Highlights

- We examine the nature of relationship between real economic activity, and the stock and gold market volatility shocks using the Nonlinear Autoregressive Distributed Lag model, Granger causality tests, and spillover analysis following Diebold & Yilmaz (2009; 2012).

- We find asymmetries in the short- and long-term relationships among these variables.

- The causality tests further indicate a feedback effect between real economic activity shocks and these market volatility indexes, except for the gold market which has a unidirectional causality with the real economic activity shocks.

- Finally, the spillover analysis suggests a stronger integration among the partial sums, with the energy market as the dominant net-transmitter of both positive and negative shocks while the gold market is a net-receiver of shocks.
Economic Activity, and Financial and Commodity Markets’ Shocks: An Analysis of Implied Volatility Indexes

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Abstract – This paper examines the dynamic short- and long-run asymmetric interactions and causality between real economic activity and stock and gold markets volatility shocks using both the cointegration Nonlinear Autoregressive Distributed Lag and Granger causality tests. In a further analysis, we used both the original and the partial sums decomposition of these variables to examine the level of market integration under different market conditions using the spillover index of Diebold & Yilmaz (2009; 2012; 2014). Our results indicate asymmetries in the short- and long-term relationships among these variables. In the long run, both positive and negative shocks from the energy market increase stock market volatility. However, only positive shocks on the gold market increase stock market volatility, while positive (negative) shocks on economic activity reduce (increase) stock market volatility. Also, an increase in both stock and energy markets volatility shocks are detrimental to real economic activity. We find a feedback effect between real economic activity shocks and these market volatility indexes, except for the gold market which has a unidirectional causality with the real economic activity shocks. Finally, the spillover analysis suggests a stronger integration among the partial sums, with the energy market as the dominant net-transmitter of both positive and negative shocks while the gold market is a net-receiver of shocks. Our results hold crucial implications for both investors and policymakers.

Keywords: Economic Activity; Energy Market; Stock Market; Asymmetric Shocks; NARDL; Connectedness

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1. Introduction

Conventionally, the stock market is known for offering investors an investment avenue to put their surplus funds, while availing firms the opportunity of pooling funds from different investors and expand their business. Among others, while this earlier placed financial market performance as one of the essential areas of economic inquiry, anecdotal evidence over the past two decades underscores trading in commodities, in both cash and derivatives markets, as an alternative investment class to traditional portfolios (Batten et al., 2010). Hence, understanding the determinants of both markets is of utmost importance to policymakers, investors, and consumers. From a policy perspective, understanding the drivers and consequences of volatility in either of the markets is pivotal for formulating policies that would ensure financial and macroeconomic stability (Chinzara, 2011; Corradi et al., 2013). For investors and consumers, on the other hand, such knowledge would help them forecast prices, diversify risks, and formulate strategies for hedging, derivatives trading, and portfolio optimization (Chinzara, 2011; Corradi et al., 2013; Mo et al., 2018).

In line with the foregoing, there is now an enormous body of literature examining how macroeconomic conditions affect the performances of financial and commodity market (e.g., Schwert, 1989; Kearney & Daly, 1998; Errunza & Hogan, 1998; Binder & Merges, 2001; Beltrattia & Morana, 2006; Chinzara, 2011; Mo et al., 2018; Prokopczuk et al., 2019; Hollstein et al., 2020). To date, however, empirical analysis on the interrelationship between both markets and macroeconomic conditions is lacking. Importantly, as an empirical proxy of macroeconomic conditions, studies in this literature often employ one or more aggregate time-series indicators such as unemployment rate, industrial production, GDP growth, and inflation. These variables are only available on monthly or quarterly averages with a considerable lag, and therefore, mask a lot of information (Lewis et al., 2020).

From a theoretical standpoint, different channels have been espoused in the literature to underpin the nexus between macroeconomic conditions and stock market volatility. Arnold & Vrugt (2006) argue that these nexus have become appealing given the potential of macroeconomic conditions to influence company cash flows and overall systematic risk. Two main approaches to measuring stock market returns such as the dividend discount model and the arbitrage pricing
theory offer an important theoretical framework on the links between macroeconomic conditions and stock prices. For instance, as an absolute pricing model, the dividend discount model predicts that any (un)anticipated arrival of new information about real economic activities will alter stock prices/returns through the impact on expected dividends and/or the discount rate (Chinzara, 2011). On the other hand, as a relative pricing model, the arbitrage pricing theory predicts the expected return of an investment based on its risk, which is measured based on the sensitivity of an individual asset to the market index return. The macroeconomic condition affects stock market volatility which affects asset pricing and risk.

In this paper, using volatility indexes of financial (as measured by the SP 500 implied volatility) and commodity (as measured by the energy and gold implied volatility) markets, and a novel indicator of real economic activities that is available at a high-frequency level, we contribute to the above literature by examining the interaction among macroeconomic conditions, and financial and commodity markets. In particular, while our study focuses on the United States (US), it makes three notable contributions to the literature. First, unlike the conventional approach of measuring the existing macroeconomic condition with one or more aggregate indicators, we utilize the newly developed Weekly Economic Index (WEI) by Lewis et al. (2020). The index uses daily and weekly relevant high-frequency data that is based on ten different economic activities covering consumer behavior, the labor market, and production, to propose a single index that tracks real economic activity in the US. The index, therefore, captures the different dimensions of real economic activities. Also, given that other economic activity indicators are at best, available on a monthly frequency that masks much information and blurs informative economic decisions, the high-frequency WEI is more comparable to the evolution of volatility indicators especially, the financial and commodity markets volatility indexes.

Second, we analyze the dynamic short- and long-run relationships between WEI and the market volatility indexes. To do this, we use the nonlinear cointegrating autoregressive distributed lag (NARDL) model of Shin et al. (2013) which introduces short- and long-run asymmetries via positive and negative partial sum decomposition of the explanatory variables. Also, we explore the causal relationship between the partial sums of the WEI and the market volatility indexes using the Granger causality test. Finally, we use both the original and the partial sum
decomposition of these variables to examine their level of integration under different market conditions using the spillover index of Diebold & Yilmaz (2009; 2012; 2014). Hence, our study offers a more comprehensive analysis as compared to previous studies.

As a preview of our empirical findings, we document evidence of asymmetries in the short and long-term relationships among the WEI and the market volatility indexes. In particular, the long run results show that both positive and negative shocks from the energy market increase stock market volatility. However, only positive shocks on the gold market increase stock market volatility, while positive (negative) shocks on economic activity reduce (increase) stock market volatility. Also, an increase in both stock and energy markets volatility shocks are detrimental to real economic activity. We find a feedback effect between real economic activity shocks and these market volatility indexes, except for the gold market which has a unidirectional causality with the real economic activity shocks. Regarding the spillover analysis, we find a stronger integration among the partial sums, with the energy market as the dominant net-transmitter of both positive and negative shocks while the gold market is a net-receiver of shocks. More importantly, although the integration is higher when we consider the negative partial sums of all the variables, the WEI becomes a net-receiver of shocks while both the financial and energy markets are net-transmitters.

