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Effects of oil market sentiment on macroeconomic variables

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ABSTRACT

This paper aims to evaluate the effects of oil price shocks on macroeconomic variables, for the economies of the United States and Brazil. We develop a variable that measures the volatility of oil prices, from a textual sentiment analysis. We evaluate oil price shocks using the Local Projection method. Our results suggest that changes in oil prices cause larger impacts on the US economy, compared to the effects on the Brazilian economy. The responses of the US and Brazilian variables were similar when using the sentiment indicator or the VIX volatility index. Finally, we find that decreasing the frequency of the variables, together with changing the method, does not change the response trajectories of the macroeconomic variables.

1. Introduction

The effect of world oil prices on economic activity is reflected in several channels. Kilian (2009) points out that the path of oil prices affects the economy in several segments, from household budgets to corporate profits. In this sense, major global recessions have a high correlation with abrupt increases in oil prices.

In general, the economic literature has several studies on impacts of oil price shocks on macroeconomic variables. In a pioneering study for the North American economy, Hamilton (1983) indicates a possible causality between oil price increases and economic activity. Subsequently, various works relate oil price shocks on macroeconomic variables from the technique of Vector Auto-Regressive Vectors (VAR), such as Bernanke et al. (1997), who tests the identification of the response of monetary policy to oil shocks.[1] Other authors evaluate the impacts of oil shocks through alternative models, such as the Dynamic Stochastic General Equilibrium (DSGE) model, a study conducted by Zhao et al. (2016). To measure oil shocks, Kocaaslan (2019) uses the Oil Volatility Index (VOX) as a proxy for uncertainty to assess its effects on economic activity. In turn, Kocaarslan et al. (2020) analyze oil shocks from an uncertainty variable, constructed from a GARCH model on the oil price series.

During the history of the United States, major recessions have been highly linked to oil supply or demand shocks, which impact oil prices and, consequently, its derivatives. According to Peersman and Van Robays (2009) and Kilian and Park (2009), the impact of oil price shocks on US economic activity has been reduced over time, due to the emergence of alternative fuels. These authors indicate that oil price shocks are consequences of indirect demand and supply shocks.

In turn, there is still no consensus on the impacts of oil price shocks on the Brazilian economy. Cavalcanti and Jalles (2013) signals that oil shocks have little impact on economic activity and inflation, as well as on the volatility of Brazilian GDP, during the period from 1980 to 2010. However, oil production in Brazil has been growing at rates above 2% since 2011, according to the National Petroleum Agency (ANP). Also according to this agency, Brazil is among the top 10 producers of this commodity. Future results may express a greater dependence of the Brazilian economy on the behavior of oil prices. We emphasize that, since 2016, Brazil has adopted an international oil price parity rule for pricing fuels and other oil products.

Thus, the objective of this study is to analyze the effects of oil shocks on economic activity in the United States and Brazil. The analysis for these two countries is relevant because they may react in different ways to oil shocks, due to the heterogeneous compositions of economic aggregates, distinct institutions and policies, as well as the dependence on oil imports. Moreover, the largest share of crude oil production in the world is concentrated in the United States. In turn, Brazil is the

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[1] For other studies that use extensions of autoregressive vector models to analyze oil price shocks on economic activity, see Burbidge and Harrison (1984), Hamilton and Herrera (2004), Kilian (2009), and Aastveit et al. (2015), among others.

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largest oil producer in Latin America, according to IEA (2020a). In this case, the responses of three macroeconomic variables will be analyzed: GDP, inflation and interest rate. The choice of response variables was based on Bernanke et al. (1997).

This essay contributes to the literature on oil shocks by constructing a textual sentiment index for the oil market based on the monthly reports of the Organization of the Petroleum Exporting Countries (OPEC) for the period January 2001 to December 2020. The reports explored deal with the price movements of oil produced by OPEC member countries, referred to in the literature as Basket. The development of variables from textual sentiment techniques is still limited in this literature of oil shocks.[2] de Medeiros et al. (2022) develop an indicator that captures oil market sentiment, for the period 1995 to 2017, however, the oil index is based on reports from the International Energy Agency. In addition to developing a new index for the oil market, we estimate the responses of macroeconomic variables to oil shocks from the local projection method employed by Jordà (2005).

In addition to this introduction, this essay is divided into three more sections. Section 2 is reserved for a contextualization of the relationship of oil with macroeconomic variables, such as inflation, GDP, and nominal interest rate. Section 3 shows the detailed construction of the textual sentiment index for the oil market. Section 4 is reserved for the empirical approach and the data used. Section 5 presents the results obtained by the study. Section 6 is dedicated for additional results (robustness). And finally, Section 7 shows the main conclusions.

2. Oil market and macroeconomics

According to the IEA (2020b), oil has a high impact on the world economy, where it corresponds to more than 31% of global primary energy, and is most used in the transportation sector. In this sense, Hamilton (1996) indicates that shocks in the oil market impact macroeconomic variables through various transmission channels, for example, with an increase in transportation costs, which causes an increase in inflation in the economy.

According to IEA (2020a), oil represents 32% of the world's energy supply, followed by coal (27%) and natural gas (23%). Although the participation of oil in electricity generation has decreased over time (25% in 1973 to 3% in 2019), it remains the main energy source in other segments, for example, it accounts for 91% of energy consumption in the transport sector and 70% of consumption of raw materials in the chemical and petrochemical sectors.

The largest producers of crude oil in the world are: United States (1st), Saudi Arabia (2nd), Russia (3rd), Brazil (8th), among others. According to IEA (2020a), the United States produced more than 725 million tons of crude oil in 2020. In turn, Brazil produced more than 156 million tons of oil, for the same period. The Fig. 1 shows the evolution of crude oil production of the United States and Brazil, for the period January 1973 to December 2020.

With regard to oil consumption, the United States also leads the world ranking, followed by the countries China (2nd), India (3rd), Brazil (8th), among others. The US and China account for more than a third of the world's demand for oil. In turn, Brazil demands a little more than 2% of this *commodity*. The Fig. 2 shows the trajectory of oil consumption for the US and Brazil. The statistics indicate that, as a result of the difference between suppliers and demanders, oil is highly commercialized, whether it is crude oil or any derivative products.

In particular, for the year 2020, we find that there has been a decrease in oil production in the world, especially from large producers (U.S., OPEC member countries, among others). According to data from OPEC reports, in certain months of 2020, oil supply was lower than world consumption, which caused an increase in oil prices, as shown in Fig. 3. This result is a consequence of the Covid-19 pandemic, notified in December 2019.

According to OPEC reports, the Covid-19 pandemic and its measures to restrict urban mobility have unprecedented impacts on global oil demand. For example, over 2020, there has been a reduction in global oil demand of 9 mb/d (million barrels/day). On the other side, as oil supply has shrunk sharply, oil prices have increased and have affected inflation indicators for the global economy. As already demonstrated, since the transport sector is highly dependent on crude oil, the end result is an increase in inflation worldwide, given the increased cost of transporting goods.

In order to analyze the effect of the oil market on the macroeconomy, Hamilton (1983) tests the causality between oil prices and macroeconomic variables in the United States. The study indicates a high relationship between oil prices and US GDP, with the *commodity* being responsible for part of the recessions in this country since World War II. It is also highlighted that the performance of the economy is directly related to the energy sector, especially after the creation of the OPEC. Fig. 3 signals a high relationship between oil price increases and US recessions, in a historical series from January 1973 to December 2020.

The first hatched area indicates a recession in the North American economy, a consequence of the first oil shock in the 1970s. A few years later, the second oil shock emerges in the world economy, which causes price increases of this commodity and, consequently, periods of recession in the United States. After the oil shocks, the great crisis experienced by the United States happens after the commodities boom, as a result of the subprime crisis, which causes a high reduction in oil prices. Finally, we have the effects of Covid-19 during the year 2020, which initially reduced the price of crude oil, but leads to a significant increase in the price of oil, because of the low global supply.

2.1. Empirical literature review

The literature of oil shocks on macroeconomic variables is extensive, however, there are still gaps that can be explored, as we present in this study. For a study during the 1970s, Burbidge and Harrison (1984) test the effect of an increase in oil prices on macroeconomic variables in the United States, Japan, Canada, and Germany. Based on autoregressive vector models, the authors indicate that the oil crisis in the 1970s (1973–74) explains part of the performance of industrial production in each country analyzed, which corroborates the result found by Hamilton (1983). However, the high volatility of oil prices in the 1979–80 period had a low impact on industrial production.

