On the relationship between liquid commodities and financial variables: a Bayesian VAR approach

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Abstract: Nowadays, investors and policy-makers are paying special attention to the relationship between commodity markets and financial variables. This paper offers evidence to which way do ‘liquid commodities’ interact with key financial variables (S&P 500 equity VIX, federal funds rate, and exchange rates). Using a Bayesian VAR analysis, we simulate a shock on each variable and evaluate its impacts on the other. The empirical evidence highlights that different relationships exist among the commodities and financial variables. Common features exist even if differences are detected among the variables. Another general finding is that responses are immediate and have duration in time.

Keywords: oil prices; commodities prices; financial variables; Bayesian VAR.


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1 Introduction

Nowadays, commodities are taking an important place on markets. In fact, most commodity prices are determined in auction markets with efficient information; they reflect demand or supply shocks more rapidly. But they are prone to speculations by financial players such as hedge funds and day traders. Hence, speculative behaviour in commodity prices may have implications on all markets. On the same time, policymakers are paying attention to the relationship between oil prices, and both economic and financial variables as they seem to be instable and complex.

Looking to the literature, most of the studies on commodities focus on the co-movements between commodities among themselves or with macroeconomic variables (Creti et al., 2013). Moreover, Bernanke et al. (1997) state that “it is surprisingly difficult to find an indicator of oil price shocks that produces the expected responses of macroeconomic and policy variables in a VAR setting”. The Bayesian VAR (BVAR) model has exposed by a number of empirical studies for providing better forecasts than the standard VAR and for a number of financial variables (De Mol et al., 2008, Banbura et al., 2010 and Kaabia et al., 2013). Its main desired feature is its ability to overcome the over-parameterisation, where VAR models suffer from a loss of degrees of freedom when the number of variables increases significantly (Bernanke et al., 2005).

Therefore, in this paper, we propose to investigate the relationship between “liquid commodities” and key financial variables. The main contribution of the present study is providing empirical evidence on how “liquid commodity” prices and financial variables do react using a Bayesian VAR model to capture nonlinearities, rather than a standard VAR.
The results reveal that different relationships exist among the variables. They may be positive, negative or even insignificant between commodities prices and financial variables. Not all “liquid commodities” react in the same way to financial variables shocks and vice versa.

The remaining of this paper is organised as follows. Section 2 reviews the studies related to the current study. Section 3 presents the Bayesian VAR methodology and characterises the data. The penultimate section discusses the empirical findings. The last one concludes and points to some directions for future research.

2 Literature review

This section will review the related studies. First, given the importance of oil in industrial and real economic activities, many papers focus on the causal relationship between oil prices and stock returns.

Sadorsky (2001), and Boyer and Filion (2007) show that an increase in oil prices positively affect Canadian Oil & Gas companies’ stock returns. El-Sharif et al. (2005) emphasise on the oil and gas sector returns in the UK, pointing to a weak link between non-oil and gas sectors and oil price changes.

Nandha and Faff (2008) consider data of thirty-five global industries, and find that the rise in price of oil has a negative impact on all industries but not those of oil and gas. Park and Ratti (2008) employ a standard VAR model. They state that oil price shocks impact significantly real stock returns in the US and 13 European countries. They also discover little evidence of asymmetric effects on real stock returns of positive and negative oil price shocks for oil importing European countries. Aloui and Jammazi (2009) focus on the role of regime shift while investigating the linkage between oil prices and stock market prices. They apply a regime Markov-switching EGARCH model. They claim that oil prices’ increase does not only determines stock market volatility but also transact probability regime-wise.

Miller and Ratti (2009) examine the relationship between crude oil prices and stock markets returns for OECD countries. Their results show that all variables have co-integration and real oil prices shocks inversely affect real stock returns in the presence of bubbles. Similarly, Apergis and Miller (2009) use a vector error correction analysis to investigate the relationship between structural oil prices shocks and stock prices for Australia, Canada, France, Germany, Italy, Japan, the UK, and the USA. They find that stock market returns are significantly affected by oil-supply shocks, aggregate-global-demand shocks as well as idiosyncratic-demand shocks. Filis et al. (2011) apply a DCC-GARCH-GJR approach to investigate the relationship between oil prices and stock markets for oil exporting and importing economies. They conclude that demand-side shocks have positive correlation with stock returns but the relationship between supply-side shocks and stock returns is statistically insignificant. Furthermore, their analyses indicate that stock markets returns are negatively affected by oil prices shocks confirmed by lagged correlation analysis. The relationship becomes negative after the global financial crisis in 2008, indicating that oil market is not “safe haven” during economic turmoil. Chang et al. (2013) study the association between oil prices and financial markets using daily data for the period of January 1998 to November 2009. They apply many models: CCC, VARMA-GARCH, VARMA-AGARCH as well as DCC models for empirical analyses. They conclude insignificant and low correlation between
oil prices and stock market prices index by mainly all the models except for DDC confirming a significant relationship. Further, they find a little relationship between oil prices and stock market prices confirmed by VARMA-GARCH and VARMA-AGARCH approaches. Chang and Yu (2013) employ an MS-ARJI-GJR-GARCH-X model to examine how much oil price shocks predict the behaviour of stock market returns. They find mixed impact on stock market returns due to past and current oil price shocks. Filis (2014) apply a time-varying approach – i.e. Scalar-BEKK model – to investigate the relationship between oil prices and stock market prices shocks. He finds a strong correlation between the variables.

