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Which oil shocks are recessionary, and which are inflationary?*

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ABSTRACT

The role of oil price shocks in economic activity and inflation is a controversial but key input to economic policy. To examine these relations, we employ a refined measure of oil shocks based on decomposing realized volatility and estimated using intraday oil futures data. In new results, we find that asymmetric shocks driven by oil price increases (decreases) are *actually* associated with rising (falling) economic activity, particularly in the US case; while a symmetric volatility channel confirms that increasing oil price volatility negatively affects economic activity, particularly for the EU. Finally, we show that the inflationary effect of rising oil prices holds not only for the US economy, but for the rest of the world.

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1. Introduction

The impact of oil price fluctuations on US economic activity and inflation has been a widely discussed topic in the oil-macroeconomics literature. Historically, rising oil prices have been associated with subsequent economic recessions, with this relation demonstrating an asymmetry: oil price increases have a more recessionary impact on the economy than the positive impact of oil price decreases (Hamilton 2011; Kilian and Vigfusson 2017; Nguyen, Okimoto, and Tran 2022). Moreover, there is extant literature showing the significant macroeconomic effects of oil price uncertainty on the rest of the world, including G7, OECD and European economies (Cadena-Silva, Lara, and Fernández 2025).

On the other hand, another strand of the literature promulgates the breaking of the oil-macroeconomy relation (Bachmeier, Li, and Liu 2008). For example, Hooker (1996) shows that oil price shocks do not (Granger) cause US real output for the post-1973 period. In addition, while many studies identify an asymmetric relationship between oil prices and economic activity, some work provides evidence in favor of a symmetric relationship between oil prices and economic activity with increased oil price volatility resulting in falling US real output growth (Elder and Serletis 2010; Serletis and Xu 2019).

In summary, the results of the extant literature are inconclusive and contested. Several questions arise: do changes in oil prices and/or volatility help us predict economic activity or inflation, or both? And 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 price-based measures able to capture any asymmetry in the oil-macroeconomy relation.

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Nevertheless, while isolated price shocks may 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 2004; Eraker, Johannes, and Polson 2003). This latter observation is reinforced by the finding that jumps in price and volatility tend to happen together (Jacod and Todorov 2010). Moreover, it is difficult to capture any asymmetric effect of oil price shocks based on low frequency price series, as commonly attempted thus far in the literature (Hamilton 2003; Lardic and Mignon 2008; among others). As suggested by the results in Kilian and Vigfusson (2017), such effects are only discernible for large price shocks, whereas oil price innovations tend to be quite small measured at the monthly and quarterly frequency (Edelstein and Kilian 2009).

To overcome this difficulty and in our first contribution to the literature, we identify oil price shocks using highly accurate realized variance estimated from the intra-day (5-minute) returns of nearby crude oil futures.¹ The use of realized variance allows us to conveniently evaluate a symmetric effect (i.e. any effect driven by changes in realized variance) and asymmetric effects that are captured by decomposing realized variance into semi-variance and signed jump variation. These asymmetric components can be directly linked to either increases or decreases in prices and therefore provide a more refined measure of oil price shocks. This is the first study to use high-frequency (intra-day) time series data for the estimation of symmetric and asymmetric oil price volatility and jump tail risk measures in this context, ensuring more accuracy and less estimation error in the respective oil volatility and jump tail risk series (Andersen et al. 2001; Barndorff-Nielsen and Shephard 2006).²

Furthermore, the second contribution to the literature is to assess both the static and dynamic impact of the new oil shock identification on economic activity and inflation for the US, G7, OECD, and European economies. To this end, we estimate least-squares predictive regressions to estimate the former and a small-scale SVAR model, in which output growth and inflation are included as endogenous variables, to ascertain the dynamic impact.

Finally, in the third contribution, the new empirical results shed new light on prior findings in the literature. In particular, the oil-macroeconomy relation is shown to still operate, doing through both a symmetric volatility channel and asymmetric changes to economic activity. Our findings also provide clear evidence showing that asymmetric oil price shocks are inflationary, while symmetric oil shocks (i.e., rising oil price volatility) are recessionary. The econometric analysis shows that ‘good’ volatility (volatility attributed to positive oil price changes) is associated with rising inflation and economic activity (the latter particularly in the US case), while the ‘bad’ component of volatility (volatility attributed to negative price changes) predicts falling inflation in the US, G7, OECD, and EU27 economies.

To summarize the most important findings, we show for the first time in the oil-macroeconomics literature that (i) asymmetric oil price shocks do not typically cause recessions, but inflationary pressures instead, (ii) the most important (in terms of its recessionary impact) oil-related shock is the symmetric (oil price volatility) shock, and (iii) the EU27 economies are more sensitive to the negative impact of oil price shocks compared to the US, G7, and OECD countries.

The rest of the paper is organized as follows. Section 2 provides the literature review and theoretical motivation, while Section 3 outlines the empirical methodology and describes the data. Section 4 presents the results of the least-squares and SVAR analysis, while Section 5 discusses the robustness checks. Finally, Section 6 concludes and provides policy recommendations.

2. Literature review and theoretical motivation

The study of the oil-macroeconomy relation is a well-established field in the macroeconomics literature. Work has shown that major oil price increases are typically followed by sudden drops in economic activity and consequently, US economic recessions (Hamilton 1983; 2003; 2011; Kilian and Vigfusson 2013; 2017; Lardic and Mignon 2008; Mory 1993; Nguyen, Okimoto, and Tran 2022; Ravazzolo and Rothman 2013). For instance, Hamilton (1983; 2011) was among the first to show that oil price increases have a more recessionary effect on the US economy when compared with the expansionary effect of oil price decreases, thereby identifying an asymmetry in the oil-macroeconomy relationship. These results are reinforced by the findings of Kilian and Vigfusson (2017) who show that net oil price increases explain most of US economic recessions, while Ravazzolo

and Rothman (2013) report a significant out-of-sample forecasting power of oil prices on real US GDP growth, especially for long-run forecast horizons. Carrying on in this vein, Hwang and Kim (2024) identify significant non-linearities in the oil-macroeconomy relation by showing that oil shocks have a more contractionary impact on US employment and industrial production during recessions when compared to that of normal times. Furthermore, there is a growing literature showing the significant macroeconomic effects of oil price uncertainty globally (Cadena-Silva, Lara, and Fernández 2025; Cunado and De Gracia 2003; Tissaoui et al. 2024; Tissaoui and Zaghdoudi 2025; Tlili et al. 2024; Zaghdoudi et al. 2023; among others).

There is still an ongoing and lively debate in the literature regarding the recessionary (and/or the inflationary) impact of oil price shocks, when controlling for systematic monetary policy reactions. Bernanke, Gertler, and Watson (1997) were the first to show that oil price shocks might not be a primary cause of US economic recessions since the monetary authority typically reacts to these shocks by raising short-term interest rates to counteract inflationary pressures. However, Hamilton and Herrera (2004) criticize these findings, concluding that the Federal Reserve does not always eliminate the recessionary consequences of oil shocks (such as the oil shock of 1974), while Bernanke, Gertler, and Watson (2004) show that under SVAR identification schemes, the monetary policy response still accounts for about half of the dampening impact of oil shocks on output. Entering the debate, Leduc and Sill (2004) find that US monetary policy contributes to approximately a 40% drop in output following a rise in oil prices while Carlstrom and Fuerst (2006) provide some empirical support to the findings of Bernanke, Gertler, and Watson (1997) by showing that most US economic recessions are associated with both rising oil prices and monetary policy tightening, making it difficult to disentangle the exact recessionary impact of these two effects. Interestingly, the more recent empirical findings of Kara (2017) note that although the Federal Reserve includes oil prices in its policy rule, the weight assigned to these prices is much smaller compared to their share in the US economy. Therefore, the first hypothesis to be tested is the following:

H1: Asymmetric oil price shocks have a significant recessionary effect on real output growth

On the other hand, another strand of the oil-macroeconomics literature identifies the significant impact of symmetric oil price shocks on US economic activity. For example, while Kilian and Vigfusson (2011) show that oil price increases have a roughly equal (in magnitude) effect on US GDP growth compared with the analogous but opposite effect of oil price decreases, Ferderer (1996) shows that symmetric effects (quantified by oil price volatility) have a higher (in magnitude and persistence) effect on US economic activity when compared with their asymmetric counterparts. Elder and Serletis (2010), as well as Jo (2014), show that conditional (GARCH) oil price volatility has a persistently negative impact on US economic activity, whereas Henzel and Rengel (2017) show that oil and commodity price uncertainty has a greater recessionary effect than business cycle uncertainty.³ The theoretical underpinning of this strand of research lies in the real options theory of investment under uncertainty, according to which increased uncertainty about oil prices leads to postponement of investment and to economic downturns due to the irreversible nature of investment decisions (Bernanke 1983; Pindyck 1991; among others). For instance, higher oil price uncertainty leads firms to exercise their option to delay or postpone investment until the resolution of the oil price uncertainty episode. Amin, Wang, and Aktas (2023) provide further insights into the real option channel of oil uncertainty shocks by showing that firms postpone their investment decisions when faced with oil price uncertainty shocks driven by supply shortages. The findings of this strand of the literature lead to the formulation of the second hypothesis:

H2: Symmetric oil price shocks have a significant recessionary effect on real output growth.

