Valenti, D., Manera, M. and Sbuelz, A., 2020. Interpreting the oil risk premium: Do oil price shocks matter?. Energy Economics, p.104906

Interpreting the oil risk premium: do oil price shocks matter?

Daniele Valenti* Matteo Manera† Alessandro Sbuelz ‡

Abstract

This paper analyzes the link between the economic fundamentals of the global crude oil markets and the oil futures risk premium. The compensation for risk required by speculators in the oil futures market is modelled as part of the endogenous transmission of oil price shocks. The empirical approach is based on a Structural Vector Autoregressive model of the international market for crude oil. The dynamic response functions show a negative relationship between the risk premium and the real price of oil, triggered by shocks to economic fundamentals. Moreover, the expected returns of a long futures investment are largely explained by a specific shock component related to oil speculators and a shift in the global demand for crude oil.

Keywords: Crude oil; Futures risk premium; Bayesian SVAR models; Oil price speculation.

JEL Codes: Q40; Q41; Q43; E32.

*University of Milan - Department of Environmental Science and Policy (DESP), Milan, Italy - Email address: daniele.valenti@unimi.it.

†Corresponding author. University of Milan-Bicocca - Department of Economics, Management and Statistics (DEMS), and Center for European Studies (CefES); Fondazione Eni Enrico Mattei (FEEM), Milan, Italy - Email address: matteo.manera@unimib.it.

‡Catholic University of Milan (UCSC) & BAFFI CAREFIN Research Fellow - Department of Mathematics for Economic, Financial and Actuarial Sciences, Mathematical Finance and Econometrics, Milan, Italy - Email address: alessandro.sbuelz@unicatt.it

1 Introduction

This paper investigates the response of the crude oil futures risk premium to oil price shocks.

The international market for crude oil is exposed to price risk and futures contracts are financial instruments to facilitate risk sharing among a broad set of traders. The literature on risk premium is based on the theory of normal backwardation proposed by Keynes (1930). This theory postulates that the risk premium is jointly determined by the interactions among hedgers and speculators. Specifically, the average aggregate short hedging demand for futures outweighs the long hedging demand. As a result, in order to entice speculators to take the long side of the contracts, futures prices should be set below the expected future spot prices.

In this context, speculators are willing to become trading participants in the oil futures market if they are compensated for their non-diversified risk. Therefore, the monetary reward paid by hedgers to speculators represents the crude oil futures risk premium. The latter is defined as the difference between expected future spot prices and futures prices.

Our paper provides an aggregate analysis of the link between the economic fundamentals of the global oil market and the oil futures risk premium. On the one hand, the oil risk premium reflects the expected cost that is accrued to commercial firms for hedging against oil price fluctuations.[1] Given the crude oil's dominant role as an energy source in the economy, understanding the changes in the cost of hedging is particularly important to ensure oil supply security at the global level. In this respect, our study provides a clear picture of the dynamics of oil futures risk premium, especially during the major exogenous events in oil markets.[2] On the other hand, the oil risk premium represents an attractive investment return for oil speculators. This is motivated by the inflow of capital

[1] The aim of hedging is to stabilize future revenues and expected cash flows, especially for the upstream petroleum companies. Oil companies are very capital intensive and require large amount of cash to carry out activities of exploration, drilling and extraction. Moreover, hedging facilitates the management and the protection of the market value of storage, especially for the midstream and downstream oil sector. Finally, it helps companies whose largest operating cost is represented by crude oil to reduce their potential losses and financial risks.

[2] Some empirical studies find that a quantitative assessment of the performance of hedging during periods of oil market stress might be more informative than in periods of relative stability (see Alizadeh et al. (2004) and Chun et al. (2019)).

into crude oil futures markets from commodity index traders.[3] Indeed, financial investors benefit from trading oil futures contracts in terms of both portfolio diversification and inflation hedging. Portfolio diversification is motivated by a very low correlation between the oil futures risk premium and the excess-returns of investments in stocks and bonds markets. Inflation hedging is based on the view that economic agents pay close attention to oil prices in forming expectations on the inflation rate. In this respect, the expected returns of oil futures investments are positively correlated with inflation changes, which in turns produce negative impacts on the present value of dividend-paying stocks and bond returns. Thus, expected gains from investing in the crude oil futures markets are often interpreted by financial investors as an hedge against inflation (see Erb and Campbell (2006), Gorton et al. (2013), Szymanowska et al. (2014) and Cheng and Xiong (2014)).

Relative to the existent literature on the oil risk premium, our analysis provides three main contributions.

First, our work relates the time-varying risk premium to unanticipated shifts in global supply and demand for crude oil. Our main idea is that the oil futures risk premium can be modelled as a part of the endogenous transmission of oil price shocks. Most studies investigate the forecast performance of macroeconomic risk factors with reduced-form specifications that cannot identify the causes of oil price shocks. Predictive models are relevant to obtain unbiased expectations of future oil spot prices which are important not only for investors but also for policymakers.[4] In contrast, our study investigates the causal relationship between the time-varying oil risk premium and the economic fundamentals of the global crude oil markets and it relates to the strand of the literature dealing with the macroeconomic effect of oil price shocks. We document a negative relationship between the impact responses of the price of oil and the risk premium to global oil market-driven shocks. The economic motivations which support our empirical results can be summa-

[3]The commodity index traders, also known as money managers, purchase financial instruments linked to a commodity portfolio from institutional investors, such as financial swap dealers, investment banks and funds. The latter hedge themselves by purchasing a large amount of futures contracts encouraging an inflow of foreign capital.

[4]For example, a Central Bank is interested in accurately forecasting the risk premium in order to get the most reliable risk premium-adjusted oil futures price, which is a measure of the implied oil price expectation and plays a crucial role in driving the Central Bank's monetary policy (see Baumeister and Kilian (2014))

rized as follows: i) the expected speculative gains decline as the current real price of oil increases; ii) competition of oil speculators might cause a decline in the average prospective returns from investments in the crude oil futures markets; iii) a reduction in the compensation required by oil speculators for taking on residual risk from short hedgers could be associated with a rise (decline) in the aggregate long (short) hedging exposure in the crude oil futures market; iv) the growing interest in commodity futures contracts as a class of assets for portfolio diversification has attracted the attention of many arbitrageurs, who have induced the arbitrage profit to increase at the expense of smaller oil futures risk premiums. Therefore, understanding the effects of oil price shocks on the risk premium has important implications for oil market players with speculative and hedging purposes.

Second, our paper provides a specific investigation of the risk premium in the crude oil futures market, as opposed to most of the empirical analysis based on commodity indexes. In general, the empirical literature on risk premia considers different energy assets. For example, a benchmark for commodity futures investments is the Standard and Poor's-Goldman Sachs Commodity Index (SP-GSCI). However, the share of crude oil futures contracts is about 40% of its whole composition. This means that the energy index is not completely representative of the oil futures markets. On the contrary, the main focus of our analysis is on the crude oil risk premium estimated from the West Texas Intermediate (WTI) futures market.

Third, the empirical approach used in our paper allows us to take into account the endogeneity of crude oil risk premium with respect to macroeconomic and global oil market variables. The methodology applied to our analysis is based on a revised version of the Bayesian Structural Vector Autoregressive (SVAR) model developed by Baumeister and Hamilton (2019). The Bayesian approach allows to summarize our knowledge about the parameters' values that describe the peculiar characteristics of the global market for crude oil.[5] This allows us to express and quantify the degree of beliefs about the parameters'

[5]The Bayesian approach provides a statistical way of combining existing information, known as priors, with sample data. The latter are assumed to be fixed quantities whereas the structural coefficients of the model are considered to be random variables. Inference is based on updating prior information by adding observed data to provide a posterior distribution as a balance between priors and the likelihood function. Thus, Bayesian inference allows us to model uncertainty arising from two different sources. The

values that can be obtained from other studies. Compared to the traditional approaches based on sign-restricted and recursive SVAR models, the method proposed by Baumeister and Hamilton (2015) provides a more flexible way to recover the underlying structural shocks, which are interpreted as the fundamental driving forces of the international market for crude oil. Thus, the main idea of this method is to express the prior beliefs in the form of prior distributions of the parameters of the structural model. In this way, it is possible to account for imperfect information (uncertainty) about the structural contemporaneous parameters via a Bayesian prior distribution.

The literature attempting to model and forecast the random pay-off of long positions in oil futures markets is vast. Some empirical studies find that positive excess returns of long futures investments are correlated when hedgers are net short (see Bessembinder (1992), Bessembinder and Chan (1992) and De Roon and Veld (2000)). Consistent with previous studies, Hong and Yogo (2012) show that the hedging pressure is an important determinant of the crude oil futures risk premium. Moreover, Acharya et al. (2013) propose a theoretical model where a rise in the hedging pressure from producers or an increase in the capital constraints from speculators have negative impact on the spot price of oil. Specifically, if the cost of hedging is high, oil producers are unwilling to hold crude oil inventories. Thus, crude oil moves from the storage to the cash-market, causing the spot price of oil to fall. The empirical analysis is based on data from the oil and gas markets with a proxy for hedging demand. The authors show that limits to arbitrage, combined with producers hedging demand, affect the spot price of oil through the risk premium.

Other empirical studies (e.g. Irwin and Sanders (2012), Brunetti et al. (2013), Sanders and Irwin (2014) and Brunetti and Reiffen (2014)) investigate the role of speculation, hence of the risk premium, by exploiting the relationship between commodity index positions and prices in the energy futures markets. These works conduct time-series statistical tests with mixed results to provide evidence of a predictive link between the commodity investment index and changes in energy futures prices. The empirical design which is commmon to this strand of literature suffers from some limitations. First, a wide basket

first source is uncertainty related to the sample size. The second source is uncertainty about the correct specification of the SVAR model.

of commodities is used, rather than focusing on the market of crude oil. Second, positions from the commodity index traders are treated as exogenous to changes in the futures prices. Third, Granger-causality tests are employed, which say nothing about the causal relationship between futures prices and index speculators.

Another strand of literature investigates the link between macroeconomic factors and risk premium. For example, Pagano and Pisani (2009) emphasise the role of US business-cycle indicators in achieving accurate forecasts of the future spot price, based on the observed futures prices adjusted for the risk premium estimates. Moreover, Alquist et al. (2014) and Heath (2018) show that unspanned macroeconomic factors play an important role in explaining the behaviour of crude oil risk premium. A recent work by Hamilton and Wu (2014) describes the relationship between hedging demand from commercial producers, financial investors and arbitrageurs. The equilibrium requires that the expected returns of futures prices depend on the arbitrageurs' net exposure to non-diversifiable risk in the crude oil market. The authors find out that, starting from 2005, the inflows of money from index traders have changed the average and the volatility of crude oil futures risk premium.

In contrast to previous studies, Chang (1985) and Rouwenhorst and Tang (2012) propose empirical results which are inconsistent with the hedging pressure theory. Moreover, Gorton et al. (2013) and Alquist and Gervais (2013) find that changes in oil prices help to predict the traders' positions on the oil futures market, while the reverse does not hold.

In this context, it is worth recalling that the risk premium can be also related to the theory of storage, which focuses on the role of the convenience yield as a measure of the tightness of the physical market.

The first SVAR model to take up this feature is developed by Kilian and Murphy (2014) and it identifies the speculative demand for crude oil by exploiting data on oil inventories. An alternative approach proposed by Valenti (2018) 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. The oil futures-spot spread is defined as the percent deviation of the oil futures price from the spot price of oil and it represents a measure of the convenience yield although expressed with an opposite sign.

