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Modelling the Global Price of Oil:
Is there any Role for the Oil Futures-spot Spread?

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ABSTRACT

This paper illustrates the main benefits of accounting for the oil futures-spot spread in a Structural Vector Autoregressive model of the international market for crude oil. To this end, we replace the proxy for global above-ground crude oil inventories with the spread, which is derived by Brent crude futures prices with maturity 3-months. This model can be motivated on the basis of several economic considerations. First, the spread exploits the price discovery role in the crude oil futures markets. Second, the spread-based model alongside a proper set of identifying assumptions accounts for the presence of informational frictions and it allows for the feedback effect from futures to spot markets. Finally, the inventory proxy is affected by measurement error. The dynamic response functions show a positive relationship between the spread and the real price of oil, triggered by speculative shocks to financial markets. Moreover, this study provides a clear picture of the historical dynamic of the real price of oil and the spread during some of the exogenous events in the oil markets.

Keywords: Crude oil, Futures-spot price spread, Sign-restricted SVAR models, Oil price speculation

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1. INTRODUCTION

This paper investigates the main economic and financial drivers of the real price of oil and it relates to the strand of the literature explaining oil prices by supply and demand shocks. The empirical approach is based on a revised version of the Structural Vector Autoregressive (SVAR) model developed by Kilian and Murphy (2014).

Our main idea is to retrieve the forward-looking expectations of oil traders by replacing a physical proxy for global above-ground crude oil inventories with the oil futures-spot spread (henceforth, spread). In this work, the spread is defined as the ratio of oil futures prices over the relative oil spot prices minus one and the free-risk interest rate, after accounting for the time to maturity of the futures contract. According to the theory of competitive storage, the spread is a proxy for the net-convenience yield of oil stocks, although expressed with an opposite sign.[1] Therefore the spread

1. The spread with maturity h-months can be computed as follows: $s_{t,h} = \left(\frac{f_t^h}{p_t}\right)^{\frac{1}{h}} - 1 - r_{t,h}$ where p_t and f_t^h denote the spot and the futures prices of crude oil for delivery at time h, respectively. Moreover, $r_{t,h}$ is the nominal free-risk interest rate earned between period t and $t+h$. According to the theory of storage, $s_{t,h} = k_h - \psi_{t,h} \simeq -\psi_{t,h}$ where k_h is the per-unit cost of physical storage and $\psi_{t,h}$ is the marginal net-convenience yield. The former can be considered constant (see Kaldor, 1939; Fama E., 1987). The latter is a net-convenience yield and it can be seen a decreasing and possibly nonlinear function of inventories (see Gorton et al., 2013).

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accounts for a stream of implicit benefits to the holder of the commodity inventory during periods of oil market stress and it is highly informative about the slope of the term structure of the oil futures curve. The latter provides intertemporal price signals for all traders participating to the financial and the physical markets for crude oil.

Relative to the existent literature on modelling the real price of oil, our analysis provides three main contributions.

First, our study proposes a spread-based SVAR model of the international market for crude oil. The spread is derived by crude oil Brent futures prices with maturity 3-months, since about two-thirds of oil purchases at world level use Brent as a reference price. This suggests that the Brent market is exposed to worldwide oil price shocks and it represents a natural choice for examining the dynamics of the convenience yield at the global level. Moreover, the time to maturity of the spread plays a crucial role in the economic properties of the SVAR model since it contains information about short-term and long-term convenience yields, respectively. Thus, the short-maturity spread reflects the perceived relative importance of the amount of inventory that is available in the near future (see Alquist et al., 2014). In contrast, the long-maturity spread is less sensitive to oil price shocks, consistent with the view that consumers and producers have more time to make consumption decisions and adjust production in the long period (see Lee and Zeng, 2011).

In our analysis, the benefits of using the spread as a measure of market expectations can be motivated on the basis of several economic considerations. First, the spread exploits the price discovery role in the crude oil futures markets. Second, the spread allows for a feedback effect from futures to spot markets and it accounts for the presence of informational frictions faced by the market participants (see Singleton, 2014; van Huellen, 2020). Third, the proxy for global above-ground crude oil inventories is affected by measurement error (see Baumeister and Hamilton, 2019). Our model provides empirical evidence that the spread responds to oil price shocks differently, depending on the economic motivations behind each shock. On average, oil supply disruptions and positive shocks to global business cycle cause a large and persistent drop in the spread, consistent with the fact that inventories are used for consumption and production smoothing, respectively. Conversely, shocks to the demand for storage driven by fears of production shortage cause a small decline in the spread. Therefore, we document a negative relationship between the impact responses of the price of oil and the spread to global oil market-driven shocks.

Second, our work provides fresh evidence on how the spread-based model helps to identify the speculative component of the real price of oil triggered by the oil futures markets. Therefore, the empirical approach used in our paper allows us to provide an economic interpretation of the residual structural shock, namely the financial market shock. The latter implies that an unanticipated rise in the spread might be interpreted as a market signal of higher future oil spot prices. In this context, oil producers have the incentive to defer production, causing the spot price of oil to rise. This last type of shock induces an increase in the demand for below-ground crude oil inventories because the spot price of oil is expected to rise.

It is also important to highlight that, in presence of asymmetric information, the speculative activities in the futures markets can drive up the spot price of oil without necessarily reducing the aggregate consumption and boosting inventories, as discussed by Sockin and Xiong (2015). The temporary distortion between spread and inventories is a function of the elasticity of arbitrage, which in turn depends on physical and financial constraints faced by the arbitrageurs (see Ederington et al., 2020; Acharya et al., 2013; Etula, 2013).

Third, our study provides a clear picture of the historical dynamic of the real price of oil and the spread. To illustrate this point, we focus on four exogenous events in global crude oil

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markets: the 1990–1991 Persian Gulf War, the 2003–2008 oil price surge, the 2008–2009 global financial crisis and the 2014–2016 oil price slump.

The rest of the paper is organized as follows. The next section provides a review of the relevant literature. Section 3 discusses the economic motivations, which support the use of the spread in the SVAR models. Section 4 describes the data. Section 5 illustrates the econometric approach. Empirical results are presented in Sections 6. Finally, Section 7 concludes.

2. LITERATURE REVIEW

The traditional literature explaining oil prices by supply and demand shocks is vast, see for example Kilian (2009), Kilian and Murphy (2012), Baumeister and Peersman (2013) and Lutkepohl and Netsunajev (2014). Previous studies rely on a different set of identifying assumptions of SVAR models of the global market for crude oil. In these works, the oil demand shocks play the most important role in accounting for the historical oil price movements. However, given the lack of a forward-looking measure in the set of endogenous variables, these models cannot identify the speculative component of the real price of oil. Kilian and Murphy (2014) contribute to the issue of a measure of traders' expectations by proposing a proxy for global crude oil inventories above the ground.[2] The latter is designed to capture the expected demand and supply conditions that are not contained in the past data available to the econometrician. Therefore, the crude oil inventory plays a crucial role in the identification of the speculative component of the real price of oil.

The SVAR model proposed by Kilian and Murphy (2014) shows that shocks to the aggregate demand (likely driven by a strong growth in the economy) were the main factors in driving up the real price of oil, from early 2003 until mid-2008. These results are robust to changes in the proxy for global above-ground crude oil inventories, as discussed by Kilian and Lee (2014). Moreover, Herrera and Rangaraju (2020) show that the dynamic effect of oil supply shocks on the real price of oil is mainly related to the methodology for the identification of the structural shocks and the bounds of the implied price elasticities of oil demand and oil supply. Finally, Zhou (2019) proposes a refined version of the inventory-based detection strategy, developed by Kilian and Murphy (2014). The identification of the structural shocks is obtained by means of the narrative sign restrictions, as discussed by Antolín-Díaz and Rubio-Ramírez (2018).

In contrast to previous studies, Juvenal and Petrella (2015) use a Factor Augmented VAR model with a different set of structural assumptions. The authors find that speculative shocks were responsible of a large increase in the price of oil between 2004 and 2008. However, their results suggest that oil consumption demand shocks were the most important factors in explaining the fluctuations in the real price of oil, during the period of interest. Finally, a recent work by Baumeister and Hamilton (2019) provides some relevant contributions in this literature, which are summarised as follows. First, oil supply shocks appear to be more important in explaining the path of the real price of oil compared to earlier studies. Second, oil supply disruptions cause a reduction in the economic activity after significant lags, while a rise in the real price of oil triggered by oil consumption demand shocks are not responsible of a large drop in the global economic activity. Finally, the traditional proxy for the global above-ground crude oil inventories is considerably affected by measurement error.

2. The inventory proxy is calculated by multiplying data of the U.S. crude oil stocks by the ratio between the OECD and the U.S. petroleum stocks. Data for petroleum stocks are provided by the U.S. Energy Information Administration (EIA) and include crude oil as well as strategic petroleum reserves, unfinished oils, natural gas plant liquids and refined products.

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3. REVISITING THE ROLE OF THE SPREAD

Understanding the speculative component of the real price of oil is not a simple endeavour. Most of the oil market VAR models use an inventory-based detection strategy to identify the speculative demand for crude oil.[3] In contrast, our study provides several economic reasons to consider the spread as a reliable measure of oil market expectations.

First of all, the spread accounts for the price discovery role in the futures market (see Garbade and Silber, 1983; Gospodinov and Ng, 2013). For example, a work by Alquist et al. (2014) shows that the first-two principal components extracted from a panel of oil futures-spot spreads (with different maturities) have predictive power for the future path of the real price of oil. Moreover, according to the theory of competitive storage, the spread plays an important role in explaining the value of holding crude oil stocks, as conveyed by the futures markets. For example, a post-shock increase in the spot price of oil causes a reduction in the level of inventories and a rise in the convenience yield. The crude oil stocks are drawn down in an effort to smooth production (or demand), resulting in a reduction of the spread. Alternatively, a drop in the spread arises as a positive response of the value of storage to an increase in oil market uncertainty (see Alquist and Kilian, 2010). The reduction in the spread is consistent with the view that the oil futures market is in backwardation and it suggests that the spot price of oil is expected to decline.[4] In contrast, when oil inventories are plentiful and it is costly to hold and carry forward oil stocks, the convenience yield is low, resulting in a rise of the spread.