Bernanke et al. (1997) use VAR-based techniques to identify the response of monetary policy to oil price shocks. The results indicate that the endogenous response of monetary policy in part is the cause of the negative effects of oil shocks on the real economy. Another highlight is that not only monetary policy, but also other non-monetary and non-oil disturbances play relevant roles, such as shocks in agricultural *commodities*.

Hamilton and Herrera (2004) suggest that the magnitude of the effect of monetary policy to avoid an interest rate increase (contractionary consequence) to an adverse oil price shock is not large enough, as shown by Bernanke et al. (1997). As such, oil shocks can have a greater impact on the economy than had been shown. The justification for this result was the incorrect number of lags in the autoregressive model used by Bernanke et al. (1997). Still, Hamilton and Herrera (2004) signal that it is uncertain how effective it is to implement the monetary policy necessary to neutralize small shocks to the price of oil.

Otherwise, using least squares, Kilian (2008) suggests that only a small share of the oil price increases during the 1970s can be attributed to the reduction in oil production. In general, exogenous shocks to oil

[2] There is still a lack of literature about oil shocks from textual sentiment analysis, however, for other econometric and macroeconomic analysis there are several studies, such as the works of Fève and Guay (2019), Algaba et al. (2020) and Correa et al. (2021).

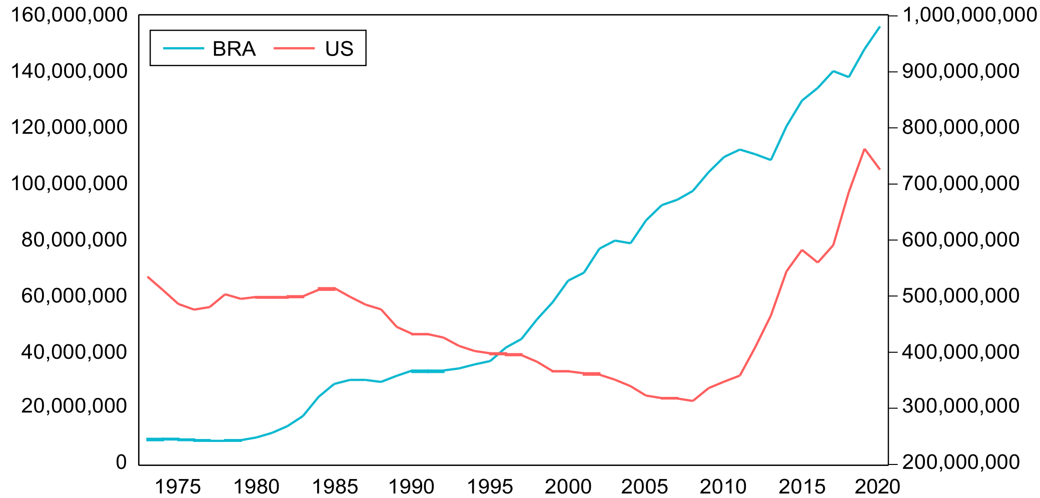

Fig. 1. US and Brazil Crude Oil Production (Tons).
Note: The vertical axis on the left represents the values from Brazil. The vertical axis on the right refers to the United States.
Source: Authors' elaboration.

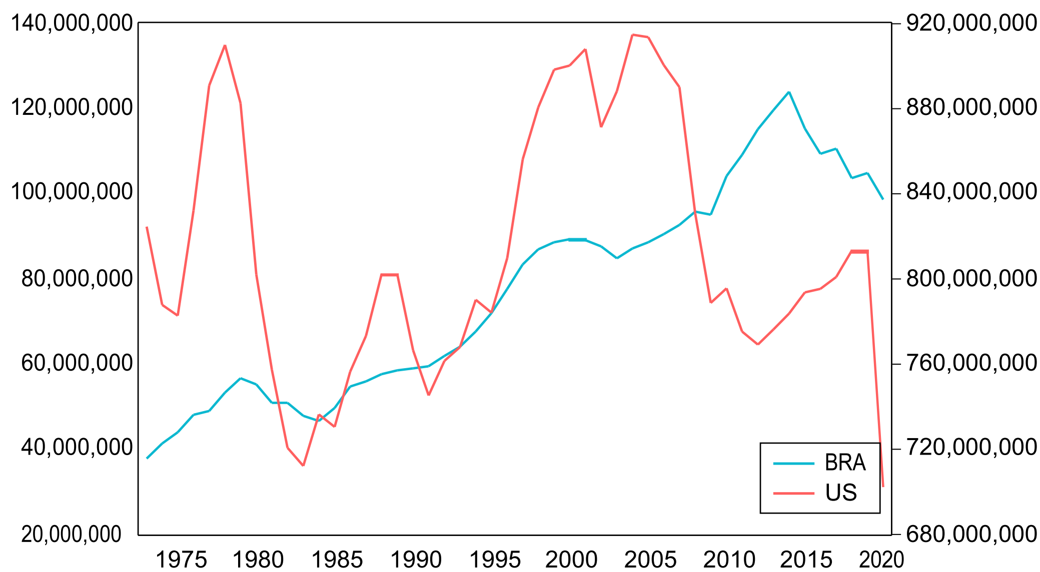

Fig. 2. US and Brazil Crude Oil Consumption (Tons).
Note: The vertical axis on the left represents the values from Brazil. The vertical axis on the right refers to the United States.
Source: Authors' elaboration.

production have low effect on the behavior of the U.S. economy since the 1970s.

Kilian (2009) uses a structural VAR model with the objective of identifying the contained demand and supply shocks in the world oil market. The study indicates that a positive oil price shock can have different effects on the real price of this commodity, with the implicit cause of the price increase determining the final trajectory of the response variable. On the other side, a high demand for oil causes a rapid, long-lasting, and large increase in the real price of oil. On the other hand, a reduction in oil supply causes a smaller and transitory increase in the real oil price in the initial periods.

The main limitation of Kilian (2009) and the other empirical studies, from the perspective of Baumeister and Peersman (2013), is that they are based on time invariant regressions, i.e., the effects of oil shocks on macroeconomic indicators do not change over time. To make the estimates more robust, Baumeister and Peersman (2013) uses a Bayesian autoregressive vector approach with time-varying parameters to analyze the effects of oil shocks on macroeconomic aggregates. The results indicate a significant reduction in the short-run price elasticity of oil demand starting in the early 1980s. Overall, the authors point out that the impacts of oil supply shocks on US economic activity were mild.

Cavalcanti and Jalles (2013) analyze oil price shocks in two different economies, Brazil and the United States. The authors evaluate oil shocks on inflation and GDP for two different periods: 1975–1984 and 1985–2008. From a multivariate autoregressive model, the results suggest that the volatility of the North American economic activity had a reduction, as well as a decrease in the effect of oil shocks in this volatility. For Brazil, such shocks have an uncertain impact on economic activity and a low effect on inflation and volatility of the product growth rate.

From the demand perspective, Aastveit et al. (2015) contribute to the literature in analyzing the relevance of demand from emerging and developed economies in the conduction of the real oil price. To this end, the authors estimate an Augmented Factor Auto-Regressive Vector (FAVAR) that involves observable indicators of world oil production and real oil price. The authors indicate that demand from developing countries, especially Asian countries, is twice as important in the role

Fig. 3. Trajectory of real WTI oil prices (solid line) and recessions in the United States (shaded area) (Barrel/US$).
Source: Macrotrends.

of fluctuations in the real oil price. Another highlight is that geographic regions are impacted in different ways by a positive shock in the real oil price.

With the perspective of studying the impact of oil price shocks on real output, inflation, and the exchange rate of Asian countries that are members of the ASEAN-5,[3] Basnet and Upadhyaya (2015) estimate an autoregressive vector model in its structural form. The results indicate that the analyzed macroeconomic variables have long-run relationship in common, as pointed out by cointegration tests. In contrast to Aastveit et al. (2015), impulse response functions (IRF) show that oil price volatility does not affect the analyzed Asian countries in the long run. This study also reveals that oil prices have no relevance in explaining macroeconomic variables in Asian countries.