Several studies also indicate that oil prices are among the key drivers of inflation (Choi et al. 2018; Gao, Kim, and Saba 2014; Hooker 2002; Khalil 2022; López-Villavicencio and Pourroy 2019; Moutos and Vines 1992; Sekine and Tsuruga 2018, among others). For example, Choi et al. (2018) find that rising oil prices result in a persistent increase of inflation for emerging and developing countries, with the effect remaining positive and significant for about two years after the initial oil price shock. A similar result is provided by López-Villavicencio and Pourroy (2019), who find a significant positive correlation between oil price changes and inflation, employing a set of inflation targeting and non-inflation targeting countries, while Nakov and Pescatori (2010) show that oil price fluctuations explain about one third of fluctuations in global inflation. Kamber and Wong (2020) provide further support to these results, in the wider context of commodity price fluctuations. By contrast, another

strand of the literature shows that after the Great Moderation (starting in the early 1980s), US inflation has become less responsive to changes in energy prices (Chen 2009; Clark and Terry 2010; Herrera and Pesavento 2009).⁴ Cunado and De Gracia (2003) show that oil price shocks have positive long-run effects on Euro Area inflation. This leads us to formulate the third hypothesis to be empirically tested in this paper as:

H3: Asymmetric oil price shocks have a significant effect on inflation.

3. Data and methodology

3.1. Macroeconomic data

We obtain monthly data for US Industrial Production (IPI), US Consumer Price Index (INFL), and the Fed Funds rate (FFR) from the FRED database. We also download monthly industrial production and inflation series for G7, OECD, and European (EU27) countries from the OECD database. We additionally download monthly series for the Euro Area monetary policy rate (EAR). The data series covers the period from January 1987 to April 2022.

3.2. Crude oil prices and volatility

For a more robust identification of oil price shocks and volatility, we use high-frequency (5-minute) prices for crude oil futures and the S&P 500 index.⁵ The high frequency identification approach is the more accurate and econometrically robust approach for modeling asymmetric and symmetric jump tail and volatility risk in financial markets (Andersen et al. 2001; Barndorff-Nielsen and Shephard 2006; among others). Intuitively, the existence of many intra-day (5-minute) observations in a monthly period makes the estimation of symmetric and asymmetric oil price risk as accurate as possible. Importantly, we have a long time series of data from 1st January 1987 till 30th April 2022. 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):

$$RV_t = \sum_{i=1}^n r_i^2 \quad (1)$$

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 variation⁶ (BV), which captures the continuous component of RV, following Barndorff-Nielsen and Shephard (2006):

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

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

$$JUMPOIL_t = RV_t - BV_t \quad (3)$$

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, Kinnebrock, and Shephard (2010):

$$\Delta J^2 = RS^+ - RS^- \quad (4)$$

with

$$RS^+ = \sum_{i=1}^n r_i^2 I\{r_i > 0\} \quad (5)$$

$$RS^- = \sum_{i=1}^n r_i^2 I\{r_i < 0\} \quad (6)$$

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

Table 1. Descriptive statistics for the oil market and macroeconomic variables.

Variable	mean	median	max	min	st.dev	Skewness	Kurtosis	ADF
OILNEGVAR	0.007	0.004	0.470	0.001	0.025	15.377	267.632	−13.347 [‡]
OILPOSVAR	0.007	0.004	0.485	0.001	0.025	17.571	338.976	−15.686 [‡]
OILRV	0.014	0.008	0.954	0.001	0.050	16.639	309.271	−14.366 [‡]
OILTOTJUMP	0.004	0.001	0.302	0.000	0.017	14.294	234.244	−14.410 [‡]
OILSIGNJUMP	0.000	0.000	0.031	−0.108	0.007	−11.060	184.797	−20.756 [‡]
OILPRICE	46.037	36.725	133.930	11.280	28.970	0.767	2.475	−2.222
INFLATION (US)	0.002	0.002	0.014	−0.018	0.003	−1.167	12.764	−11.834 [‡]
IPI GROWTH (US)	0.001	0.002	0.063	−0.144	0.01	−6.327	94.943	−14.895 [‡]
INFLATION (G7)	0.002	0.002	0.013	−0.013	0.002	−0.392	6.828	−11.952 [‡]
IPI GROWTH (G7)	0.001	0.002	0.07	−0.159	0.012	−6.121	87.931	−14.792 [‡]
INFLATION (OECD)	0.003	0.003	0.016	−0.009	0.003	0.363	5.251	−3.018 [†]
IPI GROWTH (OECD)	0.001	0.002	0.078	−0.162	0.011	−6.636	106.495	−15.109 [‡]
INFLATION (EU27)	0.002	0.002	0.023	−0.013	0.004	0.027	6.765	−0.387
IPI GROWTH (EU27)	0.001	0.001	0.122	−0.203	0.017	−3.634	61.394	−16.593 [‡]

Notes: For the ADF unit root tests, *, † and ‡ denotes statistical significance at the 10%, 5% and 1% level respectively.

Table 2. Predictive regressions for US industrial production growth (US IPI).

	(7)	(8)	(9)	(10)	(11)
CONST	−0.000 (−0.14)	0.001 (1.01)	0.002* (1.83)	0.001 (0.97)	0.004 [†] (2.48)
INFL (US)	0.598 [†] (2.29)	0.313 (1.54)	0.438 (1.60)	0.352 (1.45)	−0.000 (−0.00)
FFR	−0.001 (−0.05)	−0.007 (−0.54)	−0.016 (−0.88)	−0.006 (−0.47)	−0.013 (−0.82)
IPI (US)	0.173 [†] (2.20)	0.206 (1.55)	0.167 (1.05)	0.128 [†] (2.31)	0.222 (1.36)
OIL RV					−0.048 (−1.19)
SP500RV					−1.404 [†] (−2.11)
OILPOSVAR		0.247 [†] (2.58)			
SP500POSVAR		7.535 [‡] (5.40)			
OILNEGVAR		−0.192 [†] (−2.33)			
SP500NEGVAR		−7.947 [‡] (−6.82)			
OILTOTJUMP			0.175 (1.29)		
SP500TOTJUMP			−5.990 [‡] (−5.37)		
OILSIGNJUMP				0.194 [†] (2.56)	
SP500SIGNJUMP				8.702 [‡] (8.12)	
% adj. R^2	5.8	52.2	40.5	51.6	33.3

Notes: The regression results shown in columns (7) to (11) correspond to the OLS regression models described in Equations (7) to (11), respectively. The t -statistics (reported in parentheses) are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, †, and ‡ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

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-variances from (5) and (6). Evidently, the OILPOSVAR is our proxy for ‘good volatility’ (oil price variation due to positive oil price changes) and OILNEGVAR is our proxy for ‘bad volatility’ (oil price variation due to negative oil price changes). 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 semivariances), and SP500SIGNJUMP (S&P500 signed jump variation).

3.3. OLS predictive regression models

Following the econometric models of Stock and Watson (2003) and Gospodinov and Ng (2013), we estimate a similar set of predictive regression models for output and inflation. These multivariate models, including macroeconomic fundamentals, oil, and stock-market volatility, are given in (7) to (11) below:

$$\ln(IPI_t/IPI_{t-1}) = a + b_1INFL_{t-1} + b_2FFR_{t-1} + b_3\ln(IPI_{t-1}/IPI_{t-2}) + e_t \quad (7)$$

$$\ln(IPI_t/IPI_{t-1}) = a + b_1INFL_{t-1} + b_2FFR_{t-1} + b_3\ln(IPI_{t-1}/IPI_{t-2}) + b_4OILPOSVAR_{t-1} + b_5OILNEGVAR_{t-1} + b_6SP500POSVAR_{t-1} + b_7SP500NEGVAR_{t-1} + e_t \quad (8)$$

$$\ln(IPI_t/IPI_{t-1}) = a + b_1INFL_{t-1} + b_2FFR_{t-1} + b_3\ln(IPI_{t-1}/IPI_{t-2}) + b_4OILTOTJUMP_{t-1} + b_5SP500TOTJUMP_{t-1} + e_t \quad (9)$$

$$\ln(IPI_t/IPI_{t-1}) = a + b_1INFL_{t-1} + b_2FFR_{t-1} + b_3\ln(IPI_{t-1}/IPI_{t-2}) + b_4OILSIGNJUMP_{t-1}$$

Table 3. Predictive regressions for G7 countries industrial production growth (G7 IPI).

