EGARCH volatility transmission mechanism among energy markets and real macro activities

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Abstract

This research examines the dynamic relationship among impacts of prices and volatilities of real macro activities, interest rate, and two major energy markets: crude oil and natural gas, with main concerns on both price and volatility shocks to energy markets and monetary policy. I estimate conditional volatilities of all variables with EGARCH model and estimate the dynamic relationship from January 1986 to December 2016 with non-recursive SVAR. Parameter estimation from EGARCH suggests that crude oil volatility has negative correlation with crude oil return and natural gas volatility has positive correlation with natural gas return. Further, the inference from EGARCH also explains why implied volatility smile of options are skewed. Moreover, I conduct subsample analysis that splits estimation between pre-global financial crisis (GFC) which is characterized with high discount rate regime and post-GFC which is characterized with the so-called zero lower bound on discount rate regime. During the post-GFC when the Fed fund rate approaches zero lower bound, a positive monetary policy shock becomes effective since prize puzzle in either crude oil or natural gas no longer exists. Additionally, S&P 500 and industrial production showed that they can be resilient to either crude oil or natural gas price shocks. Interestingly, T-bill yield exhibits positive response to crude oil price shock but negative response to natural gas price shock. In the dimension of volatility transmission, all volatilities of macro activities will be heightened after crude oil volatility shock. In contrast, volatilities of crude oil, T-bill, and S&P 500 will be cooled down by natural gas volatility shock. Altogether, ever since the breakout of GFC, variations of most variables, whether in either form of price or volatility, have became much more sensitive to exogenous shocks than before the crisis. Policy makers should especially avoid huge surprise to the market and adopt phase-in approach to smooth out the impacts on real macro activities during the era of zero lower bound on interest rate.

JEL Classifications: C32, C58, E43, E52, G12, Q43

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1. Introduction

Crude oil and natural gas have each long been known as the “king” and “queen” of commodities market. Nevertheless, their characters of return distributions, volatility persistence, impacts on other macroeconomic variables, and sensitivities to exogeneous shocks may not be similar. Even as a pair between crude oil and natural gas, its quality of mean reversion indicated by cointegration has weakened. As a result, Batten et al (2017) conclude that crude oil and natural gas no longer have causal relationship ever since 2006 (p. 156). From another perspective, Brigida (2014) argues that co-movement between natural gas and crude oil had not been widely apart in the early 2000s but temporarily shifted to a regime when natural gas had outperformed crude oil in August 2000 until May 2009 when Enron collapsed (p. 54).

The main objective of this paper is to examine the dynamic effects among energy prices, energy volatilities, and macroeconomic activities with the most recent data by multivariate autoregressive linear time series model. We will uncover whether there is a structural change of the interdependence and lead-lag relation among oil, natural gas, T-bill yield, industrial production, and equity market by doing full-sample as well as subsample analysis on forecast error variance decomposition, impulse response function, and Granger causality on a vector autoregression (VAR).

The central part of this paper will be about volatility shocks of crude oil, natural gas, and monetary policy. Undoubtedly, the choice of estimation model for volatility will be essential owing to the nature of leverage effect and non-normal distribution of energy and financial markets. Today, volatility is not just simply the standard deviation of price returns or a measure of uncertainty, but it is itself an asset class in the financial market. Volatility can be traded via volatility index futures that is linear or via options that is non-linear with respects to underlying, time, and realized volatility. We can either speculate the volatility directly from volatility index futures or use realized volatility as input in options pricing models and bet on the trend of implied volatility by implementing delta-neutral and either long/short gamma or long/short vega strategies in which delta is the first derivative of option value with respect to underlying asset, gamma is the second order derivative of option value with respect to underlying asset, and vega is the derivative of options value with respect to volatility of underlying asset. Accuracy of volatility model will affect options pricing and risk measurement such as Value- At-Risk (VaR) which is widely used by financial institutions. Advanced volatility models like ARCH/GARCH and their variations helps indicating the persistence of volatility and volatility-price relationship which will be helpful for options traders to calibrate pricing models and beneficial for policy makers to estimate the impact of their decisions.

For policy implication, I will discover how monetary policy shock, in terms of yield and yield volatility, affects real crude oil and natural gas prices as well as their volatilities differently. Like many other monetary policy papers, one common major observation is to examine whether commodity exhibits phenomenon of the price puzzle. Eichenbaum (1992) defines price puzzle as persistence of inflation after enforcement of contractionary monetary policy (p. 1006). Unlike most papers, my paper will add another observation with a different dimension: volatility. A number of paper have already conducted research on discount rate shock but none of them has linked discount rate volatility shock with energy markets in a multivariate time series model. Therefore, my goal is not only to examine the effectiveness of monetary policy transmission mechanism, but the impact of monetary policy uncertainty on fear factors of financial markets and uncertainty of real output. In addition, we will also observe the differences between crude oil and natural gas shocks on moving the treasury bond market.

The distinct aspect of this paper in the context of the existing literature is that I provide insight on the dynamic relationship among energy prices, energy volatilities, as well as prices and volatilities of real macro activities under two regimes. Additionally, many papers have already focused on energy volatilities, but they all lack further analysis on option derivatives dynamics which are essential to volatility traders. To complement existing literature, I provide in-depth analysis on how volatility and interest rate regime can affect implied volatility smile and advanced options Greeks such as Volga, Vanna, Vomma, and Elasticity. With the vantage of Exponential GARCH (EGARCH) model, the inference from the asymmetric or symmetric relationship among them will be important for options traders who apply volatility arbitrage between crude oil and natural gas options or manage active global volatility portfolio. Furthermore, my subsample analysis is based on the structural break between pre- and post-global financial crisis (GFC). Concurrently, this structural break also separates the period between high Fed fund rate and zero lower bound on Fed fund rate era as the Fed had launched three quantitative easing (QE) programs from 2008 to 2014 to stimulate the economy after the GFC. With subsample analysis based on estimation from variance decomposition of forecast error variance, the estimation result will assist both policy makers and traders to observe the structural changes in sensitivities to exogeneous shocks under totally distinctive discount rate regimes which have deep impacts on all asset pricing and econometric models that depend on sensitivities to interest rate and volatility.

2. Literature review

Among all the literature, crude oil has always been a hotter topic due to the fact that it accounts for 40 percent of the world's total energy needs. For example, with data from 1947 to 1996, Sadorsky (1999) discovered that oil price movement contributed more than interest rate in explaining real stock returns since 1986; moreover, he found that effects of oil price volatility shocks on the economy have been asymmetric in which impact of positive oil price volatility shock on industrial production and real stock return is larger than that of negative oil price volatility shock (p. 466). Rewinding further back, Hamilton (1983) found that sharp oil price increase usually followed by recession and precede the business cycle peak (p. 229). Mork (1989) then extends on Hamilton's (1983) work by focusing on asymmetric response to oil price and concludes that coefficients for oil price declines are smaller (p. 743).

Among the more recent literature, Bernanke et al (2004) concluded that oil shock reduces output and raises the price level and suggested that adverse effect of oil on output will be better off if the Central Bank shut off its monetary response to ease inflation (p. 291). Kilian (2009) found that oil supply disruption causes temporary decline in real GDP but little effect on price level, positive demand shock causes positive net effect on the economy, and positive precautionary demand shocks lower real GDP and raise consumer prices (p. 1066). Kilian and Park (2009) identified aggregate demand, oil supply, and oil-specific demand shocks which together explain one-fifth of long-term variation in US stock return (p. 1285). Aguriar-Conraria and Soares (2011) utilized wavelets to analyze the relation between oil and macroeconomy and found that oil price changes after mid-1980s were more demand driven (p. 653). Arouri et al (2011) found that rise in oil price volatility positively affects stock price volatilities of Gulf Cooperation Council (GCC) countries (p. 1825). Le and Chang (2015) examine the relationship between oil price and three different kinds of oil economies: oil-refining, oil-exporting, and oil-importing and found that oil price shock has positive impact on equity returns of all three (p. 273). Kang et al (2014) concluded that oil-market specific demand has negative effect on U.S. real bond return when there is uncertainty over future oil supply (p. 24). Kang et al (2016) argued that positive oil production shock in the US is positively associated with the US real stock return and concluded that both demand and supply shocks are comparable in explaining the variation in US real stock return (p. 180).

A number of papers have concentrated only on the dynamics of natural gas and its linkage with real macroeconomic activities and financial data. Also, it is not uncommon to see papers on comparison between crude oil and natural gas on the macroeconomy. For example, Kliesen (2006) suggests that unlike changes in crude oil, changes in natural gas do not significantly predict total manufacturing output (p. 254). Others are engaged with the dynamics of natural gas, Bacon (1991) analyzes the asymmetric speed of adjustment of retail gasoline price in the UK and describes the gasoline price behavior as “rockets and feathers” which means natural gas price always shoots up like rocket and then falls down slowly like feathers (p. 217). Notwithstanding, with the introduction of the wave test and the rescaled range ratio test, Kristoufek and Lunackova (2015) argue that gasoline price does not exhibit significant signs of the “rockets and feathers” (p. 7). Furthermore, Mason and Wilmot (2014) found that the predictive power for spot price of natural gas will be enhanced after modeling natural gas with continuous time process and its volatility that allows for jump with GARCH (p. 578). Nick and Thoenes (2014) conducted SVAR model specifically for German natural gas market. They found that natural gas price is significantly affected by temperature, storage, and supply shortfalls in the short run and only will be closely tied to crude oil and coal prices in the long run (p. 522). Wiggins and Etienne (2017) uncover the origins of US natural gas price fluctuations since deregulation with the Bayesian VAR model. They found that supply and demand shocks are the main drivers between 1993 and 2015, but natural gas prices respond differently to shocks in supply and demand (p. 205). Jadidzadeh and Serletis (2017) implemented SVAR to observe how the US natural gas market reacts to demand and supply shocks in the crude oil market. They concluded that 45 percent of the variation in natural gas can be attributed to structural supply and aggregate demand shocks in the global crude oil market but shocks in the natural gas market account for about 55 percent of the long run variability of the real price of natural gas; thus, natural gas has decoupled from crude oil (p. 74).

Another peculiar group of literature has concentrated on volatility estimation as well as volatility shock specifically for energy markets. For instance, Ewing et al (2002) implemented multivariate GARCH with BEKK parameterization on both crude oil and natural gas and found that natural gas has stronger volatility persistence than crude oil. In addition, they also concluded that natural gas volatility responds more quickly to macro shocks than crude oil (p. 536). Wang and Wu (2012) apply univariate and multivariate GARCH models and found that energy volatilities tend to exhibit significant persistence and asymmetric effects (p. 2179). Ergen and Rizvanoghlu (2016) utilized GARCH model augmented with market fundamentals and found excess volatility in natural gas futures will happen during the Winter time when the demand is inelastic or when the storage level is higher than expected in other seasons (p. 64).

3. Data and methodology

3.1. Data

Monthly data is initially collected from January 1967 to December 2016. My VAR estimation only includes the time period from January 1987 to December 2016 because there has been a huge structural break between the first twenty and the last thirty years. I use industrial production as a measure of macroeconomic output, US 3-month T-bill rate as proxy for interest rate and monetary policy shock, S&P 500 as proxy for equity market index, Producer Price Index (PPI) for crude petroleum as crude oil data, and PPI for natural gas as natural gas data. Then I adjust S&P 500, PPI for crude oil, and PPI for natural gas into real prices by taking CPI inflation into account. Furthermore, the base year for CPI is set in between 1982 and 1984 and is not seasonal adjusted, the base year for industrial production is set in 2012 and is seasonal adjusted, the base year for both PPIs for crude oil and natural gas are set in 1982 and are seasonal unadjusted, and both T-bill yield and S&P 500 are seasonal unadjusted. S&P 500 index data is downloaded from Yahoo Finance and all the other data are obtained from the Economic Research database of Federal Reserve Bank of St. Louis.

3.2. Volatility estimation

My volatility estimation model is based on the foundation of Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model by Bollerslev (1986) who extended ARCH in which Engle (1982) defined as stochastic process whose variables have conditional mean zero and conditional variance with assumption that previous squared variables follow an autoregressive process (p. 988). GARCH (1, 1) is generalized from ARCH (1) by including a lagged variance term in the conditional variance which is a weighted combination of all previous squared excess returns. Sadorsky (1999) also adopted GARCH (1, 1) volatility of real crude oil price as exogeneous shock in the VAR model (p. 45).

However, GARCH (1, 1) assumes that conditional excess kurtosis, conditional skewness, and unconditional skewness are zero, believes that positive and negative error terms have same effect on volatility, and fails to capture the behaviour of non-normal distribution of asset returns. Therefore, the standard GARCH model may not be good fit for energy markets which usually exhibit high leptokurtic distribution with large skewness either to left or right. Many literature have tried to extend the standard GARCH model specifically for energy market. For instance, Sadorsky (2006) compares the forecast accuracies among various volatility models for petroleum futures and found that Threshold GARCH (Engle & Ng, 1993) fits well for both heating oil and natural gas volatility and GARCH fits well for crude oil and unleaded gas volatility (p. 486). Klein and Walther (2015) apply Mixture Memory GARCH (MM-GARCH) to capture asymmetric and long memory effects of oil price volatility (p. 57). Ewing and Malik (2017) maintain that after accounting for structural breaks in GARCH, GJR-GARCH, and EGARCH models, both good and bad news have significantly more impact on oil price volatility (p. 231).

In this paper, I select EGARCH for volatility estimation. Nelson (1991) invented EGARCH model so that good news and bad news will have different effect on the volatility (p. 351) or technically speaking, EGARCH is able to uncover the asymmetric relationship between asset return and its volatility. Compares EGARCH with standard GARCH model, EGARCH can not only capture excess kurtosis but also able to compute volatility clustering or persistence of shocks to variance in which Nelson (1991) argues that it will be difficult to measure with standard GARCH model (p. 351). Regarding the reliability of Maximum Likelihood Estimation (MLE), optimization result from EGARCH model tends to be more reliable because it does not require any restriction such as the non-negativity constraints on parameters since the equation uses log variance instead of variance. A number of recent literature have exercised EGARCH model on energy markets. Ali-Ahmed and Wadud (2011) used EGARCH to examine oil price volatility shock on macroeconomic activities in Malaysia and found asymmetric effect between oil price shock on the conditional oil price volatility is significant (p. 8068). Chang (2012) concluded that the impact of the basis on the return and volatility are asymmetric and dependent on the volatility regimes by using flexible regime-switching EGARCH with Student-t distributed error terms (p. 305). Lei et al (2016) show that the short run spillover effects of oil returns on equity uncertainty are insignificant before the financial crisis but have strong negative influence on the equity market-related uncertainty during the post-crisis period by implementing t-distribution-based bi-variable EGARCH (p. 233).

To estimate volatilities for crude oil and natural gas as well as T-bill yield, S&P 500, and industrial production, we exercise the EGARCH model with Generalized Error Distribution (GED) which accommodates various forms of distributions including normal, double exponential, and uniform distributions. Most importantly, to ensure covariance stationarity, Nelson (1999) found that GED is the most reliable in achieving finite unconditional means and variances (p. 352).

Consider a return times series:

$r_t = u + \varepsilon_t$

Where u is the expected return and ε_t is a zero-mean white noise

Conditional normal distribution assumes:

$\varepsilon_t = h_t z_t$

z_t ~ i.i.d. N(0, 1)

Where h_t is conditional standard deviation and z_t is standard Gaussian

The EGARCH equation then becomes:

$$\log(h_t^2) = \omega + \alpha\left|\frac{z_{t-1}}{\sqrt{h_{t-1}^2}}\right| + \gamma\left(\frac{z_{t-1}}{\sqrt{h_{t-1}^2}}\right) + \beta\log(h_{t-1}^2)$$

Where h_t^2 represents the conditional variance. β measures the persistence of volatility for a given shock. ω denotes constant term, α measures size effect and magnitude of news impact. Negative shocks have an impact of (α -γ) on the log of conditional variance, and positive shocks have an effect of (α+γ). Leverage effect can be tested by the hypothesis that $\gamma<0$ and the asymmetric impact is indicated if $\gamma\neq0$.

3.3 Vector Autoregression

Initially, I run through unit root and cointegration tests before moving on to VAR model (Sims, 1980) which measures the interdependence among the two major energy variables and macroeconomic activities. Technically, VAR models a system of endogenous variables that depend only on their lagged values and helps capturing the dynamics of interrelationship. Moreover, we can obtain measures of Granger causality, impulse response, and variance decomposition from the VAR model. To estimate the impulse response, I test the shocks to energy markets and monetary policy in our structural vector autoregression (SVAR) model with non-recursive approach, suggested by Leeper et al (1996), in which short-run restriction does not have to be lower-triangular. The main estimation of SVAR in the appendix section is presented with accumulated impulse response of endogenous variables to one-standard deviation exogenous shocks.

The structural form of VAR model is shown below as:

$$\Theta Y_t = \Omega_0 + \sum_{i=1}^{n} \Theta_i Y_{t-i} + U_t$$

Where Θ is coefficient matrix of Y_t and its diagonal elements are all one. Ω_0 is a parameter vector. U_t represents the structural disturbance.

Assume Θ^{-1} exists, the reduced form of VAR can be shown as:

$$Y_t = \Psi_0 + \sum_{i=1}^{n} \Phi_i Y_{t-i} + e_t$$

Where the n-dimensional vector Y includes set of endogenous variables. $\Psi_0 = \Theta^{-1}\Omega_0$.
Φ_i is the $n \times n$ matrix of coefficients, n is the optimal number of included lags which is determined based on LR test. The vector of reduced form residuals e_t is n-dimensional with the variance-covariance matrix $\sum_e$, where $E(e_t e_t') = \sum_e$.