Already Zhao et al. (2016) evaluate the impact of different oil price shocks on output and inflation in Asia's major economy, China.[4] To do this, the authors set up a DSGE model with two economies: China and the rest of the world. The simulations reveal that policy shocks by OPEC members generate short-term effects on the Chinese economy; on the other hand, the other shocks produce medium- and long-term effects. Furthermore, most of the fluctuations in economic activity and inflation in China are affected by demand shocks specific to the oil market.

In an attempt to evaluate the global economy, Choi et al. (2018) perform a systematic study of the effect of global oil price shocks on inflation in 72 emerging and developed countries for the period from 1970 to 2015. Using the estimation strategy from the local projection method proposed by Jordà (2005), the main results suggest that a 10% increase in global oil prices, on average, causes domestic inflation to increase by approximately 0.4 percentage points, with the effect being non-statistically significant two years after the shock. Over time, the oil price shock decreases on the price level of the countries analyzed is reduced due to two characteristics: monetary policy with more credibility and less need for energy imports due to higher domestic production.

In addition to testing the impacts of oil price shocks on the U.S. unemployment rate, Kocaaslan (2019) evaluates the effects of oil price uncertainty on unemployment from an autoregressive vector approach for a generalized ARCH (GARCH) model, which allows for errors in the mean. The period evaluated ranges from the second quarter of 1974 to the fourth quarter of 2017. The results indicate that oil price uncertainty increases the U.S. unemployment rate. Similarly, a positive oil price shock causes higher unemployment. In turn, Kocaarslan et al. (2020) from co-integration techniques, analyze the presence of asymmetry between oil prices, oil price uncertainty, interest rate and unemployment rate. Unlike the previous study, the results suggest that an increase in oil price uncertainty has no significant effect on unemployment.

Therefore, more specifically for recent studies focusing on the impact of oil market uncertainty on macroeconomic variables, we note that there is still no consensus in the literature indicating the exact direction of response of macroeconomic variables.

3. Development of the sentiment variable for the oil market

In order to contribute to the literature of oil shocks on macroeconomic variables, we build a sentiment variable for the global oil market. This time series for the oil market is constructed from capturing sentiment from the monthly reports made available by OPEC, ranging from January 2001 to December 2020, which totals 240 OPEC reports, with one report for each month analyzed. Because the reports are extensive, for this case, our analysis will be aimed at the section of oil price movements.[5]

After importing the reports, the second step is to clean the documents in the sense that elements that are not relevant for index estimation are removed, for example: double spaces, punctuation, line breaks, page breaks, paragraph spacing, among others. This step was

[3] ASEAN-5 stands for Association of Southeast Asian Nations. The five member countries of this association, are: Indonesia, Malaysia, Philippines, Singapore and Thailand.

[4] Four types of oil price fluctuations were studied: oil supply shocks by OPEC members, other supply shocks, demand shocks for industrial *commodities*, and demand shocks specific to the oil market.

[5] The reports used to construct the sentiment variable can be consulted at the link: https://www.opec.org/opec_web/en/.

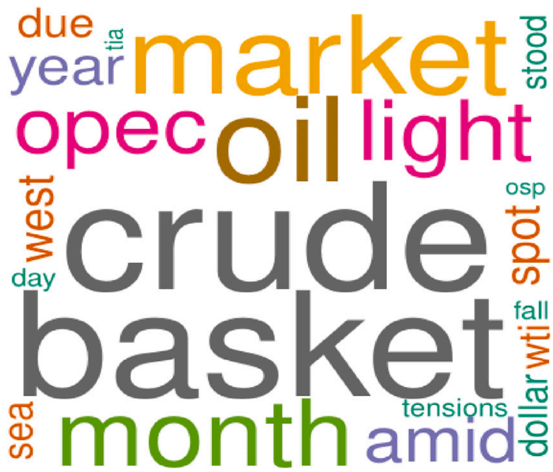

Fig. 4. Text word cloud used for sentiment development.
Source: Authors' elaboration.

performed using the package 'tm', from the R software. For example, we use the 'Smart' argument, of the "tm_map" function, to remove stop words from reports. From the cleaning performed on the texts (reports), we illustrated the most frequent words in the 240 treated reports through a word cloud, as shown in Fig. 4.

In the third step, the sentiment indicator is obtained from the Jockers (2017) algorithm, which selects words according to their positive or negative cognitive aspects. The dictionary used by the algorithm, for classifying the cognitive aspects of words, is specified by a pre-established word dictionary according to Deeney et al. (2015). Then, based on the count of positive and negative words present in the reports, we build an index that represents the tone or sentiment of the reports linked to the oil sector, as presented in Eq. (1):

$$\text{Sent}_t = \frac{\sum \text{ Positive Words } - \sum \text{ Negative Words}}{\sum \text{ Positive Words } + \sum \text{ Negative Words}} \tag{1}$$

The index $sent_t$ varies in the range $[-1, 1]$. The tone of the OPEC reports is positive if the value of the index is greater than 0. On the other hand, if the index value is less than 0, the tone is negative. Finally, when the index value is equal to 0, the tone result is neutral, something that is not expected.

Fig. 5 shows the trajectory of the Sent variable, build from textual sentiment analysis techniques, for the period January 2001 to December 2020. The value of the most positive sentiment toward the oil market is 0.70. On the other hand, the most negative tone reached −0.45. Thus, we verified more positive news about oil than negative news, for the analyzed period. The developed sentiment variable will be used for identifying the oil shock.

The Fig. 6 shows a summary of the process of data collection and estimation of the textual sentiment for the oil market. Thus, we observe that the development of the sentiment has three steps, namely: (i) access the OPEC website, collect the data from the reports; (ii) extract the words from the reports, use the dictionary and calculate the sentiment; and, finally, (iii) the last step is the decision making from the generated time series. The developed sentiment indicator can be used for economic or any other application. In this case, we use sentiment to identify shocks in economic variables, for the US and Brazil.

4. Methodology and data

4.1. Estimation by local projection

In this study, we detail the methodology used to evaluate the effects of global oil market shocks on macroeconomic variables in the US and Brazil, namely: GDP, interest rate and inflation. Such shock effects were evaluated from a stochastic investigation of the variables. The variables that will be identified as shocks are: $Sent$ (a variable based on textual sentiment analysis techniques, as described in Section 3) and the S&P 500 Volatility Index of the US stock market (VIX).

To test the effects of oil shocks on macroeconomic variables, we used the method developed by Jordà (2005), which consists of the estimation of impulse response functions from local projections.[6] According to that author, this method has some advantages over the conventional model by autoregressive vectors, such as: (a) it can be estimated via linear regression by OLS; (b) they are more robust to specification errors; (c) performing joint or pointwise analytical inference is simple; and (d) it allows for strongly nonlinear and flexible characteristics that are complex in multivariate form. Similar to this study, Hamilton (2011) and Choi et al. (2018) test the effects of oil price shocks on macroeconomic variables.

In this study we estimate impulse-response in two ways: shock identified as endogenous (Jordà, 2005) and shock identified as exogenous (Ramey and Zubairy, 2018). The main difference between both is that the estimation in an exogenous way is considered from an exogeneity vector, that is, a pre-established shock.[7]

In particular, Eq. (2) in reduced form is estimated for monthly data:

$$y_{t+h} = \alpha_h + \psi_h(L)x_{t-1} + \beta_h S_t + \epsilon_{t+h} \tag{2}$$

with $h = 0, \ldots, 10$ and where y_t is the variable of interest; α is a constant; ψ is a lag operator polynomial; x represents a set of lagged variables used as a control; β is the response of x at time $t+h$ given the shock at time t; S indicates the sentiment variable captured by the oil market; and ϵ a residual term. We estimate Eq. (2) in individual form by OLS. Finally, we estimate the impulse-responses without the Newey and West (1986) standard error correction proposed by Jordà (2005), since Montiel Olea and Plagborg-Møller (2021) indicate that correction is not necessary.

In a comparison with VAR estimation, Jordà (2005) suggests that the local projection method is more robust in modeling misspecification when compared to VAR IRFs, since direct estimation by local projection is more effective than the iterated process by autoregressive vectors. Inference for VAR impulse responses is complex because the IRF coefficients are high-dimensional nonlinear functions of the estimated parameters.

Montiel Olea and Plagborg-Møller (2021) indicate that inference by local projection is robust to two intrinsic features in macroeconomic applications, namely: (i) persistent data and the estimation of impulse-responses for long horizons. In turn, Plagborg-Møller and Wolf (2021) show that local linear projections and VARs estimate the same impulse-responses in the population. Some implications are considered: (i) based on VAR structural identification, with inclusion of short-run, long-run or sign restrictions, can be performed similarly with use of local projection, and the opposite is also valid; (ii) structural estimation with a *proxy* (instrument) can be obtained from the ordering of the first instrument in a recursive VAR, even under non-invertibility; (iii) linear VARs are as robust to non-linear as linear local projections.