	(7)	(8)	(9)	(10)	(11)
CONST	−0.000 (−0.11)	0.001 (0.86)	0.002 (1.27)	0.001 (0.61)	0.003 [‡] (2.69)
INFL (G7)	0.323 (1.02)	0.172 (0.93)	0.249 (0.71)	0.304 (0.96)	−0.192 (−0.83)
FFR	0.007 (0.56)	−0.004 (−0.34)	−0.014 (−0.75)	−0.004 (−0.24)	−0.009 (−0.61)
IPI (G7)	0.261 [†] (2.34)	0.306 [†] (2.17)	0.312 (1.57)	0.119 (1.33)	0.362 [†] (2.10)
OIL RV					−0.102 [†] (−2.21)
SP500RV					−1.675 [‡] (−2.85)
OILPOSVAR		0.232 (1.64)			
SP500POSVAR		7.777 [‡] (4.33)			
OILNEGVAR		−0.087 (−0.62)			
SP500NEGVAR		−8.755 [‡] (−5.52)			
OILTOTJUMP			−0.318* (−1.66)		
SP500TOTJUMP			−6.799 [‡] (−5.60)		
OILSIGNJUMP				0.077 (0.59)	
SP500SIGNJUMP				11.080 [‡] (6.74)	
% adj. R^2	7.3	57.6	43.3	53.3	43.0

Notes: The regression results shown in columns (7) to (11) correspond to the OLS regression models described in Equations (7) to (11) respectively. The t -statistics (reported in parentheses) are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, [†] and [‡] denote statistical significance at the 10%, 5%, and 1% level, respectively.

$$+ b_5 SP500SIGNJUMP_{t-1} + e_t \quad (10)$$

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

We additionally estimate analogous least-squares models with $INFL$ as the dependent variable. For each dependent variable, we estimate regression models (7) to (11) for G7, OECD, and EU27 economies. Of course, for the EU27 economies, we use, instead of the FFR , the EAR as our proxy for the monetary policy rate.

3.4. Structural VAR model

Following Bernanke, Gertler, and Watson (1997), we estimate a small-scale structural VAR (SVAR) model in which we include inflation and output growth as endogenous variables. In this way, we control for the inflationary impact of oil price shocks and for interaction between oil price fluctuations, inflation and economic growth (Beckerman and Jenkinson 1986; Bernanke, Gertler, and Watson 1997; Kara 2017; Kilian and Lewis 2011). Our SVAR model is given in Equation (12) below:

$$A_0 Y_t = c + A_1 Y_{t-1} + \dots + A_k Y_{t-k} + \varepsilon_t \quad (12)$$

where A_0 is a vector of constants, Y_t is the vector of endogenous variables, A_0 is the matrix of contemporaneous variables, A_1 to A_k are matrices of coefficients and ε_t is the vector of serially uncorrelated disturbances, with zero mean and variance-covariance matrix $E(\varepsilon_t, \varepsilon_t') = \sigma_\varepsilon^2 I$. The lag-length (k) in the VAR model is selected using the Schwarz (SBIC) optimal lag-length information criterion.⁷ Following Bernanke, Gertler, and Watson (1997) and

Table 4. Predictive OLS regressions for OECD countries' industrial production growth (OECD IPI).

	(7)	(8)	(9)	(10)	(11)
CONST	0.000 (0.20)	0.001 (1.20)	0.002* (1.66)	0.001* (0.99)	0.003‡ (2.89)
INFL (OECD)	0.288 (1.26)	0.145 (1.11)	0.229 (0.94)	0.251 (1.06)	−0.059 (−0.31)
FFR	−0.004 (−0.33)	−0.010 (−1.09)	−0.026* (−1.78)	−0.013 (−0.94)	−0.014 (−1.09)
IPI (OECD)	0.276† (2.41)	0.397‡ (2.92)	0.402* (1.95)	0.155* (1.68)	0.433‡ (2.59)
OIL RV					−0.113† (−2.50)
SP500RV					−1.693‡ (−2.75)
OILPOSVAR		0.340‡ (2.91)			
SP500POSVAR		6.995‡ (4.13)			
OILNEGVAR		−0.164 (−1.60)			
SP500NEGVAR		−8.072‡ (−5.48)			
OILTOTJUMP			0.367* (1.86)		
SP500TOTJUMP			−7.110‡ (−5.86)		
OILSIGNJUMP				0.161* (1.71)	
SP500SIGNJUMP				10.555‡ (7.07)	
% adj. R^2	8.1	64.6	50.1	58.2	48.4

Notes: The regression results shown in columns (7) to (11) correspond to the OLS regression models described in Equations (7) to (11), respectively. The t -statistics (reported in parentheses) are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, †, and ‡ denote statistical significance at the 10%, 5%, and 1% level, respectively.

Kilian and Lewis (2011) who examine the endogenous interactions between oil price shocks, inflation, and real output, we estimate a 4-factor reduced-form VAR with the following ordering:⁸

$$Y_t = [OILSIGNJUMP_t \ OILRV_t \ INFL_t \ IPI_t] \quad (13)$$

To recover orthogonal shocks, we use a Cholesky decomposition. Our SVAR ordering identification scheme is similar to that of Caggiano, Castelnuovo, and Groshenny (2014) and Bloom (2009). The assumptions behind our VAR ordering are that shocks instantaneously influence the (highly flexible) oil market, then consumer prices and then quantities (output). Moreover, by placing the OILSIGNJUMP and OILRV variables first in the VAR, we treat oil price and volatility shocks as an exogenous shock to the economy.⁹

Following the US, we estimate identical SVAR models for the G7, OECD, and EU27 group of countries. Finally, for robustness purposes, we follow standard practice in the literature by estimating our baseline SVAR model using (instead of our measure of asymmetric oil price jumps, OILSIGNJUMP), the monthly growth rate of the WTI oil price (Hamilton 2003; Kilian 2009; Kilian and Vigfusson 2017; Ravazzolo and Rothman 2013; among others).

4. Econometric results

4.1. Descriptive statistics

In this section, Table 1 presents the descriptive statistics for our variables along with Augmented Dickey-Fuller (ADF) unit root tests.

Table 5. Predictive regression for EU-27 countries industrial production growth (EU27 IPI).

	(7)	(8)	(9)	(10)	(11)
CONST	0.000 (0.31)	0.001 (0.43)	0.002 (1.27)	0.002 (1.01)	0.003 [†] (2.13)
INFL (EU27)	0.108 (0.52)	0.164 (0.86)	0.259 (1.26)	0.181 (0.91)	0.100 (0.59)
EAR	−0.003 (−0.07)	0.005 (0.18)	−0.026 (−0.89)	−0.018 (−0.38)	0.009 (0.34)
IPI (EU27)	0.129 (0.91)	0.191 (1.23)	0.360* (1.88)	−0.077 (−0.68)	0.284 (1.61)
OIL RV					−0.199 [‡] (−3.69)
SP500RV					−2.373 [‡] (−2.84)
OILPOSVAR		0.290 (0.93)			
SP500POSVAR		11.114 [‡] (2.61)			
OILNEGVAR		0.003 (0.01)			
SP500NEGVAR		−12.627 [‡] (−3.32)			
OILTOTJUMP			0.825 [‡] (5.56)		
SP500TOTJUMP			−11.152 [‡] (−18.37)		
OILSIGNJUMP				0.113 (0.33)	
SP500SIGNJUMP				16.118 [‡] (4.30)	
% adj. R^2	0.6	59.6	55.3	50.3	46.2

Notes: The regression results shown in columns (7) to (11) correspond to the OLS regression models described in Equations (7) to (11), respectively. The t -statistics (reported in parentheses) are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, [†], and [‡] denote statistical significance at the 10%, 5%, and 1% level, respectively.

From Table 1, we see that several oil-related variables are positively skewed, and that the OILPOSVAR has higher skewness and kurtosis compared to OILNEGVAR. Additionally, we report similar mean values for OILPOSVAR and OILNEGVAR, which shows that the average variation of positive and negative oil price changes is similar. By contrast, the mean and standard deviation figures of our jump measures are quite different, showing that the distribution of jump variables is quite different from that of the oil variance and semivariance measures. Moreover, the OILSIGNJUMP variable has a zero mean value and median and highly negative skewness, indicating that the sample contains a small number of highly negative price spikes (the most important being the COVID-19 oil depreciation). Moreover, we reject the unit root hypothesis for all of our explanatory variables used on the right-hand side of the predictive regressions; specifically, ADF unit root tests reject the hypothesis of a unit root at the 1% confidence level for all of our oil-related variables used in the OLS predictive regressions.¹⁰ In fact, the only variables that are not stationary even at the 10% level are the oil price level and the EU27 inflation.

With respect to the macroeconomic variables, average inflation appears to be very similar between the different groups of countries in our sample, with the US, G7, and EU27 having identical inflation rates, whereas the OECD average is slightly higher; perhaps reflecting that the OECD comprises a more diverse group of countries. Moreover, IPI growth is almost identical across all four groupings and measures of the average (i.e., except for the median rate for the EU27, which is slightly lower). If one examines the standard deviation of inflation and IPI growth estimates, it is interesting to note that the highest variability around the mean is found in the EU27. This can be attributed to high heterogeneity across the different countries in the EU, reflecting heterogeneous shock exposure (energy/trade), propagation (wage bargaining, indexation, market competition), and adjustment (fiscal capacity, credit conditions, industrial composition).

Table 6. Predictive regressions for US inflation (US INFL).

