CBOE Crude Oil Volatility Index &Effects On The American Economy – VAR Based Causality Analysis

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Abstract

It is a layman belief that macroeconomic performance affects oil price stability and not the other way round. This paper attempts to empirically investigate how Crude Oil Price Volatility affects the two pillars of macroeconomic performance i.e., Inflation and GDP Growth in the case of the United States of America. The study uses a Vector Auto-Regression (VAR) system in Stata and undertakes a combination of Granger Causality Tests for the period of January, 2017 - September, 2021 using monthly data points. We find that there exists a bi-directional causal relationship between real GDP growth and oil volatility, while inflation did not express empirically any relationship with the above variables. We then discuss theoretical evidence to bolster our empirical findings and analyze them thoroughly.

KeyWords: Oil Price Volatility, Macroeconomic performance, Vector Auto-Regression

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INTRODUCTION

Oil is one of the prime commodities that forms an integral part of the business undertaken by almost every economy around the globe. Not just valuable as a final product, it also makes for an important input in multiple production processes across the economy. Consequently, its price is sensitive to a host of macro, micro and behavioral factors. More so, at a time when a majority of the Organization of the Petroleum Exporting Countries (OPEC) have been battling with internal instability and Covid-19 has significantly slowed down or altogether halted the processes of production and/or physical trade. Theoretical explanations for how variations in Oil Price translate to changes in economic growth have varied historically (Farhani, 2012) and empirical studies like Hamilton (1983) have largely concluded the relationship to be asymmetric. A breakpoint in this change of relationship in the USA is also attributed to a regime change around 1973, as been considered synonymous with rising uncertainty which in turn delays investment and may reduce aggregate output of the economy as a whole, Guo & Kliesen (2005).

Guo & Kliesen (2005) find that volatility based on daily crude oil futures prices has a negative effect on future GDP growth for a period of 1984-2004 in the United States. Rafiq, Salim and Bloch (2008) conclude a similar result of oil price volatility as reduced investment in the case of Thailand i.e., an emerging economy for the period of 1999-2004. Rafiq and Salim (2011) also conducted a similar study for India, China, Indonesia, Philippines, Malaysia and Thailand with almost similar results. Inderwildi (2014) then also concluded that, similar to independent country studies, Oil Price Volatility has a destabilizing macroeconomic impact on the world economy as a whole due to interconnectivity of trade and faster

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volatility, a measure of Realized Volatility or Realized Variance in daily Crude Oil Prices is created. This paper shall instead be novel in the field by way of using an index created by the Chicago Board of Exchange, referred to as the CBOE Crude Oil ETF Volatility Index. It is an estimate of the expected 30-day volatility of crude oil as priced by the United States Oil Fund. To study the impact on macroeconomic performance of the United States, only two major indicators i.e., GDP Growth and Inflation are included. As iterated by Salim & Rafiq (2011), inclusion of a number of macroeconomic variables together can lead to multicollinearity and in a small time series sample, as is our case, can also result in a model misspecification error. To avoid both, only these two macroeconomic indicators are taken, since they can sufficiently translate to better or worse macroeconomic performance as a whole.

There has been sufficient literature around why or more specifically, how oil price changes transmit adverse effects on macroeconomic indicators and what these transmission channels might possibly be. Farhani (2012) focuses especially on oil price increases and what role these might play in the effects recorded on the economy by way of six channels. The most notable explanation is that oil price increases in the first place because there is rising demand for oil or rising intermediate consumption cost in the production process or both simultaneously. This might also happen in the case of lower productivity in comparison to demand, which further might be attributed to depletion of natural sources like oil wells. He presented a second inspired argument that an increase in oil price will translate to a greater transfer of income from oil importing nations to oil exporting ones, since the latter have a lesser tendency to consume oil themselves. This leaves the exporters better off in terms of trade balance and the importers worse off.

The third argument is for how these oil price increases translate to higher inflation. Increase in oil and all oil related products' prices will raise the general level of inflation which will affect people's purchasing power. This will lead to workers asking for higher wages as compensation, leading to a second-round effect on prices, since increased wages once again increase the costs of production. The fourth channel, building on the third, explains how once households' purchasing powers are affected due to rising inflation and uncertainty, the spending and consumption patterns of micro agents might also get altered. As a consequence, both consumption of durable goods and expenditure on long term capital investments will decrease since these are directly related to incomes. On very similar lines, Bernake (1983) explained how increasing uncertainty about the oil price i.e., increase or decrease, can lead to producers avoiding huge investments and waiting the period out. This decline in tendency to invest, then transmits to different sectors of the economy, negatively affecting the entire performance as a whole.