Reboredo and Rivera-Castro (2014) examine the pass-through of oil prices to stock prices by using a wavelet-based decomposition approach for the case of European countries and the USA over the period of June 2000 to July 2011. Their results show the pre-crisis neutral effect between both variables but after financial crisis, stock prices lead oil price and similar is true from opposite-side. Sukcharoen et al. (2014) probe the association between oil prices and stock market returns by applying a copula approach. Their results show a strong dependence between oil prices and stock market prices for the US and Canadian economies. Ghosh and Kanjilal (2015) examine co-movements between oil prices and stock market prices using daily data from January 2003 to July 2011. Based on non-linear co-integration analysis, they state the presence of co-integration between both variables and oil price shocks causes stock market returns. This finding was confirmed by Toda–Yamamoto (1995) using Granger causality test.

Creti et al. (2014) apply a multivariate frequency approach to analyse the relationship between oil prices and financial markets for oil-importing and oil-exporting countries using monthly data covering the period of 2009–2012. They find that stock prices have a positive effect on oil prices in oil-exporting countries rather than in oil-importing countries.

Upon the first part review above, the studies suggest that the rise of oil prices would lead stock prices to decrease since oil price fluctuations negatively affect real output which, in turn, lowers corporate earnings. Thus, there is, to date, empirical evidence that oil prices and stock markets exhibit some degree of interdependence.

Second, another line of investigation looks more specifically into the links between oil prices and other financial variables. For instance, Basher et al. (2012) consider the role of exchange rates while examining the relationship between stock market prices and oil prices by applying a structural VAR model. Their empirical results show that production in oil is negatively linked with oil prices; however, economic activity leads to oil demand that raises oil prices. They also state that a rise in stock market prices is aligned with oil prices rise. Ciner et al. (2013) examine the association between stocks, bonds, gold, oil and exchange rates for the US and UK economies for the period of January 1990 to mid-2010. Their empirical results highlight that investment in gold can be safe-hedge against exchange rates compared to stocks, bonds and oil markets in both economies.

Filis and Chatziantoniou (2014) use a structural VAR model to examine the effect of oil prices shocks on financial and monetary policies for oil-importing and oil-exporting countries with monthly data from 1991 to 2010. They conclude that oil price shocks significantly affect inflation and interest rates are affected with monetary policy’s regime for each sampled economy. They report that stock market returns are inversely and strongly affected by oil price shocks.
Killian (2009), when decomposing the real price of oil, recommends employing a structural VAR model to help decomposing unpredictable changes in the real price of oil with a structural economic interpretation. Pastpipatkul and Phoewhawm (2010) study the relationship between several world oil price benchmarks, the Thailand’s stock market index and two energy-related equity sector indices namely energy & utilities and transportation & logistics, using standard VAR and BVAR models. The comparison of the VAR and BVAR models shows a normal distribution for the coefficient of the BVAR, which is more appropriate than the coefficient of the VAR. By applying the threshold co-integration approach, Zhu et al. (2011) study the relationship between oil prices and stock prices using data of OECD as well as non-OECD countries for the period of January 1995 to December 2009. Their empirical investigation shows the presence of threshold co-integration as well as a feedback effect exists between oil prices and stock market prices for OECD and non-OECD countries. Romas and Veiga (2011) determine the risk factors affecting oil-industry and gas-industry returns using data of 34 economies for the period of April 1998 to December 2009. They conclude that the global price has strong and greater impact on oil price rise in developed countries and outcome is similar for gas-industry returns. They show that the relationship between oil-industry (respectively, gas-industry) and oil prices is asymmetric, but oil prices rise affects significantly compared to oil price fall. This confirms the presence of oil-prices pass-through to oil as well as gas industries.