The key point is that it is not necessary to include a variable representing the storage market to investigate the effects of oil prices shocks on the crude oil risk premium. Understanding how unexpected oil price changes affect the risk premium requires the identification of three main structural shocks, that is shocks to oil production (supply shocks), shocks to the global business cycle (aggregate demand shocks) and oil-specific demand shocks (precautionary demand shocks). According to Kilian (2009) and Alquist and Kilian (2010), this last shock is designed to capture unexpected changes in the price of oil, driven by an increase in the demand for storage. Therefore, the presence of above-ground crude oil inventories (or oil futures-spot spread) is not needed in our model.

The rest of the paper is organized as follows. Section 2 describes the data and discusses the estimation of the oil risk premium. Section 3 illustrates the methodology. Empirical results and some robustness checks are presented in Sections 4 and 5, respectively. Finally, Section 6 concludes.

2 Data

Our analysis is based on monthly data spanning from 1983:12 to 2018:4. The set of endogenous variables includes the growth rate of global crude oil production, a worldwide measure of economic activity, the real price of oil and the crude oil futures risk premium. The latter is not observed, but it can be estimated from WTI daily futures prices. The global measure of real economic activity is the growth rate of the monthly OECD+6 world industrial production index (*wip*), as proposed by Baumeister and Hamilton (2019).[6] This measure of real output allows us to exploit some prior beliefs on the income elasticity of oil demand, given the methodology applied to recover the structural shocks. Moreover,

[6] The monthly industrial production index is available from `https://sites.google.com/site/cjsbaumeister/research` and it includes data for OECD and non-OECD countries, namely China, India, Brazil, Russia, South-Africa and Indonesia. Hamilton (2019) emphasises the benefits of using the world industrial production (*wip*) index as a proxy for the global real output, compared to the real economic activity index (*rea*) developed by Kilian (2009). A quantitative assessment of the two indicators reveals two important features. First, the cyclical component implied by the *wip* index has a higher correlation with yearly world real GDP than the *rea* index. Second, the *wip* indicator is more accurate in forecasting real commodity prices than the Kilian index. However, notice that *wip* is not without shortcoming. As pointed out by Kilian and Zhou (2018), depending on the transformation applied to *wip*, the index does not provide a unique picture of the global business cycle. A log-linearly detrended version of the index shows larger global economic slowdown than the same indicator transformed into growth rate.

wip seems to be indicated for modelling the changes in the oil future risk premium driven by global economic conditions.[7]

According to the empirical literature on interpreting the oil price shocks as shocks to the terms of trade, the US refiners' imported acquisition cost of crude oil is considered the best proxy for the international price of oil, see for example Kilian and Vigfusson (2011). Following Kilian and Murphy (2014), we take the log-transformation of the real price of oil in deviation from its sample mean.

Finally, our study presents two different approaches used in the estimation of the risk premium derived by crude oil futures prices with maturity 3-months. The first method is based on the multivariate linear regression model, where the dependent variable is the realized excess returns of crude oil futures investment and the set of exogenous variables include both macroeconomic and financial predictors. The second method is based on a Gaussian affine term structure model, proposed by Hamilton and Wu (2014). Both classes of models use data on WTI futures contracts, which are preferable to the Brent futures contracts for at least three reasons. First, WTI is the most liquid derivative market that ensures arbitrage-free conditions. Second, it allows to construct the longest available series for the risk premium. Third, there is no significant difference between the WTI and the Brent markets, when the comparison is based on their monthly realized excess returns.[8]

2.1 Predicting the oil risk premium: regression models

For the risk premium regression method the dependent variable is the realized excess returns of a crude oil futures investment, that is $ExRet_t \equiv \frac{S_{t+3}-F_{t,3}}{F_{t,3}}$, where $F_{t,3}$ denotes the price of futures contract at the end of the day of month t (with maturity 3-months) and S_{t+3} is the corresponding daily spot price at the next 3-months from period t. As discussed by Pagano and Pisani (2009), the risk premium in the commodity markets can be strongly affected by economic activity more related to the US economy. Therefore,

[7] In this study, we find that the posterior distribution of the structural parameter $a_{rp,rea}$ is substantially zero. Therefore, the contemporaneous correlation between the Kilian's index and the oil risk premium is negligible. The detailed results are available from the authors upon request.

[8] We compute the monthly realized excess returns as the difference between the three months futures contracts price and the spot price traded on both markets. The on-line Appendix provides descriptive statistics of the variables used in our analysis.

our analysis includes the yearly changes in the US industrial production index (*cip*). Moreover, we consider the composite leading indicator (*cli*), which is designed to capture early signals of turning points in the global business cycles as fluctuations of the economic activity around its long term potential level.[9] Variations in financial market liquidity play an important role in explaining the factor structure of the global business cycle and they can be correlated with the risk premium. Hence we take into account other two indicators. The first is the change in the default premium (*cdp*), defined as the difference between Moody's Baa corporate bond yield and 10-year treasury constant maturity rate. The second indicator is called junk bond premium (*jbp*) and is derived as the difference between Baa and Aaa corporate bond yields rated by Moody. Following Casassus and Collin Dufresne (2006), we consider a proxy for the slope of the yield curve, in order to capture the relationship between US government bonds and the crude oil market. We refer to the change in the term structure yield curve (*cts*), which is defined as the difference between the 10-Year Treasury constant maturity rate and the Treasury Bill of maturity 3-months. Finally, studies by Gorton and Rouwenhorst (2006) and Gorton et al. (2013) discuss situations where investors use crude oil futures contracts to hedge against inflation risks. They find that inflation rate is positively correlated with prospective returns of a commodity futures investment. Therefore, in our analysis we use changes in the US consumer price index to derive a monthly measure for annual inflation rate (inf). We include also the expected component of the inflation rate (*ei*).

The oil futures risk premium represents the average returns on oil futures contracts held to maturity and it can be computed from the regression:

$$\frac{S_{t+3} - F_{t,3}}{F_{t,3}} = \beta' x_t + \epsilon_{t+3} \tag{1}$$

where $\frac{S_{t+3}-F_{t,3}}{F_{t,3}}$ represents the normalized prediction error (or realized excess returns), x_t denotes the vector of explanatory variables and ϵ_{t+3} is mean zero error component of the risk premium regression equation. Moreover, β represents the vector of unknown

[9]The on-line Appendix provides evidence that, the cyclical measure derived from the US industrial production index exhibit a path similar to the composite leading indicator and they have positive correlation of 0.8.

parameters consistently estimated by OLS, as discussed by Baumeister and Kilian (2016). Thus, solving equation (1) for the crude oil market's expectation of the future spot price of oil, under the hypothesis of $E_t\left[\epsilon_{t+3}\right]=0$, yields:

$$E_t\left[S_{t+3}\right]=F_{t,3}\left(1+\beta' x_t\right) \tag{2}$$

Finally, the time-varying dollar oil futures risk premium (i.e. the oil futures risk premium expressed in USD) can be defined as $RP_t=E_t\left[S_{t+3}\right]-F_{t,3}$. In our analysis, we consider the oil risk premium measured as the expected percentage returns of long futures investments, namely $rp_t=\log\left(\frac{E_t[S_{t+3}]}{F_{t,3}}\right)\times 100$. The main objection to the risk premium regression method is the selection criterion for the predictors. Thus, our analysis proposes three different specifications including both macroeconomic and financial variables:

$$\text{(Risk premium 1):}\quad \widehat{ExRet}_t^{(1)}=\hat{\beta}_0^{(1)}+\hat{\beta}_1^{(1)}inf_t+\hat{\beta}_2^{(1)}jbp_t+\hat{\beta}_3^{(1)}cli_t \tag{3}$$

$$\text{(Risk premium 2):}\quad \widehat{ExRet}_t^{(2)}=\hat{\beta}_0^{(2)}+\hat{\beta}_1^{(2)}ei_t+\hat{\beta}_2^{(2)}cdp_t+\hat{\beta}_3^{(2)}cip_t \tag{4}$$

$$\text{(Risk premium 3):}\quad \widehat{ExRet}_t^{(3)}=\hat{\beta}_0^{(3)}+\hat{\beta}_1^{(3)}ei_t+\hat{\beta}_2^{(3)}cdp_t+\hat{\beta}_3^{(3)}cts_t+\hat{\beta}_4^{(3)}jbp_t \tag{5}$$

where $t=1,\cdots,422$, and the vector of coefficients $\hat{\beta}^{(i)}$, $i=1,2,3$, is consistently estimated by OLS.

2.2 Predicting the oil risk premium: term structure model

The last measure of the time-varying crude oil futures risk premium is estimated from a Gaussian affine term structure model. In contrast to the risk premium regression method, the affine term structure model postulates that all relevant information in the economy is reflected in current futures prices and no other sources of information can improve the forecasting accuracy of the expected future spot price of oil. This model imposes an affine factor structure which is common for oil futures prices and the economic fundamentals of the global oil markets. The first two factors represent the level and the slope of the nearest three contracts, while the third factor is usually interpreted as a measurement error. Thus, the risk premium is identified by the difference between the rational expectation of future spot price and observed futures prices which are collected in an unbalanced weekly dataset, where the maturity of WTI futures contracts changes with each daily observation. The set of parameters can be derived by applying the Minimum-Chi-Square Estimator (MCSE) to the unrestricted reduced form estimates. In this way, it is possible to infer the crude oil risk premium as the difference between the oil futures price based on the structural parameters under risk-neutrality assumptions ($\tilde{f}_{t,h}$) and the observed oil futures price ($f_{t,h}$): [10]

$$\text{(Risk premium 4):} \quad \tilde{f}_{t,h} - f_{t,h} \tag{6}$$

2.3 Assessing the oil risk premium measures

The risk premium plays a crucial role in retrieving the rational expectation of the futures spot price of oil from the observed futures prices. A measure of accuracy for the risk premium is the Mean-Squared Prediction Error (MSPE), computed on the risk premium-adjusted futures prices, that is on $F_{t,3} + RP_t$.[11] In our analysis, the most reliable risk premium estimate is obtained by selecting the specification that provides the largest MSPE reduction for the implied oil price expectation. Table 1 reports the predictive accuracy of the risk-adjusted futures prices against the benchmark of a random walk without drift. The forecast accuracy of risk-adjusted oil futures prices is based on two metrics, the MSPE and the Mean Absolute Prediction Error (MAPE) ratio, respectively. A ratio below one indicates an improvement on the forecasting accuracy relative to the monthly no-change

[10] Hamilton and Wu (2012) show that the MCSE minimizes a quadratic form in the difference between the reduced-form parameters implied by the structural model and the OLS estimates derived from the reduced-form model. The quadratic form corresponds to the information matrix and the MCSE is asymptotically equivalent to the Full Information Maximum Likelihood estimator. Moreover, note that a monthly risk premium with maturity 3-months is the corresponding weekly risk premium at the end on month t, computed on 12-week futures contract.

[11] The predictive accuracy of the risk-adjusted oil futures prices is based on the assumption that, in the absence of a risk premium, the oil futures prices minimize the MSPE under quadratic loss (see Granger (1969), Baumeister and Kilian (2016) and Pak (2018).