3.4 Optimal lag selection

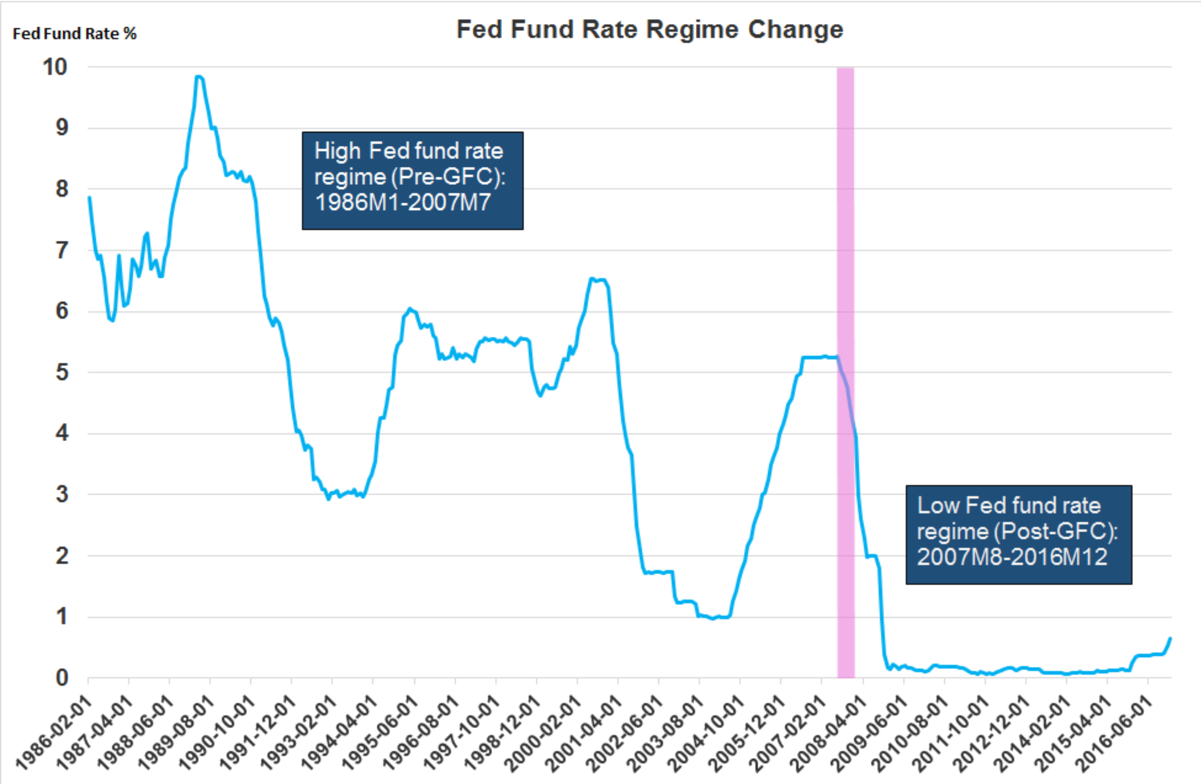
To eliminate autocorrelation that results in inaccurate computed variance and standard error of forecast, we use Likelihood Ratio (LR) test, which has been commonly used in macroeconomic literatures such as Sims (1980), Blanchard (1989), Bernanke and Mihov (1998), and Hamilton and Herrera (2004), for executing optimal lag selection. Among the aforementioned literature, Hamilton and Herrera (2004) argue that LR test works best for adjusting for seasonal factors of oil price in a monthly VAR (p. 277).

3.5 Subsample analysis

We can then use Granger causality/Block exogeneity test, accumulated impulse response, variance decomposition of forecast error after 24 months to uncover the interrelationship as well as lead-lag relationship among variables. The full sample period is estimated from

January 1986 to December 2016, a total of thirty years of monthly data. Most importantly, we will execute subsample analysis to analyse the impact of regime changes. The subsample will be split into two periods: January 1986 to July 2007 and August 2007 to December 2016. Figure 1 shows that the first (pre-GFC) and the second (post-GFC) estimated period can also be characterized as high and low discount rate regime, respectively. The structural change of Fed fund rate has been notably high since the breakout of GFC. The average of Fed fund rate during the pre-GFC period was 4.90 and the average of Fed fund rate during the post-GFC was 0.21. A huge difference by 469 basis points.

Figure 1: Trend and regime change in Fed fund rate from 1986 to 2016



3.6. Identification and contemporaneous restriction

My variables for SVAR estimation is based on the foundation of Sadorsky (1999). As extension, natural gas price/volatility is added to the model and the ordering scheme will be reshuffled. Ferderer (1996) and Sadorsky (1999) both put T-bill yield as the first variable in the order because they assume that monetary policy shock should be independent of contemporaneous disturbances to the other variables. My ordering scheme is based on the liquidity and transaction volume of observable underlying spot. Fixed income is the largest market by trading volume, followed by equity, crude oil, and natural gas. Industrial production is the last in the order because it does not have any underlying that is tradable in the financial market. Regarding non-recursive short-run restriction, my explanation for identification is in the following: T-bill yield is not affected by any other variables in the short-run. S&P 500 is contemporaneously affected by the T-bill. Crude oil is contemporaneously affected by T-bill but not affected by S&P 500. Natural gas is contemporaneously affected by T-bill and crude oil but not affected by S&P 500. S&P 500 shock cannot be exogeneous to energy markets in the short-run because energy markets are mostly explained by their own supply and demand shocks suggested by Kilian (2009) as well as Wiggins and Etienne (2017). Moreover, whenever there is a notable shock to all asset classes, the shock usually does not come from S&P 500 which is just a stock index. Also, even if there is corporate earning shock in energy sector within S&P 500, it is still unlikely to be exogeneous to the energy market in the short run because ever since 2009, the weight of energy sector in S&P 500 has diminished to less than seven percent. Finally, industrial production is contemporaneously affected by all other variables except S&P 500 because it takes a long time for industrial production to absorb the fluctuation from S&P 500. The matrix form with non-recursive identification that exhibits the relationship between the reduced form errors and the structural disturbances is shown below:

$$\begin{bmatrix} \mathrm{Ur} \\ \mathrm{Urs} \\ \mathrm{Uco} \\ \mathrm{Ung} \\ \mathrm{Uip} \end{bmatrix} \begin{bmatrix} 1 & \square & \square & \square & \square \\ X & 1 & \square & \square & \square \\ X & \square & 1 & \square & \square \\ X & \square & X & 1 & \square \\ X & \square & X & X & 1 \end{bmatrix} = \begin{bmatrix} 1 & \square & \square & \square & \square \\ \square & 1 & \square & \square & \square \\ \square & \square & 1 & \square & \square \\ \square & \square & \square & 1 & \square \\ \square & \square & \square & \square & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{\mathrm{r}} \\ \varepsilon_{\mathrm{rs}} \\ \varepsilon_{\mathrm{co}} \\ \varepsilon_{\mathrm{ng}} \\ \varepsilon_{\mathrm{ip}} \end{bmatrix}$$

Where r denotes T-bill yield, rs denotes real stock price of S&P 500, co denotes real crude oil price, ng denotes real natural gas price, and ip denotes industrial production; X is the coefficient to be estimated. Optimal lag length of 6 is chosen for all panels.

Furthermore, there will be four panels with the same system to examine the dynamic relationship among prices and volatilities of these five variables. Panels A, B, C, and D are described below:

A: Y_t=[Δ(r), Δlog(rs), Δlog(co), Δlog(ng), Δlog(ip)]

B: Y_t=[Δ(r), Δlog(rs), Δlog(ov), Δlog(ng), Δlog(ip)]

C: Y_t=[Δ(r), Δlog(rs), Δlog(co), Δlog(nv), Δlog(ip)]

D: Y_t=[Δlog(rv), Δlog(rsv), Δlog(ov), Δlog(nv), Δlog(ipv)]

Where ov denotes volatility of co, nv denotes volatility of ng, rv denotes volatility of r, rsv denotes volatility of rs, ipv denotes volatility of ip.

4. Finding and discussion

4.1. Statistical character of each variable

First, we should fully understand the characters of each variable because they are the roots of all research findings. From Table 1, the Jarque-Bera test shows that, at one percent significance level, none of crude oil, natural gas, T-bill yield, industrial production, and S&P 500 returns is normally distributed which assumes expected skewness of zero and expected excess kurtosis of zero. Nonetheless, to make a fair comparison, we should exclude T-bill yield because usually we only measure the return and its distribution from bond price. In bond pricing, the higher the interest rate, the lower the bond price; furthermore, bond valuation exhibits a non-linear phenomenon called convexity in which bond price is more sensitive to decline in interest rate than to increase in interest rate. Thus, it is still important to analyse the distribution for T-bill yield which has extremely high excess kurtosis and large positive skewness. The characters of T-bill yield distribution indicate that T-bill yield is likely to have huge jump overnight shocked by monetary policy and likely to have more large positive elevations in yield.

If we exclude T-bill yield, natural gas would be the most jumpy which has the highest standard deviation and the largest excess kurtosis among all. The nature of heavy-tailed in natural gas implies that it will have higher frequencies of large negative or positive returns than would be expected. Similarly, crude oil and S&P 500 also exhibit excess kurtosis with the former being more heavily-tailed. In terms of skewness, all have negative skewness except natural gas which is among the only variable that has positive skewness or has distribution that shows long tail to the right. This implies natural gas is likely to have more large positive returns than large negative returns. Conversely, S&P 500 and crude oil are all likely to have more large negative returns than large positive returns. Details are shown in Table 1.

Table 1: Statistical characters of each variable

	Δlog(co)	Δlog(ng)	Δlog(r)	Δlog(ip)	Δlog(rs)
Mean	0.0039	0.0049	-0.0037	0.0018	0.0021
Median	0.0000	0.0055	0.0000	0.0020	0.0064
Maximum	0.4850	0.5059	1.7918	0.0238	0.1432
Minimum	-0.3674	-0.4916	-1.8458	-0.0440	-0.2480
Std. Dev.	0.0845	0.1003	0.2137	0.0073	0.0441
Skewness	-0.4344	0.0213	0.3021	-1.1230	-0.6688
Excess Kurtosis	4.3943	5.6114	28.0002	5.2883	2.3195
Jarque-Bera	500.7705***	785.9262***	19576.77***	823.9017***	178.9314***

*** denotes rejection of the hypothesis at the 1% level only for Jarque-Bera test

4.2. Unit root test

To avoid spurious regression as suggested by Granger and Newbold (1974), I first ensure that all time series are stationary. Among them, prices of crude oil and natural gas were especially highly volatile. S&P 500, industrial production, and T-bill yield rate have also contained stochastic trend. Initially, we observe whether log(industrial production), T-bill yield, log(real crude oil), log(real natural gas), and log(real stock price) can all be stationary at five percent level of significance by conducting Phillips and Perron (PP) (1988) and Augmented Dickey Fuller (ADF) (1979) unit root tests. The test regressions by levels had conducted with intercept only and with both intercept and time trend. However, neither of them is stationary at five percent significance level. Then I move on to examine them by taking the first difference. This time, only the intercept is included in the test regression with first differences. Table 2 shows that they will be stationary eventually after taking the first differences.

Table 2: Unit root test

	PP	ADF
Variables	Z(tâ)	Z(tâ)
In levels (intercept only)		
r	-1.73	-1.92
log(co)	-1.85	-1.92
log(ng)	-1.95	-1.95
log(ip)	-1.31	-1.35
log(rs)	-0.28	-0.15
In levels (time trend and intercept)		
r	-2.95	-2.57
log(co)	-2.60	-2.78
log(ng)	-1.94	-1.96
log(ip)	-1.97	-2.31
log(rs)	-2.20	-2.11
In first differences (intercept only)		
Δr	-20.94***	-20.67***
Δlog(co)	-23.29***	-23.24***
Δlog(ng)	-23.27***	-19.35***
Δlog(ip)	-19.12***	-8.86***
Δlog(rs)	-23.29***	-23.24***

***, **, and * denote that a test statsitics is significant at 1, 5, 10% significance level

4.3. Cointegration test

Next, Johansen (1991) cointegration test is conducted with log(industrial production), T-bill yield, log(real crude oil price), log(real natural gas price), and log(real stock price) under assumption of linear deterministic trend that contains intercept and time trend. Lag length 6 is chosen using likelihood ratio test. As we can see from Table 3, both the trace test and the max-eigen test indicate no cointegration at five percent significance level. Consequently, we found no evidence of cointegration among them, then the five-variable system (Δlog(industrial production), Δ(T-bill yield), Δlog(real crude oil), Δlog(real natural gas), and Δlog(real stock price of S&P 500)) may be modelled as a vector autoregression.

Table 3: Johansen cointegration test

Hypothesis	None	$r \leq 1$	$r \leq 2$	$r \leq 3$	$r \leq 4$
Trace test	85.384	47.855	26.652	10.442	4.147
λ max test	37.529	21.203	16.210	6.295	4.147

* denotes rejection of the hypothesis at the 5% level

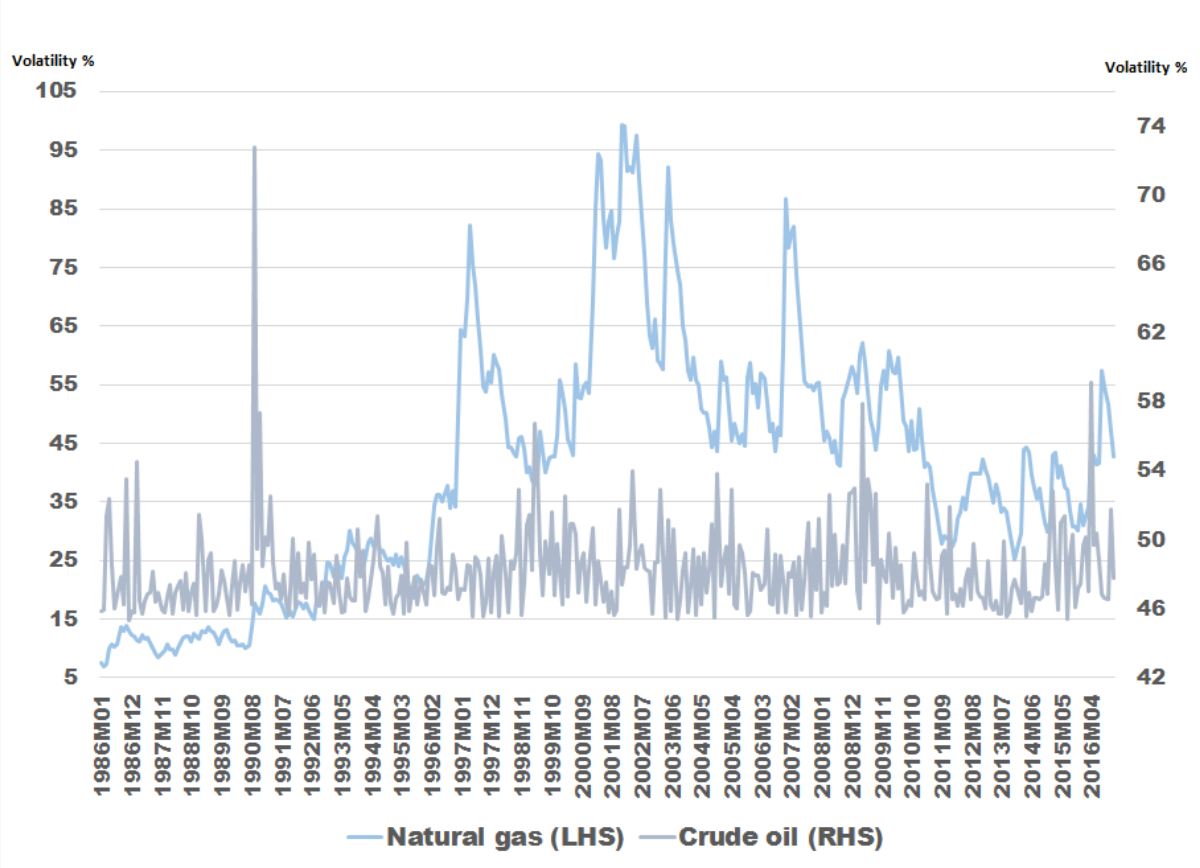
4.4.1. EGARCH estimates for volatilities of crude oil and natural gas

Table 4 shows the EGARCH estimation for crude oil and natural gas. Negative γ in crude oil suggests that asymmetric relationship exists between crude oil return and its conditional volatility. In contrast, positive parameter γ in natural gas implies that symmetric relationship between yield and volatility exists in the natural gas market. When natural gas price goes up, its conditional volatility is also more likely to shoot up. The above inference from EGARCH is consistent with the implied volatility smile of options markets in which out-of-money (OTM) put contains higher risk premium than out-of-money call in crude oil options, and OTM call contains higher risk premium than OTM put in natural gas options. From the half-life estimation, it takes about four months and seven months for crude oil and natural gas volatility shocks, respectively, to be halved. The comparison in half-life also indicates that volatility of natural gas is much more persistent and much slower in mean reversion process than crude oil. Lundbergh and Teräsvirta (2002)'s Lagrange Multiplier test for no remaining ARCH effect in standardized error, linearity, and parameter constancy is designed to test the adequacy of the estimated GARCH models (p. 419). Interestingly, the test suggests that there is no remaining ARCH effect in crude oil but significant remaining ARCH effect in natural gas, at one percent significance level with lag length 1 and at five percent significance level with lag length 6. Consequently, volatility of natural gas also exhibits strong clustering.

Table 4: EGARCH parameters of crude oil and natural gas

	Crude Oil		Natural Gas	
Parameters	**Coefficients**	**p-value**	**Coefficients**	**p-value**
ω	-0.893667***	0.0060	-0.128277***	0.0011
α	0.343841***	0.0001	0.117947***	0.0055
β	0.86743***	0.0000	0.990244***	0.0000
γ	-0.097454***	0.0000	0.082376**	0.0175
Half life (months)	4		7	
Unconditional volatility (Annualized)	29.28		34.75	
ARCH- LM (Lag 1)	0.125512	0.7233	11.14539***	0.0009
ARCH- LM (Lag 6)	0.427227	0.8607	2.646459**	0.0159
*****, **, and * denote significant at 1, 5, 10% level**				

Figure 2: Conditional annualized volatilities of crude oil and natural gas



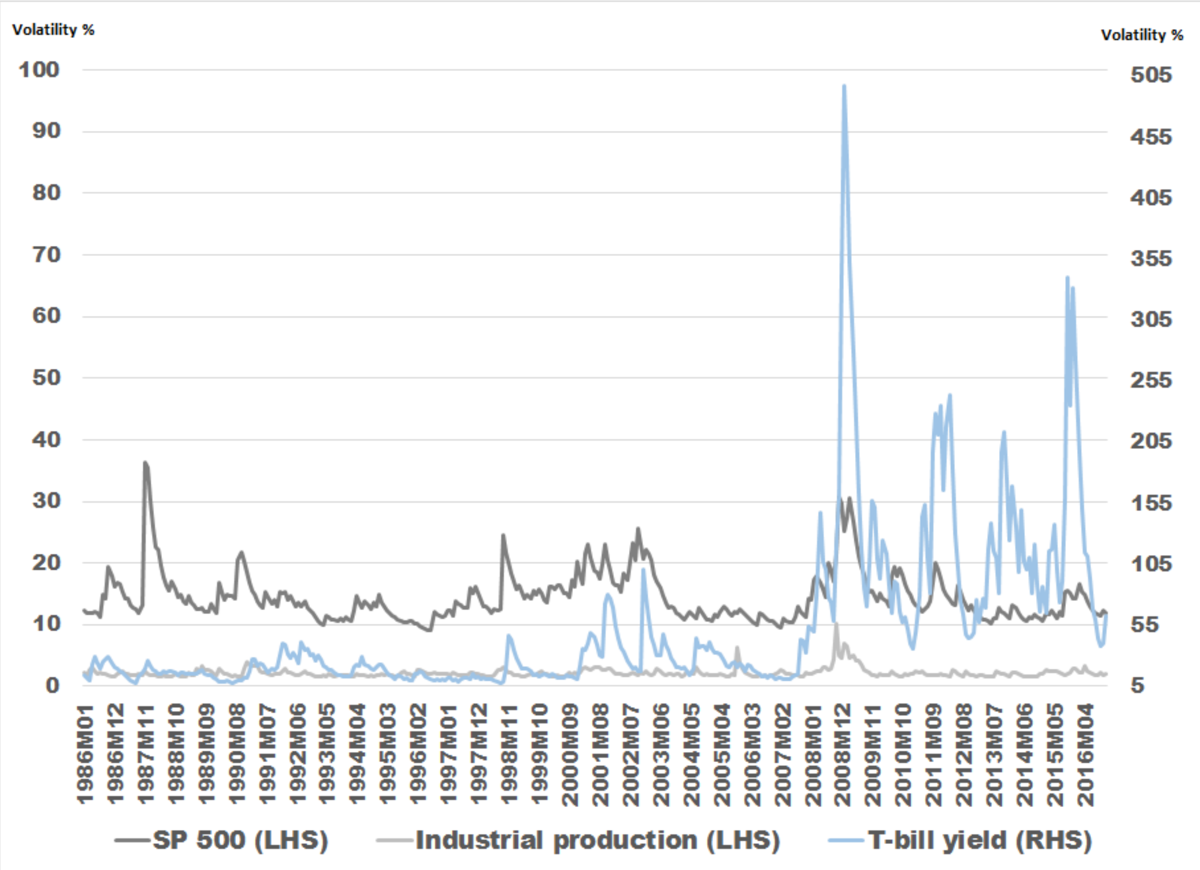
4.4.2. EGARCH estimates for T-bill yield, S&P 500, and industrial production

Table 5 shows the EGARCH estimation of T-bill yield, S&P 500, and industrial production. Positive γ in T-bill yield suggest that symmetric relationship between yield and volatility exists in T-bill yield market. We know that T-bill yield is inversely related to T-bill price. Therefore, T-bill yield (price) return would have symmetric (asymmetric) relationship with yield (price) volatility. Same situations exist in all other US interest rate products. Negative γ in either S&P 500 or industrial production implies that asymmetric relationships between return and volatility exist in both S&P 500 and industrial production. Hence, in options derivatives market, out-of-money put would have higher risk premium then out-of-money call in S&P 500 index options and all other price based fixed income options. Regarding half-life, all of them need around two quarters for their volatility shocks to cut into halved. Among them, S&P 500 is the fastest, followed by T-bill yield and industrial production. In the LM test of no ARCH, only T-bill yield shows significant remaining ARCH effect at one percent significance level in both lag length 1 and 6.