	(7)	(8)	(9)	(10)	(11)
CONST	0.001 [‡] (3.94)	0.001 [‡] (4.97)	0.001 [‡] (4.12)	0.001 [‡] (4.71)	0.001 [‡] (5.86)
INFL (US)	0.457 [‡] (6.33)	0.374 [‡] (5.46)	0.448 [‡] (5.99)	0.437 [‡] (6.30)	0.373 [‡] (5.81)
FFR	0.009 [†] (2.18)	0.008* (1.80)	0.008* (1.93)	0.009 [†] (2.20)	0.007 (1.58)
IPI (US)	0.009 (0.93)	0.018 (1.00)	0.008 (0.44)	0.006 (0.66)	0.014 (0.76)
OIL RV					0.006* (1.78)
SP500RV					−0.194 [‡] (−3.22)
OILPOSVAR		0.068 [†] (2.14)			
SP500POSVAR		−0.616 (−1.42)			
OILNEGVAR		−0.053 (−1.64)			
SP500NEGVAR		0.226 (0.74)			
OILTOTJUMP			0.009 (0.63)		
SP500TOTJUMP			−0.313 [‡] (−4.47)		
OILSIGNJUMP				0.057 [†] (1.51)	
SP500SIGNJUMP				0.392 [‡] (0.96)	
% adj. R^2	23.8	32.2	24.9	28.6	31.6

Notes: The regression results shown in columns (7) to (11) correspond to the OLS regression models described in Equations (7) to (11), respectively. The t -statistics (reported in parentheses) are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, †, and ‡ denote statistical significance at the 10%, 5%, and 1% level, respectively.

4.2. OLS predictive regression results

In this section, we present the results of our OLS regression models for inflation and economic activity, which are described in Equations (7) to (11). Tables 2–5 present the regression results of our predictive models for the US, G7, OECD, and EU27 Industrial Production Index (IPI) growth, respectively. The G7, OECD, and EU27 IPI growth series are the monthly growth rates of the aggregated Industrial Production of the G7, EU27, and OECD group of countries, respectively.

The results shown in Table 2 are in contrast to some findings in the literature on the role of asymmetric oil price shocks in the US economy (Hamilton 1983; 2003; Kilian and Vigfusson 2013; 2017; among others). While this strand of the oil macroeconomics literature has identified a non-linear relationship between oil price returns and US output, with oil price increases having a severe contractionary effect on the US economy, our OLS regression results do not support this finding. Specifically, asymmetric oil price shocks (OILPOSVAR, OILNEGVAR, OILSIGNJUMP) are significant predictors of US IPI growth but with an opposite sign to the one anticipated: in particular, oil price increases appear to predict an increase in US IPI growth and vice versa. This result for the US may be attributed to the transformation of the country from an oil importing economy to one of the biggest oil exporters in the world. On the other hand, a rise in the general level of symmetric oil and stock market volatility (OIL RV, SP500RV) and jumps (OILTOTJUMP, SP500TOTJUMP) is either insignificant, in the case of the oil variables, or predicts a fall in US economic activity, for the stock market analogs. These results support and extend the literature showing that rising stock market volatility has a dampening effect on US economic activity; however, in contrast to some other work, the effect of oil market volatility is muted (Elder 2018; Elder and Serletis 2010; Guo and Kliesen 2005).

Table 7. Predictive regressions for G7-countries inflation (G7 INFL).

	(7)	(8)	(9)	(10)	(11)
CONST	0.001 [‡] (3.81)	0.001 [‡] (4.86)	0.001 [‡] (3.99)	0.001 [‡] (4.08)	0.001 [‡] (5.11)
INFL (G7)	0.538 [‡] (10.21)	0.491 [‡] (9.43)	0.537 [‡] (9.92)	0.539 [‡] (10.56)	0.497 [‡] (9.99)
FFR	0.007* (1.91)	0.007* (1.78)	0.006* (1.75)	0.008 [†] (2.17)	0.006 (1.45)
IPI (G7)	0.003 (0.42)	0.003 (0.27)	−0.002 (−0.20)	−0.001 (−0.25)	−0.005 (−0.40)
OIL RV					0.003 (1.27)
SP500RV					−0.131 [‡] (−3.15)
OILPOSVAR		0.085 [‡] (3.41)			
SP500POSVAR		−0.936 [‡] (−3.02)			
OILNEGVAR		−0.075 [‡] (−3.14)			
SP500NEGVAR		0.620 [†] (2.45)			
OILTOTJUMP			0.004 (0.36)		
SP500TOTJUMP			−0.219 [‡] (−5.53)		
OILSIGNJUMP				0.078 [‡] (2.83)	
SP500SIGNJUMP				−0.105 [‡] (−0.33)	
% adj. R^2	30.8	36.6	31.3	33.9	34.8

Notes: The regression results shown in columns (7) to (11) correspond to the OLS regression models described in Equations (7) to (11), respectively. The t -statistics (reported in parentheses) are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, [†], and [‡] denote statistical significance at the 10%, 5%, and 1% level, respectively.

The results shown in Tables 3–5 reveal that for two country groups (i.e., G7 and EU27), the asymmetric oil price shocks (OILPOSVAR, OILNEGVAR, OILSIGNJUMP) are everywhere insignificant in predictive regressions of IPI growth, and for the OECD, evidence is more mixed.¹¹ This emphasizes a degree of US exceptionalism in the results, where, as noted previously, asymmetric oil price shocks are always significant. When considering symmetric measures, results show that oil price volatility (OILRV) is a statistically significant and negative predictor of IPI growth for G7, OECD, and EU27 economies.¹² These results are the first to show that increased oil price uncertainty (proxied by rising OILRV) predicts a fall in economic activity for other major advanced economies, but in contrast to the US. Interestingly, we report larger (in an absolute sense) coefficients for OILRV when predicting the IPI growth rate of EU27 economies, highlighting the increased dependence and sensitivity of European economies to oil price volatility shocks. The economic rationale behind this finding is that European economies are, in their vast majority, oil importers, with a relatively small share of global crude oil production taking place in Europe. The increasing dependence of most European economies on crude oil imports makes them more vulnerable to fluctuations in crude oil prices. For example, Cappelli and Carnazza (2023) provide further empirical support for this argument by showing that oil dependency is a major policy issue for many EU27 economies, with the degree of oil dependency reaching very high levels for some major oil-importing EU member states.

Before moving on, it is evident from Table 5 that the persistence of the EU27 IPI series is much weaker when compared to that of the US, G7, and OECD IPI growth series (lagged EU27 IPI growth being an insignificant predictor of subsequent EU 27 IPI growth). One potential underlying factor explaining the low persistence of the EU27 IPI growth is the degree of economic integration (especially in regard to country-level business cycles

Table 8. Predictive regressions for OECD countries' inflation (OECD INFL).

	(7)	(8)	(9)	(10)	(11)
CONST	0.001 [‡] (4.76)	0.001 [‡] (4.36)	0.001 [‡] (4.78)	0.001 [‡] (4.94)	0.001 [‡] (5.07)
INFL (OECD)	0.615 [‡] (10.44)	0.604 [‡] (9.75)	0.614 [‡] (10.31)	0.623 [‡] (10.97)	0.596 [‡] (9.53)
FFR	0.016 [‡] (3.17)	0.017 [‡] (3.31)	0.016 [‡] (3.03)	0.017 [‡] (3.45)	0.016 [‡] (2.95)
IPI (OECD)	0.004 (0.63)	0.013 (1.19)	0.005 (0.42)	0.002 (0.23)	0.006 (0.46)
OIL RV					0.004* (1.94)
SP500RV					−0.098 [‡] (−3.68)
OILPOSVAR		0.097 [‡] (3.85)			
SP500POSVAR		−0.814 [‡] (−2.84)			
OILNEGVAR		−0.084 [‡] (−3.61)			
SP500NEGVAR		0.600 [†] (2.47)			
OILTOTJUMP			0.007 (0.66)		
SP500TOTJUMP			−0.191 [‡] (−3.70)		
OILSIGNJUMP				0.086 [‡] (3.36)	
SP500SIGNJUMP				−0.226 [‡] (−0.83)	
% adj. R^2	48.8	52.2	49.0	51.1	50.5

Notes: The regression results shown in columns (7) to (11) correspond to the OLS regression models described in Equations (7) to (11), respectively. The t -statistics (reported in parentheses) are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, †, and ‡ denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 9. Predictive regressions for EU-27 countries' inflation (EU27 INFL).

	(7)	(8)	(9)	(10)	(11)
CONST	0.001 [‡] (4.28)	0.001 [‡] (4.19)	0.001 [‡] (4.14)	0.001 [‡] (4.05)	0.001 [‡] (4.25)
INFL (EU27)	0.193 [‡] (2.90)	0.199 [‡] (2.89)	0.193 [‡] (2.88)	0.200 [‡] (2.93)	0.193 [‡] (2.90)
EAR	0.014 (1.32)	0.017* (1.65)	0.014 (1.36)	0.017* (1.68)	0.014 (1.33)
IPI (EU27)	0.007 (0.98)	0.012 (0.94)	0.010 (0.69)	0.009 (1.12)	0.007 (0.55)
OIL RV					0.001 (0.43)
SP500RV					−0.024 (−0.51)
OILPOSVAR		0.142 [†] (2.27)			
SP500POSVAR		−1.631 [†] (−2.52)			
OILNEGVAR		−0.134 [†] (−2.18)			
SP500NEGVAR		1.440 [†] (2.45)			
OILTOTJUMP			0.003 (0.25)		
SP500TOTJUMP			0.050 (0.93)		
OILSIGNJUMP				0.137 [†] (2.12)	
SP500SIGNJUMP				−1.119* (−1.92)	
% adj. R^2	3.3	4.4	2.6	4.5	2.7

Notes: The regression results shown in columns (7) to (11) correspond to the OLS regression models described in Equations (7) to (11), respectively. The t -statistics (reported in parentheses) are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, †, and ‡ denote statistical significance at the 10%, 5% and 1% level, respectively.

and other structural differences) among EU member states, which has remained low even after the adoption of the single Euro currency among major European member states (Bekaert et al. 2013; among others).