4.2. Database

The estimation of Eq. (2) is based on data with monthly periodicity. The study sample starts in January 2001 and finishes in December 2020, with 240 observations available. The period analyzed is justified by data availability, especially for the development of the shock variable (oil market sentiment).

[6] The identification of the parameters is performed through the Cholesky decomposition.

[7] The estimation by local projection is performed by the R software, inspired by the study of Adämmer (2019).

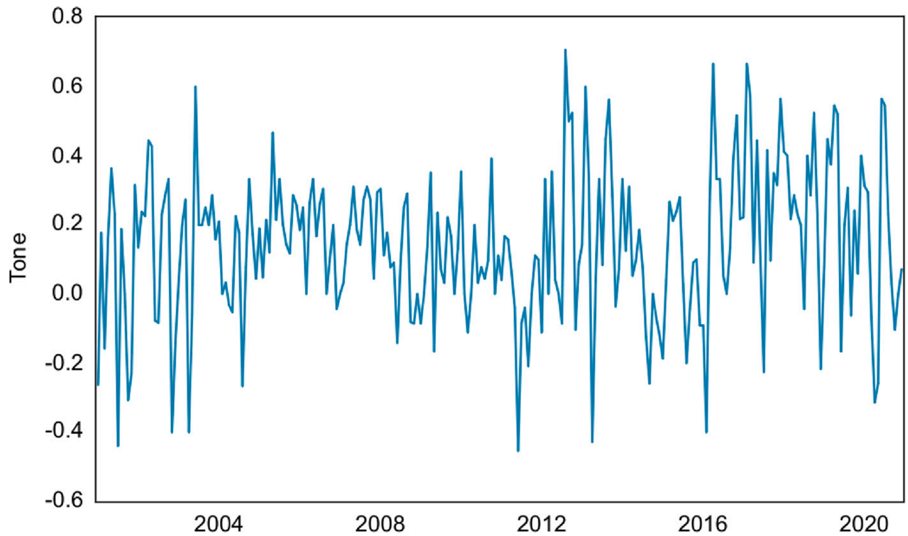

Fig. 5. Trajectory of the oil market sentiment variable (Sent).
Source: Authors' elaboration.

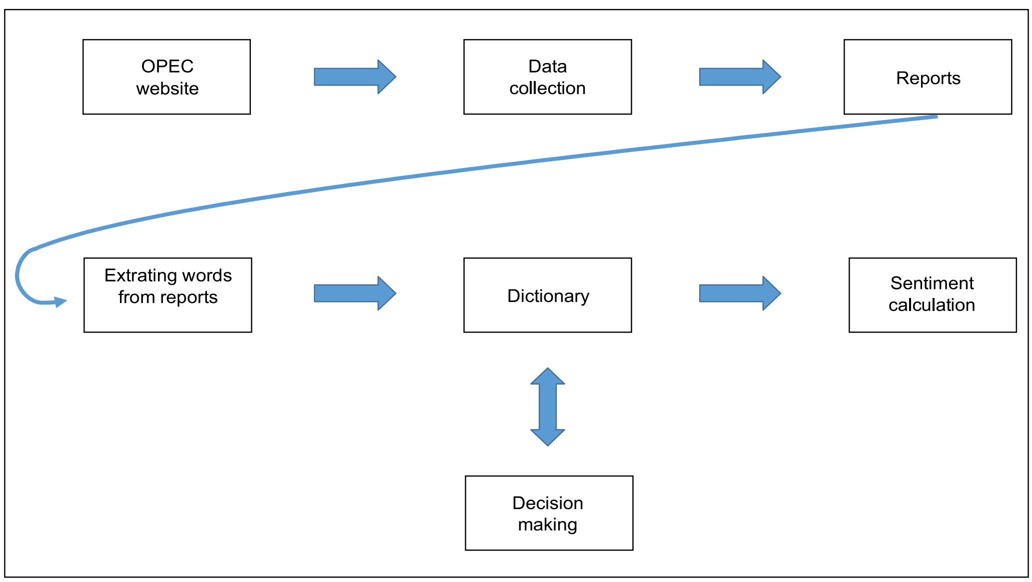

Fig. 6. Diagram of the process of collecting and estimating textual sentiment.
Source: Authors' elaboration.

The sentiment variable used for shock, built from textual sentiment analysis techniques, was obtained through monthly reports provided by OPEC, as shown in Section 3. In addition to this variable, we used three macroeconomic variables of interest for each country analyzed, in this case were Brazil and the United States, they were: output of the economy, inflation and interest rate. The choice of the variables of interest was based on Bernanke et al. (1997). Finally, we used the US stock market's S&P 500 Volatility Index (VIX) as the variable to be identified as a shock, as a way to compare with the results obtained from the shock identified from the created sentiment variable. Table 2 in Appendix presents a summary of the main descriptive statistics of the variables used in the study.

For the United States, the data set consists in: the seasonally adjusted index of industrial production as a proxy for gross domestic product; the effective interest rate or federal funds; and the inflation rate represented by the percentage change in the consumer price index for all urban consumers. The variables were obtained from the Central Bank of St. Louis.

Similarly, the variables for Brazil are: annualized Selic interest rate; 12-month accumulated GDP; and the inflation rate represented by the 12-month accumulated National Wide Consumer Price Index (IPCA). All variables were obtained from the Time Series Management System of the central bank of Brazil. Table 1 shows a summary of the macroeconomic variables used in the study.

5. Results and discussion

We explore the system of equations, from the method proposed by Jordà (2005), from the analysis of Impulse Response Functions (hereafter IRF's) for a two standard deviation shock to the oil shock variables, *Sent* and VIX. An IRF identifies the effect of a single residual shock on the current and future values of the endogenous variables.

The optimal lag of the IRF's is chosen based on three criteria, namely: Akaike (AIC), Hannan-Quin (HQ) and the Bayesian of Schwarz (1978). The optimal lag choice will be the one in which the criterion presents the lowest value. However, when there is divergence for the

Table 1
Summary of the variables used.
Source: Authors' elaboration.

Variable	Description	Source
United States		
Industrial Production (proxy for GDP)	Index for seasonally adjusted industrial production	Central Bank of St. Louis
Interest	Effective interest rate or federal funds	Central Bank of St. Louis
Inflation	Consumer price index for all urban consumers	Central Bank of St. Louis
Brazil		
GDP	12-month accumulated Gross Domestic Product	Central Bank of Brazil
Interest	Annualized Selic interest rate	Central Bank of Brazil
Inflation	12-month accumulated Broad Consumer Price Index (IPCA)	Central Bank of Brazil
Variables used for shock identification		
Sent	Variável Variable constructed from OPEC oil market sentiment	Authors
VIX	S&P 500 Volatility Index of the US stock market	Yahoo Finance

Table 2
Descriptive statistics of the variables used.
Source: Authors' elaboration.

Variable	Mean	Median	Maximum	Minimum	S. deviation	Observations
GDP - US	96.62	98.00	104.18	84.73	4.96	240
Interest - US	1.49	1.01	5.98	0.05	1.64	240
Inflation - US	219.69	220.83	261.56	175.60	25.12	240
GDP - Brazil	4108924	3908022	7475380	1209046	2043350	240
Interest - Brazil	12.34	11.74	26.32	1.90	5.10	240
Inflation - Brazil	6.17	5.90	17.24	1.88	2.79	240
Sent	0.14	0.14	0.70	−0.45	0.22	240
VIX	19.84	17.30	59.89	9.51	8.43	240

lag between criteria, we opt for the choice of the smaller *lag* or when the optimal lag is common to only two criteria.

Fig. 7 shows the responses of macroeconomic variables (GDP, Inflation and Interest Rates) to an oil shock, for the United States. For estimation, we consider the oil shock as endogenous, and this shock is identified by the sentiment variable (*Sent*) and the VIX index. The justification for this is due to the high representativeness of the US in the world oil production and consumption. Since the identification of the shocks is by Cholesky decomposition, the estimation considers the following ordering of the variables: shock, GDP, Inflation and Interest Rates.