Table 5: EGARCH parameters of T-bill yield, S&P 500, and industrial production

	T-bill yield		S&P 500		Industrial Production	
Parameters	Coefficients	p-value	Coefficients	p-value	Coefficients	p-value
ω	-1.809009	0.2077	-1.091439*	0.0517	-5.697443***	0.0009
α	0.194788	0.5349	0.275679*	0.0617	0.427904***	0.0002
β	-0.216673	0.8158	0.863854***	0.0000	0.487137***	0.0024
γ	0.011341	0.9617	-0.132772	0.1081	-0.271409***	0.0015
Half life (months)	7		5		8	
Unconditional volatility (Annualized)	74.04		15.28		2.54	
ARCH- LM (Lag 1)	55.47338***	0.0000	0.068936	0.793	0.102141	0.7495
ARCH- LM (Lag 6)	12.23661***	0.0000	0.093469	0.997	0.856094	0.5274
***, **, and * denote significant at 1, 5, 10% level						

Figure 3: Conditional annualized volatilities of T-bill yield, S&P 500, and industrial production



4.5.1 Variance decomposition (Price shocks)

Table 6 shows the full/sub sample analysis of variance decomposition for price shocks from January 1986 to December 2016. Standard errors come from Monte Carlo with 1000 replications. After 24 months, shocks to interest rate, S&P 500, crude oil, natural gas, and industrial production account for approximately 87, 3, 3, 2, and 5 percent of the variation in T-bill yield. Then shocks to T-bill yield, S&P 500, crude oil, natural gas, and industrial production account for approximately 2, 91, 1, 1, and 5 percent of the variation in S&P 500.

For the variation in crude oil, almost all of the variance decomposition comes from movements in itself. This result is consistent with the finding of Sadorsky (1990) and implies that oil can affect macro variables but less so with the other way around. In contrast to variation in crude oil, shocks to T-bill yield, S&P 500, crude oil, natural gas, and industrial production account for approximately 4, 3, 6, 86, and 1 percent of the variation in natural gas. Lastly, shocks to T-bill yield, S&P 500, crude oil, natural gas, and industrial production account for approximately 5, 12, 3, 1, and 79 percent of the variation in industrial production.

I find that shocks to all variables have all increased variations significantly to each other during the post-GFC. For example, shock to natural gas had increased the variation in industrial production by 90 percent and shock to crude oil had increased the variation in S&P 500 and industrial production by 45 and 344 percent, respectively. Macro activities are also more sensitive to monetary policy shocks during the post-GFC. For example, shock to T-bill yield had increased the variations in S&P 500, crude oil, natural gas, and industrial production by 5.22, 4.64, 2.95, 3.64 times, respectively.

4.5.2. Variance decomposition (Volatility shocks)

Table 7 presents the full/sub sample analysis of variance decomposition for volatility shocks. After 24 months with full sample, shocks to volatilities of interest rate, S&P 500, crude oil, natural gas, and industrial production account for approximately 88, 7, 2, 1, and 2 percent of the variation in T-bill yield volatility. Then shocks to volatilities of T-bill yield, S&P 500, crude oil, natural gas, and industrial production account for approximately 1, 93, 2, 1, and 3 percent of the variation in S&P 500 volatility. For the variation in crude oil volatility, almost all of the variance decomposition comes from movements in itself. Similar result has happened for variation in natural gas volatility except that crude oil volatility shock is consists of nearly 11 percent. Lastly for variation in industrial production volatility, besides nearly all of the variance decomposition comes from the fluctuation in itself, S&P 500 volatility shock is consists of slightly more than five percent.

Similar to the results with price shocks, volatility shocks to all variables have all increased variations significantly during the post-GFC. For example, shock to natural gas volatility had increased the variation in industrial production volatility by 1.9 times and shock to crude oil volatility had increased the variation in S&P 500 volatility and industrial production volatility by 2.68 and 4.68 times, respectively. During the zero lower bound period, volatilities of macro activities are also more sensitive to interest rate volatility shocks. For example, shock to T-bill yield volatility had increased the variations in volatilities of S&P 500, crude oil, natural gas, and industrial production by 1.37, 2.36, 6.73, 1.37 times, respectively.

Table 6: Variance decomposition of forecast error variance after 24 months

	Shocks to				
Full sample: 1986M1-2016M12	**r**	**rs**	**co**	**ng**	**ip**
Δr	86.923	2.878	2.761	2.053	5.385
	(4.47)	(2.09)	(1.91)	(1.96)	(3.33)
Δlog(rs)	1.984	90.761	0.962	1.078	5.215
	(1.66)	(3.22)	(1.28)	(1.31)	(2.24)
Δlog(co)	2.618	1.824	90.451	3.149	1.958
	(1.96)	(1.55)	(3.59)	(1.99)	(1.65)
Δlog(ng)	3.985	2.513	6.006	86.063	1.434
	(1.97)	(1.89)	(2.26)	(3.62)	(1.29)
Δlog(ip)	4.828	12.118	3.262	0.821	78.972
	(3.21)	(4.06)	(1.79)	(1.29)	(4.97)
Sub-sample: 1986M1-2007M7 (PI)					
Δr	83.735	3.631	4.421	1.459	6.755
	(6.46)	(3.58)	(2.54)	(2.15)	(4.90)
Δlog(rs)	2.370	92.744	1.205	2.075	1.605
	(2.47)	(4.10)	(1.74)	(2.08)	(1.98)
Δlog(co)	4.011	6.627	83.630	3.243	2.489
	(2.62)	(2.90)	(4.79)	(2.39)	(2.12)
Δlog(ng)	4.588	3.678	5.252	85.813	0.669
	(2.57)	(2.75)	(2.69)	(4.54)	(1.47)
Δlog(ip)	6.203	6.063	2.845	2.444	82.446
	(3.11)	(3.48)	(2.18)	(2.07)	(4.90)
Sub-sample: 2007M8-2016M12 (PII)					
Δr	73.075	9.122	4.308	7.075	6.420
	(9.50)	(5.61)	(4.79)	(6.68)	(4.83)
Δlog(rs)	14.737	55.817	13.853	3.959	11.634
	(6.89)	(8.71)	(5.66)	(4.77)	(4.20)
Δlog(co)	14.765	7.973	61.031	8.511	7.720
	(6.51)	(5.12)	(8.52)	(5.99)	(4.26)
Δlog(ng)	15.750	4.356	8.753	68.506	2.635
	(6.64)	(4.35)	(5.17)	(8.45)	(2.85)
Δlog(ip)	28.786	12.667	12.645	4.647	41.256
	(9.59)	(6.40)	(5.50)	(5.64)	(7.61)

Monte Carlo constructed standard erros are shown in parentheses

Table 7: Variance decomposition of forecast error variance after 24 months

	Shocks to				
Full sample: 1986M1-2016M12	**rv**	**rsv**	**ov**	**nv**	**ipv**
Δlog(rv)	87.687	6.961	1.738	1.155	2.460
	(3.57)	(2.69)	(1.50)	(1.42)	(1.69)
Δlog(rsv)	1.223	93.380	1.956	0.810	2.630
	(1.52)	(2.98)	(1.61)	(1.27)	(1.79)
Δlog(ov)	1.450	1.997	91.048	2.262	3.243
	(1.48)	(2.03)	(3.48)	(1.70)	(2.10)
Δlog(nv)	1.088	1.524	11.195	84.895	1.297
	(1.49)	(1.47)	(2.85)	(3.45)	(1.48)
Δlog(ipv)	1.470	5.444	1.231	1.053	90.802
	(1.65)	(2.70)	(1.28)	(1.42)	(3.38)
Sub-sample: 1986M1-2007M7 (PI)					
Δlog(rv)	85.650	7.424	0.914	1.381	4.632
	(4.58)	(3.08)	(1.54)	(1.75)	(2.95)
Δlog(rsv)	4.601	92.006	1.135	0.781	1.476
	(3.03)	(4.27)	(1.64)	(1.68)	(2.00)
Δlog(ov)	2.398	1.835	92.827	2.159	0.781
	(2.21)	(2.11)	(4.28)	(2.24)	(1.80)
Δlog(nv)	2.580	2.574	10.855	82.291	1.700
	(2.26)	(2.17)	(3.35)	(4.63)	(2.10)
Δlog(ipv)	5.750	2.819	0.995	0.985	89.451
	(3.31)	(2.49)	(1.71)	(1.93)	(4.68)
Sub-sample: 2007M8-2016M12 (PII)					
Δlog(rv)	76.641	7.798	7.106	4.117	4.338
	(8.16)	(4.99)	(5.00)	(4.55)	(4.00)
Δlog(rsv)	10.917	70.946	9.391	2.878	5.869
	(6.31)	(8.65)	(5.35)	(4.07)	(4.25)
Δlog(ov)	4.878	3.383	74.047	5.726	11.967
	(5.73)	(4.56)	(8.93)	(4.82)	(6.07)
Δlog(nv)	8.416	4.420	27.246	56.160	3.758
	(4.97)	(4.63)	(6.15)	(7.35)	(3.96)
Δlog(ipv)	7.885	16.587	9.992	5.603	59.933
	(5.90)	(6.55)	(5.62)	(4.34)	(7.87)

Monte Carlo constructed standard erros are shown in parentheses

4.6. Granger causality/Block-exogeneity test

Table 8 and 9 exhibit the results of full and subsample analysis using Granger causality/Block exogeneity test from 1986 to 2016 under prices and volatilities, respectively. The significance level is set at five percent. Enders (2015) notes that Block exogeneity is one of the variations of Granger causality tests and can be used to detect whether to incorporate an additional variable into a VAR (p. 306). Similar to the original Granger causality model, we can use this test to determine whether lags of one variable Granger cause other variables.

4.6.1 *Granger causality/Block-exogeneity test among prices*

Starting with full sample analysis for prices with estimated period from January 1986 to December 2016, S&P 500 and crude oil Granger cause T-bill yield, crude oil and T-bill yield Granger cause natural gas, and at last, S&P 500, crude oil, and T-bill yield Granger cause industrial production, and at last, industrial production Granger cause S&P 500. For the estimation period from January 1986 to July 2007 before the breakout of GFC, S&P 500 and crude oil Granger cause T-bill yield and at last, crude oil and T-bill yield Granger cause industrial production. For the estimated period from August 2007 to December 2016, T-bill yield Granger cause natural gas, crude oil and T-bill yield Granger cause industrial production, and at last, industrial production and crude oil Granger cause S&P 500. All of the above assume significance level at five percent.

4.6.2 *Granger causality/Block-exogeneity test among volatilities*

With full sample analysis on Block-exogeneity test among volatilities with estimated period from January 1986 to December 2016, S&P 500 volatility Granger cause T-bill yield volatility, oil volatility Granger cause natural gas volatility, and at last, S&P 500 volatility Granger cause industrial production volatility. For the estimation period from January 1986 to July 2007 during high Fed fund rate regime, S&P 500 volatility Granger cause T-bill yield volatility, oil volatility Granger cause natural gas volatility, and at last, T-bill yield volatility Granger cause industrial production volatility. For the estimated period from August 2007 to December 2016 during low Fed fund rate regime, natural gas volatility and oil volatility can Granger cause each other, and at last, S&P 500 volatility Granger cause industrial production volatility. All of the above assume significance level at five percent.

4.6.3 Comparison between price and volatility of Block-exogeneity tests

From 1986 to 2017, both price and volatility of S&P 500 Granger cause those of T-bill yield, both price and volatility of crude oil Granger cause those of natural gas. During the pre-GFC period, both price and volatility of S&P 500 Granger cause those of T-bill yield and both price and volatility of T-bill yield Granger cause those of industrial production. During the post-GFC period, there is no similar result between price and volatility in Granger causality.

Table 8: Granger causality/Block exogeneity test among prices

Full sample			**Sub-sample: 1986M1 to 2007M7**			**Sub-sample: 2007M8 to 2016M12**		
Dependent variable			**Dependent variable**			**Dependent variable**		
Δr			Δr			Δr		
Excluded variable	**Chi-Sq**	**P-value**	**Excluded variable**	**Chi-Sq**	**P-value**	**Excluded variable**	**Chi-Sq**	**P-value**
Δlog(co)*	17.63	0.0072	Δlog(co)*	13.51	0.0357	Δlog(co)	10.74	0.0967
Δlog(ng)	8.30	0.217	Δlog(ng)	5.13	0.5276	Δlog(ng)	6.42	0.3781
Δlog(ip)	11.10	0.0853	Δlog(ip)	10.55	0.1033	Δlog(ip)	4.50	0.6098
Δlog(rs)*	18.01	0.0062	Δlog(rs)*	13.16	0.0405	Δlog(rs)	11.01	0.0881
Dependent variable			**Dependent variable**			**Dependent variable**		
Δlog(co)			Δlog(co)			Δlog(co)		
Excluded variable	**Chi-Sq**	**P-value**	**Excluded variable**	**Chi-Sq**	**P-value**	**Excluded variable**	**Chi-Sq**	**P-value**
Δr	5.84	0.4413	Δr	6.79	0.341	Δr	6.32	0.3888
Δlog(ng)	8.25	0.2206	Δlog(ng)	7.64	0.2654	Δlog(ng)	10.90	0.0915
Δlog(ip)	5.10	0.531	Δlog(ip)	5.74	0.4533	Δlog(ip)	7.56	0.2721
Δlog(rs)	6.59	0.3608	Δlog(rs)	9.33	0.1559	Δlog(rs)	2.43	0.8766
Dependent variable			**Dependent variable**			**Dependent variable**		
Δlog(ng)			Δlog(ng)			Δlog(ng)		
Excluded variable	**Chi-Sq**	**P-value**	**Excluded variable**	**Chi-Sq**	**P-value**	**Excluded variable**	**Chi-Sq**	**P-value**
Δr*	17.36	0.0081	Δr	10.44	0.1075	Δr*	12.78	0.0466
Δlog(co)*	22.19	0.0011	Δlog(co)	8.66	0.1935	Δlog(co)	9.79	0.1337
Δlog(ip)	3.43	0.7529	Δlog(ip)	0.48	0.9981	Δlog(ip)	3.42	0.7549
Δlog(rs)	6.79	0.3405	Δlog(rs)	5.97	0.4266	Δlog(rs)	3.54	0.7386
Dependent variable			**Dependent variable**			**Dependent variable**		
Δlog(ip)			Δlog(ip)			Δlog(ip)		
Excluded variable	**Chi-Sq**	**P-value**	**Excluded variable**	**Chi-Sq**	**P-value**	**Excluded variable**	**Chi-Sq**	**P-value**
Δr*	13.70	0.0332	Δr*	17.35	0.0081	Δr*	33.00	0.0000
Δlog(co)*	12.75	0.0471	Δlog(co)*	13.94	0.0303	Δlog(co)*	17.67	0.0071
Δlog(ng)	2.25	0.8951	Δlog(ng)	6.52	0.3678	Δlog(ng)	3.45	0.7502
Δlog(rs)*	35.93	0.0000	Δlog(rs)	9.00	0.1734	Δlog(rs)	9.15	0.1654
Dependent variable			**Dependent variable**			**Dependent variable**		
Δlog(rs)			Δlog(rs)			Δlog(rs)		
Excluded variable	**Chi-Sq**	**P-value**	**Excluded variable**	**Chi-Sq**	**P-value**	**Excluded variable**	**Chi-Sq**	**P-value**
Δr	7.87	0.2478	Δr	6.78	0.3419	Δr	7.06	0.3151
Δlog(co)	2.55	0.8626	Δlog(co)	2.22	0.8988	Δlog(co)*	20.35	0.0024
Δlog(ng)	4.46	0.6144	Δlog(ng)	5.49	0.4826	Δlog(ng)	5.34	0.5008
Δlog(ip)*	22.39	0.001	Δlog(ip)	4.99	0.5456	Δlog(ip)*	22.50	0.001