Consider Tables 6–9 show the results of our inflation predictive regression models for the US, G7, OECD, and EU27 group of countries, respectively. Specifically, the tables show that oil volatility changes attributed to price increases (OILPOSVAR) are significantly and positively associated with subsequent inflation rates. More generally, while rising positive semi-variance is associated with rising inflation, rising negative semi-variance (OILNEGVAR) is typically significantly associated with falling inflation. 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. 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.

Finally, note that Tables 6–9 and non-oil explanatory variables reveal some interesting results. For example, inflation shows persistence in all cases, and we typically find a positive coefficient for the monetary policy rate (i.e., FFR and EAR) when predicting the one-month ahead inflation (aside from the EU27), and this result is typically in line with those of the monetary economics literature. Specifically, this literature has shown that a positive interest rate shock results in a hump-shaped response of inflation, with a short-term increase being followed by a subsequent long-lasting decline (Mojon 2008; among others).

4.3. SVAR analysis

To assess the dynamic effect of oil price shocks on global economic activity and inflation, we estimate the Orthogonalized Impulse Response Functions (OIRFs) for inflation and economic activity from the VAR model (12)

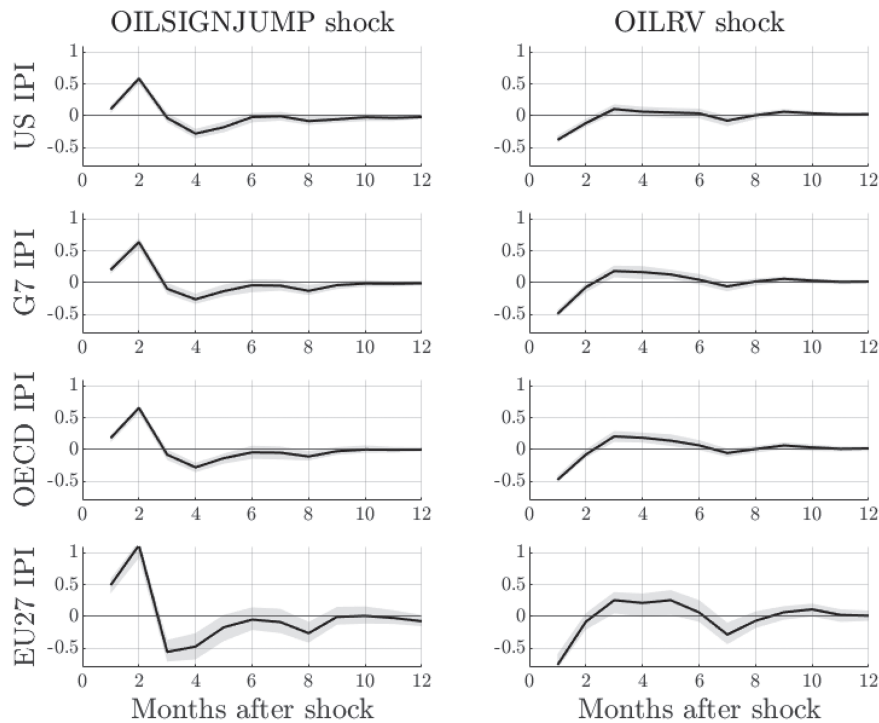


Figure 1. IPI growth responses to shocks in asymmetric oil price jumps (OILSIGNJUMP) and oil price volatility (OILRV).

Notes: The plot presents the estimated Orthogonalized IRFs (solid black line) of IPI growth to OILSIGNJUMP and OILRV shocks along with the 90% bootstrapped confidence intervals (shaded gray area). The estimated OIRFs of the US, OECD, G7, and EU27 IPI growth rates are expressed in percentages (%). The bootstrapped confidence intervals have been estimated using 1000 repetitions.

described in Section 2.4. In this section, we report the results of our VAR analysis for the US, G7, OECD, and EU27 group of countries.

Figure 1 reports the OIRFs of IPI growth to OILSIGNJUMP and OILRV innovations, with this choice of figure allowing the former variable (i.e., OILSIGNJUMP) to represent asymmetric effects, while the latter (i.e., OIL RV) captures symmetric effects from the oil market. As we see from Figure 1, the effect of OILSIGNJUMP has a positive effect on US IPI growth, with US IPI growth initially increasing by about 0.5 percentage points two months after the OILSIGNJUMP shock and then becoming statistically indistinguishable from zero. These results are in sharp contrast with those of Hamilton (1983; 2003) and Kilian and Vigfusson (2017), who show that US output growth declines after sharp increases in the WTI oil price, attributing most of US economic recessions to oil price spikes. Moreover, our VAR model for G7 and OECD economies also shows the positive impact of OILSIGNJUMP on the real output of the G7 and OECD group of countries, with an increase of approximately 60 basis points in G7 and OECD IPI growth two months after the initial one standard deviation shock, quickly becoming insignificant shortly thereafter.

By contrast, when examining the dynamic effect of symmetric (OILRV) shocks on economic activity, we report a negative and significant effect on US, G7, OECD, and EU27 IPI growth. More specifically, from Figure 1 we see that a positive one standard deviation OILRV shock reduces US, G7 and OECD IPI growth by almost 50 basis points 1 month after the shock, with the effect remaining negative and statistically significant until the 3rd month after the initial OILRV shock. Interestingly, the highest recessionary effect of OILRV shocks arises for EU27 economies, with EU27 IPI growth falling approximately 0.8% two months after the shock. These results are the first to show that European countries are more severely affected by oil price uncertainty shocks compared with the rest of the world economies. These results are broadly in line with evidence that Europe's energy-import dependence has risen over time and remains structurally high, reflecting stagnant domestic production and a growing reliance on extra-EU suppliers (Román-Collado and Ruíz 2024), which heightens exposure to external

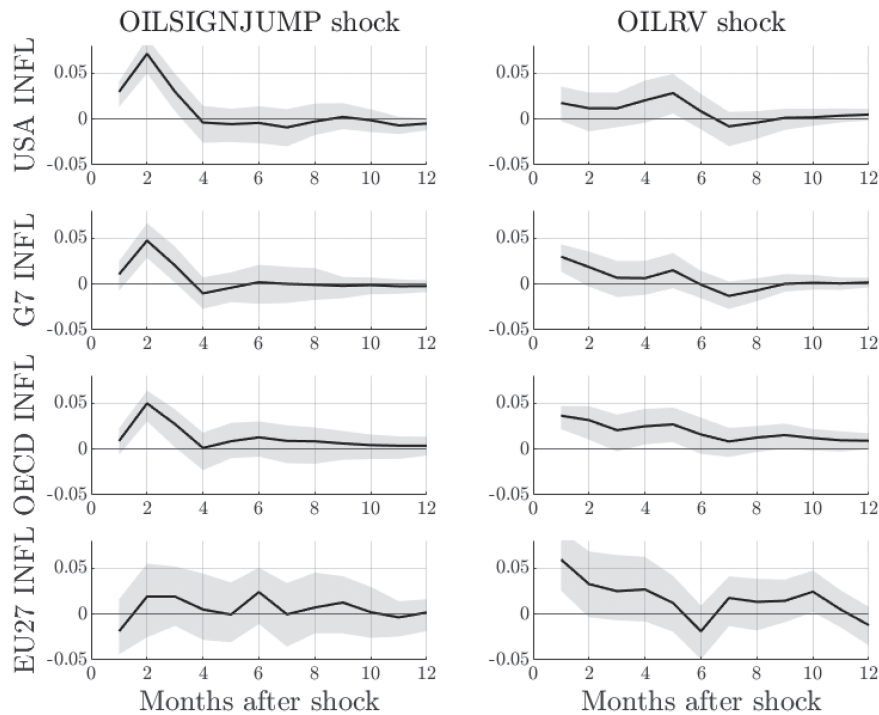


Figure 2. Inflation responses to shocks in asymmetric oil price jumps (OILSIGNJUMP) and oil price volatility (OILRV).

Notes: The plot presents the estimated Orthogonalized IRFs (solid black line) of inflation (INFL) to OILSIGNJUMP and OILRV shocks along with the 90% bootstrapped confidence intervals (shaded gray area). The estimated OIRFs of US, OECD, G7 and EU27 inflation rates are expressed in percentages (%). The bootstrapped confidence intervals have been estimated using 1000 repetitions.

price swings.¹³ Recent literature (e.g. Casoli, Manera, and Valenti 2024) also demonstrates a comparatively large and persistent pass-through from oil and gas prices to euro-area inflation and real activity. Together, these imply that uncertainty around oil prices propagates more forcefully through European prices, costs, and expectations than in less import-dependent economies.