The remainder of this paper is organized as follows. Section 2 discusses the related literature. The empirical strategy, data sources and the computation of variables are described in section 3. Section 4 presents and discusses the results, while section 4 concludes.

2. Background Literature
As is obvious by now, this paper examines the asymmetric and bi-directional causal relationship between real economic activities and the performances of the financial and commodity markets. Hence, the paper is related to three strands of literature that has rather evolved independently. They include studies examining the relationship between (i) macroeconomic conditions and financial market performance (e.g., see Chen et al., 1986; Chinzara, 2011; Beetsma & Giuliodori, 2012; Corradi et al., 2013); (ii) macroeconomic conditions and commodity market performance (e.g., see Liu et al., 2015; Ergen & Rizvanoglu, 2016; Prokopczuk et al., 2019;
Hollstein et al., 2020; Kang et al., 2020); and (iii) the nexus between financial market and commodity market (e.g. see Erb & Harvey, 2006; Chong & Miffre, 2010; Creti et al., 2013).

The literature examining the nexus between macroeconomic conditions and the financial market performance is perhaps the most developed literature among the three strands of literature listed above. Chen et al. (1986) is one of the earliest studies to examine this relationship by modeling equity return as a function of macro variables and non-equity assets returns for the US. Among others, their study shows that macroeconomic variables such as industrial production, anticipated and unanticipated inflation, and the yield spread between the long and short term government bond significantly explain the stock returns. Following this study, empirical analysis employing different sample, empirical design, and econometric techniques to examine the nexus between macroeconomic conditions and financial market performance have proliferated (e.g., see Schwert, 1989; Beltrattia & Morana, 2006; Ratanapakorn & Sharma, 2007; Engle & Rangel, 2008; Chinzara, 2011; Beetsma & Giuliodori, 2012; Paye, 2012; Christiansen et al., 2012; Corradi et al., 2013; Corradi et al., 2013). In general, these studies conclude that financial market performances as measured by stock prices, returns, and/or volatility tend to respond to the changes in macroeconomic fundamentals but the sign and causal relationship might not hold equally across studies. Conversely, several studies have also underscored pathways through which stock market volatility could potentially feedback to macroeconomic activities. For instance, Kimball (1990) and Carroll & Samwick (1998) both show that stock market volatility may lead to an increase in precautionary savings, which would depress consumption spending. On the firm side, it may also cause a delay in investments as it may raise the required compensation for bearing systematic risk in financial markets, thereby pushing up the cost of capital (Bernanke, 1983; Beetsma & Giuliodori, 2012). In line with this, unbundling this bi-directional relationship has also been the focus of some studies (e.g., Beltratti & Morana, 2006).

Regarding the relationship between macroeconomic conditions and commodity market volatility, the literature is less developed. Existing studies have both examined the relationship between real economic activity and volatility of either a particular commodity (Liu et al., 2015; Ergen & Rizvanoglu, 2016; Kang et al., 2020) or a group of commodities (Batten et al., 2010; Karali & Ramirez, 2014; Mo et al., 2018; Prokopczuk et al., 2019; Hollstein et al., 2020). For instance,
Kang et al. (2020) examine how different macroeconomic conditions such as treasury yield spreads, consumer price index, index of national activity (CFNAI), and industrial production predict oil futures volatility. On the other hand, Prokopczuk et al. (2019) examine the relationship between different economic indicators such as the growth rate of the Consumer Price Index, industrial production, money supply, and the index of national activity (CFNAI) and the volatility of four broad categories of commodities including agricultural, livestock, energy, and metals. Existing studies have also examined the feedback effect of volatility in the commodity market on real economic activities, finding significant evidence on the relation (Federer, 1996; Elder & Serletis, 2011; Rahman & Serletis, 2012). However, to our best knowledge, what is still lacking in this literature is a test on the bidirectional causality which the current study intends to do, among other research objectives.

The theoretical underpinning of studies examining the nexus between financial and commodity markets relates to the existence of possible substitution between tradable commodities and financial assets by investors, and that the information about the evolution of each market can be inferred from the other. Along this line, Creti et al. (2013) noted that comparing the dynamic volatility of raw materials and equity prices provides useful information about possible substitution strategies between commodity and stock classes. As argued further by the authors, volatility plays a key role in hedging possibilities, and impacts asset allocation across raw materials and their risk-return trade-off. Consistent with this view, several studies have examined the nexus between the financial and commodity market. Pioneer studies in this literature focused mostly on oil, examining either the comovements between stock and oil markets (e.g., see Jones & Kaul, 1996; Sadorsky, 1999; Papapetrou, 2001; Ewing & Thomson, 2007; Park & Ratti, 2008; Phan et al., 2015) or the spillovers between oil and stock markets (Malik & Ewing, 2009; Chiou & Lee, 2009; Choi & Hammoudeh, 2010; Filis et al., 2011; Ciner, 2013; Sukcharoen et al., 2014; Ewing & Malik, 2016). For instance, Park & Ratti (2008) analyzed the impact of oil price shocks on the US and 13 European countries' stock markets. They find that oil price shocks have a statistically significant impact on real stock returns. Importantly, they also find that the contribution of oil price shocks to variability in real stock returns in the U.S. and most other countries is greater than that of the interest rate. Malik & Hammoudeh (2007), on the other hand, examined the volatility and shock transmission mechanism among US equity, the global crude
oil market, and the Gulf equity markets. While they find that Gulf equity markets receive volatility from the oil market, only the Saudi Arabia equity market shows a significant volatility spillover to the oil market.

More recently, however, studies have gone beyond focusing on oil to examine the nexus between financial markets and other commodities (e.g., see Erb & Harvey, 2006; Baur & McDermott, 2010; Chong & Miffre, 2010; Mensi et al., 2013; Creti et al., 2013; Ewing & Malik, 2013; Sadorsky, 2014). For instance, Mensi et al. (2013) used the VAR-GARCH model to investigate the return links and volatility transmission between the SP 500 and commodity price indices for energy, food, gold, and beverages. They find that past shocks and past volatility of the SP 500 index have a strong influence on the oil and gold markets. Utilizing a dynamic conditional correlations GARCH Model, Creti et al. (2013) find that the correlation between stock markets and the price returns for 25 commodities covering various commodity (energy, precious metals, agricultural, nonferrous metals, food, oleaginous, exotic and livestock) in the US evolve through time and are highly volatile, particularly since the 2008 subprime mortgage crisis. Arouri et al. (2015) examined both return and volatility spillovers between world gold prices and the stock market in China using the VAR-GARCH model and several other competing multivariate volatility models. They find significant evidence of return and volatility effects between gold prices and stock prices in China. In particular, past gold returns play a crucial role in explaining the dynamics of the conditional return and volatility of the Chinese stock market. Delatte & Lopez (2013) analyzed the co-movement between commodity (metal, agriculture, and energy) and stock markets using time-varying copula functions. Among others, they find that the dependence between commodity and stock markets is time-varying, symmetrical, and occurs most of the time.