In this study, three are the main reasons to not consider a direct measure of the net-convenience yield. First, the spread can be computed from observed time-series and it follows a stationary process. Second, the use of the net-convenience yield requires the estimation of the cost of storage at the global level, which might be difficult to obtain. Finally, an estimate of the net-convenience yield adds an error component in the model, resulting in a source of potential bias of the impulse response estimates (see Carriero et al., 2015). However, the choice of the spread in the oil market SVAR model is not without shortcomings. As discussed by Kilian and Murphy (2014), a potential weakness of the spread is that, the starting date of the analysis is dictated by the creation of the oil futures markets, which in turn excludes some of the major exogenous events in oil markets prior to 1988. Moreover, futures contracts of longer maturities narrow significantly the length of the sample.[5]

3. Standard arbitrage arguments imply that the financial variables (e.g. spread, oil futures prices) are redundant in SVAR models, which rely on the inventory-based detection strategy. According to Kilian and Murphy (2014), the Giannone-Reichlin test reveals that the inventory proxy is informationally adequate. However, the Giannone-Reichlin test relies on a Granger-causality test, which is not without shortcomings. The direction of the causality tends to be sensitive to the specification of the model and to the choice of the sample period. Therefore the results provided by the Giannone-Reichlin test should be taken with cautions, since they do not provide a clear indication of the type of forward-looking variable to include in the model. Instead, our study offers some important arguments in support of the spread, which are grounded on theoretical and empirical reasons irrespective of the Giannone-Reichlin test results (see Sockin and Xiong, 2015; Figuerola-Ferretti et al., 2019; Ederington et al., 2020). The on-line Appendix provides the Giannone-Reichlin test applied to our study.

4. In this work, the definition of contango (backwardation) market is based on the relationship between the spot and the futures price. Specifically, the market is in contango when futures prices are higher than spot prices, resulting in an upward-sloping futures curve (or positive spread). Conversely, a market is said to be in backwardation, when futures prices are lower than spot prices, resulting in a downward-sloping futures curve (or negative spread).

5. It is important to bear in mind that, the reduction of the estimation window does not invalidate the results and the inference of our analysis. Moreover, the time to maturity of the spread contains information about the traders' behaviours. The on-line Appendix provides results based on Brent-spread with maturities 6 and 12 months and WTI-spread with maturity 3 months.

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3.1 The informational frictions and the limits to arbitrage in the oil markets

It is widely accepted that, the statistics from emerging economies lack of transparency. As discussed by Singleton (2014), the informational frictions arise naturally in a global crude oil markets, since data on production, inventories and real extracting costs are fairly difficult to measure. Therefore, the uncertainty around oil market data leads to disagreements about the interpretation of public information (see Cao and Ou-Yang, 2008; Banerjee and Kremer, 2010). In this context, the inventory-based SVAR models use data on oil stocks to identify the speculative component of the real price of oil. Their identification strategy implies that, unobservable changes in the expected spot price of oil must be reflected by shifts in the demand for storage, in a way consistent with the absence of arbitrage opportunities. As discussed by Sockin and Xiong (2015), these models ignore the presence of informational frictions faced by the market participants and rely on the unrealistic assumption that the agents can observe and recognise perfectly different types of structural shocks.

As opposed to most of the empirical analysis based on a perfect arbitrage condition, our paper emphasises the benefits of using the spread to examine the role of oil price speculation by accounting for possible frictions, which may limit arbitrage activity in the global market for crude oil.[6] The key point is that the spread reflects the information set available to the oil traders at the period they make their production, consumption and investment decisions, hence it accounts for the feedback effect from futures to spot markets. It is also important to highlight that, in presence of informational frictions, the speculative activities in the futures market can drive the spot price of oil with no effects on the level of stocks, as discussed by Sockin and Xiong (2015). This is consistent with the fact that the arbitrage is hindered. For example, Ederington et al. (2020) find out that, arbitrage might be constrained by the lack of available space as storage approaches capacity. The authors show that, changes in crude oil inventories away from Cushing are mostly explained by operational purposes, consistent with the view that not all U.S. storage locations are arbitrage hubs.[7] Finally, other types of arbitrage impediments typically arise when financial traders are not able to exploit riskless strategies since they are constrained in their access to capital (see Acharya et al., 2013 and Etula, 2013).

3.2 Measurement error in the proxy for global above-ground crude oil inventories

A recent work by Baumeister and Hamilton (2019) shows that the proxy for global above-ground crude oil inventories presents a number of shortcomings. First, data on OECD crude oil stocks are not available. Consequently, the inventory proxy is constructed from data on OECD petroleum product inventories, which are ready for use since 1988.[8] Second, there are no data on crude oil stocks in transit via pipelines and stored at sea in the so-called “supergiant” oil tankers. Third, there are no even data for the management of crude oil reserves. The latter are particularly important for oil-producing countries that rely on unconventional oil extraction, as discussed by

6. A growing volume of studies emphasises the role of limits to arbitrage and informational frictions in the commodity markets, see for example, Singleton (2014); Cheng and Xiong (2014); Sockin and Xiong (2015); Cheng et al. (2015); Figuerola-Ferretti et al. (2019); Ftiti and Jawadi (2019); van Huellen (2020).

7. Ederington et al. (2020) conduct an empirical analysis of the crude oil WTI market over the period 2010–2017. The authors show that the arbitrage mechanism is price stabilizing consistent with the view that arbitrageurs lead to oil coming off the market when oil prices are relatively low and going back to the market when oil prices are relatively high.

8. Before 1988, the OECD petroleum products inventories are derived by the growth rate of U.S. petroleum product inventories.

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Bjørnland et al. (2019). Finally, data on crude oil inventories above the ground for the non-OECD economies are incomplete although they play an important role in the analysis of the global price of oil.[9]

A work by Kilian and Lee (2014) uses a proxy for the global crude oil inventories, which is provided by the Energy Intelligence Group (EIG). Despite the improvement on data accuracy relative to the measure of stocks proposed by Kilian and Murphy (2014), the EIG inventories are not available before January 1985 and they do not provide a precise measure for emerging countries. As a result, the inventory-based SVAR models can offer only a partial explanation of the price-inventories relationship, as it is grounded on the theory of competitive storage. This is also consistent with the fact that data on non-OECD crude oil stocks can no longer be ignored by the inventory-based detection strategy.[10]

4. DATA AND VARIABLES

This analysis is based on monthly data spanning from June 1988 to November 2019.[11] The set of endogenous variables includes the global crude oil production, a worldwide measure of real output, the real price of oil and the spread. Data on crude oil production are measured in millions of barrels of oil per day. We use the growth rate of crude oil production and we convert it into millions of barrels per month.

Following Baumeister and Hamilton (2019), the global measure of economic activity is the growth rate of the monthly OECD+6 world industrial production index (wip). This is a global indicator of real economic activity and it includes data for OECD and non-OECD countries, namely China, India, Brazil, Russia, South-Africa and Indonesia.[12] Hamilton (2019) emphasises the benefits of using the *wip* index as a measure of global real output, compared to the real economic activity index (*rea*).[13] A quantitative assessment of the two indicators reveals three important points. First, the *wip* indicator is more accurate in forecasting the real commodity prices compared to the *rea* index. Second, the cyclical component of the *wip* index has a higher correlation with yearly world real GDP than the *rea* index. Finally, the Augmented Dickey-Fuller test reveals that the *rea* index is not stationary.

According to the strand of the literature on dealing with the effects of oil price shocks on macroeconomic activity and countries' trade patterns, the U.S. refiners' acquisition cost for crude oil imports (*rac*) is considered the best proxy for the international price of oil (see Kilian, 2009).[14] Our strategy of including the real price of oil in log-differences is consistent with the results of Figuero-

9. In February 2003, China announced a policy decision to support the creation of a strategic petroleum reserve. Nowadays, China represents the most important crude oil importer in the world, surpassing the United States in 2017.

10. Kilian (2019a) suggests that, satellite data on oil inventories can represent a new way of obtaining a more accurate measure of crude oil stocks.

11. The starting date is dictated by the availability of continuous monthly Brent futures prices with maturity 3-months.

12. The *wip* index is developed by Baumeister and Hamilton (2019) and it is constructed from the OECD Main Economic Indicators (MEI) dataset. Hamilton (2019) shows that, Chinese data on industrial production have been included in the *wip* index since 1999.

13. The *rea* index, (Kilian's indicator) is derived from the Baltic Dry Index and it represents a proxy for the volume of international shipping in the commodity markets (see Kilian, 2009; Kilian, 2019b). Further details about the construction of the *rea* index are discussed in the on-line Appendix.

14. The *rac* can be defined as the average price paid by U.S. refiners for crude oil imports. This price refers to non-U.S. crude oil booked into the refiners in accordance with accounting procedures generally accepted and historically applied by the refiners concerned. The *rac* includes transportation and other fees paid by refiners.

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la-Ferretti et al. (2019) and it supports the assumption that crude oil prices are not stationary (see Fantazzini, 2016; Gronwald, 2016; Kruse and Wegener, 2020).