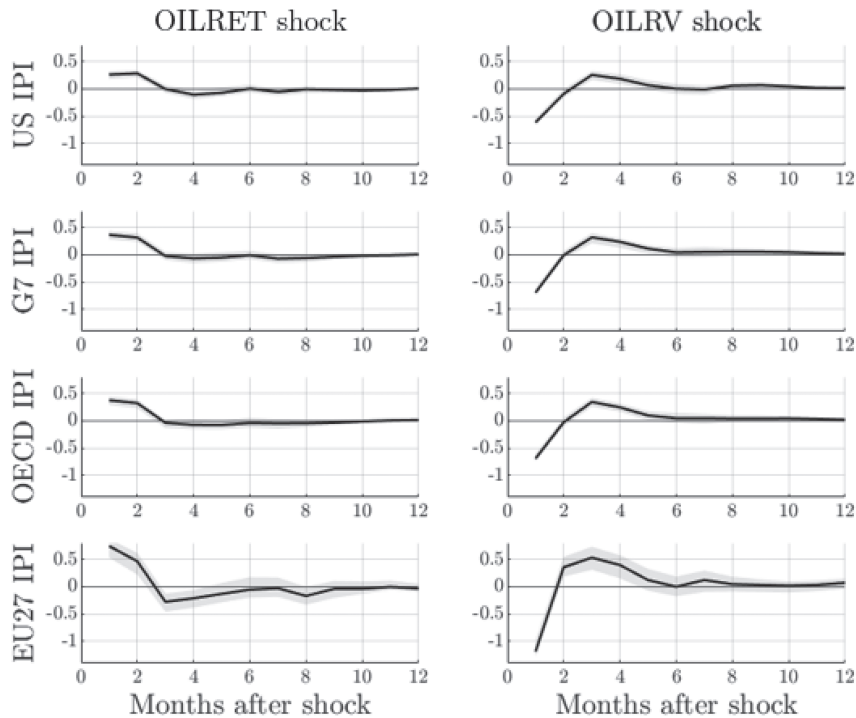
Analogously to Figure 1, Figure 2 depicts the OIRFs for the US, G7, OECD, and EU27 INFL to a positive one standard deviation shock to OILSIGNJUMP and OILRV, estimated using the model in Equation (13).

Figure 2 shows that a positive asymmetric oil shock has a positive and significant effect on US, G7, and OECD economies and an insignificant effect on EU27 inflation rates (i.e., a one standard deviation innovation in OILSIGNJUMP increases the US inflation rate by almost 5 basis points two months after the initial shock, with the effect remaining positive and significant for 4 months). This evidence clearly shows that the rising oil prices cause higher inflation, not only in the US, but also typically (although not in the EU27) across the rest of the world, and lends support to the findings of Choi et al. (2018), who show that an increase in global oil prices has a persistently positive effect on domestic inflation in major advanced economies. In contrast, when examining the dynamic effect of symmetric (OILRV) shocks on US, G7, OECD, and EU27 inflation rates, we find a much less persistent and significant positive effect, which indicates that the effect of symmetric oil price shocks is predominantly recessionary and only has a limited and transient impact on inflation. Our results support and extend the findings of Bernanke, Gertler, and Watson (1997), Cologni and Manera (2008), and Segal (2011), who show that (any) recessionary effects of rising oil prices come through the systematic response of the monetary authority to rising oil prices, given the fear of inflationary pressures. Our current findings indicate that oil price shocks are early warning signals of global inflationary pressures and add to other literature that has identified commodity price shocks as major determinants of US inflation (Cody and Mills 1991; Garner 1989, among others). Consequently, one might suggest our measure of oil price jumps as a useful information variable or ‘non-standard indicator’ for the monetary policy setting (see Woodford 2007) of inflation-targeting central banks.

Table 10. Historical decompositions of IPI growth and inflation (baseline SVAR model).

	US	G7	OECD	EU27
Panel A: IPI Variance Decompositions				
OILSIGNJUMP	43.6%	40.1%	43.8%	51.5%
OILRV	17.4%	23.8%	25.8%	20.9%
INFL	2.3%	2.3%	2.4%	2.6%
IPI	36.7%	33.8%	28.0%	25%
Panel B: INFL Variance Decompositions				
OILSIGNJUMP	9.8%	4.7%	4.8%	1.2%
OILRV	2.8%	2.8%	6.8%	4.7%
INFL	83.4%	90.6%	86.3%	92.1%
IPI	4.0%	1.9%	2.1%	2.0%

Notes: The table reports the variance decompositions of the estimated IRFs of IPI growth and inflation shown in Figures 1 and 2, when explained by the structural shocks estimated in the baseline SVAR model shown in Equations 12 and 13.

**Figure 3.** IPI growth responses to shocks in WTI oil price returns (OILRET) and oil price volatility (OILRV).

Notes: The plot presents the estimated Orthogonalized IRFs (solid black line) of IPI growth to OILRET (log-oil WTI returns) and OILRV shocks along with the 90% bootstrapped confidence intervals (shaded gray area). The estimated OIRFs of US, OECD, G7 and EU27 IPI growth rates are expressed in percentages (%). The bootstrapped confidence intervals have been estimated using 1000 repetitions.

Additionally, in Table 10 we report the variance decompositions of the IRFs of output and inflation when explained by the structural shocks estimated in the baseline SVAR model. Interestingly, the OILSIGNJUMP shocks explain 40% to 50% of the variance of global output growth, thereby being the most significant shock for explaining real output variations. When it comes to INFL variance decompositions, OILSIGNJUMP shocks contribute more toward explaining INFL variance compared to OILRV shocks, but the lagged inflation shocks present the highest contribution due to the high persistence of inflation series.

5. Robustness

In this section, we report various robustness checks for our OLS and SVAR analysis. Firstly, following the standard practice in the literature, we estimate the SVAR model using the monthly returns of WTI oil prices. The results are presented in Figures 3 and 4, which plot the estimated OIRFs for our SVAR model and employ OILRET (instead of OILSIGNJUMP) as our first variable in the SVAR ordering. From Figures 3 and 4, we observe that, even if we replace OILSIGNJUMP with OILRET, which is similar to the oil price shocks used widely in the literature (Hamilton 2003; Kilian 2009; Kilian and Vigfusson 2013; 2017), our main findings remain unaltered, with asymmetric oil price shocks (proxied by a positive shock in the monthly WTI oil price return) presenting an inflationary effect on the global economy, and symmetric shocks having a recessionary effect.¹⁴

In Table 11 we report the variance decompositions of structural shocks on output and inflation relating to the SVAR used to generate Figures 3 and 4. Interestingly, the variance decompositions show clearly that OILSIGNJUMP explains a much larger percentage of real output responses (i.e. approximately 40% to 50% – see Table 10 Panel A) when compared to that of OILRET shocks (i.e. approximately 15% to 23% – see Table 11 Panel A). On the other hand, OILRET shocks present a larger percentage of the decomposition for inflation (see Table 11 Panel B), when compared to OILSIGNJUMP (see Table 10 Panel B). This may suggest that jumps play a relatively outsized role in explaining output relative to that of inflation.

Additionally, when estimating the VAR using alternative VAR orderings and allowing for monetary policy interactions, our results remain qualitatively unaltered. Moreover, we estimate our set of predictive regressions on EMU19 and on an OECD-Europe set of countries, and we show that our results on the European economies do not depend on the selection of the European countries included in the set. These additional OLS results can be found in our online Appendix.

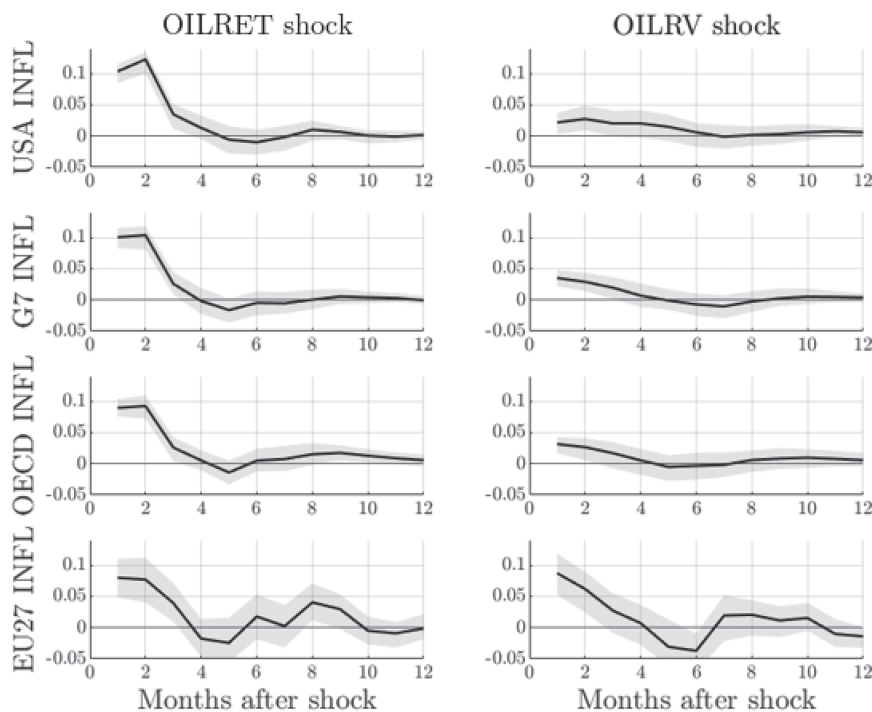


Figure 4. Inflation responses to shocks in WTI oil price returns (OILRET) and oil price volatility (OILRV).