In this paper, we synthesis the above three literature which has rather evolved independently by examining simultaneously, the asymmetric and bi-directional causal relationship between real economic activities, and financial (as measured by the SP 500 implied volatility) and commodity (as measured by the energy and gold implied volatility) markets. As an empirical proxy for economic activities, rather than rely on one or more aggregate indicators that are only available at lower frequencies as done in the literature reviewed above, we also contribute to the extant
literature by utilizing the newly developed WEI by Lewis et al. (2020). As we discuss further in the next section, in addition to being available at a weekly high-frequency, making it more comparable to the evolution of volatility indicators such as those of the financial and commodity markets volatility indexes, the index is based on ten different economic activities covering consumer behavior, the labor market, and production. The index, therefore, captures the different dimensions of real economic activities.

3. Data and Empirical Methods

3.1 Data

The dataset for this study includes the Chicago Board Options Exchange (CBOE) implied volatility indices for the stock, energy, and gold markets. In particular, we use the VIX index which tracks the volatility (uncertainty) of the S&P 500. This is largely accepted as a measure of risk in the global stock market as it reflects investors’ perception of future index movement. To capture risks in both global energy and precious metals markets, we use the VXX and GVZ indices while we use the recently introduced weekly economic index to measure the movement of the real economy. The index is in weekly frequency, while the volatility indexes are daily but are converted to weekly frequency to reduce noise and maintain similarity. The dataset covers the period from March 12, 2011, to May 02, 2020. Our sample period is limited by the start date for the energy market volatility index. Figures 1a and 1b present the time series plots of our dataset. The adverse effects of the COVID-19 pandemic may be seen in the notable drop in the WEI and a significant increase in volatility of the three markets from January 2020 till the end of our study period.

[Figure 1 about here]

[Table 1 about here]

The WEI is developed by Lewis et al. (2020). To construct the index, the authors used a weekly series from private sources like industry groups and commercial polling companies. Weekly series drawn from these sources include indexes on same-store retail sales, consumer sentiment, initial unemployment insurance claims, temporary and contract employment, steel production, fuel sales, and electricity consumption. The resulting WEI is then the first principal component
from these seven time series after transforming all series to represent 52-week percentage changes and remove most seasonality in the data. The WEI is scaled to the four-quarter GDP growth rate; for example, if the WEI reads -2 percent and the current level of the WEI persists for an entire quarter, one would expect, on average, GDP that quarter to be 2 percent lower than a year previously. Table 1 displays the summary statistics and the pairwise correlation matrix of the variables employed in our analysis. Beginning with the summary statistics, among the three market volatility indexes, VXX has the highest mean, while GVZ has the lowest mean. Interestingly, VXX (GVZ) also has the highest (lowest) standard deviation suggesting that it exhibits the highest market volatility around its mean. Regarding the pairwise correlation matrix, there is a strong positive correlation among the market volatility indexes, with the correlation between VXX and VIX being as high as 93%. These strong correlations are expected since commodity markets are closely related to the financial market (Zeng et al., 2020). Finally, and as expected, the correlation between the WEI and the respective market volatility indexes are all negative.

Table 2 shows the unit-roots as well as non-linearity tests using the endogenous structural break ADF-type unit roots and BDS tests. As noted in Basher & Westerlund (2008), a notable feature of most historical financial and macroeconomics time series is the existence of structural breaks. Previous studies have argued that the failure of unit root tests to account for the existence of structural breaks that may arise from economic events may lead to misspecification, inaccurate inference and might lead to bias and spurious rejections (see e.g., Aretis & Marascal, 1999; Chaudhuri & Wu, 2003; Ling et al., 2013). Following these reasons, we use the endogenous structural break ADF-type unit roots test of Zivot & Andrews (2002) which identifies structural changes occurring at an unknown point using innovation outliers. As shown in the table, all the series become stationary after the first difference and most structural breaks appear to be associated with the recent global economic conditions created by the COVID-19 pandemic in early 2020. This is consistent with the significant fall in the WEI, as shown in Figure 1a and the positive spike in all market volatility indexes, as shown in Figure 1b during this period. Finally, the test for non-linearity in all the series using the BDS test of Brock et al. (1996) as reported in
the final two columns of Table 2 suggests that all the series are nonlinear. This gives us some confidence that a nonlinear modeling approach is appropriate for the objectives of this study.

3.2 Empirical Methods

3.2.1. Nonlinear Relationship

To examine the nonlinear relationship between real economic activities and uncertainties in the financial and stock markets, we first specify the following baseline equations:

\begin{align}
VIX_t &= \beta_0 + \beta_1 WEI_t + \beta_2 VXX_t + \beta_3 GVZ_t + \epsilon_t \\
VXX_t &= \beta_0 + \beta_1 VIX_t + \beta_2 WEI_t + \beta_3 GVZ_t + \epsilon_t \\
GVZ_t &= \beta_0 + \beta_1 VIX_t + \beta_2 VXX_t + \beta_3 WEI_t + \epsilon_t \\
WEI_t &= \beta_0 + \beta_1 VIX_t + \beta_2 VXX_t + \beta_3 GVZ_t + \epsilon_t
\end{align}

Where $\beta_1 - \beta_3$ are coefficients while WEI, VIX, VXX, and GV Z represent the weekly economic index and implied volatility for the financial, energy, and gold markets respectively. We use the Brock-Dechert-Scheinkman (BDS) test for non-linearity proposed by Brock et al. (1987) to test for asymmetries in the relationships described above. Following previous studies such as Dhaoui et al. (2020), we examine these asymmetries in long and short-run adjustments to positive and negative shocks in the respective explanatory variables by applying the NARDL model proposed by Shin et al. (2014). This model extends the popularly known ARDL model of Pesaran & Shin (1998) and Pesaran et al. (2001) by developing a flexible dynamic parametric approach to model economic relationships that exhibit combined-longrun and shortrun asymmetries. To this end, the NARDL specification of the model for this study may be written as:
\[ \Delta \ln VIX_t = \mu + \rho \ln VIX_{t-1} + \theta_1^+ \ln WEI_{t-1}^+ + \theta_1^- \ln WEI_{t-1}^- + \theta_2^+ \ln VXX_{t-1}^+ + \theta_2^- \ln VXX_{t-1}^- + \sum_{t=1}^{p-1} \alpha_t \Delta \ln VIX_{t-1} + \sum_{t=0}^{q} \pi_{1,i}^+ \Delta \ln WEI_{t-1}^+ \\
+ \sum_{t=0}^{q} \pi_{1,i}^- \Delta \ln WEI_{t-1}^- + \sum_{t=0}^{q} \pi_{2,i}^+ \Delta \ln VXX_{t-1}^+ + \sum_{t=0}^{q} \pi_{2,i}^- \Delta \ln VXX_{t-1}^- \\
+ \sum_{t=0}^{q} \pi_{3,i}^+ \Delta \ln GVZ_{t-1}^+ + \sum_{t=0}^{q} \pi_{3,i}^- \Delta \ln GVZ_{t-1}^- \] (5)

