provide much more reliable findings since QR focuses on the individual aggregate effects of oil shocks on the quantiles of the MPU.

5. CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1. Conclusion

The study evaluates the relationship between oil shocks and MPU. First, we assess the dynamic relationship between oil shocks and MPU using the Diebold-Yilmaz (2012) and the quantile spillover framework of Ando *et al*. (2022). The study utilized four (4) oil shocks, that is oil consumption demand shocks, oil inventory demand shocks, oil supply shocks, and economic activity shocks, as well as three (3) MPU indices, namely EPU, FPU and PU from 1990M1 to 2018M7. Second, QQ is applied to analyze the quantile dependence between oil shocks and MPU.

Using the Diebold-Yilmaz spillover framework, the study concludes that there is a moderate degree of interdependence between oil shocks and MPU. This finding supports the works of Antonakakis *et al*. (2014) report of a weak to moderate connection between oil shocks and EPU. In the study's analysis of the oil shocks and MPU parameters, EPU and PU propose a greater impact on the behavior of oil shocks and MPU than other oil shocks and uncertainty parameters. Moreover, the study identifies that these oil shocks and MPU parameters are more susceptible to spillovers from PU and EPU, even though EPU is a net receiver, whilst PU is a net transmitter.

Furthermore, the study finds that at lower quantiles, EPU, FPU, and PU act as net receivers, while all the oil shocks function as net transmitters. EPU and PU have a more significant impact on oil shocks and uncertainty indices compared to other factors, and all the oil shocks and MPU components are more vulnerable to shocks originating from oil inventory demand and oil consumption demand. Additionally, there is a strong connection between oil shocks and MPU, with a TCI of 71.77%. At median quantiles, EPU and PU act as net transmitters, whereas FPU and all structural oil shocks are net receivers. Oil consumption demand shocks and PU have the most significant impact on the oil market and macroeconomy, but these markets are more susceptible to spillover shocks from EPU and PU. The analysis reveals a low degree of connectivity with a TCI of 40.89%. At upper quantiles, a high degree of connectedness between oil shocks and MPU with a TCI of 72.59% is observed. Economic activity shocks and oil inventory demand shocks act as net receivers, while oil inventory demand shocks and economic activity shocks have a greater effect on the oil market and macroeconomy. However, these markets are more vulnerable to shocks originating from PU and oil consumption demand. Overall, spillovers of oil shocks and MPU are strongly connected at lower and upper quantiles, and moderately connected at the conditional mean and median quantiles.

As expected, positive and negative relationship across quantiles of oil shocks and MPU is observed. A substantial positive relationship between upper quantiles of EPU, FPU and PU, against the upper quantiles of oil shocks. Conversely, a negative association is revealed between upper quantiles of EPU, FPU and PU against the upper quantiles of all oil shocks.

5.2. Implication for Policy

Given the preceding findings, the best policy response would be for policymakers to be more cautious when developing economic, political, and financial policies, given that oil shocks create macroeconomic uncertainties. On the other hand, these findings provide policymakers and investors with the ability to identify which oil shocks have the greatest impact on macroeconomic policy, implying that policymakers and investors should keep an eye on the trends of oil shocks and their potential effects. The dynamic connectedness analysis shows a bi-directional spillover link between EPU and PU, implying that policymakers should prioritize economic and political policies. Given the positive and negative quantile association between oil shocks, investors should understand that their markets are affected differently at different extremes; thus, during extreme periods of oil shocks, investors' attention should be drawn to macroeconomic policy uncertainty, given that MPU affects the oil markets in which they operate.

5.3. Limitations and Suggestions

Even though the study's findings provide policymakers and other economic agents with insights into oil shocks and MPU. The results do not fully portray the current relationship between oil shocks and MPU. The major limitation is due to EPU and PU data constraints. The end date for EPU and PU is 2018M7, while the end date for the remaining variables is 2022M6. Due to this limitation, the data utilized in this study could not account for topical issues such as the COVID-19 crisis and the 2022 energy crisis. If the study had used data from those events, it could have produced more reliable and up-to-date results. The correlation between FPU and all oil shocks using data spanning from 1990M1 to 2022M6 would produce better results for the spillover framework. Simultaneously, different outcomes could be observed for QQ as well.

Due to the difficulties in accessing the data, this study makes recommendations for data access improvements. The study proposes a new econometric package that could assist in resolving the data constraints issues, allowing researchers to convert the available data to any date of their choice. Future research on oil shocks and MPU should aim to overcome data constraints limitations by incorporating new methods or programs that use statistical models to learn from data and make predictions or decisions about recent data.

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