* Denotes statistically significant at 5% significance level

Table 9: Granger causality/Block exogeneity test among volatilities

Full sample			Sub-sample: 1986M1 to 2007M7			Sub-sample: 2007M8 to 2016M12		
Dependent variable			**Dependent variable**			**Dependent variable**		
Δlog(rv)			Δlog(rv)			Δlog(rv)		
Excluded variable	**Chi-Sq**	**P-value**	**Excluded variable**	**Chi-Sq**	**P-value**	**Excluded variable**	**Chi-Sq**	**P-value**
Δlog(rsv)*	22.44	0.001	Δlog(rsv)*	18.52	0.0051	Δlog(rsv)	10.39	0.1093
log(ov)	6.13	0.4089	log(ov)	7.32	0.2926	log(ov)	3.00	0.8088
Δlog(nv)	4.78	0.5718	Δlog(nv)	4.06	0.6690	Δlog(nv)	4.64	0.5913
Δlog(ipv)	5.83	0.4422	Δlog(ipv)	10.90	0.0914	Δlog(ipv)	2.49	0.8695
Dependent variable			**Dependent variable**			**Dependent variable**		
Δlog(rsv)			Δlog(rsv)			Δlog(rsv)		
Excluded variable	**Chi-Sq**	**P-value**	**Excluded variable**	**Chi-Sq**	**P-value**	**Excluded variable**	**Chi-Sq**	**P-value**
Δlog(rv)	4.43	0.6184	Δlog(rv)	8.43	0.2083	Δlog(rv)	12.53	0.0512
Δlog(ov)	7.03	0.3177	Δlog(ov)	10.71	0.0977	Δlog(ov)	6.62	0.3573
Δlog(nv)	1.83	0.9344	Δlog(nv)	1.83	0.9345	Δlog(nv)	1.94	0.9253
Δlog(ipv)	9.64	0.1404	Δlog(ipv)	4.35	0.6297	Δlog(ipv)	7.22	0.3014
Dependent variable			**Dependent variable**			**Dependent variable**		
Δlog(ov)			Δlog(ov)			Δlog(ov)		
Excluded variable	**Chi-Sq**	**P-value**	**Excluded variable**	**Chi-Sq**	**P-value**	**Excluded variable**	**Chi-Sq**	**P-value**
Δlog(rv)	7.21	0.3018	Δlog(rv)	3.22	0.7809	Δlog(rv)	6.09	0.4128
Δlog(rsv)	2.55	0.863	Δlog(rsv)	2.63	0.8542	Δlog(rsv)	3.13	0.792
Δlog(nv)	11.06	0.0867	Δlog(nv)	5.46	0.486	Δlog(nv)*	12.74	0.0473
Δlog(ipv)	9.01	0.1729	Δlog(ipv)	1.29	0.972	Δlog(ipv)	11.53	0.0732
Dependent variable			**Dependent variable**			**Dependent variable**		
Δlog(nv)			Δlog(nv)			Δlog(nv)		
Excluded variable	**Chi-Sq**	**P-value**	**Excluded variable**	**Chi-Sq**	**P-value**	**Excluded variable**	**Chi-Sq**	**P-value**
Δlog(rv)	3.099	0.7963	Δlog(rv)	5.76	0.4506	Δlog(rv)	10.67	0.0993
Δlog(rsv)	2.842	0.8285	Δlog(rsv)	3.93	0.6864	Δlog(rsv)	6.46	0.3738
Δlog(ov)*	13.939	0.0303	Δlog(ov)*	15.33	0.0178	Δlog(ov)*	36.72	0.0000
Δlog(ipv)	3.879	0.6931	Δlog(ipv)	3.68	0.7195	Δlog(ipv)	3.95	0.6828
Dependent variable			**Dependent variable**			**Dependent variable**		
Δlog(ipv)			Δlog(ipv)			Δlog(ipv)		
Excluded variable	**Chi-Sq**	**P-value**	**Excluded variable**	**Chi-Sq**	**P-value**	**Excluded variable**	**Chi-Sq**	**P-value**
Δlog(rv)	3.77	0.7081	Δlog(rv)*	12.79	0.0465	Δlog(rv)	5.33	0.5017
Δlog(rsv)*	13.47	0.0362	Δlog(rsv)	3.44	0.7517	Δlog(rsv)*	17.64	0.0072
Δlog(ov)	3.53	0.7405	Δlog(ov)	0.68	0.9949	Δlog(ov)	7.67	0.2633
Δlog(nv)	1.21	0.9763	Δlog(nv)	2.38	0.8818	Δlog(nv)	4.81	0.5681

* Denotes statistically significant at 5% significance level

4.7. Dynamic impulse response of SVAR models

The following presents the dynamic impulse responses of non-recursive SVAR model in Panels A, B, C, and D of full sample and two subsample periods with lag length 6. All of the accumulated impulse responses are caused by 1 S.D. shock to either price or volatility of T-bill yield, crude oil, and natural gas. The results are robust to varying lag lengths and changing the ordering in the VAR decompositions.

4.7.1. Dynamic impulse response of Panel A when $Y_t=[\Delta(r), \Delta log(rs), \Delta log(co), \Delta log(ng), \Delta log(ip)]$

With the estimation period from January 1986 to December 2016, an unexpected, temporary, and exogenous increase in T-bill yield shock leads to 31 basis points increase in T-bill yield by the sixth moth, 2.7 percent increase in crude oil by the fifth month, 2.3 percent decrease in natural gas by the fifth month, 0.16 percent increase in industrial production by the third month, and 0.4 percent decrease in S&P 500 by the third month but will bounce back to the baseline by the fifth month. Apparently, contractionary monetary policy shock is highly effective in deflating natural gas for six months. In contrast, although insignificant, crude oil continues to increase immediately following the contractionary monetary policy shock and not peaked until after five months. Price puzzle exists in crude oil but not in natural gas significantly during the first five months. Except for response in industrial production which continues to go up after 24 months, responses in crude oil and S&P 500 are consistent with Ferderer (1996) and Sadorsky (1999).

Shock in crude oil induces three basis point increase in T-bill yield by the third month but will be one basis points below the baseline after two quarters, 0.4 percent increase in S&P 500 by the fourth month but turns into insignificant negative region after eight months, 12.7 percent increase in crude oil by the fourth month, 6.4 percent increase in natural gas by the fifth month, and 0.15 percent increase in industrial production by the sixth month. Among them, positive response of natural gas to crude oil price shock is highly significant especially in the first five months.

In sum, it takes nearly three quarters of time for corporate earnings to be affected by increased cost of oil price. Sadorsky (1999) argues that if stock market does not respond immediately and exhibit lagged decline to positive oil shock, then that means the stock market is inefficient (p. 458). Overall, my result is inconsistent with Sadorsky (1999) because the economic activity indicated by industrial production in our estimated period does not show a negative impulse response. However, a much more updated research by Kilian (2008) claimed that positive crude oil shock is not necessarily bad news to the stock market because the sources of crude oil shock should be decomposed into demand or supply shock (p. 901). Further, Kilian and Park (2009) showed that equity return will soon be negatively affected by oil-market specific demand shock and in the mid-long run, negatively affected by oil supply shock and aggregate demand shock (p. 1275). Kilian and Park (2009) also maintain that strong economic growth that induces positive aggregate demand shock in Asia since 2003, is the reason why the stock market can be resilient to positive oil price shock (p. 1277). In terms of fixed income market's response to crude oil shock, our result is in line with Kang et al (2014) in which oil price shock will cause immediate positive response in bond yield or negative response in bond price return; in addition, they found that it will take eight months for real bond index return to return to baseline after a positive oil market-specific demand shock (p. 257).

By contrast, shock in natural gas causes seven basis points increase in T-bill yield after 24 months, 0.43 percent decrease in S&P 500 by the fourth month and accumulated 0.3 percent decline after 24 months, 2.7 percent increase and peaked by the sixth month in crude oil, 12 percent increase and peaked by the second month in natural gas, and 0.05 percent increase in industrial production by the sixth month and turns into slightly negative region after 12 months. Similar to the case in oil shock, the reactions of industrial production and S&P 500 to natural gas shock are not significant whether in the short run or long run. Among them, positive response of crude oil to natural shock is quite significant in the first six months.

4.7.1.1. Subsample analysis for the impulse response to crude oil price shock of Panel A

Following the crude oil price shock, T-bill yield will continue to fall even under the low discount rate regime. Due to the fall in interest rate at the same time, S&P 500 and industrial production will be bullish in the short run. By contrast, S&P 500 and industrial production decline right after the crude oil price shock under high discount rate regime.

4.7.1.2. *Subsample analysis for the impulse response to natural gas price shock of Panel A*

Similar to the situation with crude oil price shock, S&P 500 and industrial production are resilient to natural gas price shock under low discount rate regime. However, T-bill yield will continue to go up even during the low discount rate regime.

4.7.1.3. *Subsample analysis for the impulse response to T-bill yield shock of Panel A*

Immediately after the T-bill yield shock, S&P 500 will continue to increase (decrease) under low (high) discount rate regime. Crude oil and natural gas will both fall (increase) under low (high) discount rate regime. Only the impulse responses of industrial production are consistent throughout two subsample and full sample. Among them, the negative response of natural gas to T-bill yield shock under low rate regime is highly significant in the first five months.

4.7.2. Dynamic impulse response of Panel B when Y_t *=[*Δ*(r),* Δ*log(rs),* Δ*log(ov),* Δ*log(ng),* Δ*log(ip)]*

Shock in crude oil volatility only induces 3.1 basis points increase in T-bill yield after two years, 0.9 percent decrease in S&P 500 by the third month and then stays below the baseline for two years, 7.7 percent increase in crude oil volatility by the fourth month, 3.2 percent decrease in natural gas by the fourth month and then stays below the baseline for two years, and 0.34 percent decrease in industrial production after two quarters. Among the above results, negative responses of natural gas, S&P 500, and industrial production are significant in the short run.

Due to the asymmetric nature for crude oil and its volatility, when crude oil volatility rises, it is more likely caused by large pullback in crude oil price. So compared to the impulse response of Panel A, T-bill yield will still rise but with much smaller magnitude when there is no inflation risk. For instance, T-bill yield under Panel A(Crude oil price shock) will be increased by 1.8 basis points while T-bill yield under Panel B(Crude oil volatility shock) will be decreased by one basis point by the eighth months. Moreover, natural gas price, equity market, and industrial production are also worse off under positive crude oil volatility shock because a pullback in crude oil price also indicate some degree of economic contraction.

4.7.2.1. Subsample analysis for the impulse response to crude oil volatility shock of Panel B

T-bill yield will rise (fall) following the crude oil volatility shock under low (high) discount rate regime. The impulse responses of other variables have been consistent throughout the entire subsample analysis. The negative response of natural gas to oil volatility under low rate regime is quite significant in the first four months.

4.7.2.2. Subsample analysis for the impulse response to T-bill yield shock of Panel B

In contrast to the estimates under high discount rate regime, both S&P 500 and industrial production continue to increase and natural gas price will be bearish eventually under low discount rate regime.

4.7.3. Dynamic impulse response of Panel C when Y_t=[Δ(r), Δlog(rs), Δlog(co), Δlog(nv), Δlog(ip)]

Shock in natural gas volatility causes two basis points decrease in T-bill yield after four months, accumulated 0.3 percent increase in S&P 500 after four months, 1.8 percent decrease in crude oil price, 6.7 percent increase in natural gas volatility after ten months, and 0.1 percent decline in industrial production by the fifth month. However, none of them presents significant trend.

Due to the symmetric nature for natural gas and its volatility, when natural gas volatility rises, it is more likely caused by jump in natural gas price. Compare to impulse response to natural shock in Panel A, T-bill yield will not go up but rather go down by a small margin, S&P 500 will decline immediately but bounce back to the baseline by the third month, crude oil and industrial production will be negatively affected but insignificant. The situation under uncertainty in natural gas measured by the natural gas volatility will be slightly worse than the situation under positive natural gas price shock. Uncertainty in natural gas will drag down both the stock market and industrial production immediately. Positive price shock in natural gas also brings down the stock market immediately but does not hurt industrial production.

4.7.3.1. Subsample analysis for the impulse response to natural gas volatility shock of Panel C

Unlike the situations under high discount rate regime, S&P 500 will fall immediately after the shock to natural gas volatility. Other variables exhibit similarly consistent pattern throughout the entire subsample analysis.

4.7.3.2. Subsample analysis for the impulse response to T-bill yield of Panel C

In contrast to the estimates under high discount rate regime, the bullish trends in S&P 500 and industrial production are highly persistent; however, crude oil price will be effectively lowered by the T-bill yield shock after six months under low discount rate regime. In addition, natural gas volatility will be indifferent to the T-bill yield shock under low discount rate regime.

4.7.4. Monetary policy shock comparison among Panels A, B, and C (Full-Sample)

For the estimated period between January 1986 and December 2016, an unexpected, temporary, and exogenous increase in T-bill yield leads to two percent decrease in crude oil volatility by the fifth month and continue to stay below the baseline for two years. The same shock also leads to one percent decrease in natural gas volatility by the third month and continues to stay below the baseline for two years. Going back to Panel A to check the same shock on prices of crude oil and natural gas, it leads to 2.7 percent increase in crude oil by the fifth month and 2.3 percent decrease in natural gas by the fifth month. From here, we can once again see that asymmetric relationship exists between oil price and its volatility and symmetric relationship exists between natural gas and its volatility.

4.7.5. Dynamic impulse response of Panel D when Y_t=[Δ(rv), Δlog(rsv), Δlog(cv), Δlog(nv), Δlog(ipv)]

In Panel D, I convert all time series to EGARCH volatilities to conduct the observation purely on volatility transmission from the shocks of monetary policy, crude oil, and natural gas uncertainties. The shock in T-bill yield volatility ignites 20.6 percent increase in its volatility after 24 months, two percent increase in S&P 500 volatility after five months, 0.6 percent increase in oil volatility after seven months, 0.5 percent decrease in natural gas volatility after four months but since then gradually come back to the baseline two months after, and two percent increase in industrial production volatility. In general, T-bill volatility shock ignites all other volatilities of macro and energy variables. One exception is that natural gas is negatively affected in the beginning and is the least affected to monetary policy uncertainty overtime. Among them, the positive response of S&P 500 volatility to T-bill yield volatility is highly significant.

The shock in crude oil volatility causes 5.2 percent hike in T-bill yield volatility by the fourth month, 1.4 percent increase in S&P 500 volatility by the third month, 8.6 percent increase in crude oil volatility after two quarters, 3.9 percent increase in natural gas volatility after two quarters, and 2.2 percent increase in industrial production after two months. Overall, T-bill yield volatility is the most responsive to shock in crude oil volatility while S&P 500 and industrial production volatilities are relatively indifferent to uncertainty in crude oil market. Moreover, the positive responses of volatilities of T-bill yield, natural gas, and industrial to crude oil volatility shock are all significant in the first three months.

The shock in natural gas volatility triggers 5.5 percent decrease in T-bill volatility after two quarters, 0.7 percent decrease in S&P 500 volatility after five months, 0.9 percent decrease in crude oil volatility by the third month, 5.6 percent increase in natural gas volatility after five months, 0.7 percent decrease in industrial production volatility by the fourth month. The increase in natural gas volatility is generally a good signal for the macro economy since both uncertainties for monetary policy and fear factor in stock market are cooled down. Among them, the negative response of T-bill yield volatility to natural gas volatility shock is highly significant in the first two quarters.

4.7.5.1. Subsample analysis for the impulse response to crude oil volatility shock

Following the crude oil volatility shock, volatilities of crude oil, S&P 500, and industrial production under low discount rate regime will increase in the beginning and return to baseline after about two quarters. In contrast, accumulated volatilities of most of variables under high discount rate regime will continue to grow but with diminishing return. The positive responses of S&P 500 and natural gas volatilities to oil volatility shock under low rate regime are quite significant in the first quarter.

4.7.5.2. Subsample analysis for the impulse response to natural gas volatility shock

Most of the results under high and low discount rate regimes are consistent with that of the full sample. However, negative response of T-bill yield volatility under low discount rate regime will be just one third of that under high discount rate regime after six months and positive response of natural gas volatility will significantly retreat toward the baseline much faster under low discount rate regime.

4.7.5.3. *Subsample analysis for the impulse response to T-bill yield volatility shock*

In response to T-bill yield volatility shock, T-bill yield volatility under low discount rate regime will be persistently high relative to that under high discount rate regime. Volatilities of S&P 500 and industrial production also exhibit similar pattern. However, volatilities of crude oil, natural gas, and industrial production all fall immediately under low discount rate regime. In addition, the negative responses of volatilities of natural gas and industrial production to T-bill volatility shock during low rate regime are significant in the first two months.

5. Conclusion

Despite crude oil and natural gas are among the two biggest players in energy market, their statistical characters are not alike. Natural gas return is more heavily tailed than crude oil return. Besides leptokurtic distributions, crude oil return has a long tail to the left while distribution of natural gas return has long tail to the right. Altogether, natural gas is the most jumpy (if exclude T-bill yield) and has higher probability with large positive returns. Compares crude oil with other variables, crude oil is more peaked than S&P 500 but less peaked than industrial production. Similarly, crude oil, industrial production, and S&P 500 have higher probabilities with large negative returns while natural gas and T-bill yield have higher probabilities with large positive returns. In addition to the nature in their non-normal distributions, EGARCH model further catches the phenomenon of asymmetric relationship between return and conditional volatility in crude oil, industrial production, and S&P 500 as well as that of symmetric relationship in natural gas and T-bill yield.

In Panel A, contractionary monetary policy shock is effective in cooling off natural price but ineffective in keeping the crude oil price down in full sample. Both equity market and industrial production have been resilient to the oil price shock due to strong economic growth in Asia since 2003. Nevertheless, S&P 500 and industrial production would be discouraged by natural gas shock. After splitting into subsample analysis between pre-GFC (high rate regime) and post-GFC (low rate regime), contractionary monetary policy shock is effective in easing both crude oil and natural gas prices but continues to encourage bullish trend in S&P 500 under low rate regime. Surprisingly, crude oil price shock continues to boost the bullish trends in S&P 500 and industrial production when interest rate approaches zero lower bound. In contrast, natural gas price shock will make T-bill yield higher even under the low discount rate regime. However, S&P 500 and industrial production are more resilient to natural gas price shock under low discount rate regime than under high discount rate regime. In Panel B, crude oil volatility shock not only may signal a pullback in crude oil price, but also signal incoming contraction in the business cycle. Natural gas, S&P 500, and industrial production all react negatively to the crude oil volatility shock. T-bill yield will rise (fall) following the crude oil volatility shock under low (high) discount rate regime. In contrast to the estimates under high discount rate regime, both S&P 500 and industrial production continue to increase and natural gas price will be bearish eventually under low discount rate regime. In Panel C, although symmetric relation exists between natural gas and its volatility, natural gas volatility shock does not cause significant elevation in T-bill yield because volatility shock may also come from sharp dive in natural gas. Crude oil, S&P 500, and industrial production all fall but insignificantly as uncertainty in natural gas heightens unexpectedly. At last, in Panel D where I present a pure volatility transmission mechanism with focus on T-bill, crude oil, and natural gas volatility shocks. Elevated uncertainty in monetary policy drives up all the other macro volatilities. S&P 500 volatility is the most sensitive while natural gas volatility is the least affected to T-bill yield volatility shock. The shock to crude oil volatility also causes hikes in all other volatilities. Among them, T-bill yield volatility responds most sharply while volatilities in both industrial production and S&P 500 are relatively less sensitive to the crude oil volatility shock. By contrast, the shock to natural gas volatility lowers all the other volatilities. Among the impulse responses, decrease in volatility in T-bill yield suggests that the market has no uncertainty regarding whether central bank will make a structural change in discount rate and the drop in volatility in S&P 500 implies that S&P 500 is either bullish or in bullish reversal. Moreover, shock to natural gas volatility does not mean that natural gas has to go up all the time in spite of the symmetric relation suggested by the parameter of EGARCH model. When divided into subsample analysis for volatility transmission, monetary policy uncertainty shock will make volatilities of T-bill yield, S&P 500, and industrial production persistently higher under low rate regime than under high rate regime. Conversely, volatilities of crude oil and natural gas both fall immediately under low discount rate regime. Right after the crude oil volatility shock, volatilities of crude oil, S&P 500, and industrial production under low discount rate regime will increase but much less persistent than under high discount rate regime. Following the natural gas volatility shock, natural gas volatility will significantly revert back toward the baseline much faster under low rate regime than under high rate regime. Overall, the structural break between high discount rate regime and low discount rate regime is significant due to the fact that whether in prices or in volatilities, variations of most variables become much more sensitive to exogeneous shocks during the low discount rate regime.