Notes: The plot presents the estimated Orthogonalized IRFs (solid black line) of inflation (INFL) to OILRET (log-oil WTI returns) and OILRV shocks along with the 90% bootstrapped confidence intervals (shaded gray area). The estimated OIRFs of US, OECD, G7 and EU27 inflation rates are expressed in percentages (%). The bootstrapped confidence intervals have been estimated using 1000 repetitions.

Table 11. Historical decompositions of IPI growth and inflation (OILRET-augmented SVAR model).

	US	G7	OECD	EU27
Panel A: IPI Variance Decompositions				
OILRET	15.5%	17.8%	20.0%	22.9%
OILRV	45.5%	47.4%	51.1%	48.7%
INFL	0.9%	2.6%	2.0%	3.1%
IPI	38.1%	32.2%	26.9%	25.3%
Panel B: INFL Variance Decompositions				
OILRET	38.5%	35.3%	23.9%	10.9%
OILRV	3.5%	4.5%	3.1%	10.1%
INFL	53.9%	57.5%	68.2%	76.5%
IPI	4.1%	2.7%	4.8%	2.5%

Notes: The table reports the variance decompositions of the estimated IRFs of inflation and IPI growth shown in Figures 3 and 4, when explained by the structural shocks estimated in the SVAR model.

Table 12. Predictive regressions for industrial production growth (IPI) using realized variance RV from daily data.

	US	G7	OECD	EU27
CONST	0.005 [†] (2.36)	0.005 [†] (2.31)	0.005 [†] (2.49)	0.006 [†] (2.49)
INFL	0.015 (0.06)	−0.177 (−0.55)	0.006 (0.02)	0.070 (0.40)
FFR	−0.009 (−0.42)	−0.010 (−0.43)	−0.018 (−0.90)	−0.016 (−0.37)
IPI	−0.036 (−0.29)	0.068 (0.51)	0.085 (0.56)	−0.001 (−0.01)
OIL RV (daily)	−0.060 (−1.19)	−0.003 (−0.04)	−0.001 (−0.01)	0.095 (0.56)
SP500RV	−1.021 (−1.64)	−1.535 [†] (−2.04)	−1.540 [†] (−2.10)	−2.538* (−1.73)
% adj. R^2	32.8	34.1	37.6	28.4

Notes: The regression results shown in columns correspond to the OLS regression model described in Equation (11) for the corresponding group of countries. The t -statistics (reported in parentheses) are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, [†], and [‡] denote statistical significance at the 10%, 5%, and 1% level, respectively.

In the next round of robustness checks, we perform a subsample OLS and VAR analysis, splitting the sample into pre-crisis (i.e., pre-2007) and post-crisis, and our results remain qualitatively the same across these two sub-periods. Moreover, with this check, we show that the recessionary effect of OILRV shocks is not driven by the advent of the global financial crisis. We additionally estimate the VAR model, allowing for more lags and alternative VAR orderings, allowing monetary policy to react first to oil shocks and then to changes in inflation, and our results remain insensitive to these alternative VAR orderings. We moreover estimate a VAR in which we allow for oil price shocks to be endogenously determined in the model, thereby allowing for oil-related variables to be impacted by changes in economic activity and inflation over the same month, and our results remain qualitatively the same. We also estimate a large-scale VAR model in which we control for stock market volatility and crude oil supply and demand shocks, and our results remain qualitatively the same. All these additional econometric results can be made available upon request.

Moving on, we estimate our baseline regression model by using the crude oil realized variance, estimated as the monthly realized variance of daily crude oil futures returns, as shown in the studies of Guo and Kliesen (2005) and Ferderer (1996). The results, when using the OILRV (daily) for predicting IPI growth and inflation, are shown in Tables 12 and 13, respectively. What is evident from Table 12 is that the findings regarding the significant recessionary effect of oil price volatility depend on whether we deploy high-frequency or daily oil futures data for the estimation of OILRV. The more accurate and econometrically robust high-frequency construction of OILRV, employed in Tables 2–5, reveals the significant recessionary effect (in the cases of G7, OECD, and EU27), and this disappears in Table 12 when one employs a lower frequency, less robust measure of OILRV.

Table 13. Predictive regressions for inflation (INFL) using realized variance (RV) from daily data.

	US	G7	OECD	EU27
CONST	0.002 [‡] (6.60)	0.001 [‡] (5.68)	0.001 [‡] (5.85)	0.001 [‡] (4.25)
INFL	0.365 [‡] (5.49)	0.494 [‡] (9.67)	0.597 [‡] (9.35)	0.192 [‡] (2.86)
FFR	0.007 (1.43)	0.005 (1.41)	0.015 [‡] (2.90)	0.014 (1.31)
IPI	0.008 (0.45)	−0.009 (−0.70)	−0.005 (−0.55)	0.009 (0.72)
OIL RV (daily)	0.008 (0.95)	0.003 (0.44)	0.001 (0.17)	0.004 (0.62)
SP500RV	−0.218 [‡] (−2.97)	−0.138 [‡] (−2.96)	−0.097 [†] (−2.50)	−0.038 (−0.68)
% adj. R^2	31.5	34.7	50.3	2.7

Notes: The regression results shown in columns correspond to the OLS regression model described in Equation (11) for the corresponding group of countries. The t -statistics (reported in parentheses) are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, †, and ‡ denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 14. Predictive regressions for US inflation (US INFL) with threshold effects.

	(8)		(9)		(10)		(11)	
	Low	High	Low	High	Low	High	Low	High
CONST	0.001 [‡] (5.00)	0.002 [‡] (4.72)	0.001 [‡] (6.20)	0.001 (1.20)	0.001 [‡] (6.11)	0.001 [‡] (3.99)	0.002 [‡] (6.66)	0.001 [‡] (3.19)
INFL (US)	0.235 [‡] (4.30)	0.503 [‡] (5.03)	0.315 [‡] (5.60)	0.881 [‡] (5.59)	0.165 [‡] (2.61)	0.465 [‡] (6.05)	0.246 [‡] (5.51)	0.552 [‡] (4.38)
FFR	0.017 [‡] (3.78)	−0.006 (−0.48)	0.011 [†] (2.14)	−0.017 [‡] (−0.60)	0.018 [‡] (3.89)	−0.004 (−0.37)	0.012 [†] (2.48)	0.002 (0.14)
IPI (US)	0.024 (1.32)	0.028 (1.14)	0.012 (0.68)	0.025 (0.39)	0.016 [†] (2.16)	0.024 (0.88)	0.001 (0.04)	0.071 [†] (2.11)
OIL RV							0.001 (0.29)	0.005 (0.11)
SP500RV							−0.133 [‡] (−8.55)	−0.295 [‡] (−3.81)
OILPOSVAR	0.076 [‡] (3.02)	1.792 [‡] (5.02)						
SP500POSVAR	−0.104 (−0.33)	−0.405 (−0.38)						
OILNEGVAR	−0.069 [‡] (−2.93)	−1.893 [‡] (−5.25)						
SP500NEGVAR	0.007 (0.03)	0.111 (0.12)						
OILTOTJUMP			0.007 (0.57)	−0.616* (−1.69)				
SP500TOTJUMP			−0.334 [‡] (−4.81)	0.458 (0.53)				
OILSIGNJUMP					0.070 [‡] (2.78)	1.841 [‡] (4.94)		
SP500SIGNJUMP					0.171 (0.88)	2.142* (1.88)		
Threshold Variable	Oil Price		Oil Price		Oil Price		Fed Fund Rate	
% adj. R^2	45.2		31.0		44.2		36.1	

Notes: The regression results shown in columns (8) to (11) correspond to threshold OLS regression models similar to those described in Equations (8) to (11) respectively. The t -statistics (reported in parentheses) are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, †, and ‡ denote statistical significance at the 10%, 5%, and 1% level, respectively. Two alternative threshold variables (Oil price and Fed fund rate) were considered and the specification that minimizes the sum-of-squared residuals was selected.

Table 15. Predictive regressions for EU27 inflation (EU27 INFL) with threshold effects.

	(8)		(9)		(10)		(11)	
	Low	High	Low	High	Low	High	Low	High
CONST	0.001 [‡] (3.16)	0.001* (1.90)	0.004 [‡] (4.54)	0.001 [‡] (3.07)	0.001 [‡] (2.88)	0.002 [‡] (3.34)	0.004 [‡] (5.01)	0.001 [‡] (3.30)
INFL (US)	0.163 [‡] (2.91)	0.060 (0.77)	0.205* (1.85)	0.119 [‡] (2.63)	0.169 [‡] (2.98)	0.131* (1.83)	0.418 [†] (2.55)	0.092* (1.84)
EA Rate	0.020* (1.74)	0.034* (1.95)	−0.227 [‡] (−3.25)	0.026 [‡] (2.78)	0.020* (1.92)	0.042 [†] (2.45)	−0.144 [‡] (−2.72)	0.027 [‡] (2.88)
IPI (US)	0.004 (0.33)	0.026 (0.53)	−0.050 (−1.61)	0.024* (1.71)	0.005 (0.70)	0.008 (0.16)	−0.040 (−1.28)	0.019* (1.91)
OIL RV							−0.123 [†] (−2.33)	0.004 [†] (2.00)
SP500RV							0.434 [†] (2.09)	−0.069 (−1.58)
OILPOSVAR	0.073* (1.86)	2.904 [‡] (9.54)						
SP500POSVAR	−1.044 [†] (−2.03)	−8.386 [‡] (−3.28)						
OILNEGVAR	−0.069* (−1.81)	−2.735 [‡] (−7.68)						
SP500NEGVAR	0.848* (1.91)	8.454 [‡] (3.84)						
OILTOTJUMP			−0.013 (−0.10)	0.019 (0.93)				
SP500TOTJUMP			−0.223 (−0.40)	−0.320 (−0.44)				
OILSIGNJUMP					0.071* (1.82)	2.952 [‡] (7.61)		
SP500SIGNJUMP					−0.534 (−1.38)	−8.792 [‡] (−5.18)		
Threshold Variable	Oil Price		Oil Price		Oil Price		EA Rate	
% adj. R^2	14.3		6.4		14.4		7.3	

Notes: The regression results shown in columns (8) to (11) correspond to threshold OLS regression models similar to those described in Equations (8) to (11) respectively. The t -statistics (reported in parentheses) are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, †, and ‡ denote statistical significance at the 10%, 5%, and 1% level, respectively. Two alternative threshold variables (Oil price and EA Rate) were considered and the specification that minimizes the sum-of-squared residuals was selected.