The spread with maturity 3-months can be computed as follows: $s_{t,3} \equiv \left(\frac{f_t^3}{p_t}\right)^{\frac{1}{3}} - 1 - r_{t,3}$, where f_t^3 denotes the price of Brent futures contract at the end of the day of month t (with maturity 3-months), p_t is the corresponding daily spot price in period t and $r_{t,3}$ represents the three-months U.S. Treasury bill interest rate.[15] The latter could be important in explaining the path of the oil prices by means of the cost of carry equation.[16] In this respect, Rosa (2014) provides evidence of a small but statistically significant response of daily WTI crude oil prices to federal funds rates shocks. However, Kilian and Zhou (2019) show that the effects of exogenous variations in the U.S. real interest rates on the real price of oil can be identified by aggregate demand shocks. Similarly, Alquist et al. (2020) show that monetary policy shocks affect real non-energy commodity prices primarily through their effect on global real activity. Therefore, the interest-adjusted spread does not invalidate our model and it is consistent with the view that the effects of the interest rate on the real price of oil can be captured by shocks to the global business cycle.

5. METHODOLOGY

In this section we illustrate the structural representation of the model. The methodology is based on a revised version of the Bayesian sign-restricted SVAR model developed by Kilian and Murphy (2014). The vector of endogenous variables is y_t and includes the growth rates of global crude oil and industrial production, real price of oil and the spread.

The SVAR model is the following:

$$B_0 y_t = \alpha + \sum_{j=1}^{24} B_j y_{t-j} + v_t \tag{1}$$

where B_0 is the matrix of contemporaneous structural parameters and α is the vector of constant terms. Moreover, B_j is the structural matrix of the lagged variables while v_t denotes a vector of structural shocks. The latter consists of four orthogonal structural innovations, where v_{1t} denotes a shock to the flow supply of oil (oil supply shock), v_{2t} denotes a shock to the flow demand for crude oil (aggregate demand shock), v_{3t} is a shock to the demand for storage (precautionary demand shock) and v_{4t} is a residual shock, which is designed to capture speculative activities in the futures market (financial market shock).

Imposing 24 months of lags allows the model to capture the long cycles in the real price of oil. This is consistent with the view that, the crude oil markets experience very slow moving cycles, therefore a low number of lag would fail to capture oil price shocks associated with gradual changes in the global business cycle, see for example Kilian and Lütkepohl (2018).[17] The corresponding

15. Financial data are sourced from the commercial data provider Bloomberg.

16. According to Frankel (2014), the relationship between the real price of oil and the real interest rates can be explained by three channels. First, high real interest rate encourages oil production. This allows producers to invest the proceeds at higher interest rates that were higher than the return to leaving crude oil below the ground. Second, higher real interest rates raise the cost to carry forward crude oil stocks and lower the speculative demand for storage. Third, contractionary monetary policies contribute to reductions in real price of oil. On the one hand, high real dollar interest rates cause a reduction in the demand for crude oil outside the Unites States. On the other hand, the U.S. dollar appreciation stimulates the supply of oil outside the United States.

17. The alternative way of this lag-augmentation procedure is testing the lag order using information criteria. However, the validity based on testing the goodness of fit using information criteria can be problematic, especially when there is a prior on the number of lags (see Leeb et al., 2006). Finally, Hamilton and Herrera (2004) show that, if the lag-order is too low, the

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reduced-form VAR model is obtained by pre-multiplying equation (1) by the inverse of B_0, denoted as B_0^{-1} and known as structural impact multiplier matrix. Thus, the reduced-form parameters are consistently estimated by OLS, while the structural shocks are recovered relying on a specific algorithm proposed by Rubio-Ramírez et al. (2010), which is applied to the reduced-form residual covariance matrix.[18]

5.1 Identification

Following Kilian and Lütkepohl (2018) the relationship between v_t and u_t takes the form:

$$\underbrace{\begin{bmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \\ u_{4t} \end{bmatrix}}_{u_t} = \underbrace{\begin{bmatrix} - & + & + & - \\ - & + & - & () \\ + & + & + & + \\ - & - & - & + \end{bmatrix}}_{B_0^{-1}} \underbrace{\begin{bmatrix} v_{1t} \\ v_{2t} \\ v_{3t} \\ v_{4t} \end{bmatrix}}_{v_t} \tag{2}$$

The set of sign restrictions collected in equation (2) identifies four structural shocks.[19]

A negative oil supply shock represents a shift to the left of the contemporaneous oil supply curve along the oil demand curve. This shock coincides with crude oil supply outages in the oil producing countries (e.g. OPEC strategic decisions affecting the world production of crude oil). The oil supply disruptions cause oil production to fall, the real price of oil to increase, the word industrial production and the spread to decline, on impact. The drop of the spread implies that the inventories are drawn down for consumption smoothing, resulting in an increase in the value of storage.

A positive aggregate demand shock represents a shift to the right of the contemporaneous oil demand curve along the oil supply curve. This reflects a rise in the demand for immediate consumption of crude oil associated with fluctuations in the global business cycle (e.g. crude oil demanded by China and other emerging economies). A positive aggregate demand shock induces global oil production, world industrial production and the real price of oil to increase, on impact. Moreover, this shock is associated with an instantaneous reduction in the spread in an effort to smooth production.

A positive precautionary demand shock represents a shift to the right of the instantaneous oil demand curve along the oil supply curve, which is triggered by an upward shift of the demand for storage as an insurance against uncertainty about future oil supply shortfalls (e.g. geopolitical tensions in oil-exporting countries). This is also known as speculative demand shock and it is mostly related to the physical market. Positive shocks to precautionary demand raise the convenience yield of above-ground crude oil inventories, resulting in a negative spread. This leads to an increase in the real price of oil. The stocks build-up requires global oil production to increase and oil consumption to fall. The latter is associated with a decline in the world economic activity.

inference and the estimates might be misleading. The authors find out that, there are strong claims about selection lag-order criteria based on early studies of the crude oil markets and they show that the AIC information criterion estimate could be representative of a lower bound of the number of lags.

18. Further details about the implementation of the algorithm proposed by Rubio-Ramírez et al. (2010) are discussed in the on-line Appendix.

19. All shocks are normalized to obtain an increase in the real price of oil. Missing entry means that no sign restrictions on the elements of B_0^{-1} is imposed.

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Finally, a positive financial market shock (sometimes referred to as speculative supply shock) is designed to capture a sudden rise in the spread that cannot be explained by the first-three structural shocks. This shock represents a shift to the left of the instantaneous oil supply curve along the oil demand curve and it is triggered by a speculative purchase of oil futures contracts.[20]

In our study, the financial market shocks are important factors in explaining how speculative activities in the futures markets influence the expectation formation of the economic agents. Therefore, the positive spread can be interpreted as a market signal of higher future oil spot prices. This gives the producers the option of leaving oil below the ground, rather than extracting it, causing the oil production to fall and the spot price of oil to rise. As a result, if oil producers are interested in maximizing their future profits, an optimal production decision will be to reduce the output in the current period (increases in stocks below the ground) and hope to make more profits by raising production in the near future. This last type of shock induces commercial traders to build up inventories not because of uncertainty about future oil supply disruptions (negative spread) but because future oil spot prices are expected to rise in the future (positive spread).

It is also important to notice that, speculative supply shocks are not observationally equivalent to oil supply disruptions, for at least three reasons. First, negative shocks to oil supply contribute to reduce the spread in an effort to smooth consumption, resulting in a rise in the convenience yield of oil inventories. In contrast, positive financial market shocks lead to inventory accumulation, resulting in a gradual reduction in the convenience yield of oil inventories. This is consistent with the results of Dvir and Rogoff (2009) and it supports the idea that, during a strong growth in the economy, the market participants are willing to increase their inventories for speculative reasons at the expense of consumption smoothing. Second, under the assumption of asymmetric information, speculative activities in the futures markets can drive up the spot price of oil without necessarily reducing the current consumption of crude oil and increasing inventories (see Sockin and Xiong, 2015). The key point is that, a positive spread in the futures markets can be interpreted as a market signal of strong global economic growth. Therefore the instantaneous effect of financial market shocks on the world industrial production is ambiguous. On the one hand, the structural identification used in our model allows the real price of oil to co-vary positively with the real economic activity. On the other hand, a rise in the real price of oil induces a decline in the real output. Third, oil supply disruptions and speculative supply shocks are motivated on the basis of different economic considerations. The former are linked to oil supply outages that are caused by exogenous geopolitical events in the global crude oil markets while the latter give the oil producers the option of leaving oil below the ground. In this last case, market participants voluntarily decide to destine a part of their production and refined products in the future, consistent with the theoretical results of Hotelling (1931) and the speculative argument of Smith (2009).

As discussed by Kilian and Murphy (2012), the SVAR models based only on sign restrictions are not able to identify the accurate magnitude of the impulse response of the real price of oil to each structural shock. Thus, it is common to use further restrictions on the ratio of the elements of B_0^{-1} in order to pin-down the set of admissible structural models.

A popular view is to consider these restrictions as the impact price elasticities of oil demand and oil supply. More precisely, we use an upper bound on the impact price elasticity of oil

20. It is also important to notice that, a positive financial market shock could be accompanied by an upward shift of the demand for above-ground crude oil inventories. In other words, oil refiners purchase extra barrel of oil in the current period to deal with high operational costs caused by the possible high spot price in the future. As a result, the decrease of supply and the increase of demand cause the real price of oil to rise, as discussed by Juvenal and Petrella (2015).