Table 1: Predictive accuracy of spot, futures and risk-adjusted futures prices

Predictor/Predicted $S_{(t+3)}$	**MSPE (p-value)**	**Bias**	**MAPE (p-value)**	**Success Ratio (p-value)**
S_t	104.71	6.24	0.39	–
$F_{t,3}$	0.99	0.99	0.14	0.49
	(0.30)	–	(0.27)	(0.81)
$F_{t,3}$−Risk adjusted (1)	0.90	−1.19	**0.94***	**0.61*****
	(0.13)	–	(0.07)	(0.00)
$F_{t,3}$−Risk adjusted (2)	**0.86***	−0.52	**0.93****	**0.57****
	(0.09)	–	(0.02)	(0.03)
$F_{t,3}$−Risk adjusted (3)	**0.83****	−0.30	**0.92****	**0.58*****
	(0.07)	–	(0.01)	(0.00)
$F_{t,3}$−Risk adjusted (4)	**0.91***	0.06	0.97	0.54
	(0.08)	–	(0.11)	(0.14)

Note: All MSPE and MAPE values are ratios relative to the benchmark no-change forecast model, for which we report MSPE, MAPE and the bias. MSPE reductions are evaluated based on the DM-test of Diebold and Mariano (2002), whose distribution is $\mathcal{N}(0,1)$. The forecast evaluation period spans from 1983.12 to 1989.12. The initial estimation window is 1990.1–2018.4. Boldfaces indicate a statistical significant improvement at 10% level (*), 5% level(**) and 1% level (***). The Success Ratio test is based on Pesaran and Timmermann (1992). The null hypothesis for this statistic states the absence of association between actual and predicted direction of changes in spot prices.

forecast. Moreover, Table 1 documents the bias of the forecast and the Success Ratio (SR) statistic of Pesaran and Timmermann (1992). The former is defined as the average amount by which S_{t+3} exceeds the prediction. The latter measures the number of times that the risk-adjusted oil futures prices correctly forecast the sign of the change in the spot price. Table 1 shows some important features. First, the MSPE ratio of the unadjusted oil futures price suggests a small improvement on the prediction accuracy relative to the no-change forecast. Second, all estimates of oil futures risk premium are economically plausible. Indeed, the improvement in accuracy for the risk-adjusted futures-based forecasts ranges from 9 to 17 percentage points. Third, the SR statistic reveals that most of the risk-adjusted oil futures prices provide statistically significant gains in forecasting the sign of the change in the spot price of oil. Fourth, based on the MSPE metric, the gain in accuracy is statistically significant at the 10% level for three out of four risk-adjusted oil futures prices. Finally, our preferred estimate of the time-varying risk premium in the crude oil futures market is obtained by the multivariate linear regression model specified in equation (5), since the corresponding risk-adjusted oil futures price yields the largest reduction of the MSPE ratio.

3 Econometric approach

The methodology is based on a revised version of the Bayesian SVAR model developed by Baumeister and Hamilton (2019). In this section we illustrate the structural equations and the corresponding informative prior distributions. Further details of the identification strategy are reported in the on-line Appendix. The SVAR model is the following:

$$Ay_t = c + \sum_{j=1}^{24} B_j y_{t-j} + v_t \tag{7}$$

where A is the matrix of instantaneous structural parameters and c is the vector of constant terms. The vector of endogenous variables is y_t and it includes the percent change of global crude oil production (q_t), the world industrial production index (wip_t), the real price of oil (p_t) and the risk premium (rp_t, equation (5)). The structural representation (7) can be written as a system of four equations:

$$q_t = a^s_{q,p} p_t + \tilde{b}_1 x_{t-1} + v_{1t} \tag{8}$$

$$wip_t = a_{wip,p} p_t + \tilde{b}_2 x_{t-1} + v_{2t} \tag{9}$$

$$q_t = a^d_{q,wip} wip_t + a^d_{q,p} p_t + a^d_{q,rp} rp_t + \tilde{b}_3 x_{t-1} + v_{3t} \tag{10}$$

$$rp_t = a_{rp,wip} wip_t + a_{rp,p} p_t + \tilde{b}_4 x_{t-1} + v_{4t} \tag{11}$$

where $\tilde{b}_1, \tilde{b}_2, \tilde{b}_3$ and $\tilde{b}_4$ are row vectors of structural coefficients of the lagged variables related to the first four equations, x_{t-1} is a column vector including lagged variables and a constant term, while $v_t = (v_{1t}, v_{2t}, v_{3t}, v_{4t})'$ denotes a vector of structural innovations.[12]

[12] The generic $\tilde{b}_i$, containing all structural coefficients on the lagged variables of the i^{th} equation, belongs to the i^{th} row of B_j, for $j = 1, \cdots, 24$. In other words, $\tilde{b}_i$ has dimension $1 \times (n \times m + 1)$ where n and m

Equation (8) says that the global oil supply has a current relationship only with the real price of oil through the contemporaneous structural parameter $a^s_{q,p}$, which represents the short-run price elasticity of oil supply.

In equation (9) the world industrial production is instantaneously affected by the real price of oil, via $a_{wip,p}$.

Equation (10) is the oil demand curve, where the parameters $a_{q,wip}$ and $a^d_{q,p}$ represent the income and the short-run price elasticity of oil demand, respectively. Moreover, the crude oil demand function is instantaneously related to the oil futures risk premium, through the contemporaneous structural parameter $a_{q,rp}$.

Finally, equation (11) models the determinants of the risk premium, with the contemporaneous effects of world industrial production and real price of oil, given by $a_{rp,wip}$ and $a_{rp,p}$, respectively. The former relates the changes in the oil risk premium to macroeconomic conditions (systematic risk). The latter is designed to capture the risk premium specific to the oil market (idiosyncratic risk).

Two are the main reasons to treat the oil risk premium predetermined with respect to the real price of oil. First, a fraction of the risk premium can be related to financial conditions that are not linked to the economic fundamentals of global market for crude oil, such as the willingness of investors to bear risk as well as the aggregate manager's sensitivity to hedge against price risk (see Acharya et al. (2013) and Qadan and Idilbi-Bayaa (2020)). Second, the estimation of the oil risk premium is based on a set of financial and macroeconomic predictors that are external to the oil spot market (see Bessembinder (1992), Heath (2018)).

The vector v_t consists of four different structural innovations, namely an oil supply shock (v_{1t}), an aggregate demand shock (v_{2t}), a precautionary demand shock (v_{3t}) and a residual shock (v_{4t}).

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 disruptions associated with OPEC strategic decisions, wars, strikes and instability in the oil producing countries affecting the global crude oil production.

are the numbers of endogenous variables and lags, respectively.

A positive aggregate demand shock represents a shift to the right of the contemporaneous oil demand curve along the oil supply curve, mainly driven by a strong growth in the global economy. This reflects a rise in the demand for crude oil driven by fluctuations in the global business cycle (e.g. crude oil demanded by emerging countries).

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 for speculative purposes.

Finally, a positive residual structural shock is designed to capture unexpected changes in the risk premium which are not driven by the first three structural shocks, e.g. it might reflect an increase in the price of risk due to changes in the preferences of oil speculators.

3.1 Prior information for the structural matrix

Following the Bayesian approach, we specify a set of economic prior beliefs (in terms of Student t density function) on the structural parameters of matrix A: [13]

$$A = \begin{bmatrix} 1 & 0 & -a^{s}_{q,p} & 0 \\ 0 & 1 & -a_{wip,p} & 0 \\ 1 & -a^{d}_{q,wip} & -a^{d}_{q,p} & -a^{d}_{q,rp} \\ 0 & -a_{rp,wip} & -a_{rp,p} & 1 \end{bmatrix} \tag{12}$$

The estimation of a plausible value of the aggregate elasticity of oil supply is not a simple endeavour, due to the simultaneous relationship between oil production and the price of oil. Caldara et al. (2019) derive an oil supply estimate using two different set of instrumental variables. The instruments are constructed using exogenous drops in the production of oil mainly driven by natural disasters, wars, strike and geopolitics events. The estimated oil supply elasticity is greater than 0.08 and it varies across oil producing countries, con-

[13]The Student t density function accounts for values that are far from the centre of the distribution. The t-distribution coincides with the Normal distribution when the degrees of freedom ν are equal or greater than 30. Compared to a Normal density function, the Student t distribution is more appropriate to deal with potential outliers in the data. In other words, the ability to set fat tails with a Student t distribution allows outliers to be accommodated without distorting the mean of the structural parameters. Moreover, Baumeister and Hamilton (2015) show that one of the benefit of using the Student t density function with the degree of freedom $\nu \geq 3$ is that the posterior distributions of the associated parameters have finite mean and variance.

sistent with the view that OPEC producers provide the largest volume of spare capacity in response to an oil supply disruption. Moreover, using the mean group estimator of Pesaran and Smith (1995), the estimated short-run price elasticity of oil supply becomes 0.13. It is widely accepted that the extraction technology of oil producers plays a crucial role in determining the elasticity of oil supply. Bjørnland et al. (2019) estimate the short-run price elasticity of oil supply from a large panel-dataset based on more than 16000 crude oil wells in North Dakota over the period 1990-2017. The authors show that the response of shale production to price movements ranges from 0.3 to 0.9, depending on wells and firm characteristics. As opposed, the short-run price supply elasticity for conventional vertical production in North Dakota is 0.03 with a standard error of 0.05. According to the theoretical model provided by Anderson et al. (2018), the responsiveness of conventional oil producers to changes in oil prices reflects the supply-side rigidities which are mainly motivated by the large costs of production (see Pindyck (1994) and Pindyck (2001)). Therefore, despite the large debate on the magnitude of the short-run price supply elasticity, our prior belief on $a^s_{q,p}$ is a Student t positive truncated distribution, with mode at $c_{(q,p)^s} = 0.1$, scale parameter $\sigma_{(q,p)^s} = 0.2$ and degrees of freedom $\nu_{(q,p)^s} = 3$.

The choice of the prior mode for $a_{(q,p)^s}$ is within the range of the empirical estimates of oil supply elasticity reported by Baumeister and Hamilton (2019), Caldara et al. (2019), Bjørnland et al. (2019) and Newell and Prest (2019).

For the structural parameter $a_{wip,p}$, we would expect a weak effect of oil price changes on the economic activity. This is motivated by a small share of energy expenditure compared to the total GDP. The Energy Information Administration (EIA) provides a world indicator about oil intensity. This index consists of an aggregate oil-weighted GDP indices based on relative magnitudes of oil consumption in each country. During the last decade, the oil-weighted GDP growth rate has declined from 5% to 2%. Thus, following Hamilton (2013) and Baumeister and Hamilton (2019), we put a Student t prior distribution truncated to be negative, with mode at $c_{wip,p} = -0.05$, scale parameter $\sigma_{wip,p} = 0.2$ and $\nu_{wip,p} = 3$ degrees of freedom. This is also consistent with the view that an increase in the real price of oil causes a reduction in the economic activity index.

The structural coefficient $a_{q,wip}$ represents the income elasticity of oil demand. According to Csereklyei et al. (2016), the relation between primary energy consumption and income per capita is remarkably stable across countries and consistent over time at around 0.7. Moreover, Gately and Huntington (2002) document country-specific income elasticities of oil demand. The authors show that the oil income elasticity for the OECD countries is 0.6, while for the developed countries the income elasticities rise up to 1. Thus, we use a Student t prior distribution with mode at $c_{(q,wip)^d} = 0.7$, scale parameter $\sigma_{(q,wip)^d} = 0.2$, degrees of freedom $\nu_{(q,wip)^d} = 3$ and truncated to be positive.