\[ \Delta \ln VXX_t = \mu + \rho \ln VXX_{t-1} + \theta_1^+ \ln WEI_{t-1}^+ + \theta_1^- \ln WEI_{t-1}^- + \theta_2^+ \ln VXX_{t-1}^+ + \theta_2^- \ln VXX_{t-1}^- \\
+ \sum_{t=1}^{p-1} \alpha_t \Delta \ln VXX_{t-1} + \sum_{t=0}^{q} \pi_{1,i}^+ \Delta \ln WEI_{t-1}^+ \\
+ \sum_{t=0}^{q} \pi_{1,i}^- \Delta \ln WEI_{t-1}^- + \sum_{t=0}^{q} \pi_{2,i}^+ \Delta \ln VXX_{t-1}^+ + \sum_{t=0}^{q} \pi_{2,i}^- \Delta \ln VXX_{t-1}^- \\
+ \sum_{t=0}^{q} \pi_{3,i}^+ \Delta \ln GVZ_{t-1}^+ + \sum_{t=0}^{q} \pi_{3,i}^- \Delta \ln GVZ_{t-1}^- + \epsilon_t \] (6)

\[ \Delta \ln GVZ_t = \mu + \rho \ln GVZ_{t-1} + \theta_1^+ \ln WEI_{t-1}^+ + \theta_1^- \ln WEI_{t-1}^- + \theta_2^+ \ln VXX_{t-1}^+ + \theta_2^- \ln VXX_{t-1}^- \\
+ \sum_{t=1}^{p-1} \alpha_t \Delta \ln GVZ_{t-1} + \sum_{t=0}^{q} \pi_{1,i}^+ \Delta \ln WEI_{t-1}^+ \\
+ \sum_{t=0}^{q} \pi_{1,i}^- \Delta \ln WEI_{t-1}^- + \sum_{t=0}^{q} \pi_{2,i}^+ \Delta \ln VXX_{t-1}^+ + \sum_{t=0}^{q} \pi_{2,i}^- \Delta \ln VXX_{t-1}^- \\
+ \sum_{t=0}^{q} \pi_{3,i}^+ \Delta \ln VXX_{t-1}^+ + \sum_{t=0}^{q} \pi_{3,i}^- \Delta \ln VXX_{t-1}^- + \epsilon_t \] (7)
\[
\Delta \ln WEI_t = \mu + \rho \Delta \ln WEI_{t-1} + \theta^+_1 \Delta \ln GVZ_{t-1}^+ + \theta^-_1 \Delta \ln GVZ_{t-1}^- + \theta^+_2 \Delta \ln VIX_{t-1}^+ + \theta^-_2 \Delta \ln VIX_{t-1}^-
\]
\[
+ \sum_{t=1}^{p-1} \alpha_t \Delta \ln WEI_{t-1} + \sum_{t=0}^{q} \pi^+_1 \Delta \ln GVZ_{t-1}^+ + \sum_{t=0}^{q} \pi^-_1 \Delta \ln GVZ_{t-1}^- + \sum_{t=0}^{q} \pi^+_2 \Delta \ln VIX_{t-1}^+ + \sum_{t=0}^{q} \pi^-_2 \Delta \ln VIX_{t-1}^-
\]
\[
+ \sum_{t=0}^{q} \pi^+_3 \Delta \ln VXX_{t-1}^+ + \sum_{t=0}^{q} \pi^-_3 \Delta \ln VXX_{t-1}^- + \epsilon_t
\] (8)

where \( \ln vix^+, \ln vix^-, \ln vxx^+, \ln vxx^-, \) and \( \ln wei^+, \ln wei^- \) are the partial sums of positive and negative changes in the respective explanatory variables while \( \beta^+ = -\theta^+ / \rho \) and \( \beta^- = -\theta^- / \rho \) are the associated asymmetric long-run parameters. The estimation procedure of NARDL is similar to the linear ARDL model, proceeding with the estimation of the conditional nonlinear error correction model through OLS regression before examining the presence of long-run relationships using the modified F-test with the bounds testing procedure proposed by Pesaran et al. (2001) (i.e. the joint null hypothesis: \( \rho = \theta^+ = \theta^- = 0 \)). The bounds testing for this study is carried out in line with Shin et al. (2014) by using both the F-statistics \( F_{pss} \) proposed by Banerjee et al. (1998). Furthermore, we utilize the Wald test to examine the existence of long-run and short-run asymmetries. Lastly, the short-run and long-run asymmetry paths denoted by the cumulative dynamic multiplier effect on a respective dependent variable \( y_t \) of a unit positive change \( (\beta^+_t) \) and negative change \( (\beta^-_t) \) may be represented as:

\[
m^+_h = \sum_{j=0}^{h} \frac{\delta y_{t+1}}{\delta x^+_t}
\]
\[h = 0,1,2,...\] (9)

\[
m^-_h = \sum_{j=0}^{h} \frac{\delta y_{t+1}}{\delta x^-_t}
\]

where \( h \to \infty \), the \( m^+_h \to \beta^+ \) and \( m^-_h \to \beta^- \), while \( \beta^+ \) and \( \beta^- \) are as defined earlier.
3.2.2. Asymmetric Connectedness

To examine the asymmetric integration between WEI and the chosen markets. First, we distinguish between positive and negative shocks to the WEI and explore the level of connectedness when either positive or negative shocks occur to economic activity. Positive and negative shocks to WEI are denoted by:

\[
WEI^+ = \begin{cases} 
    WEI_t, & \text{if } WEI_t > 0 \\
    0, & \text{if otherwise}
\end{cases}
\]

\[
WEI^- = \begin{cases} 
    WEI_t, & \text{if } WEI_t < 0 \\
    0, & \text{if otherwise}
\end{cases}
\]

Second, we investigate the level of integration assuming that both the market volatility indexes and WEI simultaneously receive either positive or negative shocks. To achieve these objectives, we retrieved the partial sums decompositions from the NARDL model. This objective is broadly motivated by documented empirical findings where the real economic sector and the financial and commodities markets appear to exhibit asymmetric interactions (see e.g. Urom et al., 2019). To do this, we rely on the spillover index proposed of Diebold & Yilmaz (2009, 2012, & 2014). This technique offers a single spillover measure based on forecast error variance decomposition which conveys significant information about aggregate spillover effects among markets.

Consider, an \( x \)-variable VAR(\( p \)) model written as follows:

\[
x_t = \varnothing + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \cdots + \beta_p x_{t-p} + u_t
\]

where \( x_t \) is an \( N \times 1 \) vector of conditional volatilities, \( x_{t-1} \) is an \( N_p \times 1 \) conditional vector while \( \beta_t \) is an \( N \times N_p \) dimensional time-varying coefficient matrix and \( u_t \) denotes an \( N \times 1 \) vector of error terms. The parameters \( x_t \) depend on their past values \( x_{t-1} \) up to \( x_{t-p} \).