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supply, which is equal to 0.0258.[21] Our value of supply elasticity is identical to the benchmark reported by Kilian and Murphy (2014). This value reflects the supply-side rigidities in the oil market, which are mainly motivated by the presence of adjustment costs of production for the oil industry and it is also consistent with the empirical estimates reported by Newell and Prest (2019). Following Kilian and Murphy (2014), we limit the short-run price elasticity of oil demand to lie between 0 and –0.8. The latter represents the benchmark of the long-run price elasticity of oil demand, which is consistent with the empirical results of Yatchew and No (2001). Moreover, the identification of the financial market shock is based on additional restrictions on the impact responses of production and spread. More precisely, our identification allows for the oil supply disruptions to have larger impact on production compared to the financial market shocks. This is consistent with the fact that a reduction in the oil production is costly even for speculative purposes. Finally, we limit the average response of the spread to a positive financial market shock to be nonnegative for 12 months, consistent with the fact that, the timing of the informational signal provided by futures markets must be realistic for the oil traders.

6. EMPIRICAL RESULTS

6.1 Impulse Response Functions

Figure 1 reports the impulse response estimates of global crude oil production, real price of oil, world industrial production and Brent-spread with maturity 3-months to each structural shock for any given horizon, together with posterior credibility set at 95% level.[22] An unanticipated flow supply disruption reduces production by about 0.5 % and leads to an increase in the real price of oil, which rises by 2% on impact and it remains fairly stable over the subsequent months. On the real side, the impact response of the industrial production is negative and gradually declines up to –0.18%, after the seventh month after the shock. An unexpected positive aggregate demand shock induces an instantaneous increase in the world industrial production of about 0.35%. The response becomes even larger and more persistent in the subsequent periods. Moreover, this shock causes an instantaneous increase in the global oil production, accompanied by a hump-shaped response of the real price of oil, with a peak after three months. Finally, a positive precautionary demand shock yields a contemporaneous increase in the global oil production and in the real price of oil but it causes a reduction in the world industrial production. The dynamic responses of the oil physical market variables to supply and demand shocks are qualitatively similar to those reported by Kilian and Murphy (2014).

Figure 1 provides empirical evidence that the spread responds to oil price shocks differently, depending on the economic motivations behind each structural innovation. A disruption to oil supply is responsible of a large reduction in the spread, on impact. This shock induces a drop in the spread up to –1%. Its negative effect on the forward-looking variable declines gradually during the horizon of reference. A one-unit increase in the aggregate demand shock reduces the spread by about 0.5%, on impact. The response remains persistent after the fifth month after the shock. Conversely, a

21. It is worth noting that, the impulse response estimates to each structural shock are remarkably robust to imposing a less restrictive upper bound of 0.09.

22. The impulse response functions are robust to changes in the proxy for global real economic activity. To this end, we estimate two separate models by replacing the *wip* index with the *rea* index and the Global Economic Conditions (GECON) indicator. The latter is developed by Baumeister et al. (2020). Further details of the robustness checks are reported in the online Appendix.

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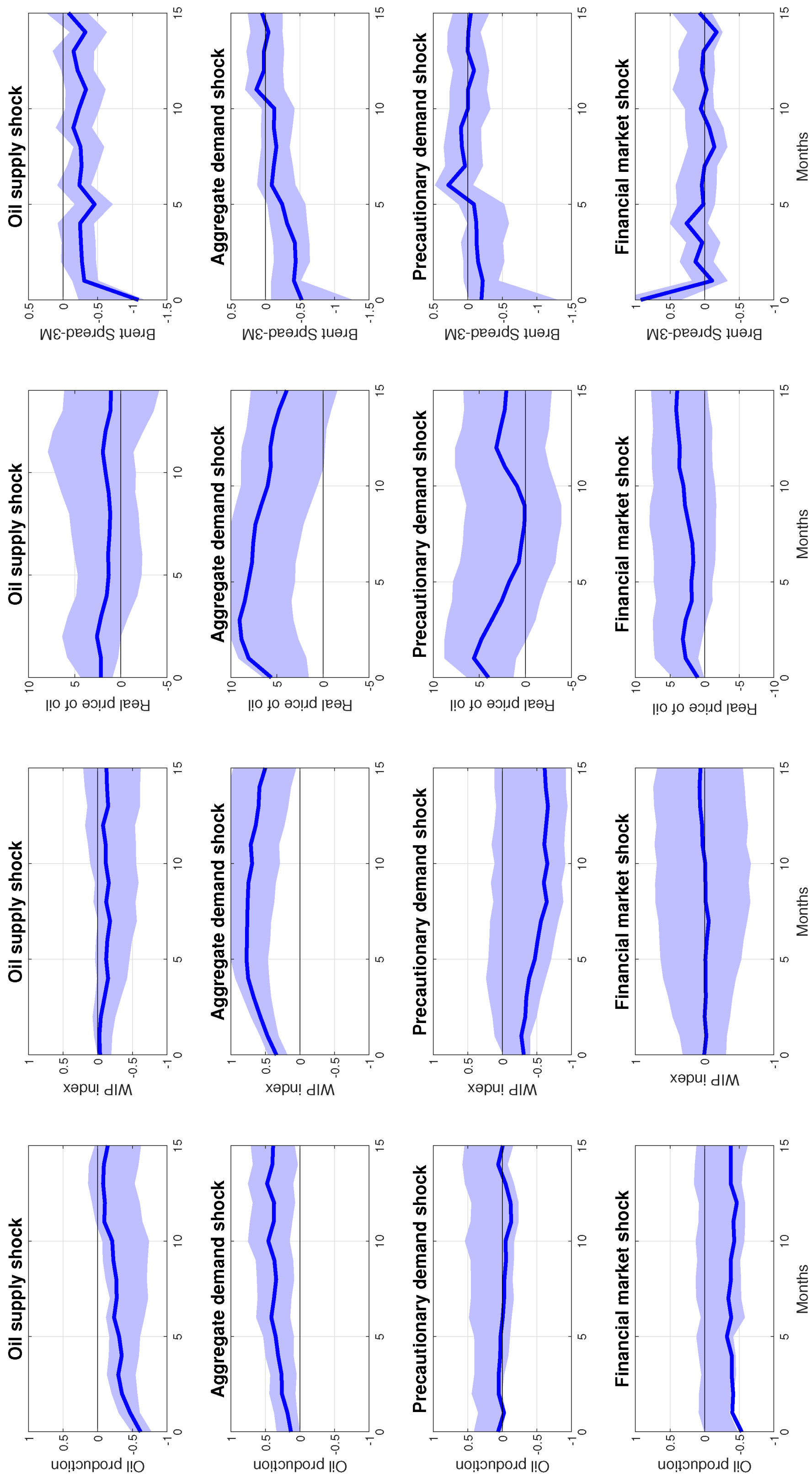
Figure 1: Impulse response functions of the endogenous variables to each structural shock



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positive precautionary demand shock produces a small reduction in the spread, on impact. Its effect seems to be less persistent, indeed the response estimate shows a quick reversion to pre-shock level over the subsequent periods. A positive financial market shock causes an immediate, although temporary, jump in the spread. After the impact, the decline in the spread is associated with a gradual increase in the real price of oil and a persistent reduction in the global oil production. Finally, a positive financial market shock causes a small increase in the world industrial production, on impact. Its effect on the real economy is negligible during the horizon of reference.

In our study, we find that shocks to economic fundamentals of the international market for crude oil cause a rise in the real price of oil and a reduction in the spread, on impact. Our empirical results can be motivated on the basis of the following considerations. First, in case of unexpected physical interruptions in supply, oil refiners are willing to release crude oil inventories to smooth consumption. Thus, a temporary drawdown of oil inventories is associated with a rise in the convenience yield, accompanied by a reduction in the spread, on impact. The latter suggests that the flow of benefits that accrues to an owner of the physical commodity is expected to be high in the next three months. This is consistent with the view that, an oil supply shock affects the value to future inventories in anticipation of perceived declines in the level of stocks for consumption smoothing. Second, shocks to the global business cycle cause stocks to be drawn down in an effort to smooth production, causing the convenience yield of oil inventories to rise. This implies that the oil inventories are expected to be scarce in the future in the face of fluctuating demand for crude oil. Third, both shocks to oil supply and aggregate demand cause a large decline in the spread. However, the reduction in the spread is less persistent in case of aggregate demand shocks and much of its initial drop is reversed within 12 months. Thus, on average, oil traders assign the highest value to future inventories in case of supply shocks consistent with the fact that, the inventory replenishment takes a long time. Fourth, a negative response of the spread to positive precautionary demand shocks is consistent with the theoretical results of Alquist and Kilian (2010). Thus, an exogenous increase in the uncertainty about future oil supply shortfalls (e.g. Gulf War in 1990), initially raises the demand for crude oil inventories above the ground, resulting in a positive convenience yield. Consequently, an upward shift of the demand for stocks causes the real price of oil to increase, since in the short-period, the supply of storage is highly inelastic and the inventories cannot be immediately built. Interestingly, a positive precautionary demand shock produces a small decline in the spread, on impact. This suggests that the overshooting response of the price of oil in the spot market is slightly higher than the overshooting response of the oil futures price, which in turn causes a small increase in the value of storage in the next three months. Moreover, a reduction in the spread is gradually reversed as the adverse effects of uncertainty on the supply side decline and the crude oil productions are added to future inventories. The confidence about the sign of the response of the spread to a precautionary shock becomes unclear after the first month after the shock.

Finally, a positive financial market shock implies that, the oil futures prices are traded above the corresponding oil spot prices consistent with a speculative purchase in the futures market. This leads to a positive spread, which in turn affects the expectation formation of market participants. Thus, a gradual increase in the real price of oil is associated with a decline in oil production, since producers are willing to hold oil back from the market in anticipation of higher prices in the future (see Juvenal and Petrella, 2015).[23] Moreover, the change in the spread represents valuable

23. Some empirical studies based on micro data show that shale oil producers change flow supply in response to price signals (see Bjørnland et al., 2019; Bornstein et al., 2018). Moreover, a work by Miller and Zhang (1996) shows that oil field development decisions are affected even if rises in oil price are only temporary, consistent with the view that the current fluctuations in oil prices have effects on future production of crude oil.