The fifth channel as cited by Farhani (2012) is an increase in monetary supply by the central banks since increase in oil prices will generate a more than usual monetary demand. The final channel, that results in a reallocation of sector-wise capital and labor resources, stems from the explanation that as profitability of oil-centric sectors decreases, production patterns will have to be altered and newer strategies adopted. Studies like Hamilton (1988) and Lilien (1982), however, have shown that oil price shocks can lead to rising aggregate unemployment, more so when these shocks become variable. This is because the labor in uncertain sectors would still wish to believe this shock is temporary and wait the period out than go out and search for employment opportunities in better performing sectors.

While oil price shocks have made for more specific research in the past, Oil Price Volatility as a daily phenomenon still does not have very wide-ranging literature available on it. In contrast to most of the previous studies that use a standard deviation measure of daily crude oil prices, this study uses an index that is a relatively recent creation. Thus, we also study a newer time period in the context of the USA, including years of the start of Covid-19. While the USA is a developed economy, and there has been substantial research in this field surrounding developed nations, we chose this country since it was the world's second largest consumer of energy after the People's Republic of China, consuming 94 quadrillion BTU of primary energy as of 2012 Taghizadeh-Hesary & Yoshino (2015). Just like oil consumption and its price changes have been proven integral to other parts of the economy, USA's performance and its relationship with its crude oil is fundamental to other countries and its trade partners around the globe. Hence, understanding the causality effects of oil price volatility shall make an interesting read and augment the existing literature. The paper specifically attempts to examine the following null hypothesis:

***H_0*: Oil Volatility does not significantly impact Inflation and Real GDP growth**

We are mainly interested in doing a causality analysis in the light of available theoretical background. To achieve this objective, the paper is further divided into 3 sections. Section 2 describes the data and methodological framework used along with VAR model setting. Section 3 records our analysis of the results of causality of underlying variables and Section 4 concludes the paper.

2. DATA, METHODOLOGICAL FRAMEWORK AND VAR MODEL SETTING

We mainly try to explore the relationship between oil volatility, inflation and real GDP. Oil volatility (*oilvol)* is represented by the Monthly Average of CBOE Crude Oil ETF Volatility Index. We represent inflation through the monthly average of Trimmed Mean PCE Inflation Rate (Seasonally Adjusted). Finally, we look at real GDP change through the monthly average of the Brave-Butters-Kelley Real Gross Domestic Product (Seasonally Adjusted) (*bbk)*. The Brave-Butters-Kelley Index, first illustrated by the Chicago Fed in 2019 is constructed from a panel of monthly macroeconomic time series and quarterly real gross domestic product growth[1]. The data is gathered for the three variables from January, 2017 - September, 2021 using monthly data points. To explore the interlinkages between the above variables, we utilize a Vector Autoregression (VAR) after carefully controlling for the stationarity of the underlying series and establishing the optimal lags by minimizing the joint Akaike Information Criterion (AIC) and Bayesian or Schwartz Information Criterion (BIC) scores. Once the VAR model with optimum lags is set, we run Granger Causality tests to appreciate the feedback mechanism between the involved variables, interchanging them as endogenous and exogenous variables to exhaust all options before finalizing the results. We are restricting ourselves to causality analysis and refraining from forecasting and structural specification and estimation including Impulse response analysis and forecast error variance decomposition (Sahlan (2017)). The study is restrictive in that sense.

In the first step, we checked for the stationarity of the underlying series. Inflation presented some concerns and we investigated non-stationarity of inflation using Augmented-Dicky-Fuller test. We used the first order differences of inflation (*dinflation)* to ensure stationarity, since inflation displays non-stationarity.

As a second step, we tried to establish the optimum lags to establish the autocorrelation of the involved three variables viz. oilvol, dinflation and bbk. We ran the series on Python to ensure minimization of the joint score of AIC, HQIC and SBIC. We observed that the optimal number of lags for our model is 3 (Observe the asterisk where *Final Prediction Error* (FPE) and *Akaike Information Criterion* (AIC) are minimized). The results are summarized below in Table 1.

[1] https://www.chicagofed.org/publications/chicago-fed-letter/2019/422

Table 1VAR model Lag Selection order-criteria

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-379.139				367.505	14.4204	14.4632	14.5319
1	-332.907	92.466	9	0.000	90.2492	13.0153	13.1869	13.4614
2	-280.992	103.83	9	0.000	17.9384	11.3959	11.6961*	12.1766*
3	-271.604	18.775*	9	0.027	17.839*	11.3813*	11.8102	12.4966

Source: Stata Output; Log Likelihood; LR: Likelihood Ratio; FPE: Final Prediction Error; AIC: Akaike Information Criterion; HQIC: Hannan-Quinn Information Criterion; SBIC: Schwartz Bayesian Information Criterion

Hence, we employ a VAR (3) model in accordance with the lag-length criterion of Akaike Information Criteria (AIC). We, then, applied the Lagrange Multiplier Test for Autocorrelation of the residual terms. The initial hypothesis is that there is no correlation in the residual terms at the given lags. However, autocorrelation is evident if the probability value at a given lag is less than 5%. It is quite evident in our data that there is no observed evidence to reject the null hypothesis of no autocorrelation since all p-values are greater than 5% (See table 2). So, none of the values fall in the rejection region.