The structural coefficient $a^d_{q,p}$ represents the short-run price elasticity of oil demand. We put a Student t prior distribution with mode at $c_{(q,p)^d} = 0.1$, scale parameter $\sigma_{(q,p)^d} = 0.2$, degrees of freedom $\nu_{(q,p)^d} = 3$ and truncated to be negative.[14] This is coherent with the empirical estimates of the price elasticity of oil demand in the short run that are available in the literature (see West and Williams (2004), West and Williams (2007), Tiezzi and Verde (2014) and Coglianese et al. (2017)).

The structural coefficient $a_{q,rp}$ represents the effect of changes in the oil risk premium on the global oil demand. The sign of the relationship between the demand for crude oil and the oil futures risk premium is not clear a priori. For example, a rise in the risk premium can be associated with a decline in the demand for storage and in the spot price of oil. This is consistent with the results of Acharya et al. (2013) and supports the idea that limits to arbitrage in the financial market cause an increase in the cost of hedging for commercial firms, since speculators require a higher compensation per unit of risk. As a result, the optimal response for oil companies will be to mitigate their current exposure to price risk in the physical market by reducing the amount of unhedged crude oil stocks. This leads to a decline in the current spot price of oil and a rise in the expected future spot price. On the other hand, speculators might rise the risk premium in anticipation of perceived increases in the real price of oil. This can be followed by an upward shift of the total demand for crude oil, mainly explained by precautionary purposes. However, given the

[14]The numerical value of the short-run price elasticity of oil demand is equal to the oil supply elasticity, except for the sign. In this way we put equal weight on the prior knowledge about the effects of oil supply and oil demand shocks. It is worth recalling that the standard deviation of the truncated Student t prior is 0.25, which is sufficiently large to not influence the posterior results of our analysis.

lack of sufficient information on the structural parameter $a^d_{q,rp}$ in the existent literature, we put a relative uninformative Student t prior distribution with mode at $c_{(q,rp)^d} = 0$, scale parameter $\sigma_{(q,rp)^d} = 1$, degrees of freedom $\nu_{(q,rp)^d} = 3$.

For the structural parameters of the risk premium equation, we act as follows. A strong growth in the economy could be associated with a rise in the oil risk premium and in the real price of oil. Thus, if the real price of oil co-vary positively with the global economy, we would expect that an oil investment return exceeds the monetary reward in a risk-free investment. This implies a positive market beta in the context of the Capital Asset-Pricing Model (CAPM) (see Dusak (1973) and Pindyck (2001)). As a consequence, investors will expect the spot price of oil to rise above the current oil futures price, on average.[15]

In contrast, the rise in the real price of oil could be associated with a decline in the oil risk premium. For example, a strong economic growth might induce investors to increase their long positions in the oil futures markets. This leads to a pressure from buyers to sellers of oil futures contracts, resulting in a reduction of the oil risk premium, consistent with the results of Juvenal and Petrella (2015). However, the oil risk premium could be also negatively related to the global business conditions. In this case, a slowdown of the economy should be associated with a drop in the aggregate level of income and a rise in the expected returns on a risky investment. This can be induced by a substitution effect from consumption to investment (see Sadorsky (2002), Cochrane and Piazzesi (2005) and Cochrane (2011)). For these reasons and given the lack of knowledge on the structural parameters $a_{rp,wip}$ and $a_{rp,p}$, we assign completely uninformative Student t prior distributions, with location parameters set at 0, scale parameter set at 10 and degrees of freedom set at 3.

There are five zero-restrictions in the structural matrix. Specifically, two exclusion restric-

[15] According to Pindyck (2001), the expected return for an oil risky investment, over one period, must equal the current spot price (P_t) with a risk-adjusted discount rate (ρ_T). In other words, $E_t(P_T) - P_t + \psi_{t,T} - k_{t,T} = \rho_T P_t$, where $\psi_{t,T}$ is the convenience yield and $k_{t,T}$ is the cost of storage. Moreover, let r_T be the risk-free interest rate and $F_{t,T}$ the oil futures price with delivery in $T-t$ period. Knowing that $\psi_{t,T} - k_{t,T} = (1 + r_T)P_t - F_{t,T}$, the expected returns of a long futures investment can be proxied by $E_t(P_T) - F_{t,T} = (\rho_T - r_T)P_t$, where the term $(\rho_T - r_T)$ is also known as the market beta of the risky investment. It is worth noting that, if the risk-adjusted discount factor for the commodity is equal to the risk-free interest rate, the risk premium will be zero.

tions on the elements of the global oil supply equation, that is $a_{q,wip} = a_{q,rp} = 0$. These restrictions are coherent with the assumption that global oil production does not respond to any change in the measure of economic activity and crude oil risk premium, within the same period. This implies that global crude oil production depends only on the real price of oil in the current month. The measure of economic activity is instantaneously affected by the real price of oil, resulting in two exclusion restrictions, that is $a_{wip,q} = a_{wip,rp} = 0$. Moreover, we set a zero restriction on the structural coefficient $a_{rp,q}$, because we model the current changes in the oil risk premium attributed to the oil market only through their relationship with the price of oil.

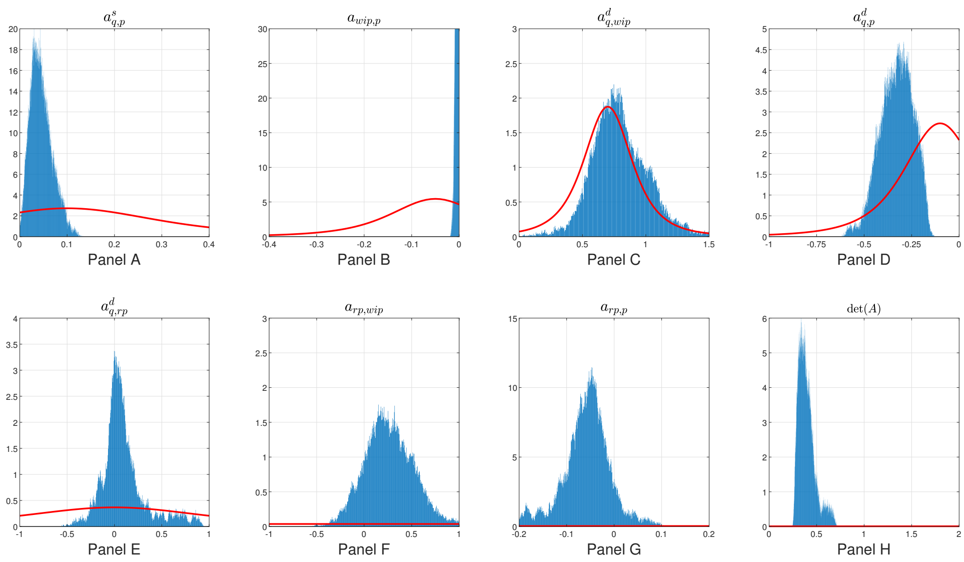
Finally, following Baumeister and Hamilton (2018), we use a prior asymmetric t distribution to assign a large probability of observing a positive determinant of A, $h_1 = det(A) > 0$. The prior density of matrix A is given by the product of all Student t densities of the structural parameters subject to their sign restrictions and the prior density of its determinant.

4 Empirical results

4.1 Prior and posterior distributions of structural parameters

This section provides a comparison of the prior and the posterior distributions of the structural parameters used in our study. Figure 1 plots the prior and posterior distributions for the unknown structural parameters considered in model (7). The posterior median of the short-run price elasticity of oil supply is reported in panel A of Figure 1 and it is equal to 0.04. Our value of oil supply elasticity is close to the benchmark reported by Newell and Prest (2019) and Bjørnland et al. (2019) for conventional oil producers and it is consistent with the theoretical results of Anderson et al. (2018). Thus, after combining our prior on a^s_{qp} with the data, values above 0.1 are substantially less plausible. This is quite reasonable, if we consider that most of the conventional crude oil producers are subject to supply-side rigidities which are mainly motivated by the large costs of production and the fraction for shale oil is only 8% of the world crude oil pro-

Figure 1: Prior and posterior distributions for structural parameters in model (7).



Note: Prior (red lines) and posterior (blue histograms) distributions considered in model (7).

duction (see Pindyck (1994), Pindyck (2001) and Kilian (2019a)). Panel D of Figure 1 shows that the posterior median of the short-run price elasticity of oil demand, a^d_{qp}, is -0.39. This value is significantly larger than the value anticipated by our prior but it is coherent with the empirical estimates available in the literature (see Coglianese et al. (2017) and Baumeister and Hamilton (2019)). Finally, panel C of Figure 1 shows that the posterior distribution of the income elasticity of oil demand is quantitatively similar to the value anticipated by our prior knowledge, with a posterior median of 0.9. Panels F and G of Figure 1 show that the prior distributions are flat lines when viewed on the scale adjusted for the posterior distributions for $a_{rp,wip}$ and $a_{rp,p}$, respectively. Although we set a prior mode equal to zero for the structural parameters of the risk premium equation, the large variance used for $a_{rp,wip}$ and $a_{rp,p}$ does not distort the information contained in the likelihood. In other words, the uninformative priors used for modelling the risk premium equation does not represent a possible source of bias for our posterior results. Given the lack of knowledge about the effect of world industrial production and real price of oil on the risk premium, we use agnostic priors for $a_{rp,wip}$ and $a_{rp,p}$, respectively. Of particular interest are the posterior distributions for these two parameters after examining the data. For the structural coefficient $a_{rp,wip}$, the posterior has most of its mass in correspondence of the positive values. This result is consistent with a positive market beta of a risky investment in the context of CAPM model. In other words, when business conditions are good, the return of a on oil risky investment is expected to co-vary positively with the global economy, because strong economic growth stimulates the demand for crude oil, and increases its price. Moreover, we provide empirical evidence that most of the mass of the posterior distribution for $a_{rp,p}$ is negative and centred at -0.05. After considering the data, the model reveals that the price of oil is negatively related to the oil futures risk premium.

4.2 Impulse responses

In this section we examine the dynamic responses of the endogenous variables to each structural shock.[16] Figure 2 reports the median impulse responses of oil and industrial production, the price of oil and the risk premium to each structural shock for any given horizon, together with posterior credibility sets at 68% and 95% levels.