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information for all investors participating to the oil futures markets (see Figuerola-Ferretti and Gonzalo, 2010). A negative response of the spread to supply shocks, global business cycle shocks and precautionary demand shocks suggests that the crude oil futures market is in backwardation. This is consistent with the view that, the spot price of oil is expected to decline in the future. Moreover, investors use backwardation to make a profit through a rolling strategy. The latter is easily done by selling the expiring contract and use the proceeds to buy another futures contract for delivery at a more distant date (see Erb and Campbell, 2006; Valenti et al.; 2020).

6.2 Forecast Error Variance Decomposition

Table 1 presents the percentage contributions to each structural shocks arising the international market for crude oil to the overall variability of the real price of oil and spread, based on the forecast error variance decomposition (FEVD) of the SVAR model at 1, 3,6 12 months, as well in the long run (denoted as ∞).[24]

Table 1: Percentage contribution of each shock to the variability of real price of oil and Brent spread-3M

Panel (a) Variance decomposition of the real price of oil

Horizon	Supply shocks	Aggregate demand shocks	Precautionary demand shocks	Financial market shocks
1	8.6	59.2	30.2	1.9
3	7.6	54.5	30.6	7.3
6	7.4	53.3	32.1	7.2
12	7.6	50.4	34.0	8.0
∞	12.7	45.2	32.6	9.5

Panel (b) Variance decomposition of the Brent spread-3M

Horizon	Supply shocks	Aggregate demand shocks	Precautionary demand shocks	Financial market shocks
1	50.4	11.7	1.7	36.2
3	42.4	26.3	4.0	27.3
6	45.4	25.0	5.7	23.9
12	47.9	24.2	5.7	22.2
∞	48.9	22.8	7.3	21.0

Note: Forecast error variance decomposition (FEVD) for the real price of oil and spread based on the SVAR model reported in equation 1. FEVD at horizon "∞" is approximated by FEVD at horizon 500.

Panel (a) of Table 1 shows that the explanatory power of financial markets shocks for the real price of oil is, on average small. On impact, speculative shocks in the futures markets account only for a tiny percentage of the variation in the real price of oil, with 1.9%. In contrast, shocks to the aggregate demand and precautionary demand for crude oil account for 59.2% and 30.2%, respectively. On impact, shocks to supply explain 8.6% of the variation of the real price of oil. In the long run, both shocks to financial markets and oil supply gain importance and explain 9.4% and 12.7% of the variation of the real price of oil. The explanatory powers of shocks from aggregate demand and precautionary demand for oil remain high and are equal to 45.2% and 32.6%, respectively.

Panel (b) of Table 1 shows that, 50.4% of the variation in the spread is driven by oil supply shocks, followed by financial market shocks with 36.2%. Moreover, the explanatory power of

24. The long-run contribution of each shock is approximated by computing the FEVD at horizon 500 (i.e. 41 years from the shock)

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shocks from the global business cycle for the spread is 11.7%. Interestingly, precautionary demand shocks have negligible impact on the spread, with 1.7%. This finding casts doubts on the economic interpretation of the spread as an indirect measure of expectations shifts in the demand for storage, driven by precautionary purposes. In the long run, 48.9% and 21.0% of the variation in the spread can be attributed to oil supply shocks and financial market shocks, respectively.

6.3 Historical Decomposition

Figure 2 plots the historical decomposition of the real price of oil and the Brent spread implied by the structural model (1). In order to understand the main forces that drive the movement of the real price of oil, it is useful to assess their relative importance during some of the exogenous events in the oil markets. To illustrate this point, we focus on four important episodes involving large changes in the oil prices: the Persian Gulf war of 1990–91, the 2003–2008 oil price surge, the global financial crisis in mid-2008 and the 2014–15 oil price slump.[25]

Figure 2 shows that the oil price spike associated with the Persian Gulf War of 1990–91 was mainly related to supply shocks and precautionary demand shocks. The latter contributed to raise the real price of oil in August of 1990, when the Iraqi Army invaded and occupied Kuwait. In particular, unanticipated oil supply disruptions were responsible of a large increase in oil prices from July to August of 1990, as illustrated in the periods 2 and 3 in the left-most panel of Figure 2. At the same time, positive shocks to precautionary demand for oil associated with the threats to Saudi Arabian oil production contributed to raise the real price of oil until December 1990. Throughout this period, our results suggest that the speculative activities in the futures markets play a marginal role in driving up the real price of oil. Figure 2 illustrates also that the large reduction in the real price of oil is mostly related to negative shocks to precautionary demand for oil. The latter are associated with the U.S. military intervention that contributes to restore confidence in the oil markets. Finally, there is no evidence that positive supply shocks contributed significantly to the reduction in the real price of oil.

From early 2003 until mid-2008, the aggregate demand shocks, likely driven by emerging Asia and OECD countries, contributed to raise the real price of oil, as shown in the second top left-most panel of Figure 2. Our analysis suggests that positive supply shocks contributed to lower the real price of oil, between 2003 and 2005, consistent with the fact that, OPEC production rose steadily after 2003, reaching a historic high of 31.11 mb/d in 2005.[26] However, since 2006, the stagnant global oil production contributed to raise the real price of oil. Moreover, since 2005, the speculative activities have been important factors in explaining the rise in the real price oil. Over this period, the volume of futures trading started growing significantly and the futures markets have been in contango, consistently with the view that oil prices were expected to increase (see Hamilton and Wu, 2014; Singleton, 2014).[27]

25. For each panel, solid, dashed, dotted and dash-asterisk lines depict the historical contributions of oil supply, aggregate demand, precautionary demand and financial market shocks to the real price of oil and the Brent spread with maturity 3 months. The historical decomposition of the real price of oil is the cumulated values of the fitted growth rates (multiplied by 100) from June 1990 to November 2019. The periods of the exogenous episodes are the following: the "Persian Gulf War" from June 1990 to February 1991; the "Oil Price Surge" from January 2003 to June 2008; the "Global Financial Crisis" from June 2008 to December 2009; The "Oil Price Slump" from June 2014 to March 2016.

26. See OPEC (2006) report: https://www.opec.org/opec_web/en/publications/338.ht

27. During the period of financialization of the commodity markets, we find that positive financial market shocks cause a reduction in global crude oil production. Therefore, positive spread in the futures market contributes to change the expectation

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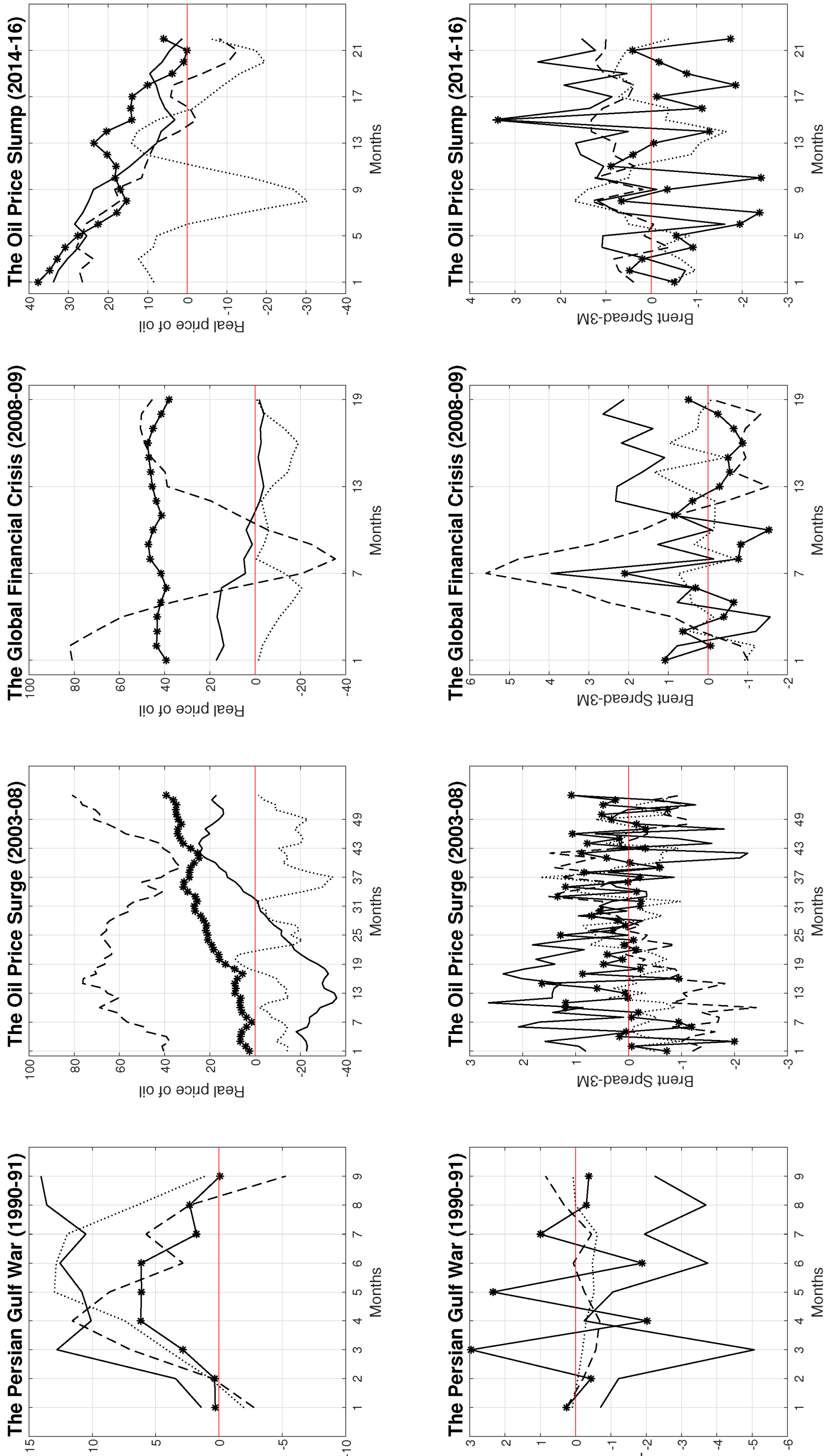
Figure 2: Historical decompositions of the real price of oil and the Brent spread-3M