Equation 11 may be written as the moving average equation:
Using the generalized variance decomposition method (GVD), the contribution of market \( i \) to the system may be computed since the results of variance decomposition are correlated to the order of the variables in the VAR model. The contribution of variable \( x_j \) to variable \( x_i \) may be expressed as:

\[
\gamma_{ij}^H(H) = \sigma_{ij}^{-1} \sum_{h=0}^{H-1} \left( e'_{i} A - h \sum e_j \right) / \sum_{h=0}^{H-1} \left( e'_{i} A_h \sum A' e_i \right)
\]

(14)

where \( \sigma_{ij} \) represents the standard deviation of \( \nu \) for the \( j \)th equation. \( e \) is a selection vector which is equal to one in the \( i_{th} \) element and zeros otherwise, while \( \sum \) denotes the variance matrix of the error term. The total directional connectedness from the system \( j \) to market \( i \) may be expressed as follows:

\[
C_{i\rightarrow j}^H = \sum_{j=1}^{N} d_{ij}^H \quad j \neq i,
\]

(15)

while the total directional connectedness from market \( i \) to the system \( j \) is given as:

\[
C_{i\rightarrow j}^H = \sum_{j=1}^{N} d_{ij}^H \quad i \neq j,
\]

(16)

The net total directional connectedness is computed as \( C_i^H = C_{i\rightarrow i}^H - C_{i\rightarrow j}^H \), while the total connectedness is denoted as:
The total connectedness measure ranges from 0 to 1, with 1 implying perfect integration while 0 implies perfect segmentation. This enables us to account for time variation in the level of integration among economic activity and implied volatility indexes for the financial and energy markets. Following Diebold & Yilmaz (2009), the forecast horizon ($H$) is set to 10 weeks.

\[ C^H = \frac{1}{N} \sum_{i,j=1}^{N} d_{ij}^H \quad i \neq j, \]  \hspace{1cm} (17)

4. Results and Discussion

4.1 NARDL Estimates

Estimation results from the NARDL model for each market and the WEI as defined in Equations 5 - 8 are presented in Table 3. We follow Rehman et al. (2019) in the appropriate lag selection for each model. The table contains the main estimation coefficients and diagnostic checks; the long-run asymmetries; and the Wald test for non-linearity of long-run and short-run estimates. The Durbin-Watson test for autocorrelation is within the appropriate bounds while the test statistics $X_{SC}^2$ and $X_{HC}^2$ suggest the absence of serial correlation and heteroskedasticity, respectively. The diagnostic results further confirm the stability of the NARDL estimates across all the models. Also, the Wald tests confirm the asymmetry of short- and long-run coefficients.

Results suggest that in the short-run, positive volatility shocks on energy and gold markets lead to an increase in stock market volatility, while the effect of the real economic activity appears to be non-significant even after the first lag. On the other hand, negative volatility shocks on both the energy and gold markets reduce equity market volatility only after the first lag, while a negative shock on economic activity impacts positively on it. An increase in energy market volatility appears to be largely driven by positive shocks on stock market volatility while positive shocks on economic activity reduce it. Negative shocks on stock market volatility only reduce energy market volatility after the second lag while economic downturns increase energy market volatility. A negative volatility shock on the gold market reduces energy market volatility only after the second lag. This implies that in the short-run, volatility in the energy market is mainly
driven by economic activity downturn. Until now, existing studies have largely focused on the
effect of energy market volatility on real economic activity (e.g., Guo & Kliesen, 2005; van de
Ven & Fouquet, 2017). Our result provides novel evidence that, indeed, negative economic
activity shocks such as those caused by economic crises and pandemics tend to drive up energy
market volatility due to a fall in energy demand following a decrease in economic activities.

Furthermore, both positive and negative shocks on equity and energy markets increase volatility
in the gold market. However, after the first lag, a negative volatility shock from the equity
market seems to reduce gold market volatility. These results imply that short-run volatility
changes in equity prices spill over to the gold market as investors mostly move their funds to
precious metals as indicated by the concept of flight to safety (see e.g. Sarwar, 2017; Troster et
al., 2019). However, as volatility reduces in the market for fundamental assets, investors tend to
move back to reap higher returns. On the other hand, positive economic activity shock tends to
increase volatility in the gold market. This may not be unconnected with the fact that during
economic prosperity, demand for ostentatious goods including gold tends to increase, and so
does their prices change rapidly. Regarding economic activity, positive (negative) stock market
volatility shocks seem to have negative (positive) effects on economic activity after second lags.
However, an increase in energy market volatility appears to have an immediate positive effect on
economic activity but this becomes detrimental after the second lag. This result suggests that an
immediate increase in energy market volatility sends good signals to the real economy while a
sustained increase in energy market volatility becomes detrimental to economic activity. Lastly,
negative volatility shock from the gold market seems to promote economic activity while
positive shocks are non-significant at all lags.

Concerning the longrun estimates, results show in the longrun, that both positive and negative
shocks from the energy market increase stock market volatility. Positive shocks on gold market
volatility also increase stock market volatility but positive (negative) shocks on economic
activity reduce (increases) stock market volatility. This implies that in the long run, a sustained
increase in real economic activity largely reduces uncertainties in the equity market while
economic recessions increase uncertainty. Similarly, both positive and negative shocks on equity
market volatility increase uncertainties in the energy market. However, only negative shocks
from the gold market impact positively on energy market volatility while both positive and negative shocks on economic activity reduce energy market volatility. This implies that in the long term, both upwards and downward movements in economic activity reduce energy market uncertainty unlike in the short-run where a sudden drop in economic activity and demand for energy leads to an increase in energy market volatility.

Also, in the long run, positive shocks on the stock and energy markets increase the gold market volatility while positive economic activity shock reduces it. Negative volatility shocks on both the stock market and economic activity reduce gold market volatility. An increase in both stock and energy markets volatility shocks are detrimental to real economic activity growth while a negative shock on stock market volatility increases economic activity. However, a negative shock on gold market volatility appears to increase economic activity. These findings are consistent with the expectation that real economic activity tends to flourish under calm energy and equity market conditions (see e.g., Kimball, 1990; Carroll & Samwick, 1998; Guo & Kliesen, 2005; van de Ven & Fouquet, 2017). Lastly, the null hypotheses of symmetry in the effects of both short-run and long-run coefficients of the variables are rejected in almost all the cases except for gold in the short run. This confirms that the partial sum coefficients of positive and negative shocks have asymmetric effects on the respective dependent variables in each model estimated. This confirms the appropriateness of the nonlinear estimation approach adopted in this study.