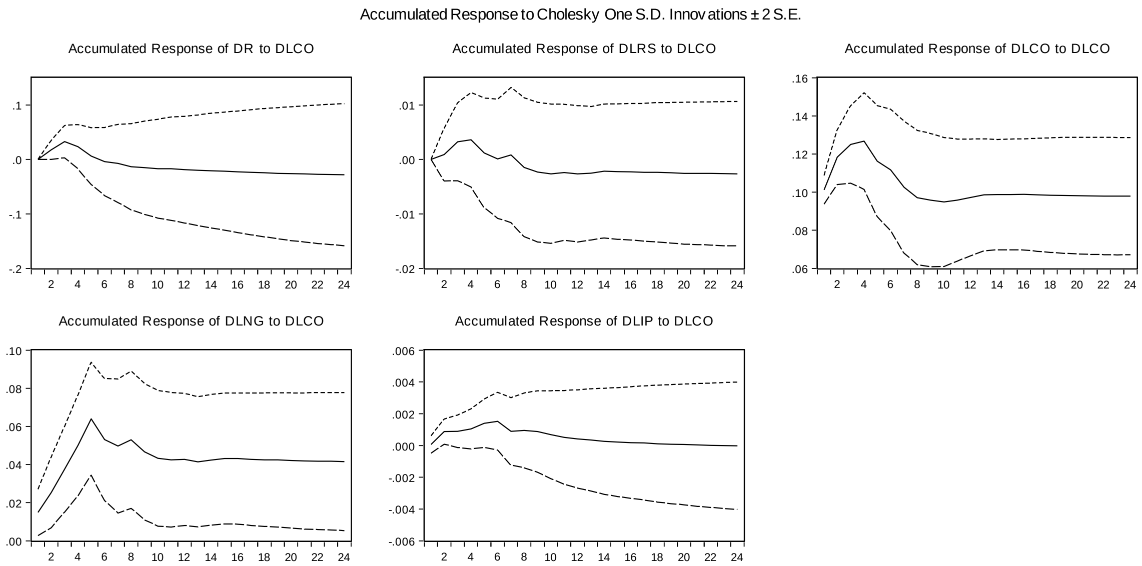
For policy implication, monetary policy shock is apparently more influential when discount rate approaches zero lower bound since there will be no evidence of price puzzle in either natural gas or crude oil. The Fed should provide a more transparent and consistent guideline on its monetary policy especially during the low discount rate period to reduce the volatilities of financial markets and all other real macro activities. Moreover, Central Banks around the world should try to smooth out their impacts on real macro activities with phase-in approach and avoid surprise especially when discount rate is already at zero lower bound.

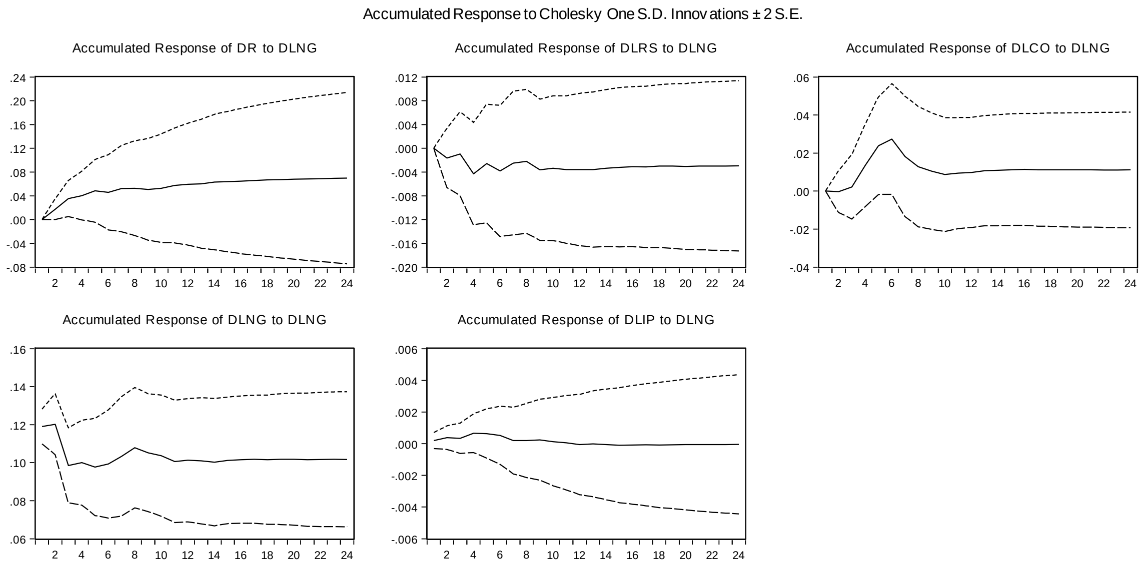
For the implications on derivatives pricing and trading, the asymmetric/symmetric relationship inferred from the EGARCH has significant implication on the options derivatives market. Looking at implied volatility smile, out-of-money put would be more expensive than out-of-call in both S&P 500, crude oil options, and price based fixed income options. Due to the asymmetric nature, investors have expectation that there will be more likelihood of large negative returns than large positive returns and so they will tend to hedge the risk for large negative returns and result in higher risk premium in OTM put. Because of higher premium in OTM put, any put spread based strategy with –gamma/-vega would enjoy higher time value than call spread strategy for S&P 500, crude oil options and priced based bond options, and vice versa. More interestingly, the post-GFC is characterized with not just low interest rate and low volatility. What is causing more trouble is that implied volatility tends to be lower than realized volatility, so options seller will be trading at discount rather than premium. On the other hand, the volatility discount will be beneficial to options buyer but they tend to hold much smaller position. Overall, the lower the volatility, the lower the risk premium, the higher the sensitivity of options Greeks, and the higher the elasticity of deep-OTM options, delta neutral trader should take the advantage of high elasticity of deep-OTM options by buying them to reduce the kurtosis risk or fat tail even during the post-GFC era. Appendix V shows the comparison between low interest rate and high interest rate in advanced options Greeks: volga, vanna, zomma, and elasticity where volga is the second derivative of the option value with respect to the volatility, vanna represents the sensitivity of the option delta with respect to change in volatility, zomma, indicates rate of change of gamma with respect to changes in volatility, and elasticity simply measures the percentage change of option value with respect to percentage change of the underlying price of the US 10-year treasury bond.

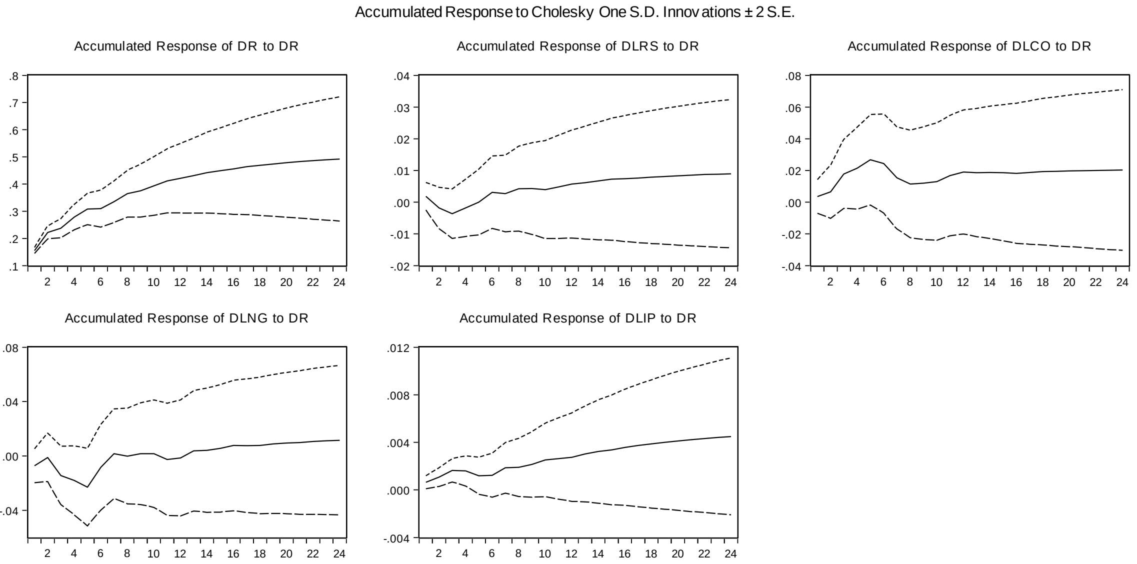
There are four directions that I can extend in the future. Firstly, the same models in this paper should be extended with various non-linear VAR models to observe the differences. Secondly, to get close to the reality of financial market, I must use daily frequency or high-frequency data instead and I should calculate volatility on open-close or high-low basis that better reflects the daily transaction cost of options gamma scalping trader. Thirdly, for the methodology of volatility estimation, I plan to apply Normal Mixture GARCH (1, 1) with two states or NM (2)-GARCH (1, 1) model. Vlaar and Palm (1993) first introduced the concept of normal mixture in GARCH model with the attempt to capture high kurtosis (p. 357). Wong and Li (2001) invented the mixture autoregressive conditional heteroscedastic model (MAR-ARCH) which appears to capture features of data by allowing more ranges of shape-changing predictive distribution and more flexible squared autocorrelation structure (p. 992). Haas et al (2004) argue that excess kurtosis that is detrimental to GARCH (1, 1) can be adequately fixed with two components and can capture Blacks' (1976) leverage effect after extending conditional distribution with mixture of normals in GARCH model (p. 212). Alexander and Lazar (2006) claimed that NM-GARCH can replicate options implied volatility smiles better than normal, Student's t, and several asymmetric GARCH models even without a risk premium and can capture time varying feature of volatility and kurtosis accurately (p. 313). As of now, none of the research has used NM-GARCH model on energy market and test it on the volatility smile of options pricing; therefore, it would be interesting to see how well NM-GARCH model can fit the energy volatility. Lastly, I should expand my portfolio into electricity market. Similar to natural gas, electricity also exhibits positive skew and leptokurtic distribution. What's special is that volatility of electricity is even higher than that of natural gas and other energy variables. Then I can test them with VAR for stationary process, VECM for cointegration process, SDE for Ornstein-Uhlenbeck process, Constant Elasticity of Variance (CEV) options pricing model for calibration. Ultimately, I can extend them into several empirical studies such as pair trading with their linear products like their delta-one products: futures and ETF as well as volatility trading and pricing with options.

Appendix

I. Accumulated impulse responses of crude oil, natural gas, and T-bill shocks in Panel A:

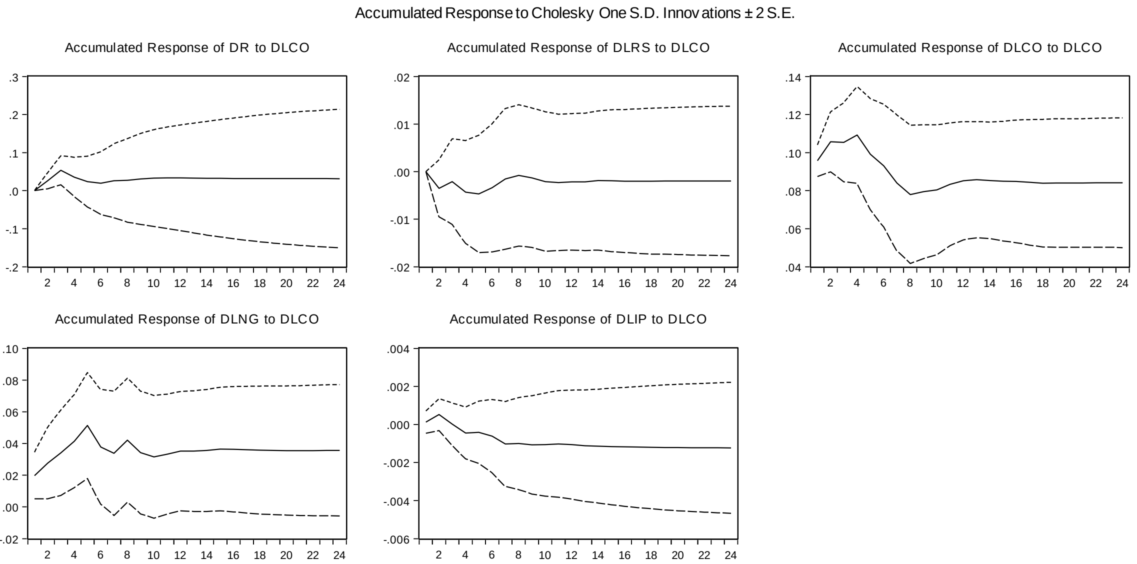




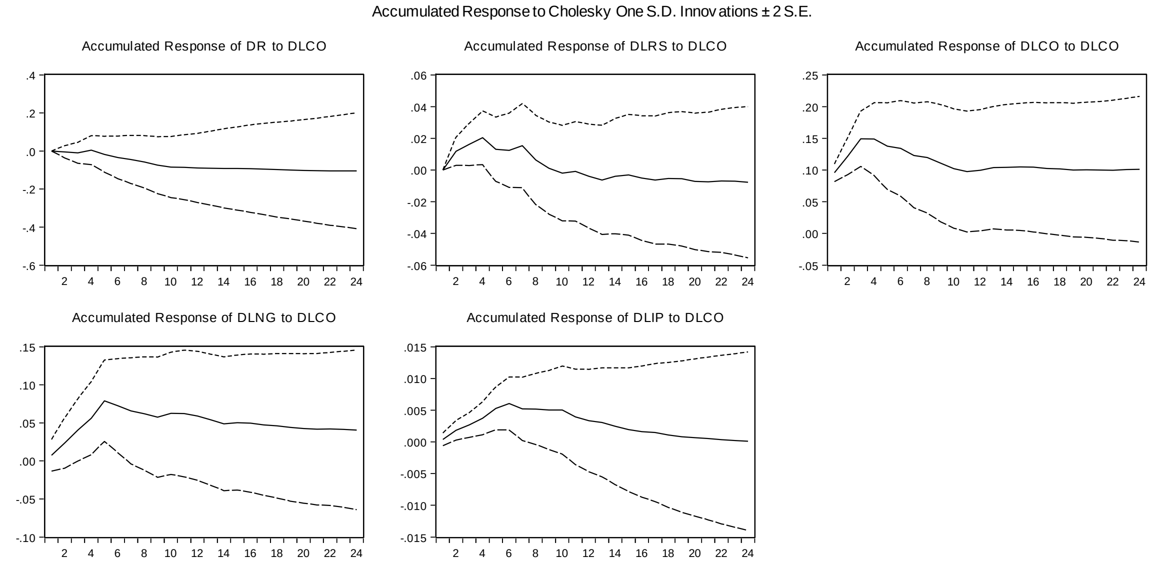


I.1. Subsample analysis for crude oil price shock in Panel A

Pre-GFC (High discount rate regime)

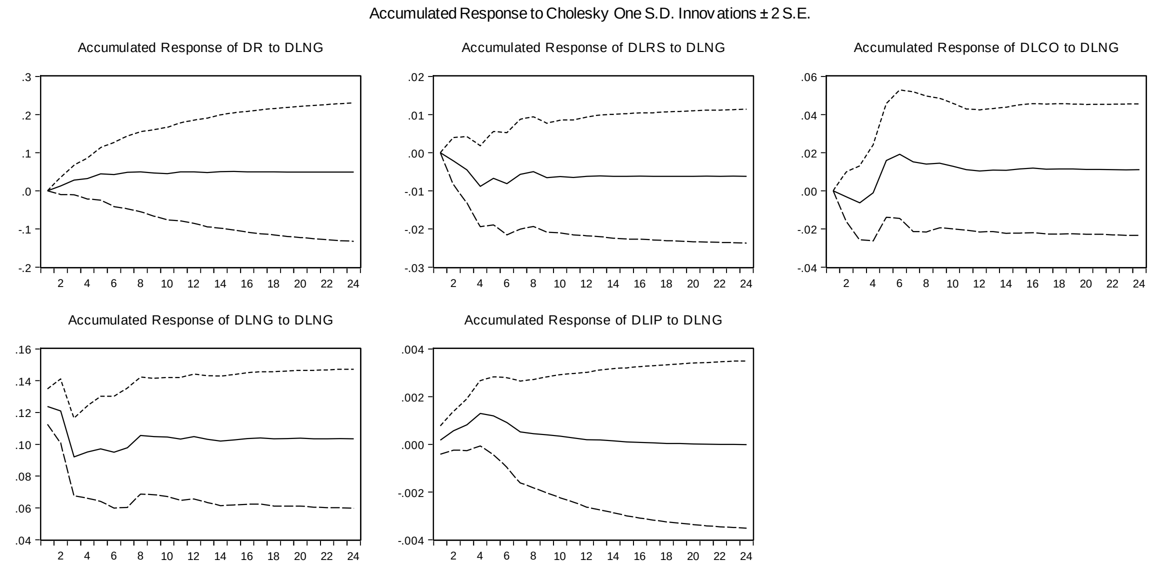


Post-GFC (Low discount rate regime)

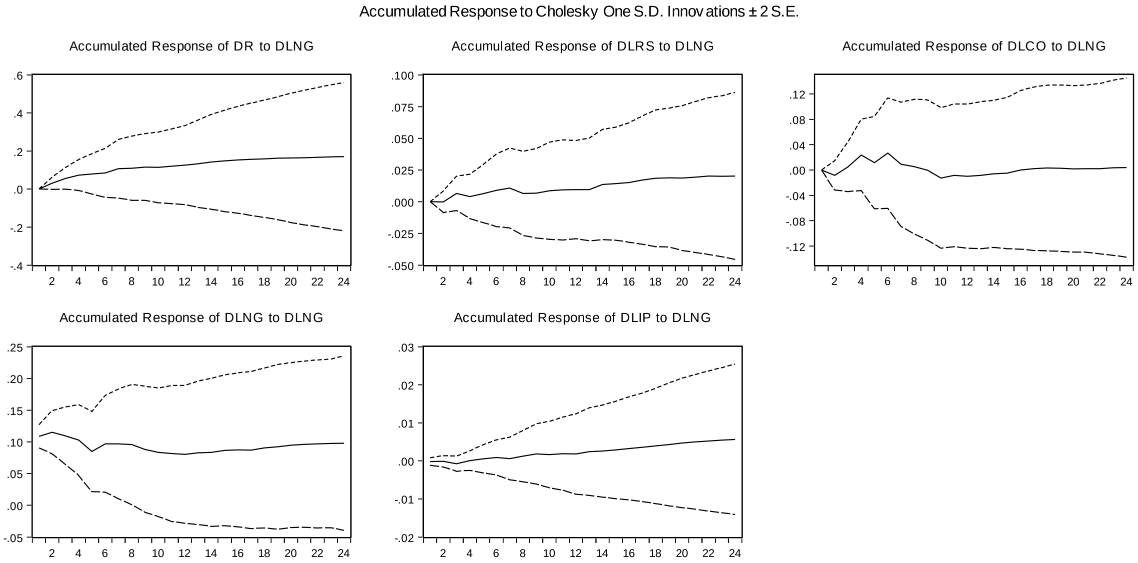


I.2. Subsample analysis for natural gas price shock in Panel A

Pre-GFC (High discount rate regime)