Wen et al. (2012) investigate the association between energy and stock markets prices by employing a time-varying copula approach during the financial crisis. They illustrate the high dependence between both markets, i.e. contagion effects defined by Forbes and Rigobon (2002). Kang and Ratti (2013) inspect the relationship between oil shock, policy uncertainty and stock market returns for the US economy. The results show a negative impact of policy uncertainty on stock returns.

Chen et al. (2013) use a factor analysis procedure (Panel Analysis of Non-stationarity in Idiosyncratic and Common Components) developed by Bai and Ng (2004) to analyse a panel of 51 international commodity prices, including non-fuel commodity indices, food index, beverage index, and agricultural raw material index, from January 1980 to December 2009. They find that exchange rates are the most important common factor driving the persistent movement of international commodity prices. Creti et al. (2013) examine the relationship between commodity market volatility and stock markets over the period of January 2001 to September 2011. The findings highlight high volatility in the correlation between commodity prices and stock market returns during the financial crisis. Speculation-phenomena is also found between the correlation of oil, coffee and cocoa with stock market prices. Souček (2013) determine the co-movements between gold future, crude oil and equity prices and reported the positive correlation between oil prices and stock market prices.

Wang and McPhail (2014) study the impact of energy price shocks on the US agricultural productivity growth and volatility of commodity prices. They use a structural VAR model covering the period of 1948–2011. Their results display that energy prices shock has a negative impact on productivity growth in the short run and the impact from energy prices outweighs the contribution of agricultural productivity in the medium-term. Jebabli et al. (2014) investigate the impact of stock markets and oil price shocks on food prices using a TVP-VAR model with stochastic volatility. They find that oil prices and stock market prices affect food prices in both intermediate-and-short terms. They also reveal that shocks in oil-and-stock prices lead to risk adjustment performance of food
prices due to its diversified portfolio reinforcement. Mensi et al. (2014) investigate the interaction between energy and commodity prices by applying a VAR-BEKK-GARCH along with a VARDCC-GARCH model. They show that OPEC news not only affect oil-cereal linkages but also exerts impact on energy market i.e. oil market. Those results might be helpful in designing policy implications for investors to adjust risk-performance by diversifying the commodity portfolio. Atil et al. (2014) investigate the pass-through of oil prices to gasoline and natural gas prices by using the NARDL co-integration approach for the period of January 1997 to September 2012. The results indicate that oil price shocks affect gasoline and natural gas prices significantly and adjustment in gasoline prices is greater compared to natural gas prices due to oil price shocks. In the same line, Broadstock et al. (2014) study the linkage between oil prices and energy stocks by applying an asset-pricing model. They claim that oil price shocks directly affect energy stocks but also indirectly via the general market risk.

Olson et al. (2014) probe the relationship between equity markets by applying a multivariate BEKK model developed by Hafner and Herwartz’s (2006). Based on volatility impulse response functions, they conclude that energy prices volatility increases due to low equity market returns but the response is weak from equity returns to energy prices. Sadorsky (2014) use VARMA-AGARCH and DCC-AGARCH models to investigate the correlation between equity market prices and energy prices such as copper, oil and wheat prices. The empirical analyses reveal that investment in oil and wheat prices can be the cheapest hedge compared to investment in copper market. Chen et al. (2014) study the impact of financial shocks on oil prices to gasoline and natural gas prices by using the NARDL co-integration approach for the period of January 1997 to September 2012. The results indicate that oil price shocks affect gasoline and natural gas prices significantly and adjustment in gasoline prices is greater compared to natural gas prices due to oil price shocks. In the same line, Broadstock et al. (2014) study the linkage between oil prices and energy stocks by applying an asset-pricing model. They claim that oil price shocks directly affect energy stocks but also indirectly via the general market risk.

Hammoudeh et al. (2014) focus on the dependence between commodity future markets and stock markets by applying copula functions. They find that dependence exists between both markets. This suggested for investing in commodity and stock markets by diversifying the investment portfolio in Chinese economy. More recently, Hammoudeh et al. (2015) apply an SVAR model to study the effects of shocks in the monetary policy of the USA on groups of commodity prices. Both commodity prices and price indices of different sub-sets or sectors of commodities are considered. The empirical framework permits to consider the structural shocks to monetary policy, captured by unexpected variations in the federal funds rate, and then to quantify the effects of these shocks on the various commodities sector prices and the economic activity. Nguyen et al. (2015) employ asymmetric causality to examine the relationship between US equity markets and energy returns, metal and agriculture commodities future prices. In the presence of asymmetry, they argue the feedback effect between equity and commodity future markets.