Fig. 7 indicates that a unit shock in the variable *Sent* causes a positive response in inflation, GDP and the interest rate, being statistically significant during initial periods only for inflation. This increase in inflation may be justified by the increase of transport costs, since large shares of oil is destined for transport use, which causes increases of prices in the supply chain. We highlight that United States are also the largest consumers of crude oil in the world, which makes their imports and, consequently, petroleum derived products, more expensive. This result is similar to the Cavalcanti and Jalles (2013) study, where the authors use oil price shocks.

With regard to the economic volatility shock in the United States, measured by the VIX, we find that all macroeconomic variables respond negatively, with results statistically different from zero. The pessimistic scenario may indicate greater uncertainty and low economic predictability. This context makes households and firms more conservative in relation to their consumption and investment decisions, respectively. The combination of these components has a negative impact on economic activity and inflation indicators.

Fig. 8 shows the responses of Brazil's macroeconomic variables to unit oil shocks, as measured by the sentiment variable and the VIX volatility indicator. Unlike Fig. 7, the IRF's in the left column (in blue) and the right column (in red) were estimated from exogenous shocks, since the sentiment variable constructed is based on OPEC reports, and the literature shows that the Brazilian economy has low influence on world oil prices; and, on the other hand, the VIX variable is quoted on the New York stock exchange.

Regarding to the responses of the macroeconomic variables for Brazil, we verified similar responses to the variables relative to the United States. However, we found a lower impact for the Brazilian economy, since inflation does not show a statistically significant response, i.e., an uncertain result regarding the unit shock in oil market sentiment. In terms of economic activity, increases in the sentiment about oil prices signal a fall in Brazilian real GDP, however, the response signals are not statistically different from zero.

Except for interest rate responses to the exogenous shock in the VIX variable, all other results are statistically non-significant for the Brazilian economy, i.e., uncertain. This result corroborates the study of Cavalcanti and Jalles (2013). Thus, the results signal that changes in world oil prices have less impact on Brazil's economy, compared to the impact on the United States economy.

6. Additional results

This section presents additional results, based on robustness tests for responses of macroeconomic variables to different approaches. The first robustness approach tested is to change the method of estimating the impulse responses. In this case, we estimate the responses of the U.S. variables from Structural Vector Autoregression (SVAR), where we consider all monthly variables endogenous, similar to the estimation by local projection shown in Fig. 7.

We represent in summary form the SVAR methodology used as robustness. We consider the following vector autoregression model of order p:

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-1} + \epsilon_t \tag{3}$$

where y_t corresponds to a vector $(nx1)$ of endogenous variables, $c = (c_1, \dots, c_n)'$ is an intercept vector, ϕ_i is a matrix (nxn) of autoregressive coefficients for $i = 1, 2, \dots, p$, and $\epsilon_t = (\epsilon_{1t}, \dots, \epsilon_{nt})'$ is the generalization (n) of a white noise process. We use two lags for the endogenous variables, as indicated by the information criteria, shown in Table 8.

We use the Cholesky decomposition to identify the parameters of the SVAR model. To identify the oil shock, measured by the VIX variable,

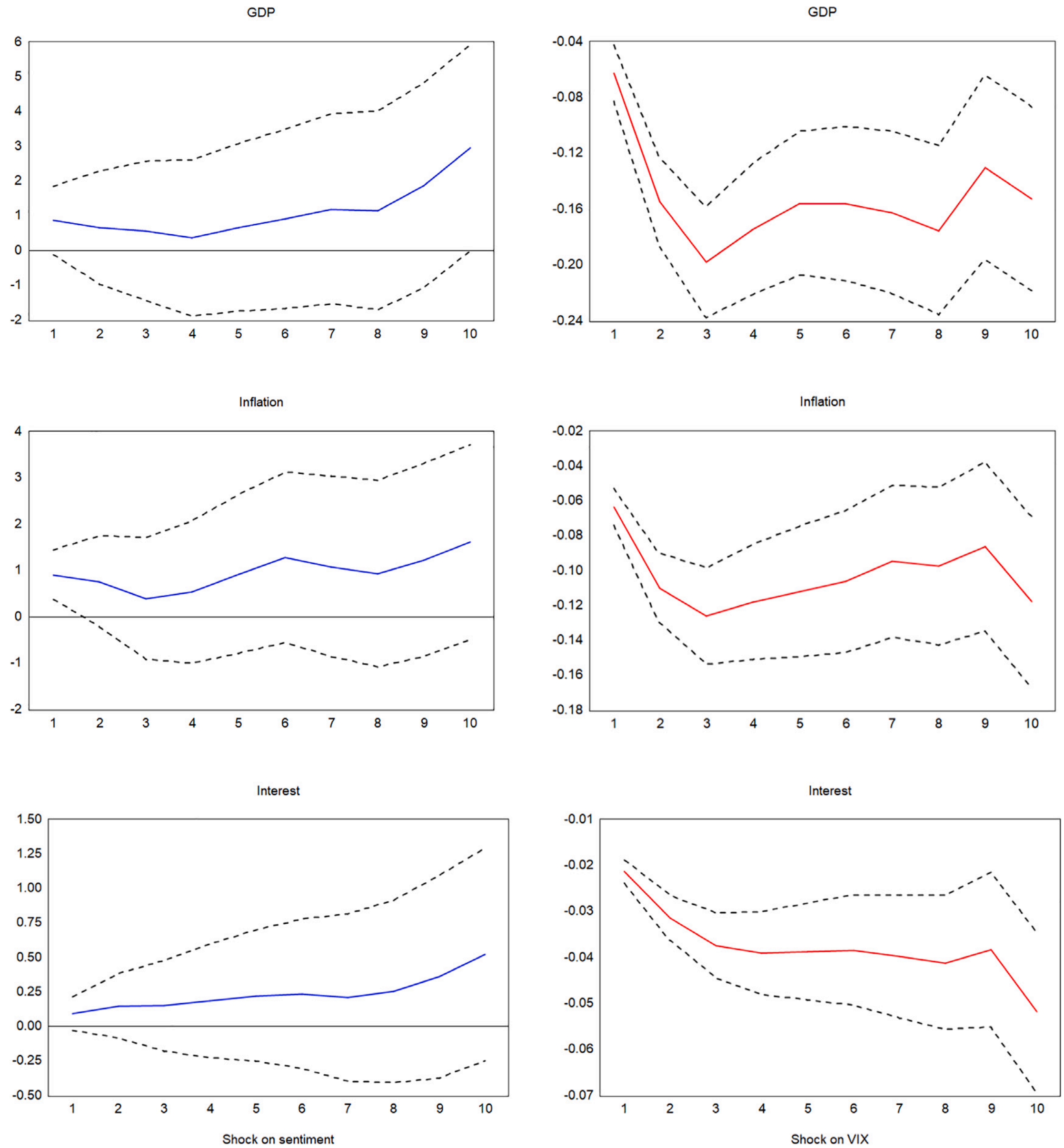

Fig. 7. Impulse Responses in Oil Shocks — United States.
Note: the left-hand column (blue line) represents the responses to an oil shock, identified from the sentiment variable *Sent*. The right-hand column (red line) represents the responses to an oil shock, identified from the VIX variable.
Note: the optimal lag of the endogenous variables used in the estimation in the left column is shown in Table 3. The optimal lag of the variables used for estimating the IRF's in the right column is shown in Table 4. The tables are in Appendix.
Source: Authors' elaboration.

we follow the literature and consider that unexpected changes in the price of oil are exogenous to the values of the other variables, that is, GDP, Inflation and Interest Rates.

According to Fig. 9, we find that the responses of the macroeconomic variables in the United States are similar to the responses estimated in Fig. 7 (red line), by local projections, the results being significant also for all periods.

Another robustness exercise consists in aggregating or averaging the monthly series to quarterly, and estimating by SVAR. This result is presented in Fig. 9, in Appendix. For the variables VIX, GDP and Inflation, we use the average for the transformation from monthly to quarterly, since the variables are in index form. In turn, we accumulate three months to form a quarter, for Interest, since their monthly values are in absolute terms. According to the impulse-response, we verify that the change in frequency of the variables does not alter the response trajectories of the macroeconomic variables. However, we point out that some periods of the responses become not statistically significant.

Finally, we perform estimation by local projection from the data used in an SVAR, by Cavalcanti and Jalles (2013). In this case, we used the quarterly data from the sub sample referring to the first quarter of 1975 to the fourth quarter of 1984, for the following variables in the United States: international oil price (WTI), GDP and inflation rate.