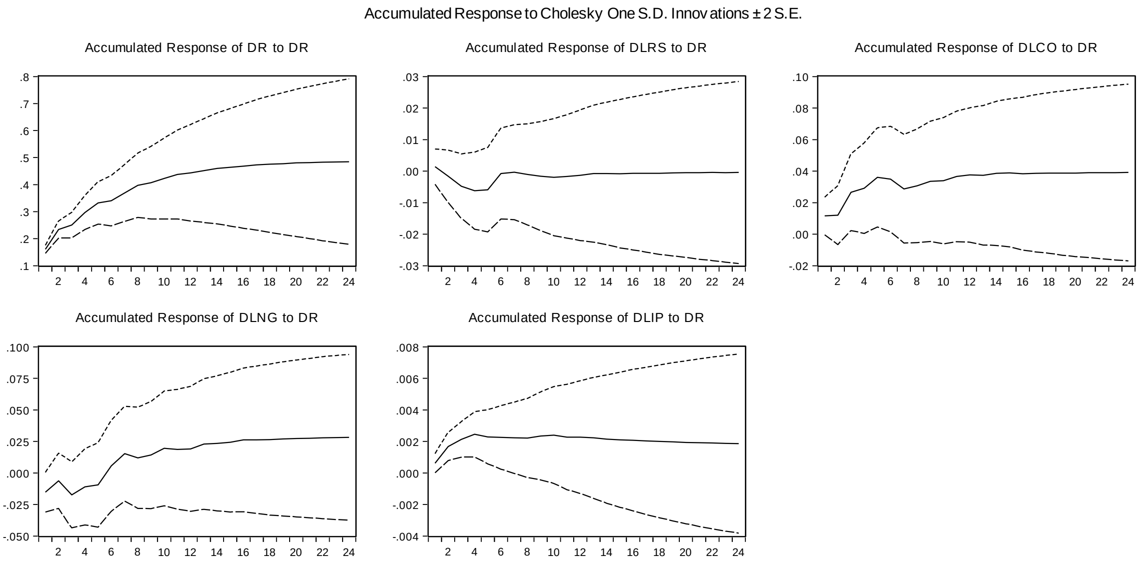


Post-GFC (Low discount rate regime)

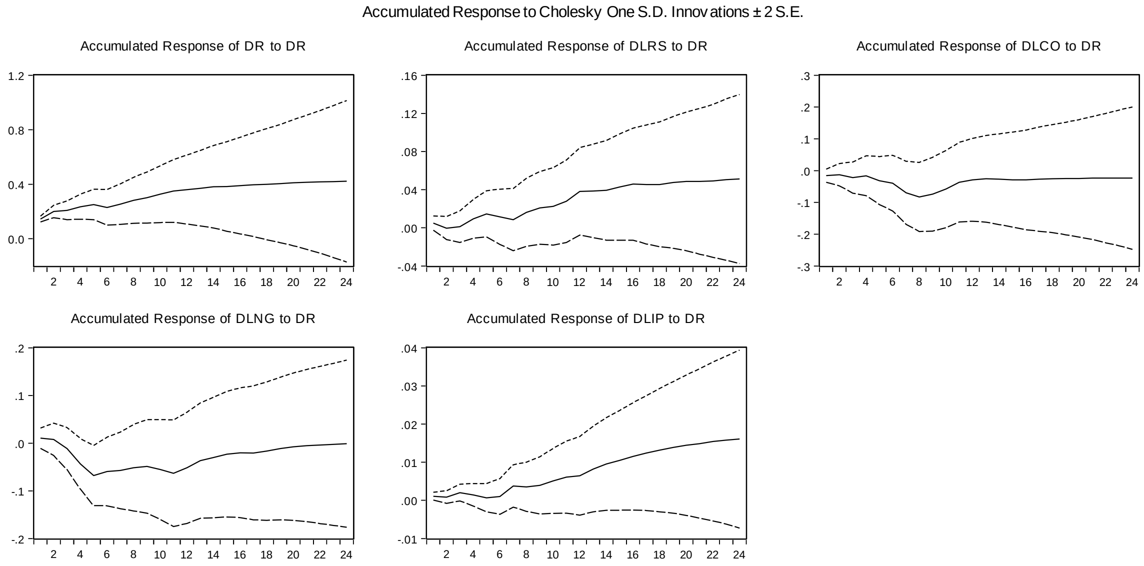


I.3. Subsample analysis for T-bill yield shock in Panel A

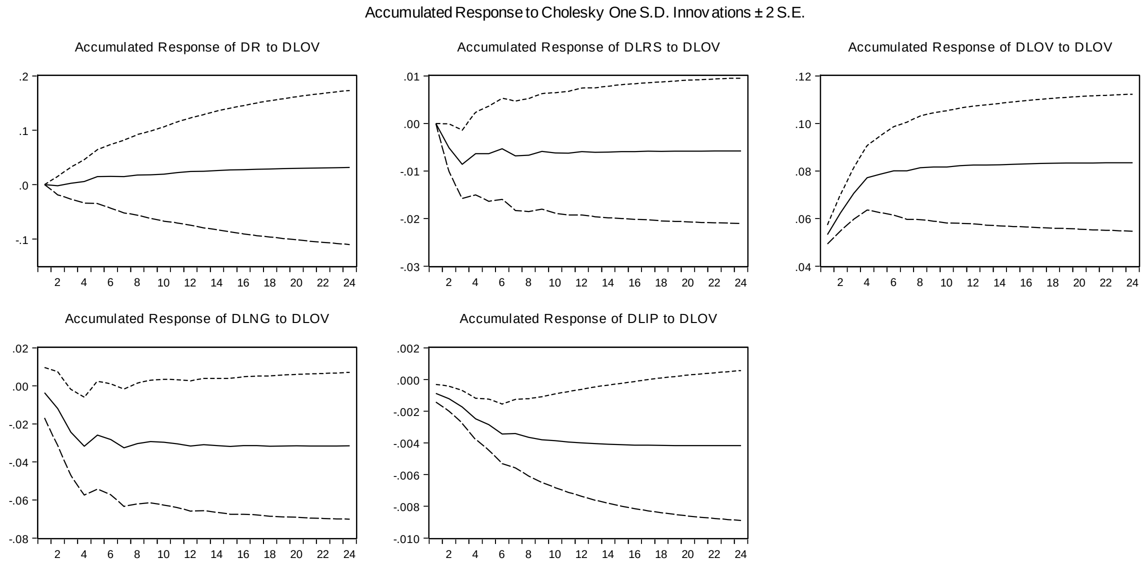
Pre-GFC (High discount rate regime)

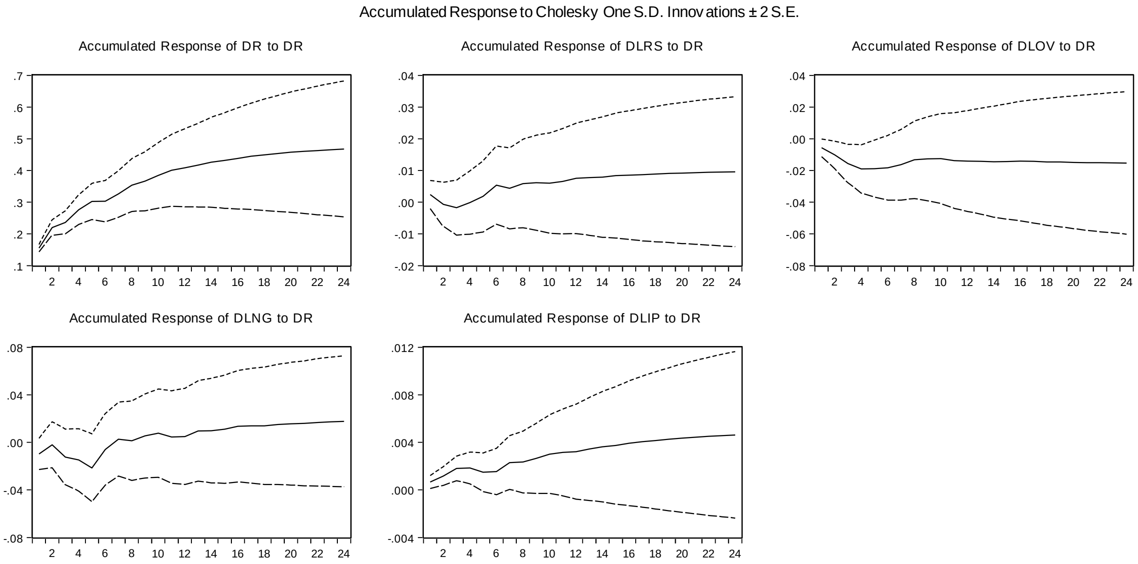


Post-GFC (Low discount rate regime)



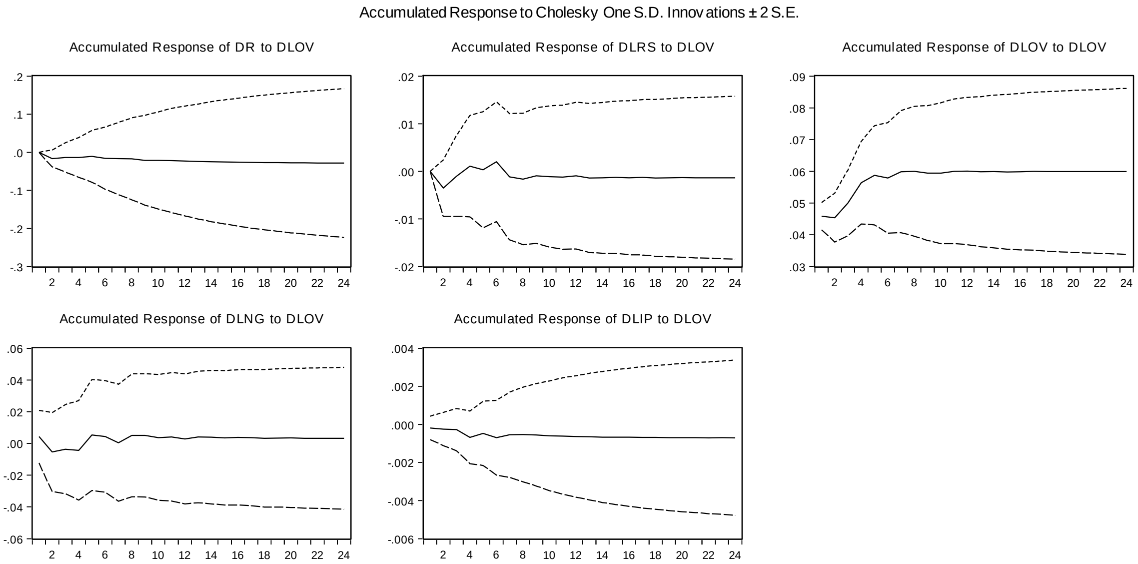
II. Accumulated impulse responses of crude oil volatility and T-bill yield shocks in Panel B:



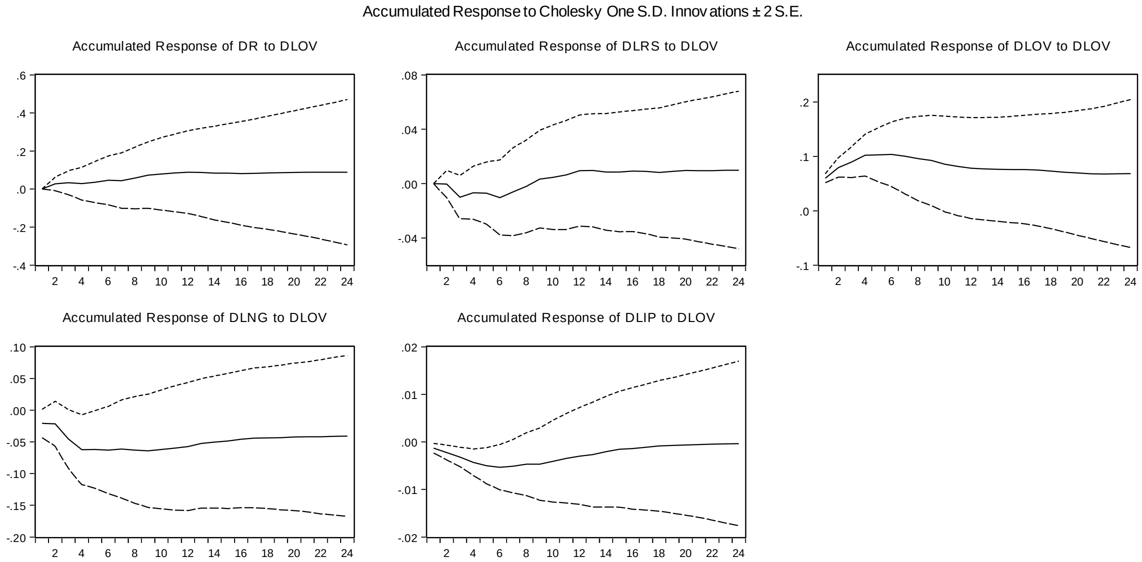


II.1. Subsample analysis for crude oil volatility shock in Panel B

Pre-GFC (High discount rate regime)

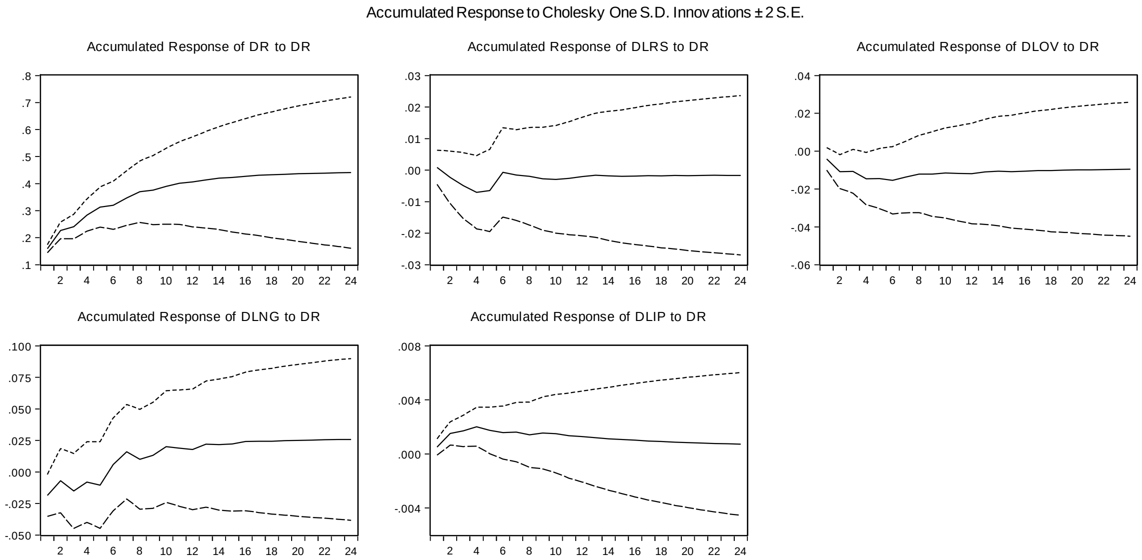


Post-GFC (Low discount rate regime)

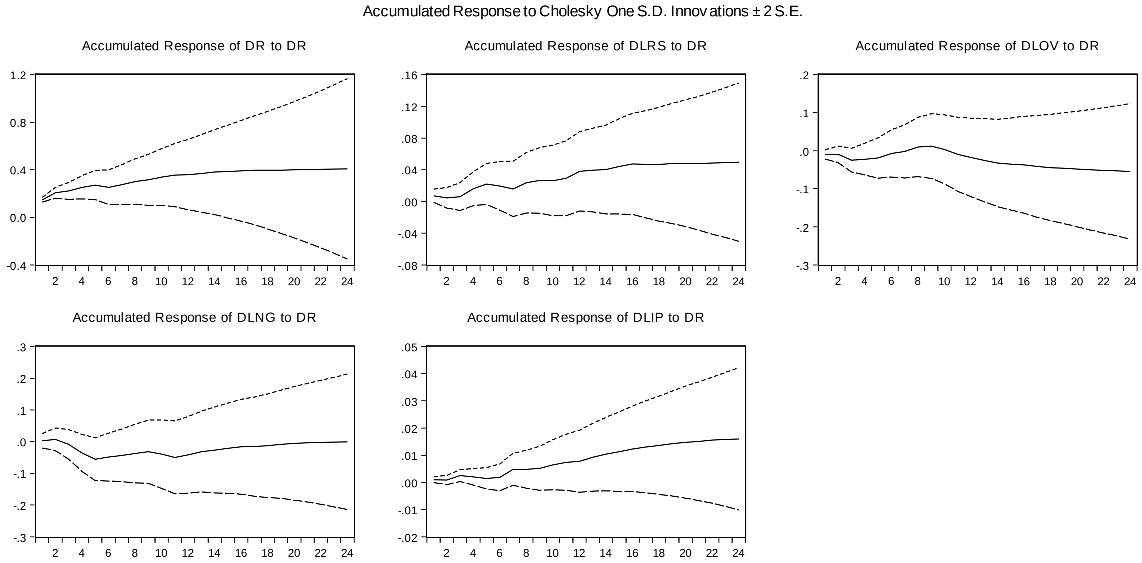


II.1. Subsample analysis for T-bill yield shock in Panel B

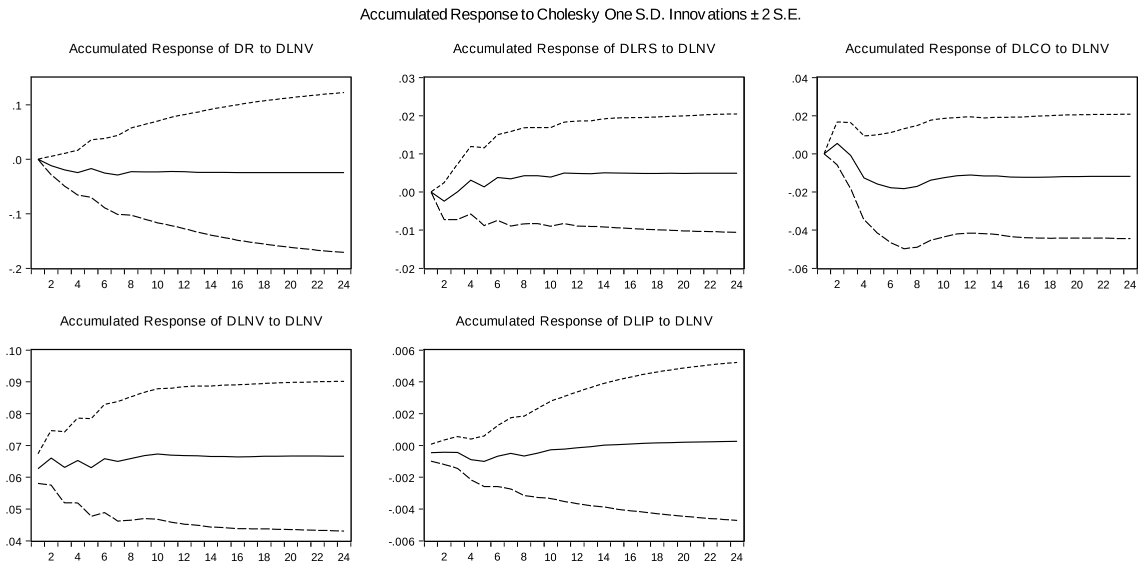
Pre-GFC (High discount rate regime)