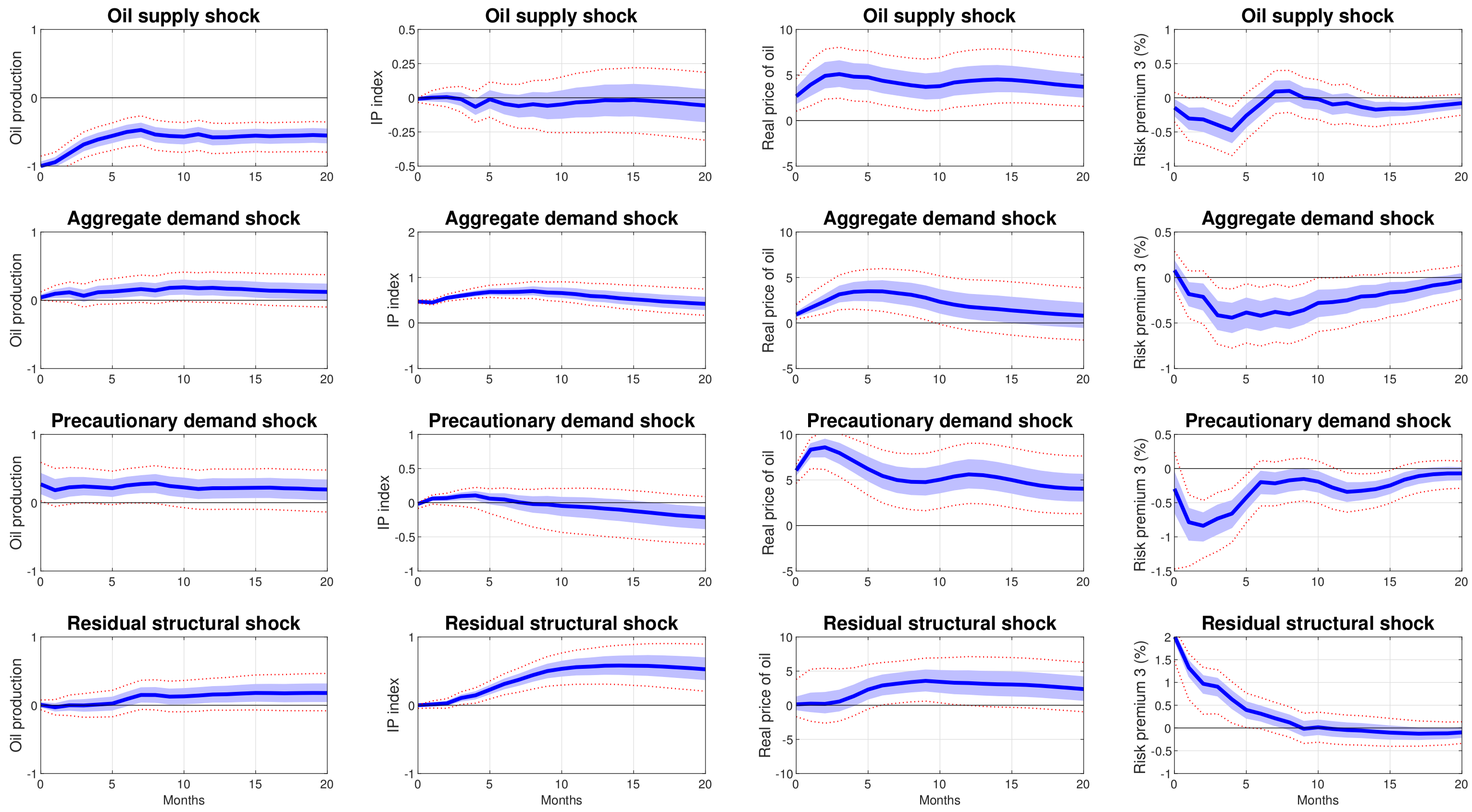
The impulse response estimates imply that an unexpected oil supply disruption causes a drop in the global crude oil production, an increase in the price of oil and a decline in the industrial production, on impact. An unanticipated positive aggregate demand shock yields an instantaneous increase in the world industrial production, in the global oil production and in the real price of crude oil. Finally, a positive precautionary demand shock induces a contemporaneous increase in the global oil production and a reduction in the world industrial production, accompanied by an hump-shaped response of the real price of oil.

The dynamic responses of the global oil market variables to demand and supply shocks are qualitatively similar to those obtained by Baumeister and Hamilton (2019). Moreover, Figure 2 provides empirical evidence that the risk premium responds to oil price shocks differently, depending on the economic motivations behind each shock.

An oil supply disruption causes a slight decline in the crude oil risk premium, on impact. The expected returns of long futures investments falls up to -0.5%. However, this effect seems to be less persistent, indeed the posterior median response estimate shows a quick

[16] It is important to bear in mind that impulse responses and historical decompositions are conditional on the model specification. However, empirical results based on different specifications, reported in the on-line Appendix, are qualitatively very similar to those presented in this section.

Figure 2: Impulse response functions of the endogenous variables to each structural shock



Note: The Bayesian posterior median responses to one-standard deviation structural shocks are reported. Blue lines indicate the median impulse response estimates, based on structural models satisfying the identification structure. Blue shaded regions and red dotted lines indicate the posterior credibility regions at 68% and 95%, respectively. The shocks have been normalized to imply an increase in the real price of oil.

reversion to previous levels over the subsequent months. The confidence about the sign of the response of oil risk premium to an oil supply disruption becomes unclear after the fifth month after the shock. A positive aggregate demand shock produces a small increase in the risk premium, on impact. The response of the expected gain of oil speculators gradually declines and its largest reduction is around -0.4%. Conversely, a one-unit increase in the precautionary demand shock is responsible of a large reduction in the risk premium, on impact. The response becomes even larger and more persistent in the subsequent periods. Its negative effect on the expected gain of the oil speculators declines gradually during the horizon of reference. This shock induces a drop in the expected monetary reward accrued to oil speculators up to -0.8%. The 95% posterior credibility region implies that the expected speculative gain of long investors could instantaneously decline up to -1.5%. A positive risk premium shock causes an immediate, although temporary, jump in the oil futures risk premium. The reduction in the risk premium in the subsequent periods is associated with a gradual increase in the world industrial production and the real price of oil. During the first year, the largest cumulative effects of oil supply shocks and aggregate demand shocks on the risk premium are about -2.3% and -3.8%, respectively. For the same period, the drop in the expected cumulative gain of long investors triggered by a positive precautionary demand shock is -5.3%. In contrast, positive residual structural shocks tend to rise the cumulative reward accrued to oil speculators by about 6% after one year. Beyond the impact period, we find that shocks to economic fundamentals of the global oil markets cause a rise in the real price of oil and a reduction in the risk premium. The economic motivations which support our empirical results can be summarized as follows. First, the expected speculative gains, hence the crude oil risk premium, declines as the current real price of oil increases. This is consistent with the fact that higher oil prices require speculators to allocate more money to purchase the same amount of contracts, forcing the marginal value of the investment to decrease.

Second, when the term structure of the oil future curve is in contango, it is very likely that a large number of speculators increases their long position in these contracts, since they expect that the price of oil will be higher in the future. Thus, the competition of oil speculators might cause a decline in the average prospective returns from investments in the crude oil futures market. It is also important to notice that a decline in the risk premium might be reinforced by a reduction in the short-hedging demand of commercial firms. Although every hedging strategy implies an off-setting gain between spot and financial markets, the higher levels of oil prices might lead to a reduction in the incentive to hedge against price drops.

Finally, the growing interest in commodity futures contracts as a class of assets for portfolio investments has attracted the attention of many arbitrageurs, causing the arbitrage profits to increase and the risk premium earned by oil speculators to decline, as discussed by Duffie (2010) and Etula (2013). The average excess returns of crude oil futures investment consist of spot and roll returns, respectively.[17] The roll-yield (and hence the crude oil risk premium received by oil speculators) could partially decline because of the arbitrageurs' attempt to profit from any possible mispricing triggered by index funds or other types of speculators during the rolling period. Therefore, roll-yield opportunities for commodity investors might cause a provisional reduction in the expiring futures price below its equilibrium. Conversely, the buying pressure of the next-to-expire contracts might cause a deviation of their prices from the oil market fundamentals. As a result, the arbitrageurs attempt to profit from this market price discrepancy through a long-short strategy. In other words, they can simultaneously short the nearby maturity contract and long the more distant contract by earning a profit from the calendar spread. The arbitrageurs will close-out their positions by longing the short-maturity contract and shorting the long-maturity contract.

Figure 2 provides evidence that the effects of demand shocks on risk premium are larger than those from supply shock. These results represent valuable information for all investors participating to the futures market for hedging or speculative purposes. For example, if aggregate demand expands quickly due to a positive shock, then a rise in the level of inflation is expected. Our results suggest that, for oil speculators, the expected gain to hedge against inflation risks tends to decline over time. Thus, understanding the

[17]The spot return is simply the appreciation (or depreciation) of the futures contract held to maturity. The roll-return (or roll-yield) arises when investors maintain a crude oil futures position. This can be easily done by selling the expiring contract and use the proceeds to buy another futures contract for delivery at a more distant date.

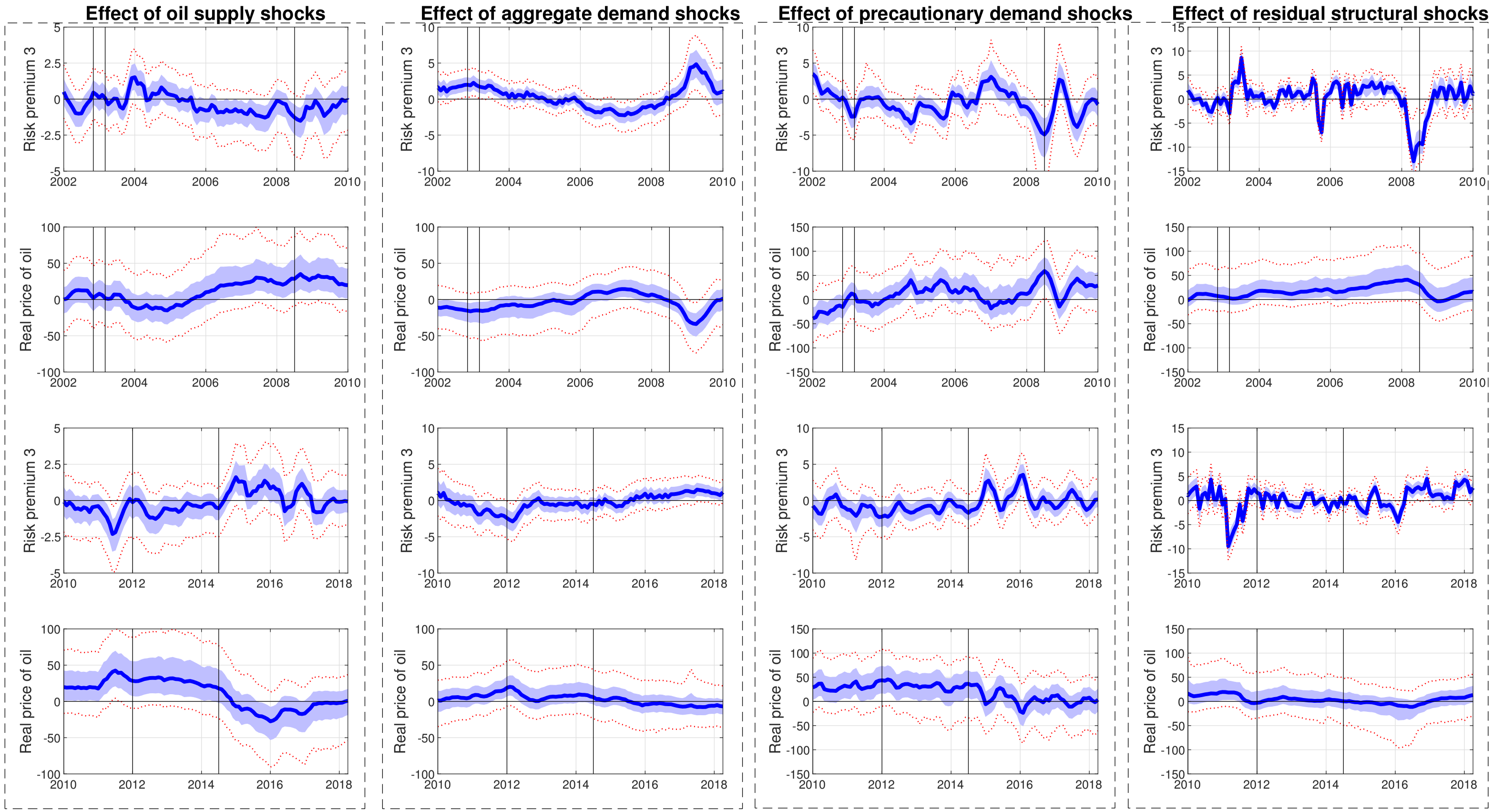
response of the crude oil risk premium to unexpected changes in the price of oil can help to implement accurate forward looking asset allocation strategies which combine optimal weights with expected returns net of the risk premium reduction.

