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"Nikolaos Vlastakis, Athanasios Triantafyllou, Neil Kellard"

Essex Business School, University of Essex, Wivenhoe Park, Colchester, CO4 3SQ
Web site: http://www.essex.ac.uk/ebs/

Measuring Oil Price Shocks

Nikolaos Vlastakis[a†], Athanasios Triantafyllou[a,b] and Neil Kellard[a]

[a] *Essex Business School, University of Essex, UK*
[b] *SC Johnson College of Business, Cornell University, USA*

Abstract

The role of oil price shocks in US economic activity and inflation is controversial but a key input to current economic policy. To clarify these relations, we employ a more refined measure of oil shocks based on decomposing highly accurate realized volatility estimated using intraday oil futures data. In reconciling prior results, we find that shocks driven by price increases (decreases) are associated with rising (falling) inflation while only a symmetric volatility channel affects economic activity.

JEL Classification: G17, E2, E31, E32, Q43.

Keywords: Oil shocks, Jumps, Realized semivariance, Economic activity, Inflation.

† Corresponding Author, Essex Business School, University of Essex, Wivenhoe Park, Colchester, Essex, CO4 3SQ, UK (nvlast@essex.ac.uk); Tel: +44 (0) 1206 874591.

1. Introduction

We examine the impact and the predictive information content of oil price shocks on US economic activity and inflation. The results of the extant literature are inconclusive; some work finding an asymmetric condition whereby oil price increases have a more recessionary impact on the economy than the positive impact of oil price decreases (e.g., Hamilton, 2011; Kilian and Vigfusson, 2013), while others (e.g., Hooker, 1996) promulgate the breaking of the oil-macroeconomy relation. Moreover, another strand of the literature indicates that oil prices are among the key drivers of inflation (Choi *et al.*, 2018).

What might help explain the apparent inconsistencies in prior results? Previous studies often identify oil price shocks differently: as the log-difference of the nominal price of oil (Hamilton, 1983), as the net oil price increase (a monthly dummy variable which takes the value of one for positive price changes and zero otherwise – see Hamilton, 2003), or as the monthly realized volatility of daily oil price returns (Elder and Serletis, 2010). Each of these identification strategies has its own advantages, with the price-based measures able to capture any asymmetry in the oil-macroeconomy relation. Nevertheless, while isolated price shocks likely have a transient impact on the distribution of returns, shocks or jumps in volatility typically have a more persistent effect and can explain large market movements (Eraker *et al*., 2003; Eraker, 2004). This latter observation is reinforced by the finding that jumps in price and volatility tend to happen together (Jacod and Todorov, 2010).

To look more closely at the role of oil, in this paper we combine the identification strategies in the literature by identifying the shock as an asymmetric change in price volatility based on high-frequency (5-minute) oil futures data. Specifically, we decompose monthly realized volatility to the part attributable to positive and negative price changes (positive and negative semi-variance, respectively), as well as a signed jump component; hence a jump in volatility is driven by either positive or negative price changes. These asymmetric components of volatility can be directly linked to either increases or decreases in prices and therefore provide a more refined measure of oil price shocks, conflating the advantages of extant measures.

Our new results reconcile prior findings. While the oil-macroeconomy relation is shown still to operate, it does so primarily through a symmetric volatility channel to economic activity rather than via asymmetric changes. Conversely, shocks are significant predictors of inflation, with positive shocks predicting rising inflation and negative shocks predicting falling inflation.

2. Data and Methodology

2.1 Prices and volatility

For a more robust identification of oil price shocks, we use high-frequency (5-minute) prices for crude oil futures and the S&P 500 index.[1] Importantly, we have a long time series of data from January 1987 till December 2017. The 5-minute frequency ensures minimal microstructure noise without diminishing the accuracy of the estimator. We estimate realized variance (RV) by summing squared intraday logarithmic returns (filtered through an MA(1) process) following Andersen *et al.* (2001):

$$RV_t = \sum_{i=1}^{n} r_i^2 \tag{1}$$

[1] Intraday data are obtained from Pi Trading for the S&P index and from Tick Data for crude oil futures.