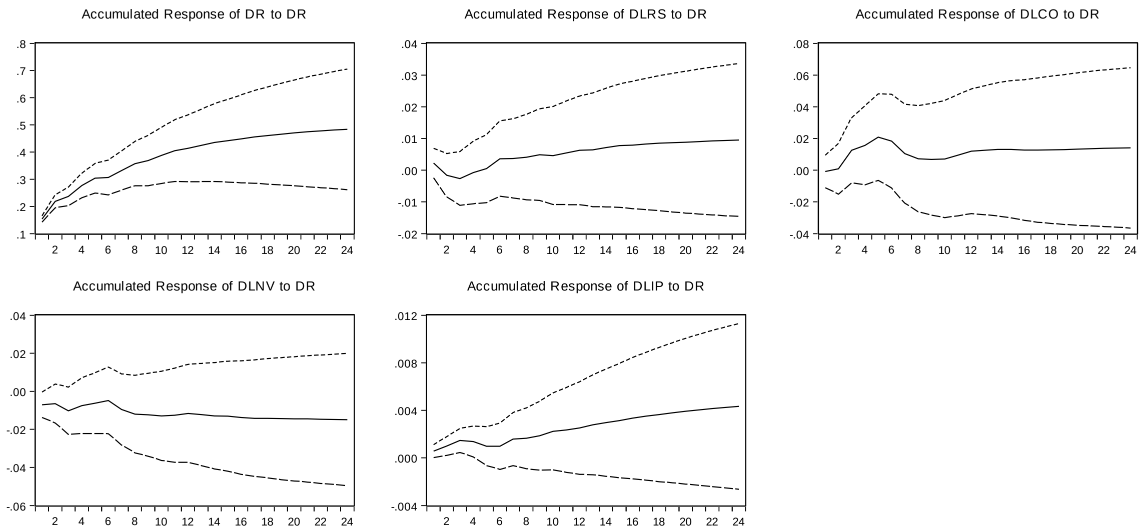
Post-GFC (Low discount rate regime)



III. Accumulated impulse responses of natural gas volatility and T-bill yield shocks in Panel C:



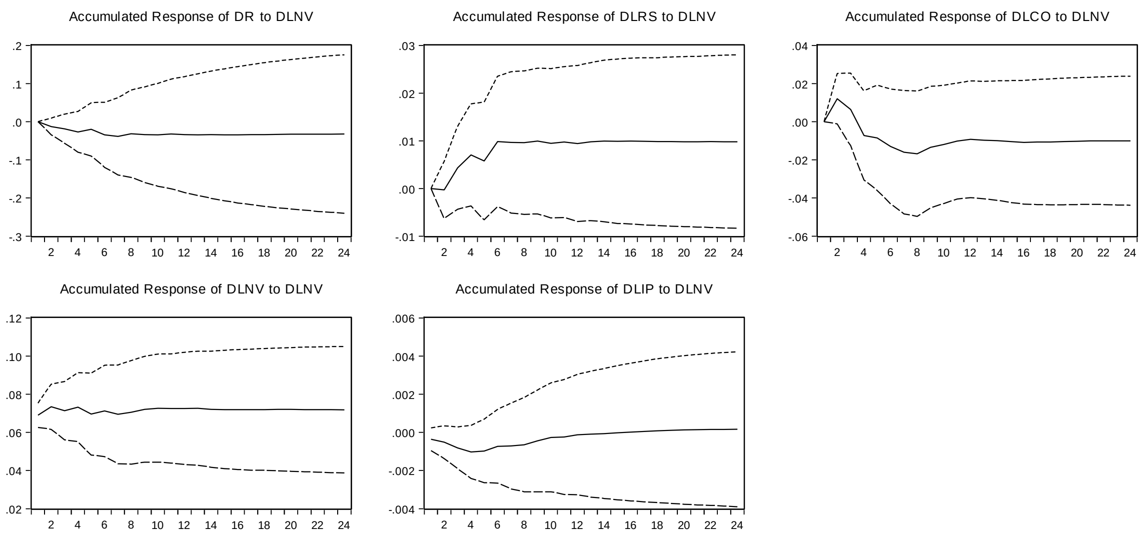
Accumulated Response to Cholesky One S.D. Innovations ± 2 S.E.



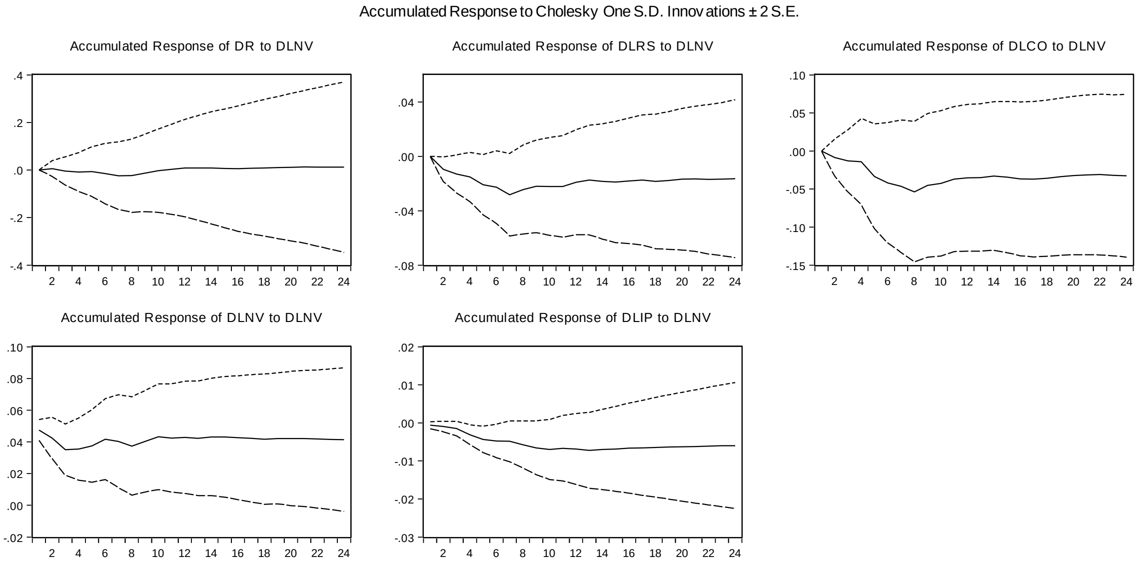
III.1. Subsample analysis for natural gas volatility shock in Panel C

Pre-GFC (High discount rate regime)

Accumulated Response to Cholesky One S.D. Innovations ± 2 S.E.

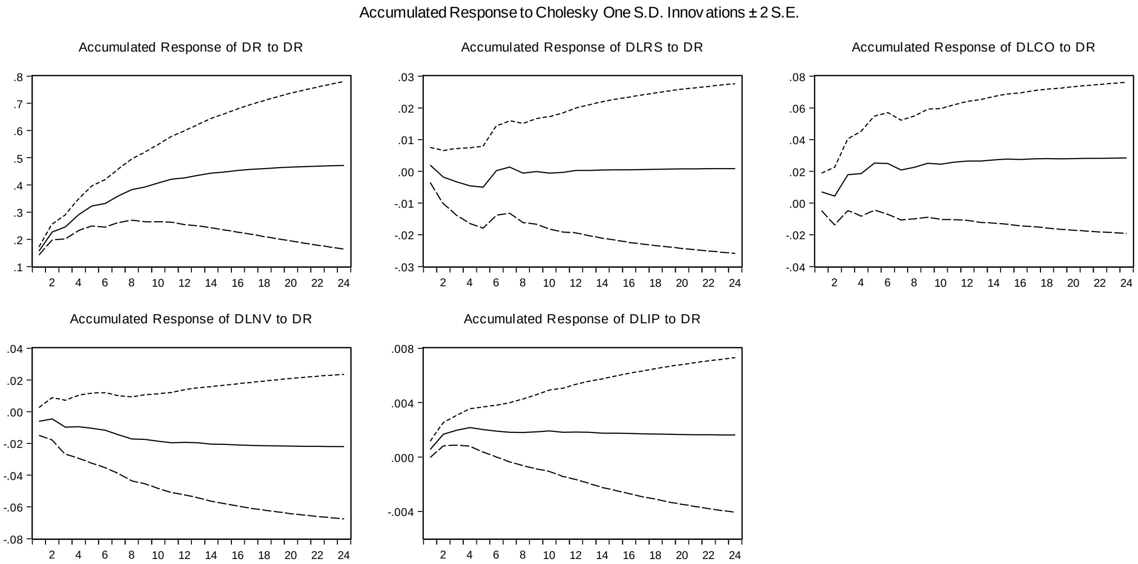


Post-GFC (Low discount rate regime)

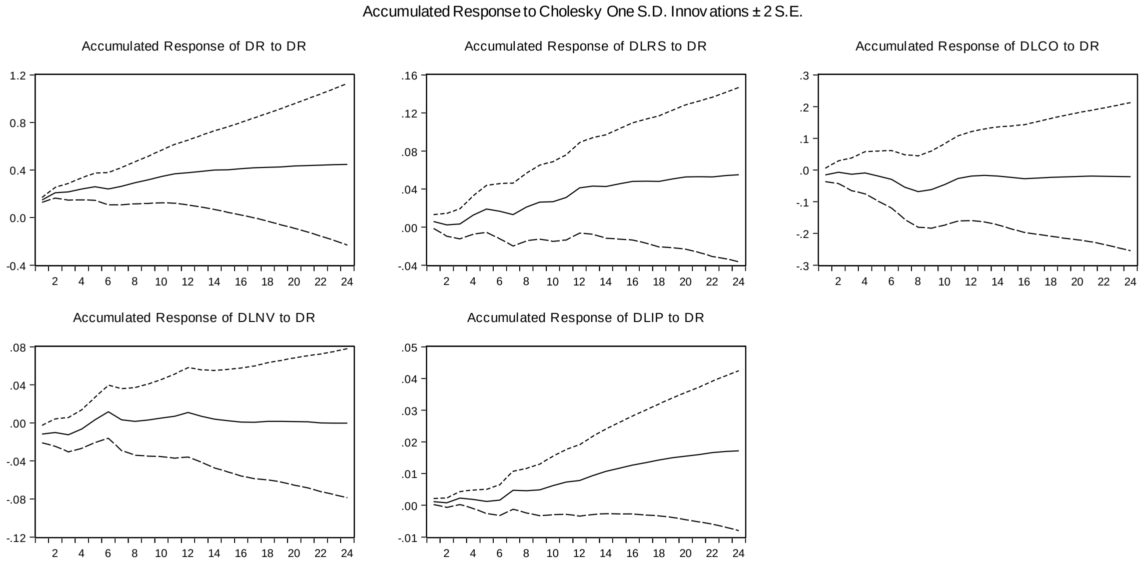


III.1. Subsample analysis for T-bill yield shock in Panel C

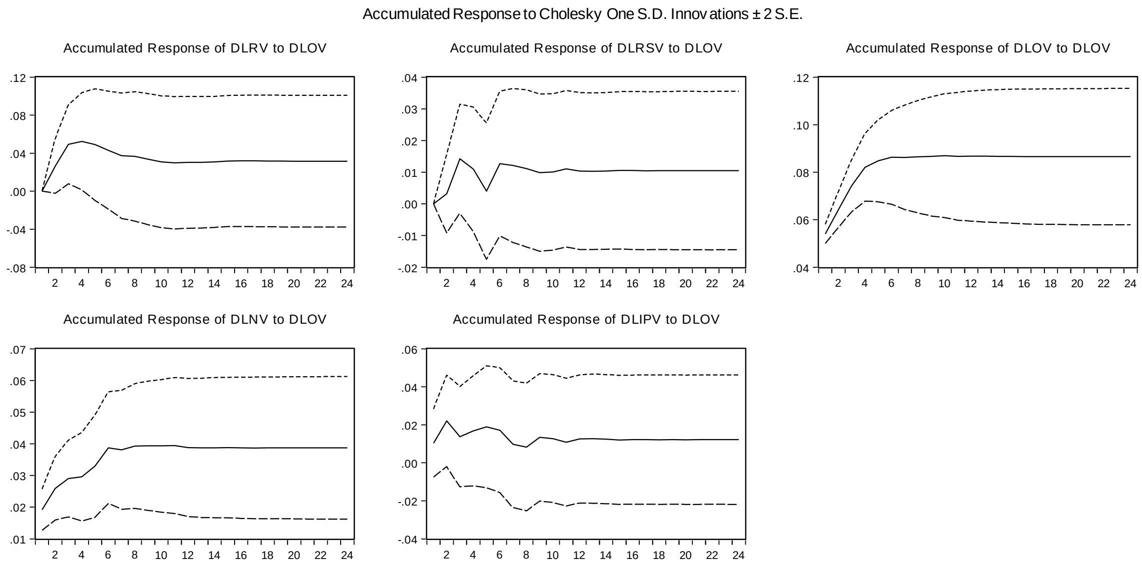
Pre-GFC (High discount rate regime)



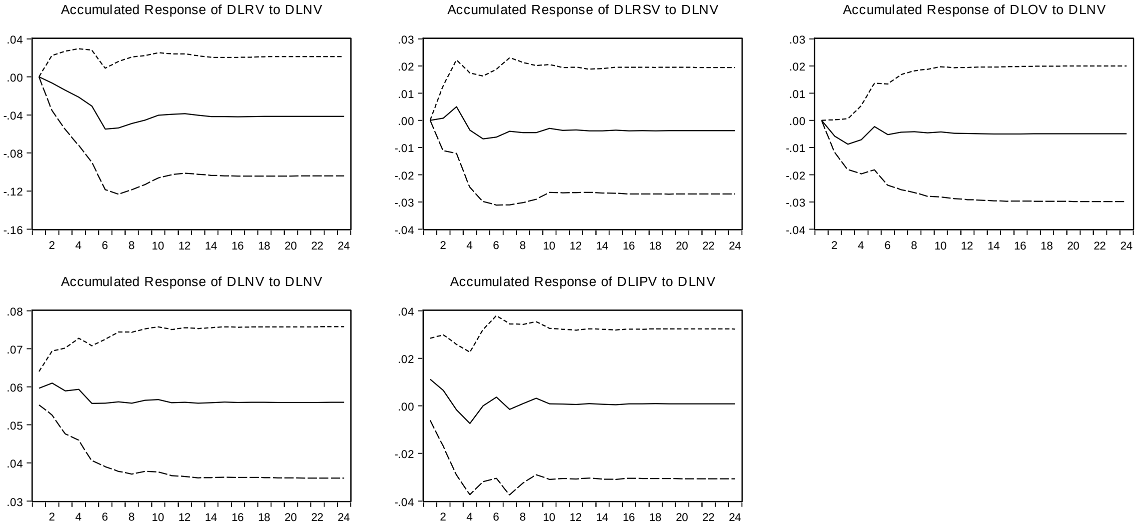
Post-GFC (Low discount rate regime)



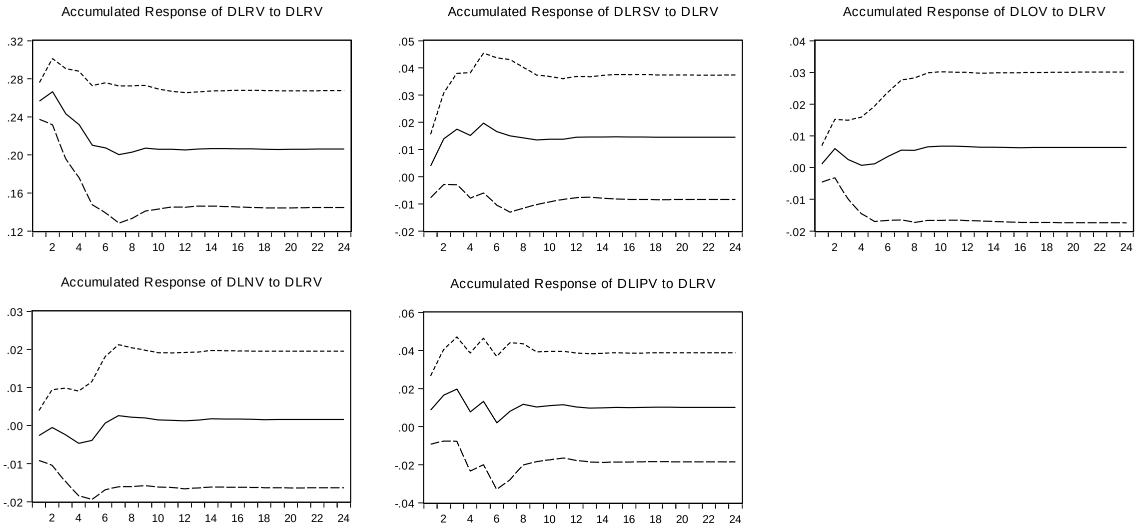
IV. Accumulated impulse response of volatility shocks of crude oil, natural gas, and T-bill yield in Panel D



Accumulated Response to Cholesky One S.D. Innovations ± 2 S.E.

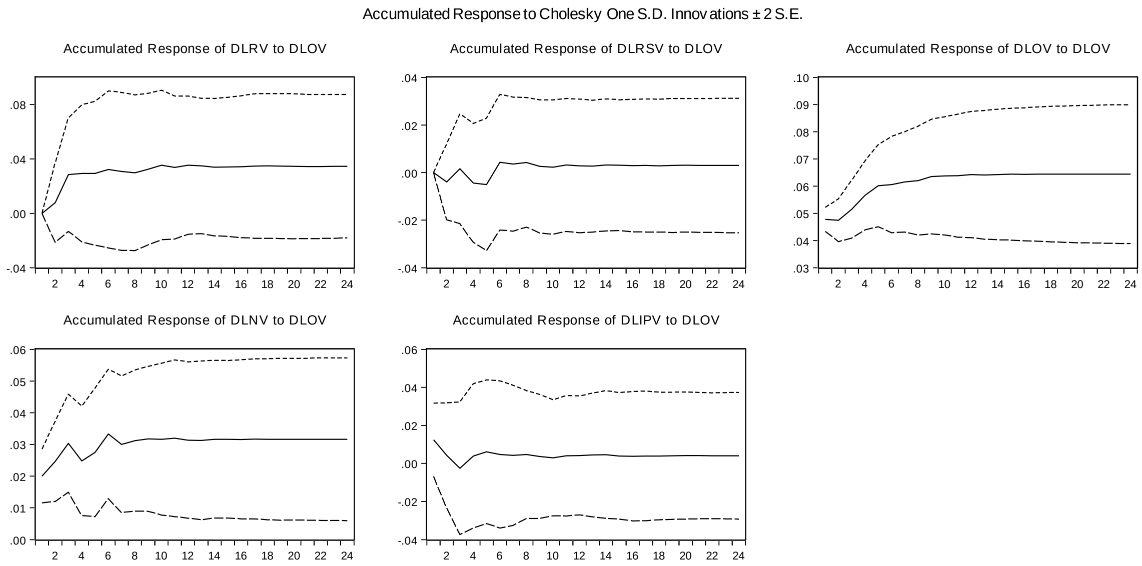


Accumulated Response to Cholesky One S.D. Innovations ± 2 S.E.