[Figure 2 about here]

4.2 Non-Linear Dynamics

Figure 2 plots the dynamic effects of positive and negative shocks on energy, stock market, and real economic activity based on Equations 5-8. Based on Figure 2, the positive impacts of positive shocks on both energy and gold market volatility on stock market volatility are confirmed. However, the accumulated effect of positive real economic activity shock on stock market volatility appears to be positive. This may be explained in terms of the effect of speculations on stock market volatility during economic expansion. This is a similar situation regarding the energy market. However, the positive effect of positive economic activity shock on
stock market volatility diminishes while the effect of negative shocks increases towards the end of the horizon. This suggests that although initial positive improvements in real economic activity may cause an increase in energy market volatility, sustained economic activity growth moderates this effect on the energy market.

Furthermore, the accumulated effects of positive shocks on both the stock and energy markets on gold market volatility are positive with stronger effects coming from the stock market. On the other hand, positive real economic activity shock reduces volatility in the gold market whereas negative economic activity shock increases it but only after the seventh week. Regarding the real economic activity, the favorable accumulated effects of negative shocks on both the stocks and energy markets are confirmed. However, a positive shock on gold volatility seems to have a positive accumulated effect on real economic activity after the third week. In all cases, these results confirm the asymmetric responses to positive and negative changes between real economic activity and the financial and energy market volatility. As presented in Figure 3 Panel A-D, in all cases, the cusum test lies within the bounds of the 95% confidence interval, indicating that the estimates are reliable across all the equations.

[Figure 3 about here]
[Table 4 about here]

Regarding the asymmetric positive and negative causality between economic activity and market volatility indexes as presented in Table 4, we can reject the null hypotheses that positive and negative shocks on stock market volatility does not granger cause real economic activity. We find similar casual relation from both positive and negative economic activity shocks on stock market volatility. This implies a bidirectional causality between economic activity and stock market volatility shocks, confirming the strong links between the real economy and the financial market.

Similarly, we find a bidirectional causality between economic activity and energy market volatility shocks. However, whereas a positive shock on energy market volatility appears to have an immediate effect on real economic activity, a negative economic activity shock granger causes energy market volatility only after the 5th lag. A unidirectional causality runs from gold market volatility to real economic activity, as both positive and negative shocks on gold
volatility granger cause economic activity shocks. However, we cannot reject the null that both positive and negative shocks on the real economic activity do not granger cause gold market volatility. This suggests that an increase in gold market volatility during economic downturns are a result of contagion effects from other financial markets and the effect of investors' interest in gold for diversification purposes during financial and economic crises.

[Table 5 about here]

4.3 Spillovers

In Tables 5 and 6, we present the results of integration among WEI and market volatility indexes using the spillover index. In Table 5, we consider the level of integration among these variables when either positive or negative shocks occur on economic activity only. Here, we decompose the WEI into positive and negative shocks as defined in Equation 10 in the previous section. As shown in the first panel of Table 5, when we consider only negative WEI shocks results show that the total spillover is about 28%. Apparently, most of the integration is due to the stronger co-movements among the three market volatility indexes, which, as reported in Table 1, exhibits a strong positive correlation. As shown in this panel, negative WEI shocks account for only 4.2% of the system's forecast error variance, while the system only accounts for about 3.3% of error variance in the forecast of negative shocks on WEI.

We find similar results in the second panel of Table 5 which reports the level of integration when positive shocks occur on economic activity. In particular, the level of integration among positive WEI shocks and the three market volatility indexes is about 29%. Positive shocks on WEI account for only 5.7% of the forecast error variance in the system, while the system only accounts for about 6.0% of forecast error variance in positive shocks to WEI. Taken together, when we focus only on either positive or negative WEI shocks, our spillover analysis suggests that the integration between WEI and the financial and the commodity markets is weak. Regarding the market volatility indexes, we find similar patterns in the net spillovers regardless of the type of WEI shocks. For instance, we find that both the gold and equity markets are net-receivers of volatility shocks while the energy market is a net-transmitter of shocks. In Figure 4 Panel a to c, we plot the directional connectedness and time-varying integration between positive
and negative economic activity shocks and implied volatility indexes using 100 weeks rolling-window. In all cases, we find strong evidence of time-variation in both directional connectedness and integration between economic activity shocks and implied volatility indexes.

Table 6 presents the level of integration assuming that both the market volatility indexes and WEI simultaneously receive either positive or negative shocks. To achieve these objectives, we retrieved the partial sums decompositions from the NARDL model. As shown in Table 6, we observe some notable differences including the increase in the level of integration. In particular, in a system where all variables receive positive shocks, the total spillover is about 38.9%. In this scenario, the WEI is a net-transmitter of shocks, accounts for about 26.9% of the forecast error variance in the system while the system accounts for about 16.7% of error variance in WEI. On the other hand, in a system where all variables receive negative shocks, total spillover is about 42%. However, WEI becomes a net-receiver of shocks from the system, transmitting only about 23.5% of volatility shocks while it receives about 29.1% from the system. Unlike in Table 5, results for WEI in Table 6 for both positive and negative shocks suggest a stronger integration between the WEI and the market volatility indexes, such that it is safe to argue that macroeconomic fundamentals play a determination in the financial and commodity market volatility as one would naturally expect. Lastly, we find that the energy market is a net-transmitter of shocks while the gold market is a net-receiver across the two scenarios considered. In Figure 5 Panel a to c, we present the directional connectedness and time-varying integration between positive and negative economic activity shocks and implied volatility with the assumption that both economic activity and volatility in commodity and financial markets received similar shocks. In all cases, we find strong evidence of time-variation in both directional connectedness and integration between economic activity shocks and implied volatility indexes.
These results are consistent with the conclusions from the NARDL model discussed in the previous sections. As the BDS test in Table 2 supports the use of a nonlinear model, differences in results presented in Tables 5 and 6 further underpin the need for a nonlinear model when it is ideal to use it. Regarding the market volatility indexes reported in Table 5, we continue to observe that they are highly integrated into the system for both positive and negative shocks, especially for VIX and VXX. This is expected since the energy and financial markets are the backbone of any economy, thus making them the highest contributors and receivers of shock in any system. Nonetheless, results on the net direct connectedness in Table 5 suggest that whether these market volatilities or WEI are net-receiver or transmitter of shocks in a system depends on whether we consider positive or negative shocks across all variables.

5. Conclusion

Understanding the nexus between macroeconomic conditions and volatility in both the financial and commodity markets is of utmost importance to policymakers, investors, and consumers. In this paper, we examine the asymmetric positive and negative responses between real economic activity and financial and energy markets volatility for the period from March 12, 2011, to May 02, 2020, covering the periods of volatility hikes due to the COVID-19 pandemic. Our econometric approach includes both the asymmetric ARDL of Shin et al. (2013) and Granger causality tests. These enable us to explore the dynamic short- and long-run asymmetric interactions and causality via positive and negative partial sum decomposition of the explanatory variables.