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Our analysis attributes a nontrivial role in the rise of the price of oil to positive financial market shocks and it supports the idea that speculative activities in the futures markets represented the second most important factor in explaining the oil price surge from 2006 until 2008. Moreover, a work by Tsvetanov et al. (2016) document a significant evidence of bubble behaviour for WTI crude oil spot and futures price series, between 2004 and 2008. The authors show that the bubble duration increases along the yield curve suggesting a disconnection between the spot and the longer maturity contracts. During the period of financialization of the commodity markets Saporta et al. (2009) document large forecast errors associated with the prediction of the future demand for crude oil mostly related to non-OECD and emerging countries. Finally, Singleton (2014) provides evidence of a positive correlation between the disagreement measure and the WTI spot price, consistent with the presence of severe informational frictions in the crude oil market over the period 2007–2008. Figure 2 provides no indication that positive precautionary demand shocks played an important role in the oil price surge between 2006 and 2008, consistent with the empirical results of Kilian and Murphy (2014) and Kilian and Lee (2014). Moreover, the V-shape reduction of the real price of oil was largely explained by aggregate demand shocks, as shown in the third top left-most panel of Figure 2.

Finally, from mid-2014 until early 2016, the drop in the real price of oil was largely explained by both supply and demand forces. In particular, from June until November of 2014, the positive supply shocks (likely driven by unconventional oil supply and OPEC strategic decisions) contributed to lower the real price of oil, as shown in the upper right-most panel of Figure 2. The OPEC meeting in November 2014 represented also an important signal on the future expected global production of crude oil for the market participants, since the members decided to keep the production level of 30 million barrels per day.

Figure 2 shows that both negative shocks to financial market and precautionary demand for crude oil might be triggered by this change in policy. The former represent a downward shift in the demand for storage in the physical market, accompanied by a reduction in the uncertainty about future oil supply shortfalls. The latter is related to the speculative selling of oil futures contracts, driven by traders' expectations on the global oil market conditions. In this respect, the speculative activities in the futures markets are associated with an increase in oil production in anticipation of lower prices in the future. Moreover our analysis corroborates the conclusions of Bataa and Park (2017) and Figuerola-Ferretti et al. (2019), that positive oil supply shocks contributed to lower oil prices. Finally, this model provides empirical evidence that the drop in the real price of oil after the OPEC's announcement on November 2014 can be also explained by negative aggregate demand shocks, as discussed by Baumeister and Kilian (2016).

7. CONCLUSIONS

In this paper we have shown that the spread-based SVAR model can be considered a valid approach for modeling the real price of oil. The spread is a realiable variable about the oil market conditions as conveyed by the oil futures markets and it accounts for the presence of informational frictions faced by the market participants. The key point is that the spread is a real-time and forward-looking variable, which accounts for how oil traders form their expectations based on public and private information. On average, we find that oil supply disruptions and positive aggregate demand shocks cause a rise in the real price of oil and a reduction in the spread in an effort to smooth consumption and production, respectively. A negative response of the spread to a positive

formation of oil producers. The detailed results of the cumulative effect of financial market shocks on the global oil production are available from the author upon request.

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precautionary demand shock suggests a sudden increase in the market value of storage. A positive shock to financial market causes the spread and the real price of oil to rise. This shock is associated with a reduction in the oil production, since producers are willing to hold oil back from the market in anticipation of higher prices in the future. Finally, our model attributes a nontrivial role in the changes of the real price of oil triggered by supply and financial market shocks, during some of the exogenous events in the oil markets.

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APPENDIX

A.1 Identification strategy

This section reports a short description of the algorithm proposed by Rubio-Ramírez et al. (2010) for the estimation of the sign-restricted structural VAR model, reported in equation (1) of our paper. It is worth recalling that, the vector of endogenous variables is y_t and includes the growth rates of global crude oil and industrial production, real price of oil and the spread derived by crude oil Brent futures prices with maturity 3-months. Therefore, the SVAR model is the following:

$$B_0 y_t = \alpha + \sum_{j=1}^{24} B_j y_{t-j} + v_t$$

where B_0 is the matrix of contemporaneous structural parameters and α is the vector of constant terms. Moreover, B_j is the structural matrix of the lagged variables while v_t denotes a vector of structural shocks. The latter consists of four orthogonal structural innovations, where v_{1t} denotes a shock to the flow supply of oil (oil supply shock), v_{2t} denotes a shock to the flow demand for crude oil (aggregate demand shock), v_{3t} is a shock to the demand for storage (precautionary demand shock) and v_{4t} is a residual shock, which is designed to capture speculative activities in the oil futures market (financial market shock).

The corresponding reduced-form VAR model is obtained by pre-multiplying equation (1) by the inverse of B_0, denoted as B_0^{-1} and known as structural impact multiplier matrix:

$$y_t = \underbrace{c}_{B_0^{-1}\alpha} + \sum_{j=1}^{24} \underbrace{C_j}_{B_0^{-1}B_j} y_{t-j} + \underbrace{u_t}_{B_0^{-1}v_t} \tag{3}$$

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where C_j is a matrix including the reduced form parameters of the model and u_t is a vector of zero-mean white noise processes with variance-covariance matrix $E[u_t u_t'] = \Sigma_u$ such that $u_t \sim \mathcal{N}(0, \Sigma_u)$. The reduced-form parameters are consistently estimated by OLS, while the structural shocks are recovered relying on a specific algorithm proposed by Rubio-Ramírez et al. (2010), which is applied to the reduced-from residual covariance matrix.

This algorithm is based on a set of static sign restrictions that are directly imposed on the elements of B_0^{-1}. Thus, the set of impact multiplier matrices that are consistent with the sign restrictions can be obtained by the product between matrices P and D. The former represents the Cholesky factorization of the reduced-form residual covariance matrix. The latter is any orthogonal square matrix derived from the QR decomposition of a matrix whose elements are random draws from independent standard Normal distributions, such that $D = Q'$.[28]

The implementation of the estimation algorithm proposed by Rubio-Ramírez et al. (2010) consists on two main steps. The first step is a repeated sampling by drawing the matrix X from independent standard Normal distributions. Then, we derive the QR decomposition of X such that $X = QR$ where Q is an orthogonal matrix and R is upper triangular matrix with the elements on the main diagonal normalized to be positive. In the second step, D is set equal to Q' and we derive the set of admissible impulse responses function from $B_0^{-1} = PD$. If all the impulse response estimates satisfy the sign restrictions reported in equation (2) we collect D, otherwise we discard D.

Finally, the estimation of the uncertainty is conducted under Bayesian method specifying a Gaussian-inverse Wishart prior distribution for the reduced form parameters and a Haar distribution for the rotation matrix X. Thus, the credible set of the impulse responses function is constructed by applying the algorithm proposed by Rubio-Ramírez et al. (2010) to each draw of the posterior distribution for the parameters of the reduced-form VAR model.

A.2 Robustness checks

This section provides empirical evidence on whether the main results are robust to changes in the specification of the spread-based SVAR model, considered in equation (1). The first robustness check relies on a change in the proxy for global economic activity. In the second robustness check, we replace the Brent spread with maturity of three months with the WTI spread of the same maturity. Thus, we illustrate the historical decompositions for the real prices of oil and the forward-looking variables implied by both specifications. Finally, we provide a discussion of some important features of the impulse response estimates of the Brent spread with maturities of 3-, 6- and 12-months to each structural shock.

A.2.1 Alternative measures of global economic activity

The first robustness check relies on two different proxies for measuring the global real economic activity, namely, the corrected version of the *rea* index discussed by Kilian (2019b) and the Global Economic Conditions (GECON) indicator developed by Baumeister et al. (2020).[29]

The Kilian's index relies on the cost of international shipping in the commodity markets. According to Kilian (2019b) the *rea* index provides some important advantages for the identification of shocks to the global business cycle, since it represents a monthly, direct and global indicator of economic activity. In this work we use the refined version of the *rea* index as proposed by Kilian

28. The matrix P is the Cholesky factorization of Σ_u, such that $PP' = \Sigma_u$ and $P = T\Lambda^{0.5}$, where Λ is a diagonal matrix in which the elements λ_i's are the eigenvalues of Σ_u and the columns of the matrix T are the corresponding eigenvectors.

29. The monthly GECON index is available from https://sites.google.com/site/cjsbaumeister/research.

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(2019b).[30] The Kilian's index is derived from the residuals of a time-trend linear regression model, where the dependent variable is the cumulative equal-weighted average of the growth rates for each of the individual dry bulk cargo freight rates, having normalized January 1968 to unity. Since 2008, the dependent variable was updated using the Baltic Dry Index of shipping costs and it was expressed in real terms using the U.S. consumer price index (see Kilian and Murphy, 2014). It is worth noting that, recently the *rea* index have exhibited some erratic behaviour that is hard to square with smooth fluctuations in the global business cycle. There are a number of possible factors such as the ship-building and scrapping cycle that might explain this increased volatility in the aftermath of the financial crisis.[31]

The GECON is an indicator for assessing the future tightness of global energy demand and it is based on eight different categories of variables, such as real economic activity, commodity prices, financial indicators, transportation, uncertainty, expectations, weather and energy-related measures. Baumeister et al. (2020) emphasise the benefits of using the GECON indicator as a proxy for the global real output, compared to those measures derived from a single category of variables. A quantitative assessment of the GECON indicator reveals three important futures. First, the multidimensional approach used to obtain the GECON indicator reduces the potential exposure of the index to its idiosyncratic shocks. Second, the GECON indicator is more accurate in forecasting the real price of oil and the global petroleum consumption compared to the Kilian's index. Third, the time-varying predictive content of the GECON indicator is preserved.