We maintain the same econometric treatment for the variables, before the estimation, that is, we consider all variables in logarithm. However, we do not apply the first difference to the variables, and we apply only one lag to the variables, rather than four lags, due to the limited number of observations and the quarterly frequency. The results indicate that inflation responds positively to a unit shock in

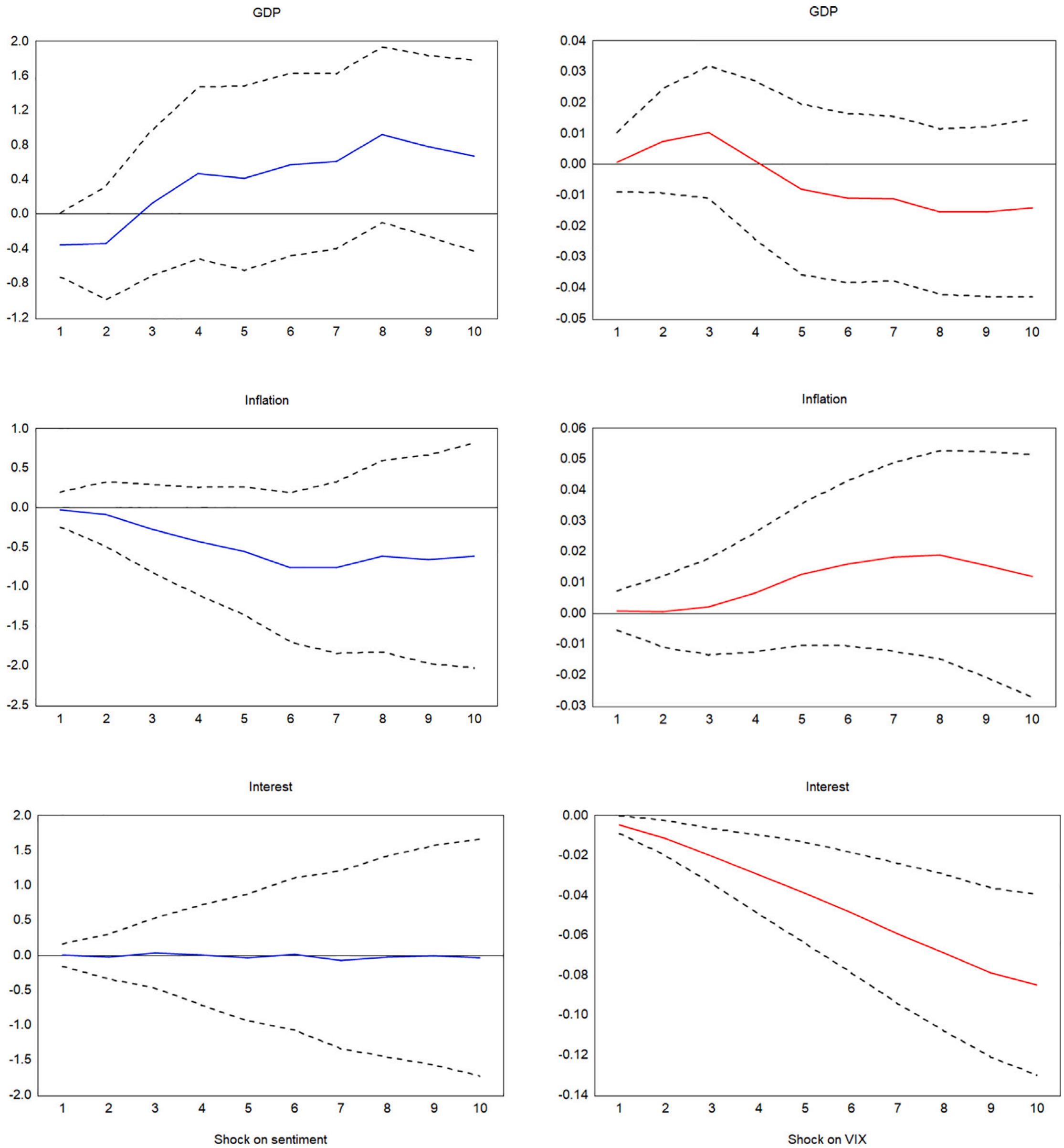

Fig. 8. Impulse Responses in Oil Shocks — Brazil.
Note: the left-hand column (blue line) represents responses to an oil shock, captured by the sentiment variable Sent. The right-hand column (red line) represents the responses to an oil shock, captured by the VIX index.
Note: the optimal lag of the shock variable used in the IRFs on the blue line is shown in Table 5. The optimal lag of the shock variable used in the IRF's in the red line is shown in Table 6. The tables are in Appendix.
Note: the lag of the remaining variables estimated as endogenous are given in the Table 7 in Appendix.
Source: Authors' elaboration.

oil prices, being statistically significant up to ten periods ahead; in turn, GDP responds positively as well, however, it is not statistically significant, according to Fig. 11. Therefore, with the lag reduction of the variables and without applying first difference, our results are more robust compared to the Cavalcanti and Jalles (2013) study, since the responses for inflation were statistically significant.[8]

[8] We kept the same criteria for identifying the shocks, by Cholesky decomposition.

7. Conclusions

Given the relevance of oil to the world economy, the investigation of the reaction of macroeconomic variables to oil shocks is essential for analysis and decision-making by public and private managers. In this study, we seek to evaluate the responses of economic activity (GDP), inflation and interest rates, for two countries with distinct economies, but dependent on oil, such as Brazil and the United States.

The literature of oil shocks on economic variables is quite extensive. However, this study advances in the literature by developing an oil market sentiment index from OPEC reports, used as a *proxy* for shock identification. Allied to this innovation, we propose the application of the method by local projections, as an alternative to other methodologies widely explored in the literature of shocks, for example, the methodology of autoregressive vectors.

Our results suggest: (i) changes in oil prices cause greater impacts on the US economy, compared to the effects on the Brazilian economy; (ii) to a large extent, the results were not statistically significant for the Brazilian economy, i.e., uncertain; (iii) the responses of the US and Brazil variables were similar regarding the use of the sentiment indicator or the VIX volatility index; (iv) the analysis based on shocks by SVAR maintains similarity with the method proposed in the study, by Local Projection; and, finally, (v) the decrease in frequency of time series, along with the change in method, does not change the response trajectories of macroeconomic variables.

Our results motivate future research that considers more oil shock variables, which can be developed from other textual analysis techniques, for example, using a time-varying dictionary with word incorporation. Furthermore, oil shock variables can be constructed based on oil futures market reports.

CRediT authorship contribution statement

Rennan Kertlly de Medeiros: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. **Edilean Kleber da Silva Bejarano Aragón:** Conceptualization, Methodology, Validation, Investigation, Data curation, Writing – review & editing, Supervision, Project administration. **Cássio da Nóbrega Besarria:** Conceptualization, Methodology, Validation, Investigation, Data curation, Writing – review & editing, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix

See Figs. 9–11 and Tables 2–8.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.resourpol.2023.103642.

Table 3
Optimal lag of endogenous variables with the inclusion of the shock variable sent – Estimation by local projection – United States.
Source: Authors' elaboration.