Table 2 Lagrange Multiplier Test to check autocorrelation of lagged error terms

lag	chi2	df	Prob > chi2
1	9.2257	9	0.41671
2	13.1068	9	0.15783
3	14.1922	9	0.11565

Source: Stata Output

We contend, based on our examination, that the VAR (3) model we set up is stable through the eigenvalue stability condition.With the initial diagnostics of our VAR (3) model figured out, we now step into running Granger Causality tests with the involved variables to understand the feedback mechanisms that explain the results of our model and review the data closely to understand the theoretical backing behind our empirical results.

3. RESULTS AND ANALYSIS

The VAR (3) model displays several relationships deserving specific examination. Analyzing the relationship between *bbk* and *dinflation*, all three lag coefficients are negative when regressing *bbk* on *dinflation* while the three lag coefficients are near zero when regressing *dinflation* on *bbk*. When *oilvol* is regressed in *dinflation*, all three lag coefficients express very large values, but also display very high standard errors.

Table 3VAR (3) Model: Dependent Variable: OilVol

	Coeff.	Std. Err.	z	P>z	[95% Conf. Interval]	
oilvol						
oilvol						
L1.	.2267887	.2577783	0.88	0.379	-.2784474	.7320249
L2.	-.2960025	.2269203	-1.30	0.192	-.7407581	.1487532
L3.	.7615727	.2000038	3.81	0.000	.3695725	1.153573
dinflation						
L1.	38.2265	28.49798	1.34	0.180	-17.62852	94.08152
L2.	42.46203	29.36747	1.45	0.148	-15.09715	100.0212
L3.	25.28655	29.48818	0.86	0.391	-32.50922	83.08231
bbk						
L1.	-2.091745	.5812591	-3.60	0.000	-3.230991	-.9524977
L2.	1.396529	.5757044	2.43	0.015	.2681695	2.524889
L3.	-.3773481	.3406603	-1.11	0.268	-1.04503	.2903338
_cons	14.48753	5.600562	2.59	0.010	3.510625	25.46443

Source: Stata Output

Table 4VAR (3) Model: Dependent Variable: dinflation

	Coeff.	Std.Err	z	P>z	[95% Conf. Interval]	
dinflation						
oilvol						
L1.	-.0010129	.0014818	-0.68	0.494	-.0039171	.0018913
L2.	.0014651	.0013044	1.12	0.261	-.0010915	.0040217
L3.	-.0012973	.0011497	-1.13	0.259	-.0035506	.0009561
dinflation						
L1.	.0262568	.1638128	0.16	0.873	-.2948103	.3473239
L2.	-.0557797	.1688108	-0.33	0.741	-.3866427	.2750833
L3.	.0238871	.1695046	0.14	0.888	-.3083358	.3561101
bbk						

L1.	.0001965	.0033412	0.06	0.953	-.0063521	.0067452
L2.	.0009206	.0033093	0.28	0.781	-.0055654	.0074067
L3.	-.0018314	.0019582	-0.94	0.350	-.0056694	.0020066
_cons	.0417565	.0321933	1.30	0.195	-.0213412	.1048541

Source: Stata Output

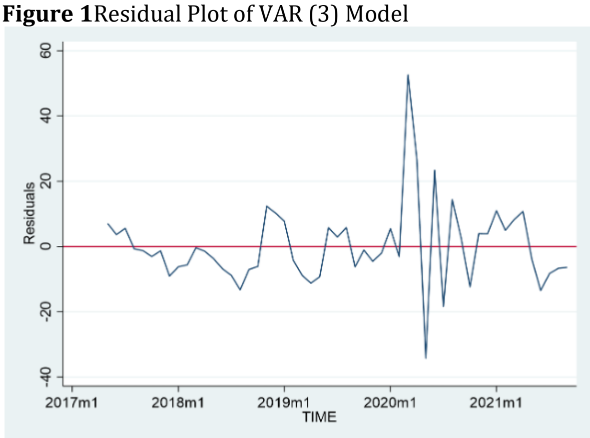
Table 5VAR (3) Model: Dependent Variable: bbk