Kang et al. (2015) rely on variance decompositions and impulse response functions, i.e. structural VAR model to examine the relationship between oil prices, stock prices and stock prices volatility using daily US data for the period of January 1973 to December 2013. They find that positive aggregate global demand negatively affects correlation between stock returns and stock volatility. They report that global oil production has positive effect on covariance between stock returns and stock volatility.

To sum up, even if the literature is rich, it is mainly twofold. On one hand, relationships exist between the economic activity and financial variables. On the other hand, interactions occur between the economic activity and commodity prices.
From a theoretical point of view, the mechanisms via which financial variables are a relevant influence on commodities, in general, and on “liquid commodities”, in particular, are discussed even if the results are very heterogeneous, and do not always reach a consensus.

Besides, the impact of the implied volatility index, represented by VIX on the major financial variables is underrepresented, whereas, volatility dependencies are well studied.

From an empirical perspective, the general strand of the literature deals with a traditional VAR model. Conscious by the limitations of this framework and by the importance of the mounting risks that plagued the financial markets, we propose including the measures of financial risks in addition of other data within a Bayesian VAR model that offers richer dynamics. Moreover, since many studies state the existence of nonlinearities in the relationships, another advantage of Bayesian VAR models is accounting for these nonlinearities through the time varying feature of parameters.

Our study attempts to address those gaps in the literature by including “liquid commodities”, in addition of key financial data within a Bayesian VAR specification.

3 Empirical strategy

3.1 The model

A VAR model with \( p \) lags, \( \text{VAR}(p) \), can be written as follows

\[
y_t = \beta_0 + \sum_{i=1}^{p} A_i y_{t-i} + \epsilon_t
\]  

(1)

where \( y_t \) is an \( l \times 1 \) vector enclosing \( T \) observations on \( l \) variables; \( \epsilon_t \) is an \( l \times 1 \) vector of residuals assumed to be normally distributed; \( \beta_0 \) is an \( l \times 1 \) vector of intercepts and \( A_i \) is an \( l \times l \) vector of parameters.

The matrix form of a \( \text{VAR}(p) \) is:

\[
Y = XA + E
\]  

(2)

where \( X = [x_1, x_2, \cdots, x_T]^T \), with \( x_t = (1, y_{t-1}, \cdots, y_{t-p}) \), and \( K = lp + 1 \).

\( A = (\beta_0, A_1, \ldots, A_p) \) and \( E \) is the vector that tacks all the error terms \( \epsilon \).

\( Y \) is an \( lT \times 1 \) vector that stacks all the \( T \) observations of the first endogenous variable, then all the \( T \) observations of the second endogenous variable, and so on.

The likelihood function can be obtained from the sampling density \( p(y / \beta, \Sigma) \). This likelihood function includes the distribution of \( \beta \) given \( \Sigma \), that is \( \beta / \Sigma, y \rightarrow N(\tilde{\beta}, \Sigma \otimes (X'X)^{-1}) \) and \( \Sigma^{-1} / y \rightarrow W(S^{-1}, T-K-l-1) \), where \( S \) is the empirical variance-covariance matrix of the errors.

Equation (2) represents the Bayesian VAR model (BVAR). Thus, a VAR model estimated using Bayesian techniques. In the literature, many priors are suggested.\(^1\) We follow the standard procedure and rely on Litterman (1986) for the priors.\(^2\) Litterman suggests shrinking all VAR coefficients toward zero, except for the coefficients on the own lags of each dependent variable. The latter are set either to one for variables that
exhibit substantial persistence or to zero, otherwise. Moreover, the Minnesota prior suggests that $\Sigma$ is a diagonal matrix and each element of the diagonal could be estimated by OLS.

As stated by Copy (2011) and Kaabia et al. (2013), MCMC methods deliver smoothed estimates of the parameters of interest based on the entire available set of data. These estimates are more efficient than the filtered estimates.

### 3.2 Data and preliminary analysis

To study the interactions between commodity prices and key financial variables, our database includes most traded commodities: a precious metal, gold; a soft agriculture, wheat; and two energy commodities, WTI crude oil and US natural gas. For oil, the West Texas Intermediate (WTI) is used as a benchmark in oil pricing and the Henry Hub is the benchmark for global natural gas.

We choose to include those four commodities in our database because they are considered as “liquid commodities” and are widely traded at huge volumes by investors, hedgers, speculators/traders and arbitrageurs both in cash and derivative markets.