Lag	AIC	HQ	SC
1	−7.7580	−7.6374	−7.4590
2	−8.4555	−8.2384	−7.9174*
3	−8.6185	−8.3050*	−7.8412
4	−8.6383*	−8.2283	−7.6218
5	−8.5526	−8.0461	−7.2970
6	−8.5858	−7.9828	−7.0910
7	−6.7953	−7.8298	−6.7953
8	−8.4411	−7.6451	−6.4679
9	−8.4140	−7.5216	−6.2017
10	−8.3636	−7.3747	−5.9121

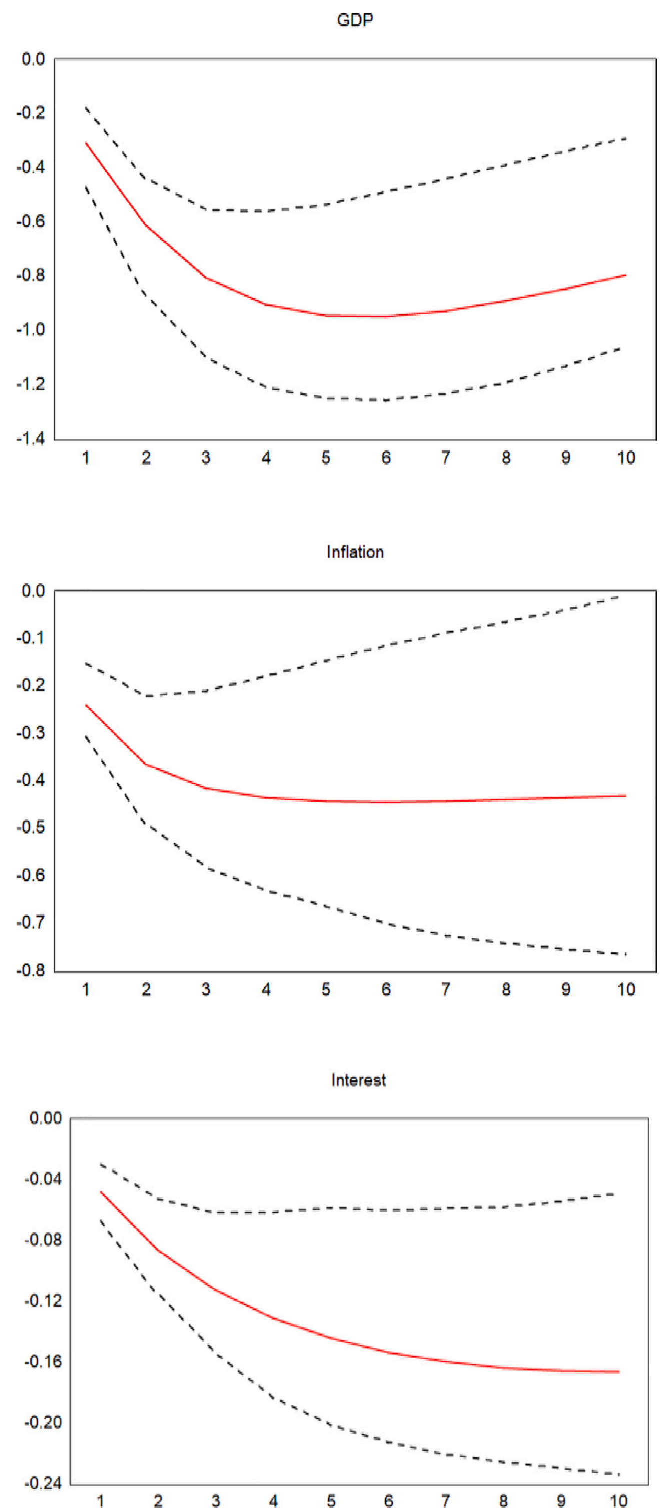

Fig. 9. Impulse responses to oil shocks with SVAR estimation.
Note: to estimate the IRF's, we used the impulse variable (shock) VIX.
Note: the optimal lag of the variables used in the estimation of the IRFs (in which all endogenous variables were considered) is presented in Table 4.
Source: Authors' elaboration.

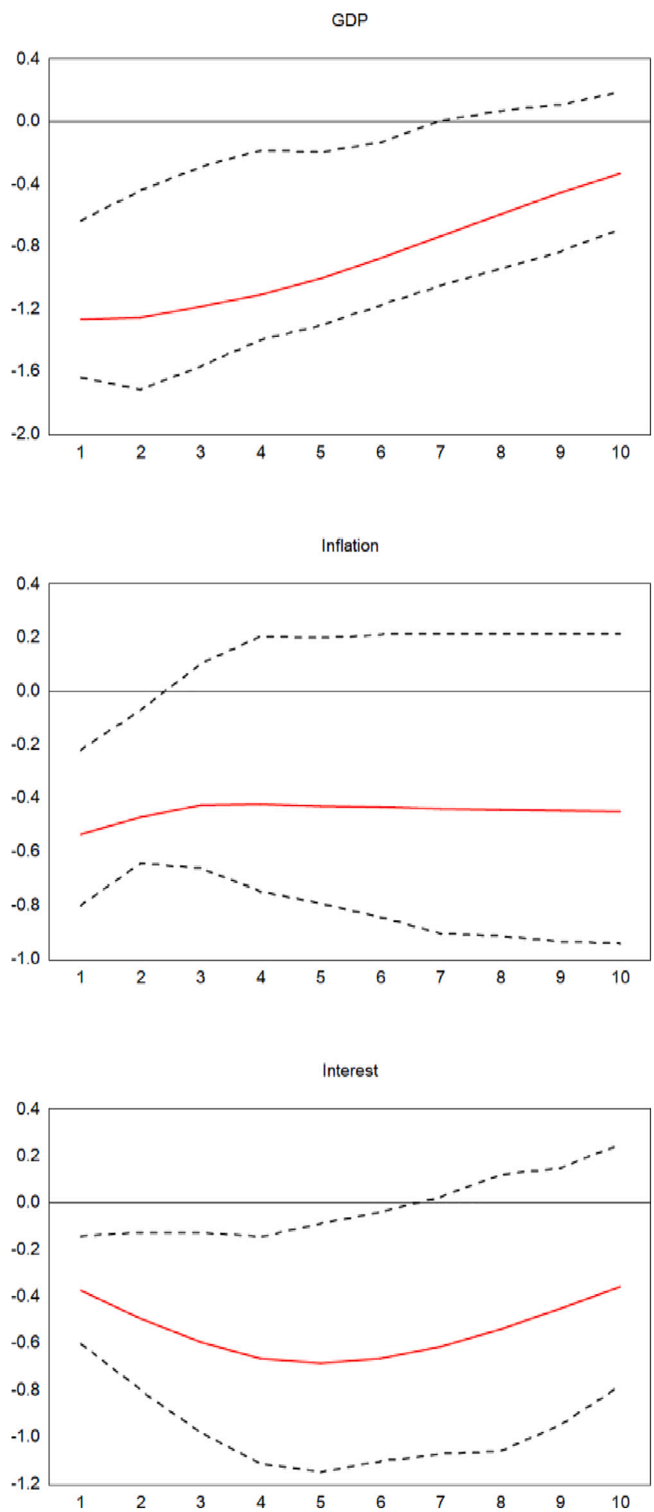

Fig. 10. Impulse responses to quarterly oil shocks.
Note: to estimate the IRF's, we used the impulse variable (shock) VIX.
Note: the optimal lag of the variables used in the estimation of the IRFs (in which all endogenous variables were considered) is presented in Table 8.
Source: Authors' elaboration.

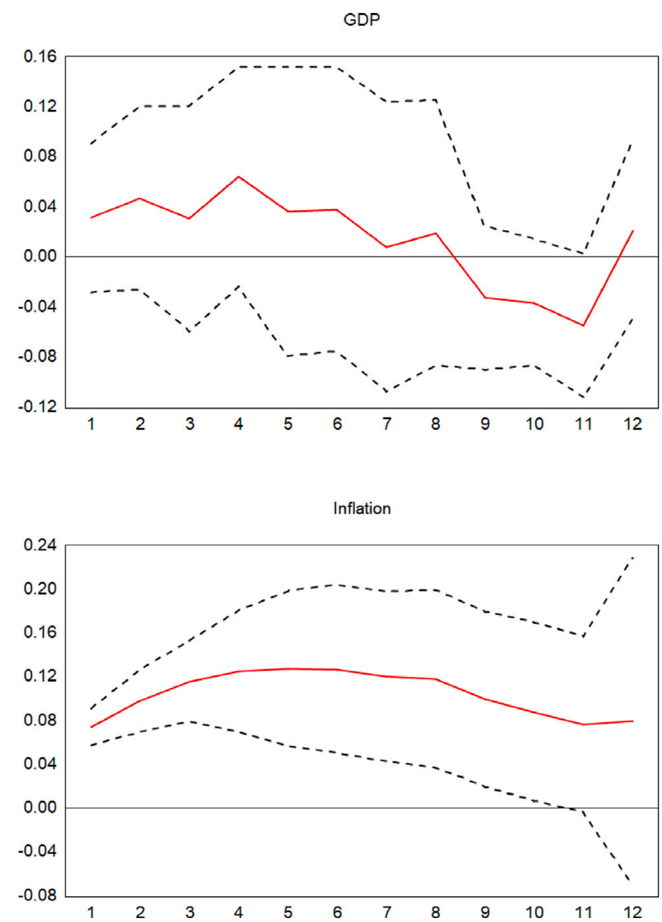

Fig. 11. Impulse responses to WTI oil price shock (Cavalcanti and Jalles, 2013) - Estimation by Local Projection.
Note: confidence intervals have a confidence level of 95%.
Note: the estimation is performed with one lag, since the number of observations is small and the frequency of the variables is quarterly.
Source: Authors' elaboration.