4.3 Historical decompositions

In order to understand the main economic and financial factors driving the movement of the oil futures risk premium, it is useful to compute the historical contribution of each structural shock. Figure 3 plots the historical decompositions of the risk premium and the price of oil between 2002 and April 2018. Figure 4 illustrates the cumulative change in the dollar oil risk premium during some of the exogenous events in the oil markets.[18] Our analysis suggests the existence of a negative relation between unexpected changes in the price of oil and risk premium, both triggered by unexpected shifts in the economic fundamentals of the global oil markets. Moreover, precautionary demand shocks play the most important role in driving the risk premium, compared to the other shocks of oil demand and oil supply. The effects of precautionary demand shocks on the expected speculative gain of long investors are consistent with the result of Hamilton and Wu (2014) and support the idea that increases in investment flows into crude oil futures market are followed by a significant decline in the average value of the risk premium. Interestingly, Figure 3 shows that a large change in the risk premium is only related to its idiosyncratic component, which is instantaneously affected by movements in the price of oil. Our analysis suggests that changes in the risk premium are able to drive partially the real price of oil between 2006 and 2008. During this period, our model provides empirical evidence that the real price of oil can be also explained by an increase in the aggregate level of risk aversion. Specifically, lower levels of risk tolerance (i.e. increased risk premium) tend to be associated with high oil prices. Thus, residual shocks are important factors in explaining the surge in the price of oil during the period of financialization of the commodity markets. Therefore, the assumption to treat the risk premium as constant over time or to assume that it is zero might understate the effect of the expected speculative gain of

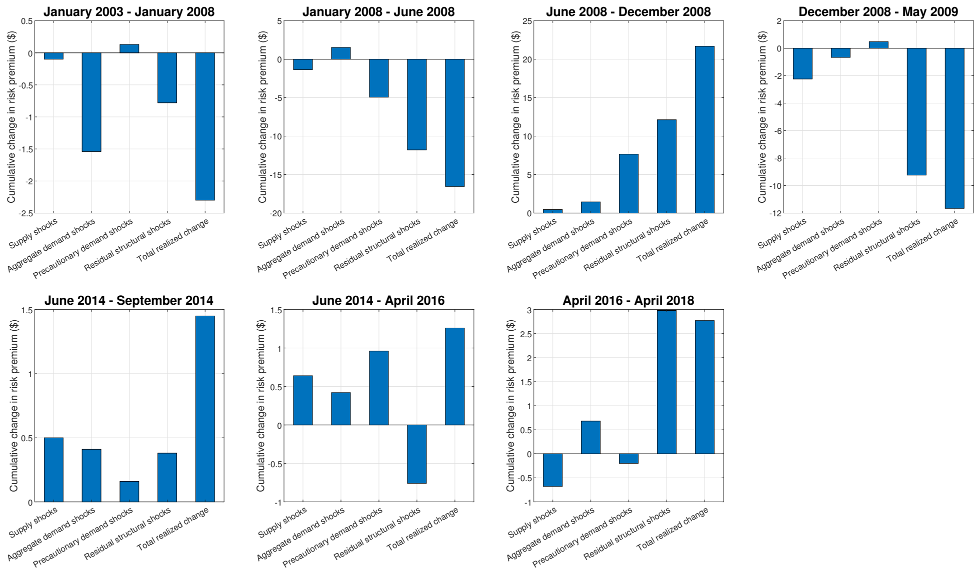
[18]The estimate of the cumulative change in the crude oil time-varying risk premium is reported in the on-line Appendix.

Figure 3: Historical decompositions of the crude oil risk premium and the price of oil.



Note: Solid blue lines indicate the Bayesian median estimates of historical decompositions of the risk premium and the real price of oil. Blue shaded regions and red dotted lines indicate the posterior credibility regions at 68% and 95%, respectively.

Figure 4: Contribution of each structural shock to change in dollar oil risk premium



Note: The contributions of the four shocks add up to the observed change in the dollar oil risk premium. The figure shows the results for the posterior median historical decomposition of model (7).

oil investors on the real price of oil (see Juvenal and Petrella (2015), Sockin and Xiong (2015) and Qadan and Idilbi-Bayaa (2020)). Finally, the historical contribution of residual structural shocks on the real price of oil becomes negligible toward the end of the sample. Figure 3 shows that, from early 2003 until mid-2008, the aggregate demand shocks (likely driven by emerging Asian and OECD countries) contributed to lower the crude oil risk premium. The reduction in the cumulative change of the expected gain of the oil speculators attributed to aggregate demand shocks amounts to about 1.5 USD, as shown in the upper left-most panel of Figure 4.

During the first half of 2008, the rise in the real price of oil was followed by a number of exogenous events in global crude oil markets, as discussed by Smith (2009). Specifically, in March 2008 there was the sabotages of two main oil export pipelines in the south of Iraq, in April 2008 the strike of Nigerian union workers and, finally, in June 2008 the closure of North Forties pipeline in UK and the mass rioting in Nigeria. These episodes are linked to oil supply security and they are largely explained by precautionary demand shocks. The latter cause a reduction in the premium paid from hedgers to speculators, as a form of insurance against down-trended prices. Thus, precautionary demand shocks account for a reduction of 5 USD, as illustrated in the second top left-most panel of Figure 4. The fall in the real price of oil from June to December 2008 is associated with a cumulative increase in the oil risk premium of 22 USD, out of which 12 USD are due to the residual structural shocks, 8 USD to the precautionary demand shocks, 1.5 USD to the aggregate demand shocks and 0.5 USD to the oil supply shocks. Figure 3 points out also that oil supply disruptions and positive precautionary demand shocks are partially responsible for a V-shape reduction of crude oil risk premium between 2010 and 2012. Positive shocks to precautionary demand for oil might be triggered by some concerns about international oil supply instabilities in the Middle-East (Arab spring) and political tensions between Iran and the European Union.[19] In early 2012 the Europe's sovereign debt crisis represents another potential factor that contributes to decline the crude oil risk premium through precautionary and aggregate demand shocks. In contrast, residual demand shocks are responsible for the high level of risk premium until the end of 2013.

Finally, between June 2014 and April 2018, a drop in the real price of oil is associated with a systematic upward trend in the oil risk premium. Specifically, positive supply shocks and negative shocks to precautionary demand contribute to rise the risk premium until April 2016, due to the demand for crude oil driven by expectations on global oil market conditions. Compared with the total increase of 1.3 USD, the contribution of oil supply and precautionary demand shocks to the cumulative change in the oil risk premium amount to 0.7 USD and 1 USD, respectively. Recently, negative aggregate demand and residual structural shocks have been the most important factors in driving up the compensation for risk required by oil speculators. The former are associated with a slowdown of the global economy mainly due to a decline in the Chinese manufacturing industry, while the latter are completely related to the investment strategies of oil speculators.

[19] The political tensions related to Iran's nuclear program lead to European foreign ministers to agree on a ban on transport, purchase and import of Iranian crude oil into Europe.

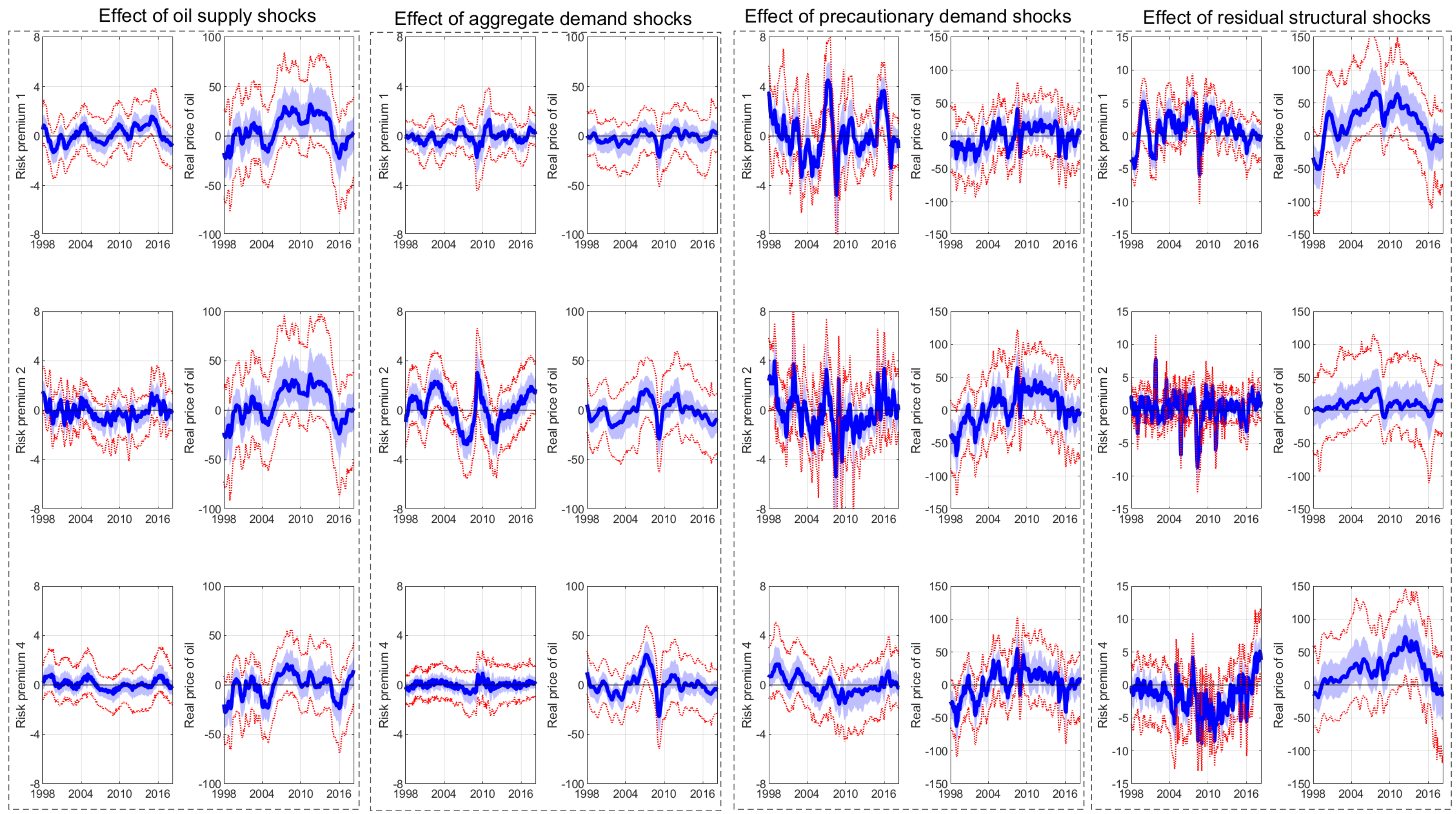
5 Robustness checks

5.1 Alternative estimates of the risk premium

This analysis presented so far includes the historical estimate of the risk premium provided by the regression model shown in equation (5), which is shown to ensures the most accurate and reliable estimates of oil price expectations. However, one of the main objections to the risk premium regression method is the criterion used to select the explanatory variables, which is highly arbitrary. In contrast, the term structure model seems to be less flexible compared to the regression method, because it is based on futures prices only. Thus, in this section we illustrate the results obtained using the alternative measures of the time-varying crude oil futures risk premium presented in Section 2.