In this section we estimate two separate models by replacing the *wip* index with *rea* and GECON indicators, respectively. Figure 3 plots the impulse response estimates of the real price of oil and the Brent-spread together with posterior credibility set at 68%, for the model with *rea* and the model with GECON. Moreover, dashed red lines indicate the impulse response estimates implied by the model with *wip*.

In the model including *rea*, an oil supply disruption causes a simultaneous increase in the real price of oil and a reduction in the spread. The effects of an oil supply disruption on the real price of oil and Brent-spread are qualitatively similar to those reported by the specification with *wip*. Analogously, a positive financial market shock causes a jump of the spread in both specifications. Beyond the impact period, the models with *rea* and *wip* produce empirical results, which are consistent with a decline in the spread and a gradual increase in the real price of oil. Moreover, after the impact, the responses of the real price of oil to a positive precautionary demand shock show a large increase. In particular, the specification with *rea* exhibits a more persistent increase in the price compared to the model with *wip*. However, the effect of this shock on the spread are similar in both models. Finally, a positive aggregate demand shock causes a similar drop of the spread, in both

30. The original version of the *rea* index is developed by Kilian (2009) and it is derived by taking double logs, resulting in a time series, which is not robust to changes in the normalization date. In our analysis we use the revised version of the *rea* index which is available from the web site http://www-personal.umich.edu/ lkilian/

31. Some fluctuations in the shipping index do not seem to be correlated to changes in world economic activity. According to Hamilton (2019), the sharp drop in the Kilian's index in early 2016 was due to an overbuilt shipping capacity rather than a global economic downturn, consistent with the view that the real shipping costs indicators might be affected by changes in the supply of market for shipping services. In contrast, Kilian (2019b) argues that the sharp drop in early 2016 represented an outlier that was quickly reversed. Further, the author highlights that the Kilian's index is designed for modelling the business cycle in industrial commodity markets and it is a proxy for changes in the volume of shipping of industrial raw materials. Thus, it is not necessary that changes in the volume of trade coincide with fluctuations in real output. Moreover, Kilian (2019b) shows that the changes in the supply of bulk dry cargo carriers is quite smooth over time, consistent with the view that the fluctuations in the *rea* index are mainly driven by the demand side of the shipping market. As discussed by Kilian (2019b), the decline in the *rea* index in early 2016 can be driven by provisory reduction in the demand from China, even if the precise causes of this reductions are not known.

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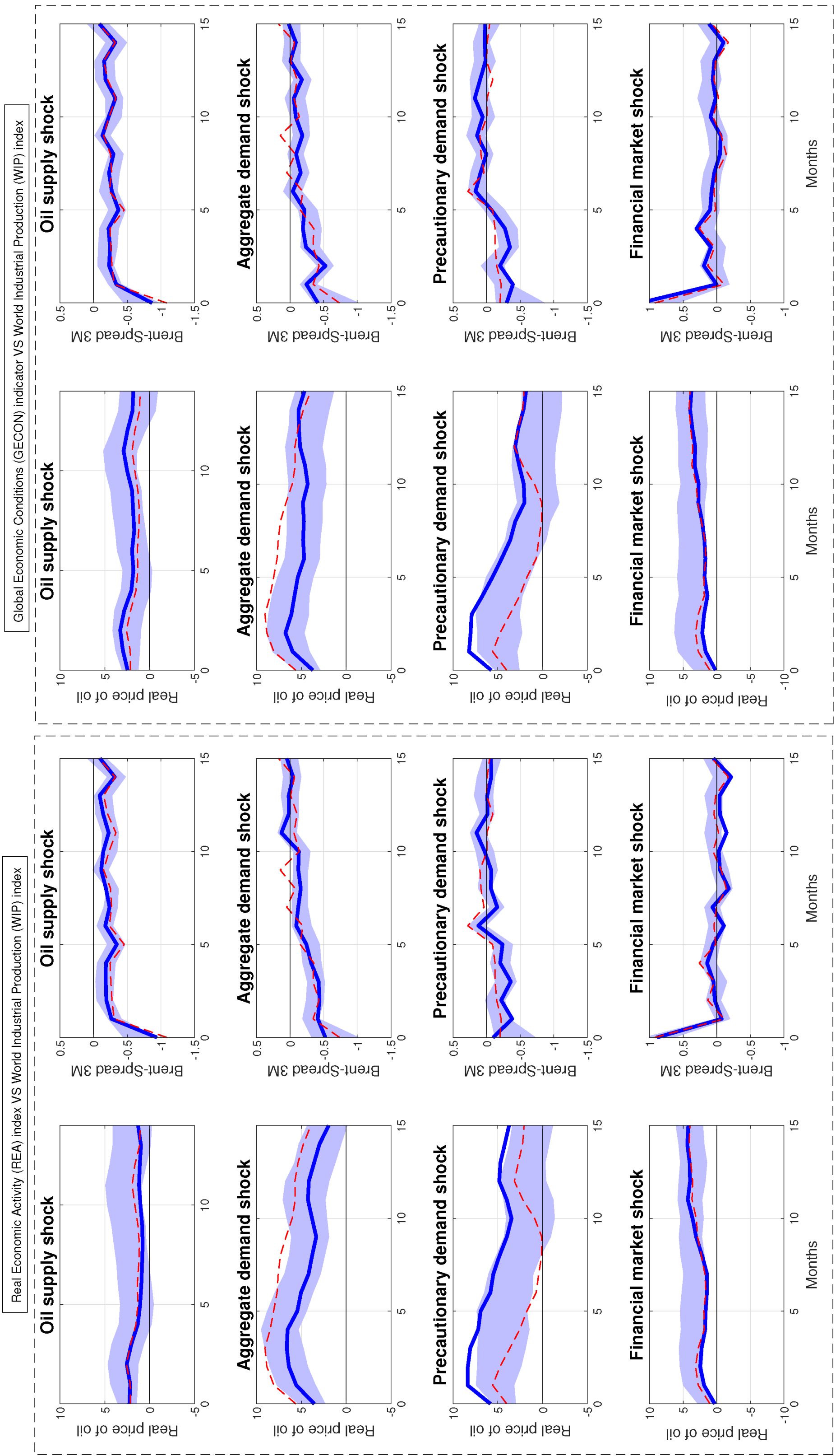
Figure 3: Impulse response functions of the real price of oil and the Brent spread-3M to each structural shock



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specifications. Conversely, the specification with *rea* exhibits a less persistent increase in the real price of oil compared to the model with *wip*.

Moving to the specification with GECON, the response of the spread to a negative oil supply shock shows a persistent reduction, which is qualitatively similar to that reported by the model with industrial production. In the model including GECON, the dynamic response of the real price of oil to an oil supply disruption is slightly smaller than that implied by the specification with *wip*. Shocks to financial market cause a jump in the spread and a gradual raise in the real price of oil, in both specifications. We highlight also some differences that can be mainly attributed to the specific measures of economic activity. Specifically, the model including GECON, attributes a somewhat larger explanatory power of fluctuations in the real price of oil to precautionary demand shocks and less explanatory power to aggregate demand shocks. In both specifications the effects of precautionary demand shocks are smaller and less persistent than those triggered by the aggregate demand shocks. Overall, the average behaviour of the spread is robust to changes in the proxy for global real economic activity.

A.2.2 The WTI spread with maturity 3-months

In this section we illustrate the results obtained by an alternative measure of the spread, which is derived by WTI crude oil futures prices with maturity 3-months. To this end, we estimate model (1) by replacing the forward-looking variable based on Brent spread with WTI spread. Although, WTI futures and oil spot prices are specific to U.S. oil supply and U.S. oil demand the WTI market is exposed to global oil price shocks as well as the Brent market.[32]

Figure 4 plots the historical decomposition for the real price of oil and the spread implied by the structural models with WTI spread-3M (solid red lines) and Brent spread-3M (solid black lines), respectively. Both specifications produce empirical results, which support the view that oil supply shocks have been important to drive the path of the real price of oil over the last two decades. For example, over the years 2006–2008, negative supply shocks were found to be important in explaining the rise in the real price of oil, consistent with the empirical results of Baumeister and Hamilton (2019). Moreover, Figure 4 provides evidence that, in both specifications, positive supply shocks played a crucial role in the mid-2014 oil price drop. However, the aggregate demand shocks contributed significantly to lower the real price of oil from late 2014 until mid-2015 (see Baumeister and Kilian, 2016; Baumeister and Hamilton, 2019). We point out that in both specifications, the aggregate demand shocks maintain their relevant role in explaining the historical fluctuations in the real price of oil compared to the other shocks, during the period 2003–2008.

We highlight also some differences that can be mainly attributed to the specific measure of the spread. The alternative specification tends to overstate the effect of precautionary demand shocks on the real price of oil, during the period March 2007-May 2008. Finally, the added explanatory power seems to come at the expense of smaller price response to financial market shocks. Overall, the cumulative effects of each structural shocks on the real price of oil is robust to changes in the spread and their primary roles across specifications are preserved.

32. In equilibrium the price of WTI should equal the price of Brent after accounting for the cost to carry and the quality discount. In principle, the difference between WTI and Brent prices depends on the quality differential of the two grades and it is affected by underlying factors that are specific to each market.