where $r_i = \log(p_i - p_{i-1})$, with p denoting the filtered price series and i the number of intraday observations in each period. We decompose RV into its continuous and jump components by first estimating realized bi-power variation[2] (BV), which captures the continuous component of RV, following Barndorff-Nielsen and Shephard (2006):

$$BV_t = \mu_1^{-2} \sum_{i=2}^{n} |r_i||r_{i-1}| \tag{2}$$

where $\mu_1 = \sqrt{2/\pi}$. The difference between RV and BV provides an estimate of the variation due to jumps:

$$JUMPOIL_t = RV_t - BV_t \tag{3}$$

To examine the asymmetric effects of jumps, we use positive and negative semi-variance (i.e., the part of variance due to positive and negative price moves) to construct signed jump variation following Barndorff-Nielsen *et al*. (2010):

$$\Delta J^2 = RS^+ - RS^- \tag{4}$$

with

$$RS^+ = \sum_{i=1}^{n} r_i^2 \, I\{r_i > 0\} \tag{5}$$

$$RS^- = \sum_{i=1}^{n} r_i^2 \, I\{r_i < 0\} \tag{6}$$

[2] Using the average of skip-0 through skip-4 bi-power variation as our estimate following Patton and Shephard (2015).

denoting positive and negative semi-variance, respectively, where *I* denotes the indicator function. We label OILRV, the monthly realized variance of crude oil from (1), OILTOTJUMP is the oil price variation due to jumps from (3), OILSIGNJUMP is the monthly oil price signed jump variation from (4), and OILPOSVAR and OILNEGVAR are the monthly positive and negative realized semi-variance from (5) and (6). We estimate the same set of measures for the stock-market i.e., SP500RV (S&P500 realized variance), SP500TOTJUMP (the jump component of SP500RV), SP500POSVAR and SP500NEGVAR (S&P500 positive and negative semi-variance) and SP500SIGNJUMP (S&P500 signed jump variation). We obtain monthly data for US Industrial Production (*IPI*), Fed funds rate (*FFR*) and US Consumer Price Index (*INFL*) from the FRED database.

2.2 Forecasting regression models

The multivariate models including macroeconomic fundamentals, oil and stock-market volatility are given in (7) to (11):

$$\ln\left(IPI_t/IPI_{t-1}\right) = a + b_1 INFL_{t-1} + b_2 FFR_{t-1} + b_3 \ln\left(IPI_{t-1}/IPI_{t-2}\right) + e_t \tag{7}$$

$$\ln\left(IPI_t/IPI_{t-1}\right) = a + b_1 INFL_{t-1} + b_2 FFR_{t-1} + b_3 \ln\left(IPI_{t-1}/IPI_{t-2}\right) + b_4 OILPOSVAR_{t-1} + b_5 OILNEGVAR_{t-1} + b_6 SP500POSVAR_{t-1} + b_7 SP500NEGVAR_{t-1} + e_t \tag{8}$$

$$\ln\left(IPI_t/IPI_{t-1}\right) = a + b_1 INFL_{t-1} + b_2 FFR_{t-1} + b_3 \ln\left(IPI_{t-1}/IPI_{t-2}\right) + b_4 OILTOTJUMP_{t-1} + b_5 SP500TOTJUMP_{t-1} + e_t \tag{9}$$

$$\ln(IPI_t/IPI_{t-1}) = a + b_1 INFL_{t-1} + b_2 FFR_{t-1} + b_3 \ln(IPI_{t-1}/IPI_{t-2}) + b_4 OILSIGNJUMP_{t-1} + b_5 SP500SIGNJUMP_{t-1} + e_t \tag{10}$$

$$\ln(IPI_t/IPI_{t-1}) = a + b_1 INFL_{t-1} + b_2 FFR_{t-1} + b_3 \ln(IPI_{t-1}/IPI_{t-2}) + b_4 OILRV_{t-1} + b_5 SP500RV_{t-1} + e_t \tag{11}$$

We also run analogous least-squares models with INFL as the dependent.

2.3 VAR model

Following and extending Kilian and Lewis (2011) who examine the endogenous interactions between oil price shocks, monetary policy responses, inflation and real output, we also estimate a 4-factor reduced-form VAR with the following ordering:

$$Y_t = [IPI_t \;\; INFL_t \;\; FFR_t \;\; OILSIGNJUMP_t] \tag{12}$$

3. Econometric results

Tables 1 and **2** present the regression results of the models shown in (7) to (11) for INFL and IPI, respectively.

[Insert Tables 1 and 2]

From **Table 1** we see that oil volatility changes attributed to price increases (OILPOSVAR) are positively correlated with subsequent inflation. More generally, while rising positive semi-variance is associated with rising inflation, rising negative semi-variance is associated with falling inflation. Notably, while the coefficient on signed volatility jumps (OILSIGNJUMP) is significantly positive, total jumps (those irrespective of the sign) contain no predictive information content for inflation.

Table 2 does not support an analogous asymmetric relation between oil and economic activity. Specifically, asymmetric oil price shocks (OILSIGNJUMP, OILPOSVAR, OILNEGVAR) are not significant predictors of IPI. Overall, our multivariate regression analysis indicates that shocks in the oil market, driven by increases in oil prices, are associated with increasing inflation and not with drops in economic activity. On the other hand, a rise in the general level of symmetric oil and stock-market volatility and jumps predict a fall in economic activity. These results are in line with literature showing rising stock-market volatility and oil price uncertainty has a dampening effect on economic activity (Elder and Serletis, 2010).