Table 16. Summary of robustness checks being conducted.

Robustness check	Description
Alternative ordering	Monetary policy reacts first
Alternative ordering	Oil variables are ordered last in the VAR (endogenous)
Alternative lags	Allowing more lags in the VAR
Large-scale VAR	Include stock market volatility and oil supply and demand
Oil price VAR	WTI oil price-augmented VAR
Subsample analysis	Estimate the VAR for the pre-2007 and post-2007 period
Alternative dependent	Employ realized variance of daily crude futures returns
Regime-switching	Estimate threshold models for low and high oil price regimes
EMU19	Predictive regressions on EMU19 economies
OECD-Europe	Predictive regressions on OECD-Europe economies

Finally, we estimate a regime-switching regression model allowing for oil prices and policy rates to change from high to low oil price and interest rate regimes. The relevant OLS regime-switching model results for the US and EU27 inflation, respectively, are reported in Tables 14 and 15. Interestingly, the results shown in Tables 14 and 15 reveal that the highest impact (largest coefficient) of asymmetric oil tail risk measures on inflation occurs during high oil price regimes, while the impact is relatively weaker during low oil price states of the global economy. This result is particularly useful for policymakers when trying to ameliorate the inflationary impact of oil price increases.¹⁵ Note that Table 16 contains a summary of robustness checks conducted.

6. Conclusions

The oil-macroeconomics literature typically debates whether oil price shocks are inflationary, recessionary, or both. Although the extant literature is inconclusive, understanding these relations is a key input to economic policy and particularly relevant given recent turmoil in energy markets. In this context, we newly identify oil price shocks by decomposing highly accurate realized variance estimated from intraday data and apply this decomposition to a dataset containing the US, G7, OECD, and European economies. In novel results, predictive regressions and SVAR analysis strikingly show that economic activity (as measured by industrial production) is affected via (i) asymmetric shocks due to oil price changes and (ii) a symmetric oil price volatility channel, while inflation is primarily driven by asymmetric measures captured by semi-variance and signed jump variation.

Focusing on economic activity, asymmetric shocks driven by oil price increases (decreases) are *actually* associated with rising (falling) economic activity, particularly in the US case. These results contrast with some in the extant literature who show that US output growth declines after sharp increases in the WTI oil price and we would attribute this new finding to growing US energy independence. However, we also typically find the expected negative effect of increasing oil volatility on economic activity, which supports the real options channel of investment under uncertainty for the global crude oil market, with rising oil price volatility resulting in postponement of investment and production by oil-dependent firms (both oil consumers and oil producers). On the aggregate level, this postponement leads to drops in industrial production in many global economies. Among other findings, our analysis shows that the recessionary effect of oil price volatility shocks for EU27 economies is larger in magnitude than for the rest of the world, suggesting that European countries are relatively more exposed to large fluctuations in oil prices. These results are broadly in line with the literature showing the increasing energy dependence of European countries.

Moving to inflation, it is shown that the inflationary effect of rising oil prices holds not only for the US economy but typically for the rest of the world. This then helps us answer the original question – yes, oil price shocks are inflationary, and they are recessionary through the symmetric volatility channel but can be expansionary through asymmetric shocks. This demonstrates how crucial it is to decompose shocks into their separate components and consequently, several policy recommendations stem from our analysis. Perhaps most importantly, a country's relative energy dependence affects both the response of its output and inflation to oil shocks, and policymakers should actively seek to achieve a desired level of (in)dependence. From a more technical standpoint, on one hand, strict inflation-targeting central banks such as the Bank of England, whose primary target is price stability, could use our measure of oil price jumps as an information variable (or a non-standard indicator) for inflationary pressures. On the other hand, central banks such as the US Federal Reserve, which adopt a flexible inflation-targeting regime involving both inflation and output stabilization as policy targets (see Svensson 2020), could use *both* our symmetric and asymmetric oil price shock measures as information variables.

Notes

1. The consensus in the financial econometrics literature is that the realized variance estimator based on high frequency (intra-day) data series outperforms other volatility models in terms of accuracy of the volatility measurement. Andersen et al. (2001) and Andersen et al. (2003) show that realized volatility is an unbiased and highly efficient estimator of integrated return volatility.
2. Our primary rationale for the use of high frequency data is the more accurate (as much as possible) estimation of crude oil price volatility and jump tail risk as compared to the volatility measures based on lower frequency returns, as has been extensively demonstrated in the financial econometrics literature (see Andersen et al. 2001; among others). Moreover, another significant advantage of our high-frequency data estimation approach is that we can infer econometrically reliable (i.e., less prone to estimation error) estimates of the jump (discontinuous) component of oil price volatility (see Barndorff-Nielsen and Shephard 2006; among others).
3. Also see work by Elder and Payne (2024), Karaki (2018), Elder (2018), Serletis and Xu (2019).
4. There is also a growing strand of the literature showing that oil price volatility is a driver of inflation and inflation expectations (Castillo, Montoro, and Tuesta 2020; Chang, Herrera, and Pesavento 2023; among others).
5. Intraday data are obtained from Pi Trading for the S&P index and from Tick Data for crude oil futures.
6. Using the average of skip-0 through skip-4 bi-power variation as our estimate following Patton and Sheppard (2015).
7. Our IRFs estimates remain robust to the choice of lags that are included in the VAR. More specifically, we have estimated the VAR using the Akaike and the Hannan-Quinn information criteria for selecting the optimal lag-length (k). Moreover, following Hamilton (2003), Elder and Serletis (2010) and Jo (2014), we have also estimated the VAR model using a one year of lags ($k = 12$).

for all variables to allow for the notion that one year of lags may be needed to fully capture the dynamic interactions between oil price fluctuations and the economy. The evidence from all these alternative versions of the VAR model shows that our main results remain unaltered, and that our findings are robust to the choice of lags used in the VAR. These additional results are available upon request.

8. We also estimated a 5-factor reduced-form VAR which included the relevant monetary policy rate as an endogenous variable. In this manner, we control for interactions between monetary policy and the oil market; hence, the estimated responses of economic activity to oil shocks are net of (any) policy effects. Again, the main results remain unaltered and are available upon request.
9. We must state at this point that our VAR results remain unaltered even if we relax the assumption of strict exogeneity of oil price and volatility shocks by placing the oil variables last in the VAR ordering. In other words, our results are insensitive to the VAR ordering. These additional VAR results are available upon request.
10. Moreover, other macroeconomic variables used in the OLS regressions have been tested for stationarity and the null hypothesis of unit root have been rejected using both the Augmented Dickey-Fuller and the Philips-Perron unit root tests. The results of the unit root tests can be provided upon request.
11. For the OECD group of countries (see Table 4), we report a positive (and significant at the 1% level) coefficient of OILPOSVAR, as well as a positive and significant at the 10% level coefficient for signed jump.
12. As we show in the robustness section of the paper (see section 5), when employing, instead of high-frequency measures, the standard monthly log-return of WTI oil prices as extensively used in the literature (Hamilton 2003; Kilian and Vigfusson 2013, 2017), our findings regarding symmetric oil price shocks differ. This shows the importance of using the most accurate and econometrically robust high-frequency construction of OIL RV.
13. See https://ec.europa.eu/eurostat/databrowser/view/nrg_ind_id/default/line?lang=en for recent trends in EU energy import-dependency ratios.
14. We note at this point that not all studies in the oil-macroeconomics literature use crude oil price changes when trying to estimate the effect of asymmetric oil price shocks on the economy. For example, Hamilton (2003) examines the effects of asymmetric oil price shocks on the US economy by using a variable which takes the value of the WTI oil price change for the monthly periods for which that change is positive and zero otherwise. Our findings remain unaltered when using the asymmetric oil price shocks in this manner. These additional results are available upon request.
15. Our regime-switching inflation forecasting regression results are similar for G7 and OECD inflation. For brevity, we do not include these additional tables in the paper, but they remain available upon request.

Author contributions

CRedit: **Nikolaos Vlastakis**: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing; **Athanasios Triantafyllou**: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing; **Neil M. Kellard**: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

The data that support the findings of this study are available from the corresponding author, N.V., upon reasonable request.

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