	Coeff	Std. Er	z	P>z	[95% Conf. Interval]	
bbk						
oilvol						
L1.	.1061573	.1177527	0.90	0.367	-.1246338	.3369484
L2.	.2244201	.1036568	2.17	0.030	.0212565	.4275838
L3.	-.2456964	.0913614	-2.69	0.007	-.4247615	-.0666314
dinflation						
L1.	-23.76412	13.01783	-1.83	0.068	-49.2786	1.750371
L2.	-14.30552	13.41501	-1.07	0.286	-40.59846	11.98743
L3.	-8.74347	13.47015	-0.65	0.516	-35.14448	17.65755
bbk						
L1.	1.742221	.2655182	6.56	0.000	1.221815	2.262627
L2.	-1.063668	.2629809	-4.04	0.000	-1.579101	-.5482345
L3.	.2403736	.1556131	1.54	0.122	-.0646225	.5453697
_cons	-3.212425	2.558328	-1.26	0.209	-8.226656	1.801806

Source: Stata Output

To evaluate the residuals of the VAR (3) model as a sign of stability for the model and the fitting on the data, a residual plot is created as seen in Figure 1. The scatter adequately captures the randomness of the residual terms of our fitted model and indicates model stability.

Figure 1 Residual Plot of VAR (3) Model



The Granger-causality Wald tests are run and an interesting outcome is observed. There is a bidirectional predictional causality relation between real GDP and oil volatility of the United States, thereby meaning they granger-cause each other. The other variables display no such interlinkages of predictive causality.

Table 6 Granger Causality Wald Test

Equation	Excluded	chi2	df	Prob >chi2
oilvol	dinflation	4.8786	3	0.181
oilvol	bbk	17.4	3	0.001
oilvol	ALL	24.006	6	0.001
dinflation	oilvol	2.9143	3	0.405
dinflation	bbk	2.129	3	0.546
dinflation	ALL	4.786	6	0.572
bbk	oilvol	12.438	3	0.006
bbk	dinflation	5.1231	3	0.163
bbk	ALL	22.593	6	0.001

Source: Stata Output

Oil volatility has an impact on real economic activity through transmission channels of supply and demand. Our results come in line with the results of Mork (1989), Lee *et al.* (1995) and Hamilton (1996), as our results display granger causality and bi-directional relation between real GDP and oil volatility. Hamilton (2003) and Jiménez-Rodriguez (2004) found evidence of a non-linear relationship between oil prices and economic activity for the United States as well. Oil volatility impacts economies through the following two ways: One, the supply side effects consider the increase in production costs that coerces firms to lower output. Two, the demand side effects echo through consumption and investment (Jiménez-Rodriguez and Sánchez, 2004).

In our VAR (3) model, we observe that inflation does not have a granger-causality relationship (unidirectional or bidirectional) with either of the other variables. This is an interesting phenomenon. As discussed in Oriakhi and Osaze (2013), the relation between oil volatility and inflation also depends on whether the country in question is a net-exporting or a net-importing economy. The United States has had a transformative journey, having recently become a netexporter of oil in November 2019 (EIA, 2019), mainly due to the large discoveries of shale oil reserves in the US. Given such a drastic transformation in oil dependence along with strict monetary oversight post the 2008 crisis, inflation has been tightly kept in check. Hence the data does not reflect granger causality between either variables and inflation, given how various feedback and transmission mechanisms were heavily controlled or regulated. This can also be seen through the insignificant Z-values of *dinflation* related to both the variables in the VAR (3) model (See Table 4). In our empirical analysis, *bbk* is impacted significantly in a lagged manner, where the second and third lag of *oilvol* displayed higher z-values, suggesting a lagged impact on real GDP growth (See Table 5). However, *oilvol* is majorly impacted by recent GDP performance, showing very high significance of the first lag of *bbk* while the second and the third lag showing lesser effect (See Table 3).

4. CONCLUSION

Oil volatility has varying impacts on macroeconomic indicators both across countries and also time periods. Previous literature has documented multiple relationships between the two for both developing as well as developed nations. This paper uses a VAR (3) model combined with granger causality tests. We see a bi-directional relationship between Real GDP change and Oil Volatility and we also see that inflation has no predictive causal relation by either of them.

A primary shortcoming of this study is less data points due to the relatively new introduction of the Crude Oil Volatility Index and future research can incorporate a longer time period. Further we have restricted ourselves to the causality analysis and have not dwelled into forecasting and structural specification and estimation including Impulse response analysis and forecast error variance decomposition. Interested researchers may ask for the data points to the corresponding author. More Macroeconomic indicators can also be included as a part of the VAR model for a more comprehensive outlook if researchers deem fit, although that may make the model unwieldy.

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