Our results show evidence of asymmetries in the short-run and long-term relationships among these variables. Specifically, in the long run, both positive and negative shocks from the energy market increase stock market volatility. However, positive and negative shocks on economic activity reduce (increases) stock market volatility, respectively. Similarly, both positive and negative shocks on equity market volatility increase uncertainties in the energy market. However, only negative shocks from the gold market impact positively on energy market volatility while both positive and negative shocks on economic activity reduce energy market volatility. Also, an increase in both stock and energy markets volatility shocks are detrimental to real economic activity growth while a negative shock on stock market volatility increases
economic activity. These nonlinear dynamics are confirmed through the accumulated effects using the dynamic multipliers. Regarding asymmetric causalities, we find that whereas there is bidirectional causality between both the stock and energy market and real economic activity shocks, there is unidirectional causality from gold volatility to economic activity shocks.

Taken together, these results hold some significant implications for investors, portfolio managers as well as policymakers. First, for both investors and portfolio managers, our findings are applicable in the forecasting of financial markets volatility (risk) based on information from commodity markets and the real economy. This is because changes in equity market volatility appear to be strongly related to changes in both the energy and gold market as well as real economic activities. This implies that returns on equity investments are significantly affected by changes in economic activities and volatility in commodity prices. Given this, our study is important for forecasting equity market volatility indices in the U.S stock market using changes in VIX. Also, with particular reference to portfolio managers, the existence of substantial volatility spillover from the energy market into the equity and gold markets has implications for diversification benefits. Specifically, as noted in Choi & Hong (2020), volatility indices are used to hedge volatility risk and are increasingly becoming a popular asset class for investors' portfolio diversification strategy, our empirical findings can be used to manage volatility risk in equities, gold, and energy portfolios by examining and evaluating volatility derivatives, such as VIX, VXX and GVZ options, and futures. Lastly, for policymakers, the effects of economic activity shocks on the financial and energy markets underscore the importance of the use of an appropriate macroeconomic policy mix. Also, our empirical findings shed light on the sensitivity of real economic activities to equity market risks and uncertainties in energy prices in the case of the U.S.
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### Table 1. Descriptive Statistics and Correlation matrix

#### Summary Statistics

|       | Mean | Min. | Max. | Std. Dev. |
|-------|------|------|------|-----------|
| VIX   | 16.8 | 9.48 | 74.6 | 7.12      |
| VXX   | 23.9 | 12.6 | 112  | 10.8      |
| GZV   | 16.7 | 9.13 | 42.4 | 5.21      |
| WEI   | 1.9  | -11.9| 3.41 | 1.43      |

#### Correlation Matrix

|       | VIX | VXX | GZV | WEI |
|-------|-----|-----|-----|-----|
| VIX   | 1.00|     |     |     |
| VXX   | 0.93| 1.00|     |     |
| GZV   | 0.67| 0.63| 1.00|     |
| WEI   | -0.43| -0.52| -0.29| 1.00|

### Table 2. ADF unit roots and BDS tests

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| Variables | Level Statistics | Break Date | First Difference Statistics | Break Date | BDS Test | BDS Statistic | p-value |
|-----------|------------------|------------|-------------------------------|------------|----------|----------------|--------|
| VIX       | -6.097***        | 2/15/2020  | -22.50***                    | 2/30/2018  | 0.137*** | (0.0000)      |
| VXX       | -5.829***        | 2/8/2020   | -19.38***                    | 2/22/2020  | 0.149*** | (0.0000)      |
| GVZ       | -3.998           | 2/08/2020  | -22.24***                    | 4/13/2013  | 0.156*** | (0.0000)      |
| WEI       | -6.926***        | 3/14/2020  | -25.91***                    | 3/14/2020  | 0.016*** | (0.0000)      |

Test critical values
- 1% level: -4.949
- 5% level: -4.443
- 10% level: -4.193

Table 3. NARDL Estimates

| VIX_t | VXX_t | GVZ_t | WEI_t |
|-------|-------|-------|-------|
| \(\Delta VIX\)_{t-1} | -0.191*** | (0.0001) |       |
| \( \Delta VIX_{t-2} \) | -0.241*** (0.0000) |
| \( \Delta VXX_{t-1} \) | 0.253*** (0.0031) |
| \( \Delta GVZ_{t-1} \) | 0.091*** (0.0002) |
| \( \Delta GVZ_{t-2} \) | 0.108*** (0.0000) |
| \( \Delta WEI_{t-1} \) | 0.314*** (0.0000) |
| \( \Delta WEI_{t-2} \) | 0.698*** (0.0000) |
| \( \Delta VIX_{t-1} \) | 0.253*** (0.0004) |
| \( \Delta VXX_{t-1} \) | 1.142*** (0.0000) |
| \( \Delta VXX_{t-2} \) | 0.945*** (0.0006) |
| \( \Delta VIX_{t-1} \) | 0.095*** (0.0000) |
| \( \Delta VIX_{t-2} \) | -0.680*** (0.0047) |
| \( \Delta VXX_{t-1} \) | 0.313*** (0.0044) |
| \( \Delta VXX_{t-2} \) | 0.847*** (0.0094) |
| \( \Delta GVZ_{t-1} \) | -1.055*** (0.0054) |
| \( \Delta GVZ_{t-2} \) | -1.156*** (0.0014) |
| \( \Delta WEI_{t-1} \) | 0.227 (0.9013) |
| \( \Delta WEI_{t-2} \) | 0.117** (0.0282) |
| \( \Delta WEI_{t-1} \) | 0.328*** (0.0000) |
| \( \Delta WEI_{t-2} \) | 0.309*** (0.0036) |
| \( \Delta GVZ_{t-1} \) | 0.087 (0.6732) |
| \( \Delta GVZ_{t-2} \) | -0.631*** (0.0023) |

### Table 3. NARDL Estimates (continued)

| \( VIX_t \) | \( VXX_t \) | \( GVZ_t \) | \( WEI_t \) |
|---|---|---|---|
| Coefficient | p-values | Coefficient | p-values | Coefficient | p-values | Coefficient | p-value |
| \( \Delta GVZ_t \) | 0.313*** (0.0044) | 0.847*** (0.0094) | 0.773*** (0.0098) |
| \( \Delta GVZ_{t-1} \) | -0.092** (0.0338) | -1.055*** (0.0054) | -0.347 (0.2351) |
| \( \Delta GVZ_{t-2} \) | -0.223** (0.0109) | -1.156*** (0.0014) | 0.763*** (0.0050) |
| \( \Delta WEI_{t-1} \) | 0.123 (0.1645) | 0.227 (0.9013) | 0.117** (0.0223) |
| \( \Delta WEI_{t-2} \) | 0.341* (0.0717) | 1.411 (0.4750) | 0.703*** (0.0000) |
| \( \Delta WEI_{t-1} \) | -0.571** (0.0481) | -2.290*** (0.0058) | 0.026 (0.1074) |
| \( \Delta WEI_{t-2} \) | -0.703*** (0.0000) | 0.084** (0.0415) | 0.372 |
| \( R^2 \) | 0.958 | 0.591 | 0.487 |
| \( Adj - R^2 \) | 0.928 | 0.571 | 0.475 |
| D-W Test | 2.025 | 2.103 | 2.024 |
| \( X^2_{S-C} \) | 1.141 | 1.591 | 1.335 |
| \( X^2_{H-C} \) | 2.991 | 2.663 | 1.649 |
| \( X^2_{E-F} \) | 1.038 | 0.638 | 1.037 |