Figure 5 plots the cumulative effect of each structural shock on the real price of oil and the alternative measures of the risk premium. We highlight that across different specifications, precautionary demand shocks and idiosyncratic shocks maintain their relevant role in driving the historical risk premium, compared to oil supply and aggregate demand shocks. In contrast, the existence of a negative relationship between changes in the price of oil and the risk premium, triggered by shocks to economic fundamentals which are typical of the global oil market, is not so clear cut. Specifically, positive shocks to aggregate demand are followed by a rise in the first regression-based measure of risk premium (risk premium 1), which is in conflict with the results obtained when the risk premium is estimated with the regression model in equation (5). When considering the measure of risk premium estimated with the term structure model (risk premium 4), it is not clear whether its dynamics is synchronous with the behaviour of the cumulative effect of the oil supply shocks on real price of oil. Finally, the results obtained by the second regression-based measure of risk premium (risk premium 2) exhibits striking qualitative similarities with our preferred estimate of the time-varying risk premium in the crude oil futures market (risk premium 3).

Figure 5: Historical contributions of structural shocks on different estimates of the risk premium and the price of oil



Note: See Figure 3. The alternative measures of the risk premium presented in the paper are described with details in Section 2. In particular: i) risk premium 1 corresponds to the fitted values of regression model (3); ii) risk premium 2 corresponds to the fitted values of regression model (4); iii) risk premium 4 corresponds to the affine term structure model (6).

5.2 Alternative proxy for global real economic activity

The second robustness check relies on a different proxy for measuring global real economic activity. To this end, we estimate model (7) by replacing the global measure of real output (wip) with the real economic activity index (rea), which is a proxy for the volume of international shipping in the commodity markets developed by Kilian (2009).[20] The Kilian's index offers some important advantages for the identification of oil price shocks, since it represents a monthly, direct and leading measure of global economic activity (see Kilian and Zhou (2018) and Kilian (2019b)). However, the choice of the Kilian's index is not without shortcoming. For example, the potential exposure of rea to its idiosyncratic shocks represents an empirical issue that could undermine the accuracy of this indicator as a measure of global business cycle (see Hamilton (2019)). On this respect, the contemporaneous structural matrix $\tilde{A}$ takes the form:

$$\tilde{A} = \begin{bmatrix} 1 & 0 & -a^s_{q,p} & 0 \\ 0 & 1 & -a_{rea,p} & 0 \\ 1 & -a^d_{q,rea} & -a^d_{q,p} & -a^d_{q,rp} \\ 0 & -a_{rp,rea} & -a_{rp,p} & 1 \end{bmatrix} \tag{13}$$

We postulate that there is no direct feedback from changes in the global oil production to changes in the real economic activity measure and in the oil risk premium, as in the structural contemporaneous matrix (12) discussed in Section 3. Therefore, we put two exclusion restrictions on the elements of the global oil supply equation, that is $a^s_{q,rea} = a^s_{q,rp} = 0$. Then we assign a Student t positive truncated distribution to the short-run price supply elasticity, $a^s_{q,p}$, with mode at $c_{(q,p)^s} = 0.1$, scale parameter $\sigma_{(q,p)^s} = 0.2$ and degrees of freedom $\nu_{(q,p)^s} = 3$. The structural parameter $a_{rea,p}$ denotes the effect of changes in the real price of oil on the real economic activity index. For the structural parameter $a_{rea,p}$ we

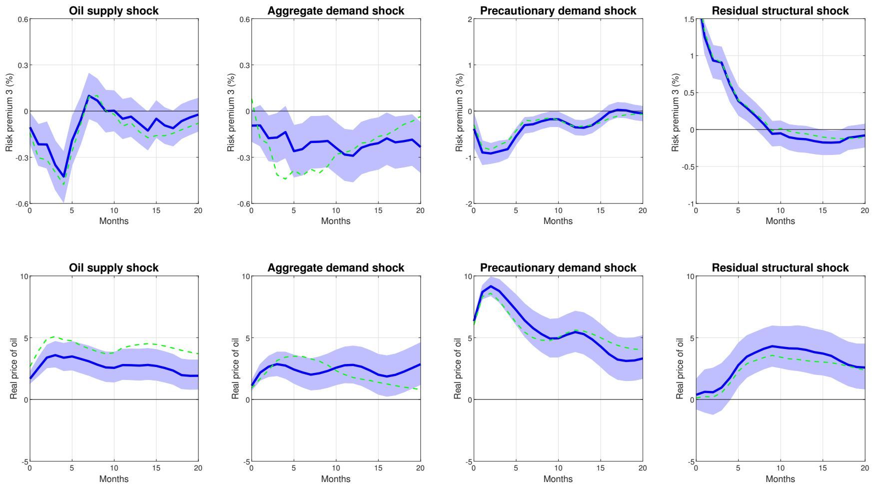
[20] rea requires row panel data for individual dry bulk cargo freight rates. This indicator is derived from the cumulative equal-weighted average of the growth rates of each series, having normalized January 1968 to unity. Moreover, rea is expressed in real terms using the US CPI index. In this analysis we use the original version of the Kilian's index available from `http://www-personal.umich.edu/~lkilian/paperlinks.html`. Despite the equal-weighted average is computed cross-sectionally, we point out that four series which are involved in the construction of the index are constant during the period 1968-1983, where 1983 is the starting year of our analysis. As a result, it is not necessary to adapt the index to the horizon of our investigation.

use a relatively uninformative Student t prior distribution truncated to be negative, with mode at $c_{rea,p} = 0$, scale parameter $\sigma_{rea,p} = 1$ and $\nu_{rea,p} = 3$ degrees of freedom. This is consistent with the view that an increase in the price of oil causes a reduction in rea, due to the potential dependence of bulk dry cargo rates on the cost of bunker fuel and hence on the price of crude oil. The structural coefficient $a^d_{q,rea}$ represents the effect of the cost of shipping in the commodity markets on the the oil demand. Thus, we use a relatively uninformative Student t prior distribution with mode at $c_{(q,rea)^d} = 0$, scale parameter $\sigma_{(q,rea)^d} = 1$ and degrees of freedom $\nu_{(q,rea)^d} = 3$. Instead, we assign a Student t prior distribution to the short-run price elasticity of oil demand, $a^d_{q,p}$, with mode at $c_{(q,p)^d} = 0.1$, scale parameter $\sigma_{(q,p)^d} = 0.2$, degrees of freedom $\nu_{(q,p)^d} = 3$ and truncated to be negative. Given the forward-looking nature of the risk premium, we use relatively uninformative Student t prior distribution with mode at $c_{(q,rp)^d} = 0$, scale parameter $\sigma_{(q,rp)^d} = 1$ and degrees of freedom $\nu_{(q,rp)^d} = 3$. Moreover, we model the current changes in the oil risk premium attributed to the oil market only through their relationship with price, therefore we impose an exclusion restriction on the structural coefficient $a_{rp,q}$. Finally, for the other parameters of the risk premium equation, namely $a_{rp,rea}$ and $a_{rp,p}$, we assign completely uninformative Student t prior distributions, with location parameter set at 0, scale parameter set at 10 and degrees of freedom set at 3.

Figure 6 illustrates the impulse response estimates of the risk premium and the real price of oil implied by the structural matrices (12) and (13), respectively. Recall that matrix A (12) refers to the SVAR model including the world industrial production index. On the contrary, matrix $\tilde{A}$ (13) includes the real economic activity index. The response of the risk premium to an oil supply disruption shows a V-shape decline beyond the impact period, in both specifications. The effect of this shock is only temporary and the impulse response of the risk premium reverts to previous levels after a limited number of periods. In the model including rea, a positive aggregate demand shock causes a simultaneous reduction in the risk premium, as opposed to the model with the industrial production index. After the impact, both specifications produce empirical results which are consistent with a decline in the oil risk premium. Specifically, the specification with rea exhibits a more persistent reduction in the oil risk premium compared to the model with the industrial production index.

A positive aggregate demand shock causes a reduction in the risk premium which is

Figure 6: Impulse response functions of the risk premium and the price of oil

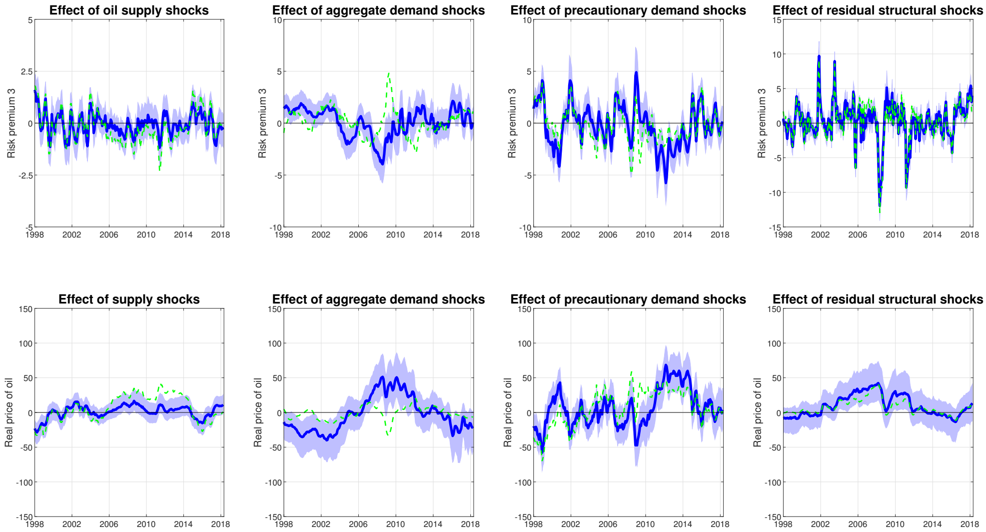


Note: Solid blue line refers to the median impulse response function of the risk premium and the price of oil to each structural shock implied by the structural matrix $\tilde{A}$ (13). The same interpretation holds for the dashed green lines, which refer to the response estimates implied by the structural matrix A (12).

persistent in both specifications. However, the reduction of the risk premium is more persistent in the specification with the industrial production index (wip), although much of its initial decline is reversed within one year. Finally, a positive risk premium shock causes a jump of the risk premium in both specifications. Overall, the average behaviour of the endogenous variables are robust to changes in the proxy for global real economic activity.

Figure 7 reports the historical decomposition of the crude oil risk premium and the price of oil for the model with rea and the model including wip. Both specifications produce empirical results which support the view that idiosyncratic shocks have been very important to drive the path of the risk premium over the period of interest. We highlight also some differences that can be mainly attributed to the specific measures of economic activity. The alternative specification shows that the historical contribution of the aggregate demand shocks to the risk premium is somewhat larger than in the case of precautionary demand shocks. This is also reflected in the changes of the real price of oil. Overall, the negative correlation between the risk premium and the price of oil in response to oil

Figure 7: Historical decompositions of the risk premium and the price of oil



Note: Solid blue and dashed green lines refer to the cumulative effects of structural shocks on the risk premium and price of oil implied by the structural contemporaneous equations associated with matrices $\tilde{A}$ (13) and A (12), respectively. Shaded regions represent the 68% posterior credibility sets associated with matrix $\tilde{A}$ (13).

market-driven shocks is preserved.