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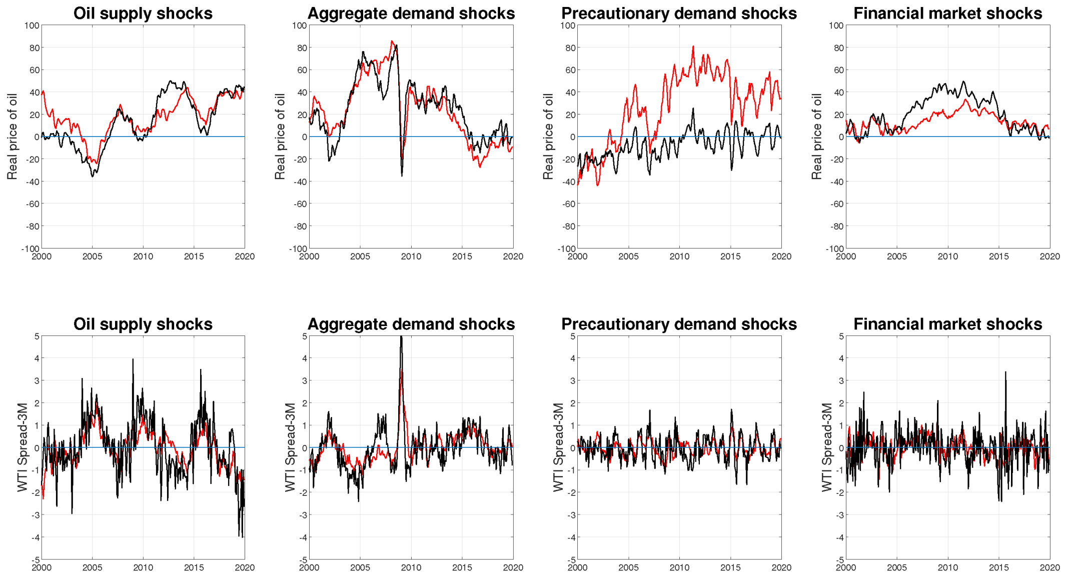
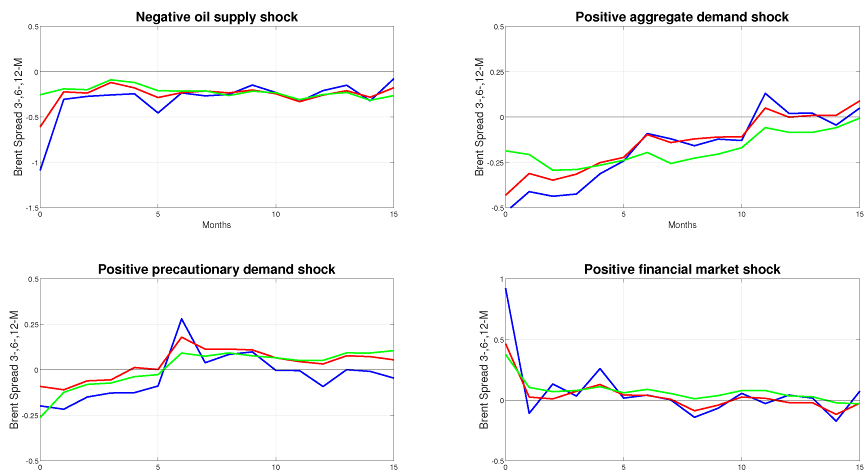
Figure 4: Historical decompositions of the WTI spread-3M and the real price of oil



A.2.3 The Brent spread with maturities 3-, 6-, 12-months

Figure 5 reports the impulse response estimates of the spread with maturities of 3-, 6- and 12-months to each structural shock.[33]

Figure 5: Impulse response functions of the Brent spread-3-, 6-, 12-M



Our results suggest that all response estimates of the spread are grounded on the economic theory. Moreover, spreads at shorter maturities are more affected by the effects of the structural shocks compared to those at longer maturities. This result is consistent with the view that the oil

33. For each of the spread with maturities 3-, 6- and 12-months we estimate three separate SVAR models considered in equation (1) of our paper. Blue, red and green lines reported in Figure 5 indicate the response estimates of the Brent spread with maturities 3, 6, and 12 months, respectively.

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production and supply of storage are highly inelastic in the short period. Therefore the convenience yield from having access to inventory holdings of oil in the near future is higher compared to the convenience yields at longer maturities. The distance between different impulse response estimates at each point in time provides information about the slope of the term-structure convenience yield curve. Indeed, net-long investors benefit from trading oil futures contracts during oil supply disruptions and positive shocks to the global business cycle, since they can exploit remunerative rolling investments strategies. Moreover, the response estimates of the spread-12M and the spread-3M can be interpreted as the back-end and the front-end of convenience yield curve, respectively.

We provide evidence that front and back ends of the term structure convenience yield curve exhibit different patterns. On the one hand, the front-end of the curve is more linked to the short-term fundamentals and it is mainly affected by the current and the expected fluctuations of oil demand and oil supply. On the other hand, the back-end of the curve is less sensitive to oil market-driven shocks, consistent with the view that, consumers and producers have more time to make decisions in the long period. Finally, Figure 5 shows that, the variability of short-maturity spread is higher than that of long-maturity spread, consistent with the Samuelson effect.[34]

A.3 Testing the informational accuracy of the spread

We investigate whether the spread-based SVAR model is informationally sufficient to identify the truly structural shocks (see Giannone and Reichlin, 2006). To this end, we estimate the augmented reduced-form specification of the SVAR model to include the inventory proxy. The set of endogenous variables includes the growth rate of global crude oil production (gop_t), the world industrial production index (wip_t) and the growth rate of the real price of oil obtained by deflating the U.S. refiners' acquisition cost for imported crude oil (rac_t) by the U.S. consumer price index. Finally, the set of observables includes the spread ($s_{t,h}$) with maturities $h = 3-, 6-, 12-$ months and a proxy for global crude oil inventories above the ground (N_t).[35] Specifically, for each of the spread with maturities 3-, 6-, and 12-months we estimate three separate unrestricted VAR models and conduct Granger causality tests. If there were additional information in the spread that is not already contained in the inventory proxy, then the spread should Granger cause the remaining variables. Table 2 reports the p-values of Granger causality tests of this proposition and it highlights that the Brent-spreads with maturities of 3, 6 and 12 months fail to Granger cause all the remaining variables of the model. However, the same interpretation holds for the inventory proxies, as illustrated in Table 3. It is worth noting that, the Giannone-Reichlin test relies on a Granger-causality test. The latter is not without shortcomings. For example, the direction of the causality tends to be sensitive to the specification of the VAR model and to the choice of the sample period.[36] Moreover, it might be that the inventory proxy and the spread exhibit nonlinear features. In this case, linear Granger-causality tests applied to a nonlinear economic relationship of the variables of interest can result in low power testing (see Bekiros and Diks, 2008). Therefore the inclusion of the spread must be supported by economic motivations rather than relying only on the Giannone-Reichlin test results.

34. The Samuelson effects rely on the assumption that the volatility of oil futures prices decreases with the maturity of the contract (Alquist et al., 2014).

35. For the Granger causality tests, we use two proxies for global crude oil inventories above the ground, which are denoted by $N_{t,KM\,2014}$ and $N_{t,BH\,2019}$ respectively. The former is developed by Kilian and Murphy (2014) and the latter is proposed by Baumeister and Hamilton (2019).

36. The detailed results are available from the author upon request.

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Table 2: Granger Causality Tests—Brent Spreads 3-, 6-, 12-months

	Spread-3M	Spread-6M	Spread-12M
Panel (a)			
Null hypothesis			
$s_{t,h} \nRightarrow gop_t$	**0.001*****	**0.001*****	**0.000*****
$s_{t,h} \nRightarrow wip_t$	0.199	0.293	0.177
$s_{t,h} \nRightarrow rac_t$	**0.000*****	**0.002*****	**0.006*****
$s_{t,h} \nRightarrow N_{t,KM\,2014}$	**0.023****	**0.096***	0.436
Panel (b)			
Null hypothesis			
$s_{t,h} \nRightarrow gop_t$	**0.001*****	**0.002*****	**0.000*****
$s_{t,h} \nRightarrow wip_t$	0.244	0.324	0.177
$s_{t,h} \nRightarrow rac_t$	**0.000*****	**0.002*****	**0.006*****
$s_{t,h} \nRightarrow N_{t,BH\,2019}$	0.016**	0.122	0.436

Note: This table reports the p-values of Granger causality tests on each of the spread. Boldfaces indicate a statistical significant result at 10% level (*), 5% level(**) and 1% level (***).

Table 3: Granger Causality Test—Inventory proxies

	$N_{t,BH\,2019}$	$N_{t,KM\,2014}$
Panel (a)		
Null hypothesis		
$N_t \nRightarrow gop_t$	**0.000*****	**0.000*****
$N_t \nRightarrow wip_t$	0.205	0.235
$N_t \nRightarrow rac_t$	0.020**	0.022**
$N_t \nRightarrow s_{t,3}$	0.007***	0.014**
Panel (b)		
Null hypothesis		
$N_t \nRightarrow gop_t$	**0.000*****	**0.000*****
$N_t \nRightarrow wip_t$	0.501	0.454
$N_t \nRightarrow rac_t$	**0.091***	**0.078***
$N_t \nRightarrow s_{t,6}$	**0.011****	**0.023****
Panel (c)		
Null hypothesis		
$N_t \nRightarrow gop_t$	**0.000*****	**0.000*****
$N_t \nRightarrow wip_t$	0.128	**0.092***
$N_t \nRightarrow rac_t$	0.248	0.202
$N_t \nRightarrow s_{t,12}$	**0.001*****	**0.001*****

Note: This table reports the p-values of Granger causality tests on each of the two proxies for the global crude oil inventories above the ground. Boldfaces indicate a statistical significant result at 10% level (*), 5% level(**) and 1% level (***).

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