Longrun Coefficients

| \( L_{VIX} \) | 0.092** (0.0129) | 0.255*** (0.0000) | -0.314** (0.0422) |
### Table 4. Nonlinear granger causality tests

| Null hypotheses | 1 Lag | 5 Lags | 10 Lags | 20 Lags |
|-----------------|-------|--------|---------|---------|
| **VIX** ↔ **WEI** |       |        |         |         |
| **VIX**⁻ does not granger cause **VIX**⁺ | 63.49*** | 015.76*** | 8.001*** | 4.026*** |
| **VIX**⁻ does not granger cause **VIX**⁻ | 0.287 | 2.303** | 1.652* | 1.081 |
| **WEI**⁺ does not granger cause **VIX**⁻ | 3.696* | 2.219* | 2.016** | 1.722** |
| **VIX**⁻ does not granger cause **WEI**⁻ | 42.21*** | 1.065 | 0.725 | 0.694 |
| **WEI**⁺ does not granger cause **VIX**⁻ | 0.249 | 0.82 | 0.999 | 1.144 |
| **VIX**⁻ does not granger cause **WEI**⁺ | 1.697 | 1.078 | 1.497 | 1.524* |
| **WEI**⁻ does not granger cause **VIX**⁺ | 0.444 | 0.379 | 0.815 | 1.077 |
| **VIX**⁺ does not granger cause **WEI**⁻ | 8.279*** | 7.626*** | 7.437*** | 3.539*** |
| **WEI**⁺ does not granger cause **VIX**⁻ | 0.575 | 0.592 | 1.936** | 1.271 |
| **VIX**⁺ does not granger cause **WEI**⁺ | 0.055 | 1.212 | 1.219 | 0.929 |
| **WEI**⁻ does not granger cause **VIX**⁺ | 88.04*** | 11.32*** | 4.588*** | 4.632*** |
| **WEI**⁻ does not granger cause **WEI**⁺ | 0.567 | 0.878 | 2.572*** | 2.034*** |

**Note:** The above table presents the results of NARDL estimations with NARDL specification based on a general to specific approach where *, **, and *** denote significance at 10%, 5% and 1% respectively. The superscripts “+” and “−” represent positive and negative shocks, respectively, while \( \beta^+ = -\theta^+ / \rho \) and \( \beta^- = -\theta^- / \rho \). Also, \((X_{\text{Lc}}^2), (X_{\text{F}}^2)\) and \((X_{\text{Nc}}^2)\) correspond to LM tests for serial correlation, normality, functional form and heteroskedasticity, respectively. \( W_{LR} \) and \( W_{SR} \) denote the Wald test for the null of long- and short-run symmetry for the respective variables. \( F_{\text{PSS}} \) represent the Pesaran et al. (2001) Bounds test statistics.
Table 5. Spillover between WEI shocks and other Markets

|     | VIX | VXX | WEI⁻ | FROM | NDC |
|-----|-----|-----|------|------|-----|
| GVZ | N.A. | 0.126 | 0.127 | 0.011 | 0.263 | -0.082 |
| VIX | 0.098 | N.A. | 0.336 | 0.015 | 0.448 | -0.040 |
| VXX | 0.075 | 0.272 | N.A. | 0.017 | 0.364 | 0.112 |
| WEI⁻ | 0.009 | 0.011 | 0.013 | N.A. | 0.033 | 0.009 |
| T0  | 0.181 | 0.408 | 0.476 | 0.042 | 0.277 |     |

|     | VIX | VXX | WEI⁺ | FROM | NDC |
|-----|-----|-----|------|------|-----|
| GVZ | N.A. | 0.125 | 0.127 | 0.012 | 0.264 | -0.073 |
| VIX | 0.098 | N.A. | 0.335 | 0.021 | 0.453 | -0.040 |
| VXX | 0.078 | 0.272 | N.A. | 0.024 | 0.373 | 0.116 |
| WEI⁺ | 0.016 | 0.016 | 0.028 | N.A. | 0.060 | -0.003 |
| T0  | 0.192 | 0.413 | 0.490 | 0.057 | 0.288 |     |

Note: +, - denote the positive and negative partial sums decomposition while ***, ** and * represent significance at 1%, 5% and 10% respectively.
|       | GVZ$^+$ | VIX$^+$ | VXX$^+$ | WEI$^+$ | FROM$^+$ | NDC  |
|-------|---------|---------|---------|---------|----------|------|
| GVZ$^+$ | N.A.    | 0.105   | 0.243   | 0.073   | 0.423    | -0.208 |
| VIX$^+$ | 0.080   | N.A.    | 0.507   | 0.090   | 0.677    | -0.400 |
| VXX$^+$ | 0.069   | 0.115   | N.A.    | 0.106   | 0.289    | 0.506 |
| WEI$^+$ | 0.064   | 0.057   | 0.046   | N.A.    | 0.167    | 0.102 |
| **To** | 0.213   | 0.277   | 0.796   | 0.269   | **0.389**|       |
|       | GVZ$^-$ | VIX$^-$ | VXX$^-$ | WEI$^-$ | FROM$^-$ | NDC  |
| GVZ$^-$ | N.A.    | 0.191   | 0.196   | 0.078   | 0.465    | -0.223 |
| VIX$^-$ | 0.071   | N.A.    | 0.344   | 0.075   | 0.490    | 0.111 |
| VXX$^-$ | 0.044   | 0.308   | N.A.    | 0.082   | 0.433    | 0.168 |
| WEI$^-$ | 0.128   | 0.102   | 0.061   | N.A.    | 0.291    | -0.056 |
| **TO** | 0.243   | 0.600   | 0.601   | 0.235   | **0.420**|      |
Figure 1. Time Series Plots

(a) The Weekly Economic Index

(b) VIX, VXX and GVZ
Figure 2. Plots of Dynamic Multipliers
Figure 2. Plots of Dynamic Multipliers (continued)
Figure 3. Stability test using the cumulative sum
(a) System contribution to positive and negative WEI shocks

(b) Contributions from positive and negative WEI shocks to the system

(c) Total spillover between positive and negative WEI and other markets

**Figure 4:** Directional and total connectedness between WEI and market volatility
(a) System contribution to positive and negative WEI shocks

(b) Contributions from positive and negative WEI shocks to the system

(c) Total spillover between positive and negative WEI and other markets

**Figure 5.** Directional and total connectedness between WEI and Market volatility
Conflicts of interest

I declare that there are no conflicts of interest related to this paper. Also, my co-author and I have not received financial support outside of our monthly salaries.

Signed

Gideon Ndubuisi