Table 4
Optimal lag of endogenous variables with the inclusion of the VIX shock variable – Estimation by local projection and SVAR – United States.
Source: Authors' elaboration.

Lag	AIC	HQ	SC
1	−1.9678	−1.8472	−1.6688
2	−2.4807	−2.2636	−1.9425*
3	−2.6352	−2.3216*	−1.8579
4	−2.6469*	−2.2369	−1.6305
5	−2.6077	−2.1012	−1.3521
6	−2.5518	−1.9488	−1.0570
7	−2.5250	−1.8255	−0.7910
8	−2.5072	−1.7113	−0.5341
9	−2.4589	−1.5665	−0.2465
10	−2.4639	−1.4750	−0.0124

Table 5
Optimal lag of the exogenous variable Sent.
Source: Authors' elaboration.

Lag	AIC	HQ	SC
1	−3.1366	−3.1246	−3.1068*
2	−3.1467*	−3.1286*	−3.1019
3	−3.1380	−3.1139	−3.0783
4	−3.1349	−3.1047	−3.0601
5	−3.1322	−3.0960	−3.0425
6	−3.1376	−3.0954	−3.0330
7	−3.1324	−3.0842	−3.0128
8	−3.1241	−3.0698	−2.9896
9	−3.1161	−3.0558	−2.9666
10	−3.1129	−3.0466	−2.9485

Table 6
Optimal lag of exogenous variable VIX.
Source: Authors' elaboration.

Lag	AIC	HQ	SC
1	3.1520*	3.1640*	3.1819*
2	3.1593	3.1774	3.2042
3	3.1574	3.1815	3.2172
4	3.1625	3.1927	3.2373
5	3.1712	3.2074	3.2609
6	3.1771	3.2193	3.2817
7	3.1765	3.2248	3.2961
8	3.1839	3.2382	3.3184
9	3.1916	3.2519	3.3410
10	3.1946	3.2609	3.3590

Table 7
Optimal lag of endogenous variables – Estimation by local projection for monthly variables (without shock variable) – Brazil.
Source: Authors' elaboration.

Lag	AIC	HQ	SC
1	15.9778	16.0501	16.1571
2	13.8600	13.9866*	14.1739*
3	13.8425	14.0234	14.2909
4	13.8037	14.0388	14.3867
5	13.7518*	14.0412	14.4693
6	13.7668	14.1105	14.6188
7	13.8242	14.2222	14.8108
8	13.8515	14.3038	14.9726
9	13.9048	14.4113	15.1605
10	13.9243	14.4851	15.3145

Table 8
Optimal lag of endogenous variables – Estimation by local projection for quarterly variables (with inclusion of the VIX shock variable) – United States.
Source: Authors' elaboration.

Lag	AIC	HQ	SC
1	4.4677*	4.7229	5.1101
2	3.9360	4.3954*	5.0924*
3	3.8905	4.5540	5.5608
4	3.9070	4.7746	6.0913
5	3.9854	5.0571	6.6835
6	4.1535	5.4294	7.3657
7	4.2671	5.7471	7.9931
8	4.4801	6.1643	8.7201
9	4.3106	6.1989	9.0646
10	4.3360	6.4285	9.6039

References

Aastveit, K.A., Bjørnland, H.C., Thorsrud, L.A., 2015. What drives oil prices? Emerging versus developed economies. J. Appl. Econometrics 30 (7), 1013–1028.
Adämmer, P., 2019. Lpirfs: An R package to estimate impulse response functions by local projections. R J. (2019) 11 (2), 421–438.
Algaba, A., Ardia, D., Bluteau, K., Borms, S., Boudt, K., 2020. Econometrics meets sentiment: An overview of methodology and applications. J. Econ. Surv. 34 (3), 512–547.
Basnet, H.C., Upadhyaya, K.P., 2015. Impact of oil price shocks on output, inflation and the real exchange rate: Evidence from selected ASEAN countries. Appl. Econ. 47 (29), 3078–3091.
Baumeister, C., Peersman, G., 2013. Time-varying effects of oil supply shocks on the US economy. Am. Econ. J.: Macroecon. 5 (4), 1–28.
Bernanke, B.S., Gertler, M., Watson, M., Sims, C.A., Friedman, B.M., 1997. Systematic monetary policy and the effects of oil price shocks. Brook. Pap. Econ. Act. 1997 (1), 91–157.
Burbidge, J., Harrison, A., 1984. Testing for the effects of oil-price rises using vector autoregressions. Internat. Econom. Rev. 459–484.
Cavalcanti, T., Jalles, J.T., 2013. Macroeconomic effects of oil price shocks in Brazil and in the united states. Appl. Energy 104, 475–486.
Choi, S., Furceri, D., Loungani, P., Mishra, S., Poplawski-Ribeiro, M., 2018. Oil prices and inflation dynamics: Evidence from advanced and developing economies. J. Int. Money Finance 82, 71–96.
Correa, R., Garud, K., Londono, J.M., Mislang, N., 2021. Sentiment in central banks' financial stability reports. Rev. Finance 25 (1), 85–120.
de Medeiros, R.K., da Nóbrega Besarria, C., de Jesus, D.P., de Albuquerquemello, V.P., 2022. Forecasting oil prices: New approaches. Energy 238, 121968.
Deeney, P., Cummins, M., Dowling, M., Bermingham, A., 2015. Sentiment in oil markets. Int. Rev. Financ. Anal. 39, 179–185.
Fève, P., Guay, A., 2019. Sentiments in SVARs. Econ. J. 129 (618), 877–896.
Hamilton, J.D., 1983. Oil and the macroeconomy since world war II. J. Polit. Econ. 91 (2), 228–248.
Hamilton, J.D., 1996. This is what happened to the oil price-macroeconomy relationship. J. Monetary Econ. 38 (2), 215–220.
Hamilton, J.D., 2011. Nonlinearities and the macroeconomic effects of oil prices. Macroecon. Dyn. 15 (S3), 364–378.
Hamilton, J.D., Herrera, A.M., 2004. Comment: Oil shocks and aggregate macroeconomic behavior: The role of monetary policy. J. Money Credit Bank. 265–286.
IEA, 2020a. IEA Atlas of Energy. Report.
IEA, 2020b. World energy balances and statistics. Report.
Jockers, M., 2017. Package 'syuzhet'. https://cran.r-project.org/web/packages/syuzhet.
Jordà, Ò., 2005. Estimation and inference of impulse responses by local projections. Amer. Econ. Rev. 95 (1), 161–182.
Kilian, L., 2008. Exogenous oil supply shocks: How big are they and how much do they matter for the US economy? Rev. Econ. Stat. 90 (2), 216–240.
Kilian, L., 2009. Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. Amer. Econ. Rev. 99 (3), 1053–1069.
Kilian, L., Park, C., 2009. The impact of oil price shocks on the US stock market. Internat. Econom. Rev. 50 (4), 1267–1287.
Kocaarslan, B., Soytas, M.A., Soytas, U., 2020. The asymmetric impact of oil prices, interest rates and oil price uncertainty on unemployment in the US. Energy Econ. 86, 104625.
Kocaaslan, O.K., 2019. Oil price uncertainty and unemployment. Energy Econ. 81, 577–583.
Montiel Olea, J.L., Plagborg-Møller, M., 2021. Local projection inference is simpler and more robust than you think. Econometrica 89 (4), 1789–1823.
Newey, W.K., West, K.D., 1986. A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix. National Bureau of Economic Research Cambridge, Mass., USA.
Peersman, G., Van Robays, I., 2009. Oil and the euro area economy. Econ. Policy 24 (60), 603–651.
Plagborg-Møller, M., Wolf, C.K., 2021. Local projections and VARs estimate the same impulse responses. Econometrica 89 (2), 955–980.
Ramey, V.A., Zubairy, S., 2018. Government spending multipliers in good times and in bad: Evidence from US historical data. J. Polit. Econ. 126 (2), 850–901.
Zhao, L., Zhang, X., Wang, S., Xu, S., 2016. The effects of oil price shocks on output and inflation in China. Energy Econ. 53, 101–110.