Figure 1 below depicts the Orthogonalized Impulse Response Functions (OIRFs) of IPI and INFL to a positive one standard deviation shock to OILSIGNJUMP, estimated using the model in Equation (12).

[Insert Figure 1]

Figure 1 reveals that a positive asymmetric oil shock has a positive and significant effect on INFL (i.e., a one standard deviation innovation in OILSIGNJUMP increases inflation by almost 7 basis points one month after the initial shock, with the effect remaining positive and significant for 3 months). Conversely, the effect of the same innovation has a sluggish and insignificant effect on

IPI growth. In particular, IPI growth initially decreases by about 2 basis points (after 1 month) and then increases 5 basis points after 3 months.

4. Conclusions

Are oil price shocks inflationary or recessionary or both? Although the extant literature is inconclusive, understanding these relations is a key input to current US economic policy. In this context, we newly identify oil price shocks by decomposing highly accurate realized variance estimated from intraday data. In reconciling prior work, our analysis shows that, whilst economic activity (as measured by industrial production) is affected via a symmetric oil price volatility channel, inflation is driven by asymmetric measures captured by semi-variance and signed jump variation.

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Table 1. Forecasting inflation using oil and stock-market jumps and volatility (1-month forecasting horizon).

	(7)	(8)	(9)	(10)	(11)
Const	0.007***	0.001***	0.001***	0.001***	0.001***
	(2.865)	(5.567)	(5.461)	(3.981)	(5.320)
INFLATION	0.373***	0.257***	0.370***	0.329***	0.269***
	(4.101)	(5.249)	(4.639)	(5.566)	(4.931)
FFR	0.001***	0.015***	0.014	0.016***	0.016***
	(4.467)	(3.310)	(3.097)	(4.473)	(3.699)
IPI	0.002	-0.014*	-0.002	0.005	-0.011
	(0.541)	(-0.534)	(-0.103)	(0.218)	(-0.409)
OILRV					-0.004
					(-0.213)
SP500RV					-0.234***
					(-3.203)
OILPOSVAR		0.537***			
		(2.781)			
SP500POSVAR		0.001			
		(0.060)			
OILNEGVAR		-0.611***			
		(-3.717)			
SP500NEGVAR		-0.320**			
		(-2.034)			
OILTOTJUMP			-0.104		
			(-1.153)		
SP500TOTJUMP			-0.197*		
			(-1.664)		
OILSIGNJUMP				0.695***	
				(2.197)	
SP500SIGNJUMP				0.441	
				(1.390)	
% adj. R^2	20.6	33.5	21.2	29.4	29.1

Notes: *t*-statistics (reported in parentheses) are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, ** and *** denotes statistical significance at the 10%, 5% and 1% level respectively.

Table 2. Forecasting Industrial Production growth (1-month forecasting horizon).

	(7)	(8)	(9)	(10)	(11)
Const	0.0003	0.003***	0.001*	0.003	0.003***
	(0.359)	(3.675)	(1.898)	(0.404)	(3.788)
INFLATION	0.429	0.245	0.398	0.423	0.248
	(1.546)	(1.198)	(1.500)	(1.552)	(1.238)
FFR	0.004	-0.017	-0.014	-0.002	-0.017
	(0.032)	(-1.580)	(1.335)	(-0.021)	(-1.564)
IPI	0.215***	0.132*	0.167**	0.218***	0.133*
	(2.755)	(1.876)	(2.216)	(2.795)	(1.915)
OIL RV					-0.311***
					(-4.149)
SP500RV					-0.275***
					(-2.942)
OILPOSVAR		-0.285			
		(-0.910)			
SP500POSVAR		-0.382			
		(-0.691)			
OILNEGVAR		-0.169			
		(-0.323)			
SP500NEGVAR		-0.341			
		(-1.007)			
OILTOTJUMP			-0.579***		
			(-4.282)		
SP500TOTJUMP			-0.103		
			(-0.338)		
OILSIGNJUMP				0.077	
				(0.201)	
SP500SIGNJUMP				0.681	
				(1.341)	
% adj. R^2	7.6	14.6	10.8	7.4	15.0

Notes: *t*-statistics (reported in parentheses) are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, ** and *** denotes statistical significance at the 10%, 5% and 1% level respectively.

Figure 1. Orthogonalized Impulse Response Function (OIRF) of Industrial production growth and inflation to an asymmetric oil price shock.