6 Conclusions

In this paper we have shown that the crude oil futures risk premium can be modelled as part of the endogenous transmission of oil price shocks. On average, oil demand and oil supply shocks that imply a rise in the real price of oil have negative and persistent effects on the risk premium. Moreover, a positive idiosyncratic shock to the risk premium causes negligible changes in the global oil market variables. Beyond the impact period, the gradual reduction in the risk premium is associated with a small increase in the real price of oil. Most of the historical contribution to the temporal evolution of the the risk premium is attributed to its idiosyncratic component. This suggests that a large part of the monetary rewards required by oil speculators is not strictly related to the global oil market conditions. Instead, it can be interpreted as changes in the preferences of oil speculators related to their investment allocation strategies. In our study, the effects of financialization of commodity markets on the real price of oil are modelled endogenously and the empirical evidence suggests that risk premium shocks are not relevant drivers for the real price of oil, except for the period from 2005-2008, when the commodity markets experienced the so-called financialization process. However, there is a large part of the changes in the expected speculative gain of oil speculators that can be attributed to shifts in the global oil markets fundamentals. In particular, oil demand shocks have significant impacts on the changes in the expected returns of long futures investments. Finally, we show that our findings become neater if we consider the measure of risk premium characterized by the highest forecast accuracy.

References

Acharya, V. V., Lochstoer, L. A., and Ramadorai, T. (2013). Limits to arbitrage and hedging: Evidence from commodity markets. *Journal of Financial Economics*, 109:441–465.

Alizadeh, A. H., Kavussanos, M. G., and Menachof, D. A. (2004). Hedging against bunker price fluctuations using petroleum futures contracts: constant versus time-varying hedge ratios. *Applied Economics*, 36:1337–1353.

Alquist, R., Bauer, G., and de los Rios, A. D. (2014). What Does the Convenience Yield Curve Tell Us about the Crude Oil Market? Staff Working Papers 14-42, Bank of Canada.

Alquist, R. and Gervais, O. (2013). The Role of Financial Speculation in Driving the Price of Crude Oil. *The Energy Journal*, 34:35–54.

Alquist, R. and Kilian, L. (2010). What do we learn from the price of crude oil futures? *Journal of Applied Econometrics*, 25:539–573.

Anderson, S. T., Kellogg, R., and Salant, S. W. (2018). Hotelling under pressure. *Journal of Political Economy*, 126:984–1026.

Baumeister, C. and Hamilton, J. D. (2015). Sign Restrictions, Structural Vector Autoregressions, and Useful Prior Information. *Econometrica*, 83:1963–1999.

Baumeister, C. and Hamilton, J. D. (2018). Inference in structural vector autoregressions when the identifying assumptions are not fully believed: Re-evaluating the role of monetary policy in economic fluctuations. *Journal of Monetary Economics*, 100:48–65.

Baumeister, C. and Hamilton, J. D. (2019). Structural Interpretation of Vector Autoregressions with Incomplete Identification: Revisiting the Role of Oil Supply and Demand Shocks. *American Economic Review*, 109:1873–1910.

Baumeister, C. and Kilian, L. (2014). What central bankers need to know about forecasting oil prices. *International Economic Review*, 55:869–889.

Baumeister, C. and Kilian, L. (2016). A General Approach to Recovering Market Expectations from Futures Prices with an Application to Crude Oil. Staff Working Papers 16-18, Bank of Canada.

Bessembinder, H. (1992). Systematic risk, hedging pressure, and risk premiums in futures markets. *Review of Financial Studies*, 5:637–667.

Bessembinder, H. and Chan, K. (1992). Time-varying risk premia and forecastable returns in futures markets. *Journal of Financial Economics*, 32:169–193.

Bjørnland, H. C., Nordvik, F. M., and Rohrer, M. (2019). Supply flexibility in the shale patch: Evidence from North Dakota. CAMA Working Papers 2019-56, Centre for Applied Macroeconomic Analysis, Crawford School of Public Policy, The Australian National University.

Brunetti, C., Buyuksahin, B., and Harris., J. (2013). Herding and Speculation in the Crude Oil Market. *The Energy Journal*, 34:83–104.

Brunetti, C. and Reiffen, D. (2014). Commodity index trading and hedging costs. *Journal of Financial Markets*, 21:153–180.

Caldara, D., Cavallo, M., and Iacoviello, M. (2019). Oil price elasticities and oil price fluctuations. *Journal of Monetary Economics*, 103:1 – 20.

Casassus, J. and Collin Dufresne, P. (2006). Stochastic convenience yield implied from commodity futures and interest rates. *Journal of Finance*, 60:2283–2331.

Chang, E. C. (1985). Returns to speculators and the theory of normal backwardation. *Journal of Finance*, 40:193–208.

Cheng, I.-H. and Xiong, W. (2014). Financialization of Commodity Markets. *Annual Review of Financial Economics*, 6:419–441.

Chun, D., Cho, H., and Kim, J. (2019). Crude oil price shocks and hedging performance: A comparison of volatility models. *Energy Economics*, 81:1132–1147.

Cochrane, J. H. (2011). Presidential address: Discount rates. *The Journal of finance*, 66:1047–1108.

Cochrane, J. H. and Piazzesi, M. (2005). Bond risk premia. *American Economic Review*, 95:138–160.

Coglianese, J., Davis, L. W., Kilian, L., and Stock, J. H. (2017). Anticipation, tax avoidance, and the price elasticity of gasoline demand. *Journal of Applied Econometrics*, 32:1–15.

Csereklyei, Z., Rubio-Varas, M. d. M., and Stern, D. I. (2016). Energy and economic growth: the stylized facts. *The Energy Journal*, 37:223–255.

De Roon, F.A., T. N. and Veld, C. (2000). Hedging pressure effects in futures markets. *Journal of Finance*, 55:1437–1456.

Diebold, F. X. and Mariano, R. S. (2002). Comparing predictive accuracy. *Journal of Business & economic statistics*, 20:134–144.

Duffie, D. (2010). Asset price dynamics with slow-moving capital. *Journal of Finance*, 65:1237–1267.

Dusak, K. (1973). Futures trading and investor returns: an investiagtion of commodity market risk premiums. *Journal of political economy*, 81:1387–1406.

Erb, C. and Campbell, H. B. (2006). The strategic and tactical value of commodity futures. *Financial Analysts Journal*, 62:69–97.

Etula, E. (2013). Broker-dealer risk appetite and commodity returns. *Journal of Financial Econometrics*, 11:486–521.

Gately, D. and Huntington, H. G. (2002). The asymmetric effects of changes in price and income on energy and oil demand. *The Energy Journal*, 23:19–55.

Gorton, G. B., Hayashi, F., and Rouwenhorst, K. G. (2013). The fundamentals of commodity futures returns. *Review of Finance*, 17:35–105.

Gorton, G. B. and Rouwenhorst, K. G. (2006). Facts and fantasies about commodity futures. *Financial Analysts Journal*, 17:35–105.

Granger, C. W. (1969). Prediction with a generalized cost of error function. *Journal of the Operational Research Society*, 20:199–207.

Hamilton, J. D. (2013). Oil prices, exhaustible resources and economic growth. In Fouquet, R., editor, *Handbook on Energy and Climate Change*, Chapters, chapter 1, pages 29–63. Edward Elgar Publishing.

Hamilton, J. D. (2019). Measuring global economic activity. *Journal of Applied Econometrics*.

Hamilton, J. D. and Wu, J. C. (2012). Identification and estimation of Gaussian affine term structure models. *Journal of Econometrics*, 168:315–331.

Hamilton, J. D. and Wu, J. C. (2014). Risk premia in crude oil futures prices. *Journal of International Money and Finance*, 42:9–37.

Heath, D. (2018). Macroeconomic factors in oil futures markets. *Management Science*.

Hong, H. and Yogo, M. (2012). What does futures market interest tell us about the macroeconomy and asset prices? *Journal of Financial Economics*, 105:473–490.

Irwin, S. H. and Sanders, D. R. (2012). Testing the Masters hypothesis in commodity futures markets. *Energy Economics*, 34:256–269.

Juvenal, L. and Petrella, I. (2015). Speculation in the oil market. *Journal of Applied Econometrics*, 30:621–649.

Keynes, J. M. (1930). A treatise on money. *Macmillan, London*, 2.

Kilian, L. (2009). Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. *American Economic Review*, 99:1053–1069.

Kilian, L. (2019a). Facts and Fiction in Oil Market Modeling.

Kilian, L. (2019b). Measuring global real economic activity: Do recent critiques hold up to scrutiny? *Economics Letters*, 178:106–110.

Kilian, L. and Murphy, D. P. (2014). The role of inventories and speculative trading in the global market for crude oil. *Journal of Applied Econometrics*, 29:454–478.

Kilian, L. and Vigfusson, R. J. (2011). Nonlinearities In The Oil Price-Output Relationship. *Macroeconomic Dynamics*, 15:337–363.

Kilian, L. and Zhou, X. (2018). Modeling fluctuations in the global demand for commodities. *Journal of International Money and Finance*, 88:54–78.

Newell, R. G. and Prest, B. C. (2019). The unconventional oil supply boom: Aggregate price response from microdata. *The Energy Journal*, 40.

Pagano, P. and Pisani, M. (2009). Risk adjusted forecasts of oil prices. *The B.E. Journal of Macroeconomics*, 9:1–25.

Pak, A. (2018). Predicting crude oil prices: Replication of the empirical results in "what do we learn from the price of crude oil?". *Journal of Applied Econometrics*, 33:160–163.

Pesaran, M. H. and Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of econometrics*, 68:79–113.

Pesaran, M. H. and Timmermann, A. (1992). A simple nonparametric test of predictive performance. *Journal of Business & Economic Statistics*, 10:461–465.

Pindyck, R. S. (1994). Inventories and the short-run dynamics of commodity prices. *Journal of Economics*, 25:141–159.

Pindyck, R. S. (2001). The dynamics of commodity spot and futures markets: a primer. *The Energy Journal*, 22:1–30.

Qadan, M. and Idilbi-Bayaa, Y. (2020). Risk appetite and oil prices. *Energy Economics*, 85:104595.

Rouwenhorst, G. and Tang, K. (2012). Commodity investing. *Annual Review of Financial Economics*, 4:447–467.

Sadorsky, P. (2002). Time-varying risk premiums in petroleum futures prices. *Energy Economics*, 24:539–556.

Sanders, D. R. and Irwin, S. H. (2014). Energy futures prices and commodity index investment: New evidence from firm-level position data. *Energy Economics*, 46:57–68.

Smith, J. L. (2009). World oil: market or mayhem? *Journal of Economic Perspectives*, 23:145–164.

Sockin, M. and Xiong, W. (2015). Informational frictions and commodity markets. *The Journal of Finance*, 70:2063–2098.

Szymanowska, M., De Roon, F., Nijman, T., and Van Den Goorbergh, R. (2014). An anatomy of commodity futures risk premia. *The Journal of Finance*, 69:453–482.

Tiezzi, S. and Verde, S. (2014). Overreaction to excise taxes: The case of gasoline. *EUI Working Paper RSCAS European University Institute.*

Valenti (2018). Modelling the global price of oil: is there any role for the oil futures-spot spread? *FEEM Working Paper No. 06.2018.*

West, S. E. and Williams, R. (2004). Estimates from a consumer demand system: implications for the incidence of environmental taxes. *Journal of Environmental Economics and Management*, 47:535–558.

West, S. E. and Williams, R. C. (2007). Optimal taxation and cross-price effects on labor supply: Estimates of the optimal gas tax. *Journal of Public Economics*, 91:593–617.