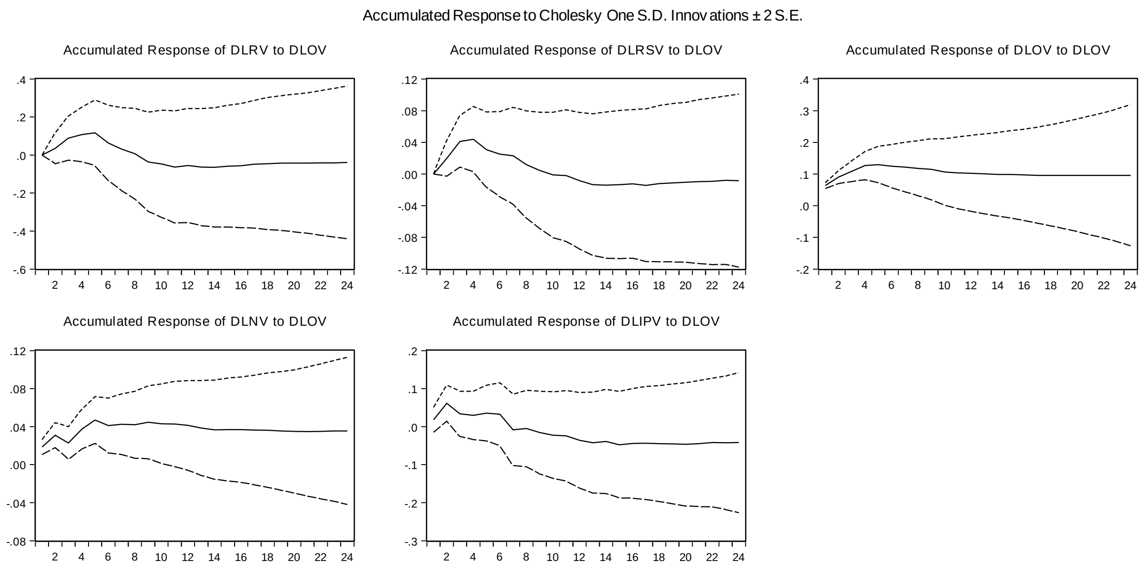


IV.1. Subsample analysis for crude oil volatility shock in Panel D

Pre-GFC (High discount rate regime)

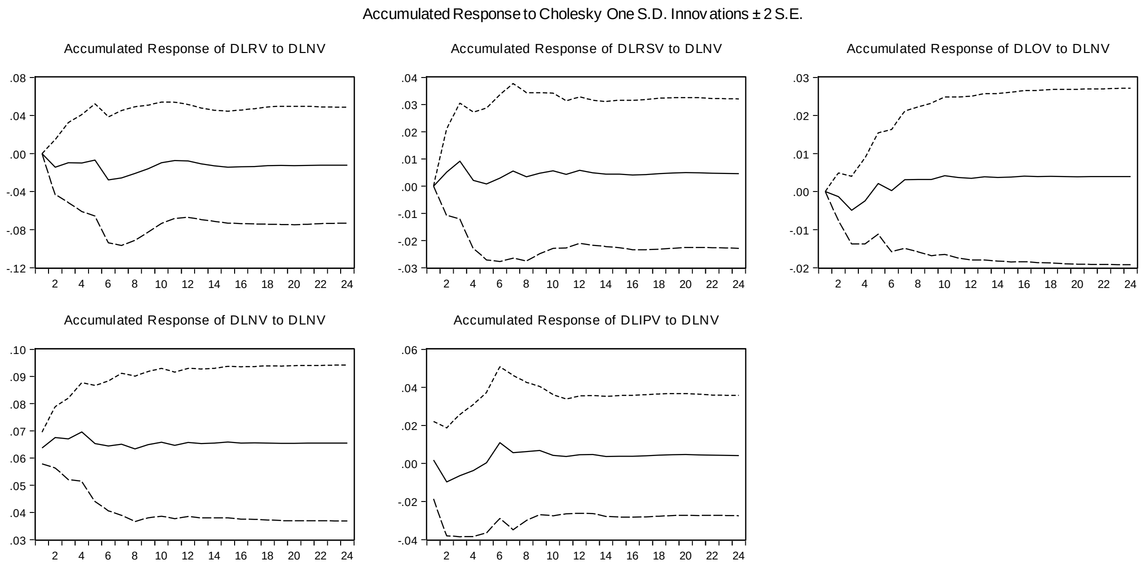


Post-GFC (Low discount rate regime)

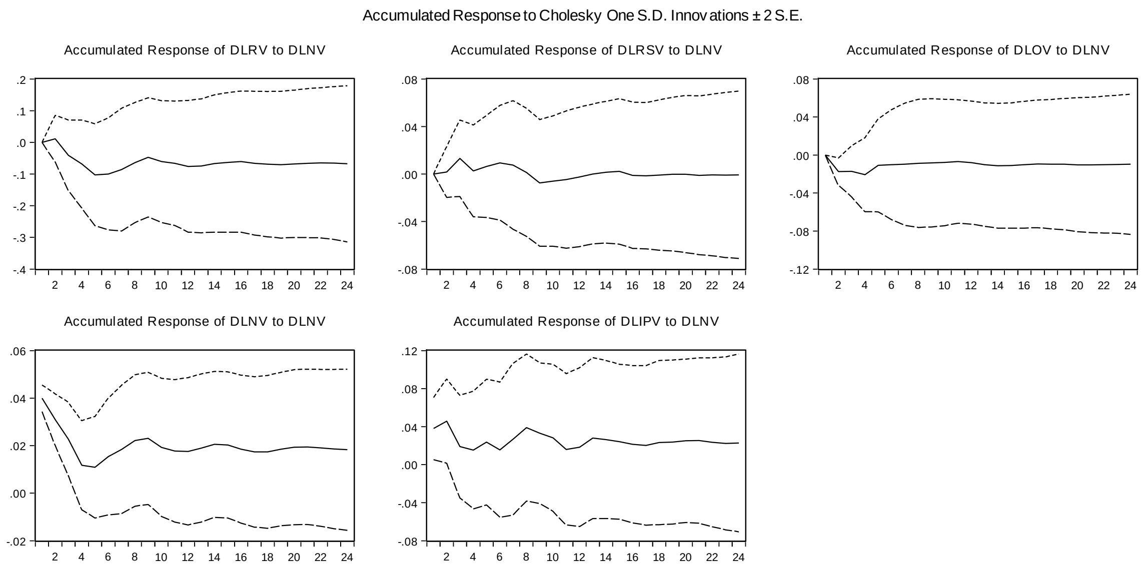


IV.2. Subsample analysis for natural gas volatility shock in Panel D

Pre-GFC (High discount rate regime)

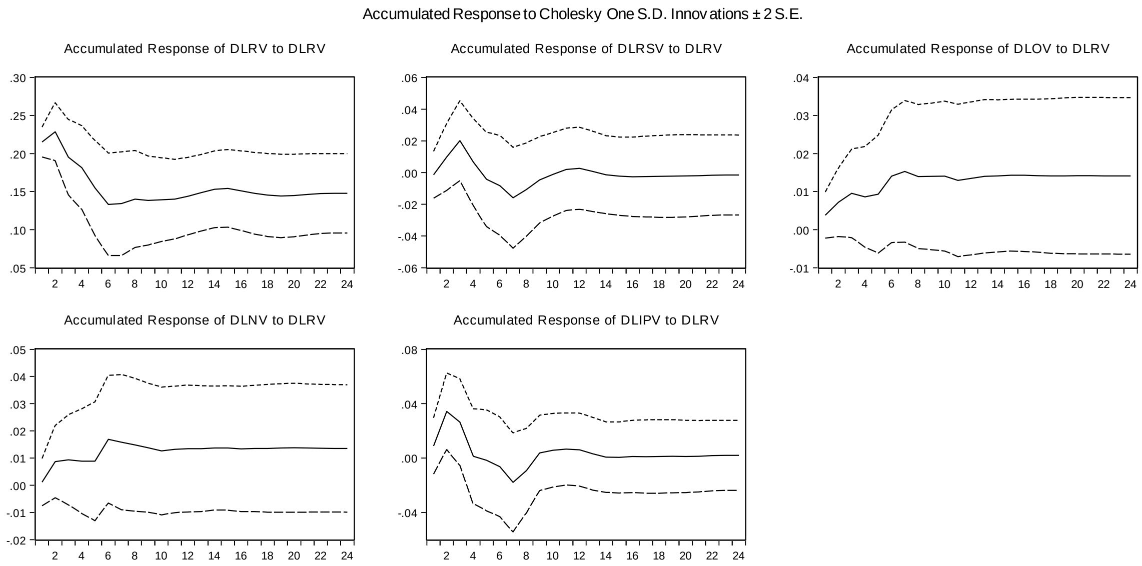


Post-GFC (Low discount rate regime)

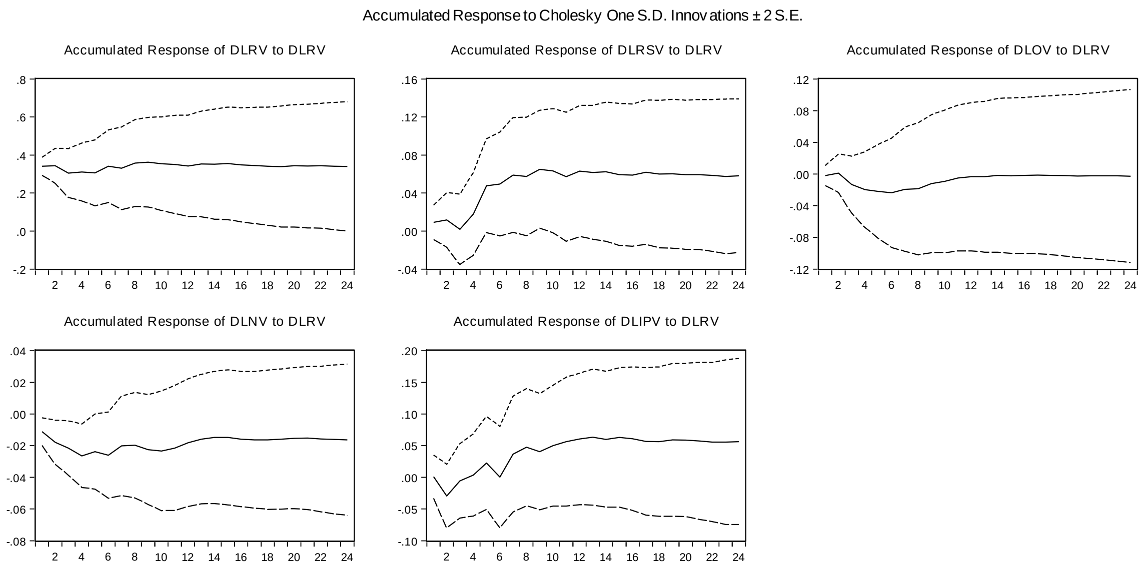


IV.3. Subsample analysis for T-bill volatility shock in Panel D

Pre-GFC (High discount rate regime)



Post-GFC (Low discount rate regime)



V. Example of options market implied volatility skew and sensitivity

V.1. Implied volatility skew due to asymmetric relation between return and volatility of US 10-year treasury note

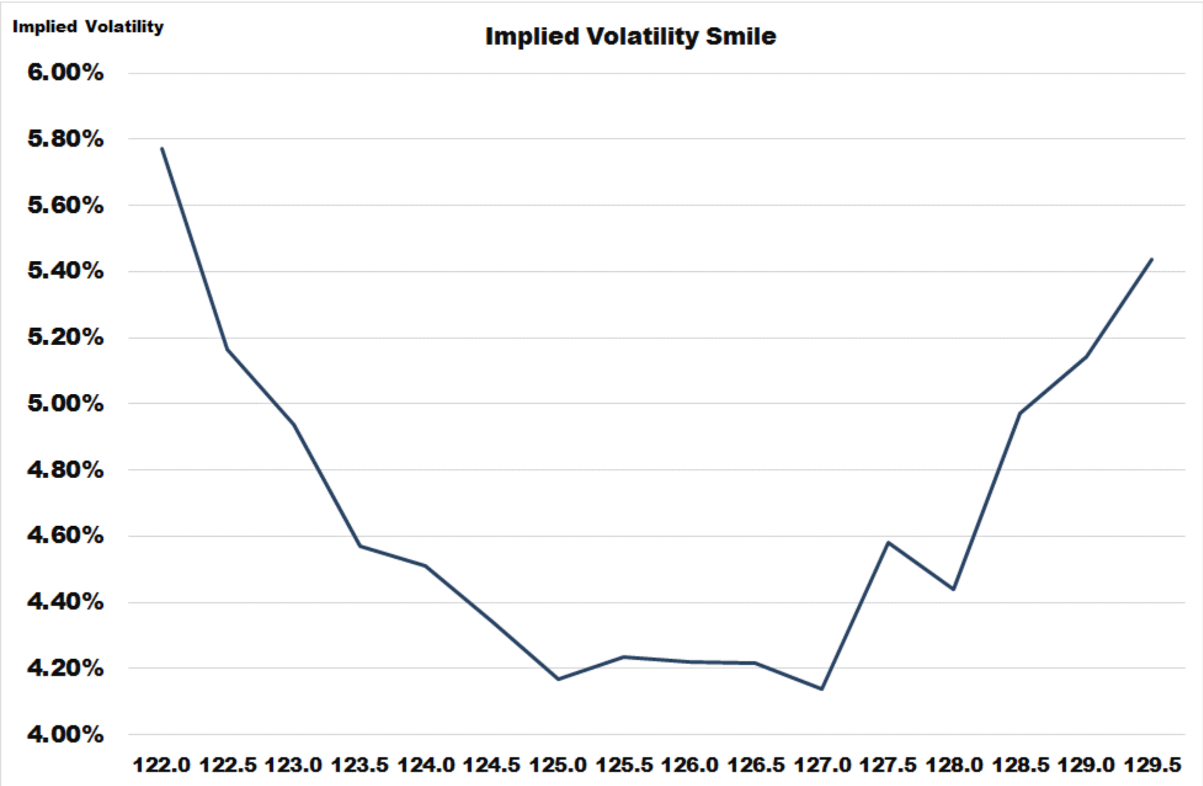
Pricing model: Black-Scholes

Product: 10-Year T-note

ATM at 126

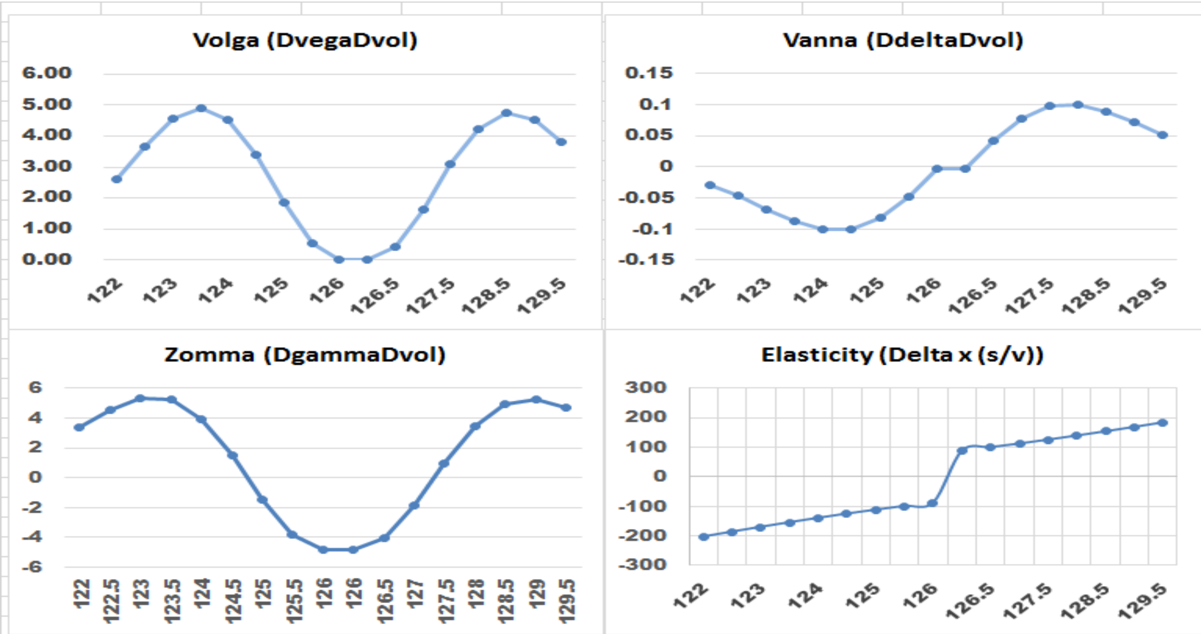
Volatility: 4.6%

Time To Maturity: 30 days

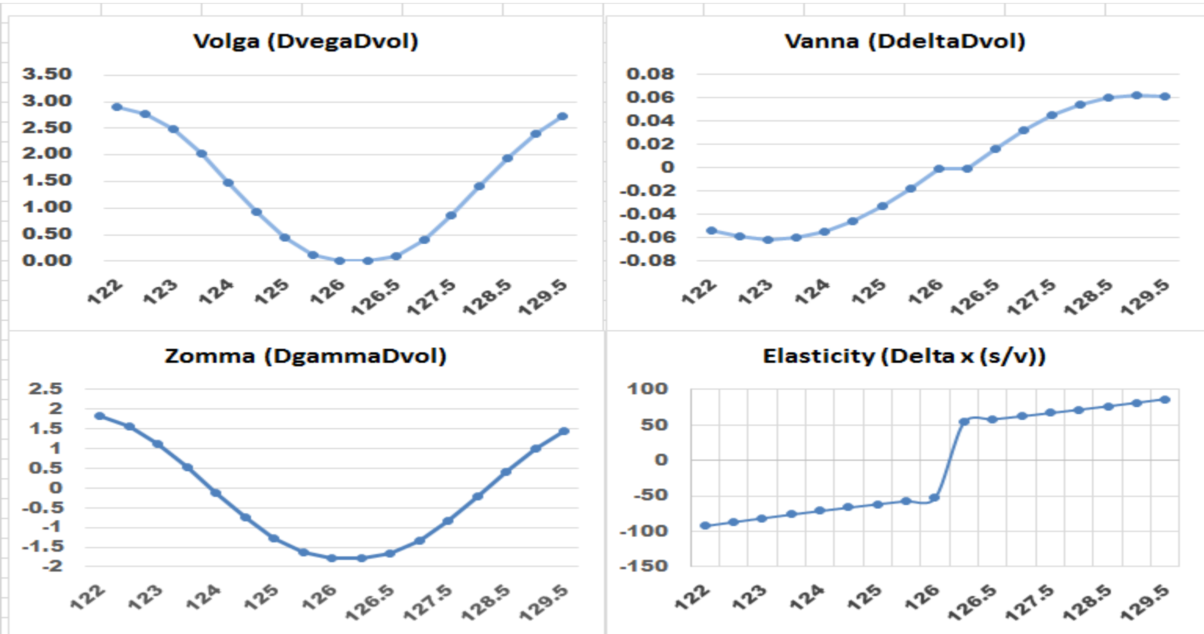


V. 2. Comparison between low volatility and high volatility on options sensitivities

Low volatility at 4.6%



High volatility at 7.6%



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