Based on Deaton (1999) and Baffes (2007), we download individual commodity prices rather than price indices. All prices are expressed in American dollar.

In addition, we download three key financial variables: First, the S&P 500 equity VIX is an index that measures expectations of volatility of the S&P 500 index over the next 30 days period. It is calculated based on the options on S&P equity index and quoted in percentage points, measuring expected credit risk.

Second, the exchange rates are a weighted average of the foreign exchange value of the US dollar against the currencies of a broad group of major US trading partners.

**Figure 1** Commodity prices and key financial variables
And finally, the Federal Funds Rate (FFR) is the interest rate at which a depository institution lends funds maintained at the Federal Reserve to another depository institution overnight. It affects monetary and financial conditions, which in turn have a bearing on key aspects of the broad economy including employment, growth and inflation.

Our database is on a monthly basis from July 1995 to February 2017, and collected from the International Monetary fund (IMF) for commodities and from DataStream and the Federal Reserve website, FRED – St. Louis Fed for financial variables.

All the data are seasonally adjusted, except for the federal funds rate and exchange rates.

Over this sample period, the relationship between commodity prices and key financial variables is ambiguous as shown by Figure 1.

Visually, it seems to be co-movements between WTI, S&P 500 equity VIX (VIX), gold and wheat. In fact, increases in wheat and gold prices are synonyms of higher production costs and investors' confidence. Graphically, the federal funds rate (FFR) and gas prices are the less volatile data.

Before studying the relationship between commodity prices and key financial variables, we investigate the order of integration of our data using three standard unit root tests: Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski et al. (KPSS) tests.3

The results show that all the price series appear to be integrated of order one, which is a standard result in the literature for such series.4 Moreover, visually speaking, the returns seem to be stationary as shown in Figure 2.

Figure 2  Return series evolution
Table 1 presents descriptive statistics and unconditional correlations among the return series.

Table 1  Descriptive statistics of return series

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</thead>
<tbody>
<tr>
<td>WTI</td>
<td>0.0078</td>
<td>0.0142</td>
<td>0.2428</td>
<td>–0.2825</td>
<td>0.0849</td>
<td>–0.3402</td>
<td>3.6802</td>
<td>10,0267</td>
</tr>
<tr>
<td>S&amp;P 500 equity VIX</td>
<td>0.0135</td>
<td>–0.0131</td>
<td>1.0233</td>
<td>–0.2838</td>
<td>0.1786</td>
<td>2.4429</td>
<td>12.5957</td>
<td>1256.099</td>
</tr>
<tr>
<td>FRR</td>
<td>0.0008</td>
<td>0.0000</td>
<td>1</td>
<td>–0.05979</td>
<td>0.1335</td>
<td>1.2042</td>
<td>18.2789</td>
<td>2591.807</td>
</tr>
<tr>
<td>EXCH</td>
<td>0.0007</td>
<td>0.0022</td>
<td>0.0668</td>
<td>–0.0467</td>
<td>0.0166</td>
<td>–0.0074</td>
<td>3.6397</td>
<td>4.43366</td>
</tr>
<tr>
<td>GOLD</td>
<td>0.0033</td>
<td>0.0033</td>
<td>0.5339</td>
<td>–0.3822</td>
<td>0.1048</td>
<td>0.4721</td>
<td>5.5338</td>
<td>79.2085</td>
</tr>
<tr>
<td>GAS</td>
<td>0.0119</td>
<td>–0.0030</td>
<td>0.6142</td>
<td>–0.3491</td>
<td>0.1335</td>
<td>1.2042</td>
<td>18.2789</td>
<td>2591.807</td>
</tr>
<tr>
<td>WHEAT</td>
<td>0.0037</td>
<td>–0.0038</td>
<td>0.4963</td>
<td>–0.2235</td>
<td>0.0770</td>
<td>1.3584</td>
<td>9.68755</td>
<td>564.468</td>
</tr>
</tbody>
</table>

Panel A: Basic statistics

Panel B: Unconditional correlations

<table>
<thead>
<tr>
<th></th>
<th>WTI</th>
<th>S&amp;P 500 equity VIX</th>
<th>FRR</th>
<th>EXCH</th>
<th>GOLD</th>
<th>GAS</th>
<th>WHEAT</th>
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</thead>
<tbody>
<tr>
<td>WTI</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S&amp;P 500 equity VIX</td>
<td>0.015</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FRR</td>
<td>0.074</td>
<td>0.023</td>
<td>1</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>EXCH</td>
<td>–0.227</td>
<td>0.153</td>
<td>–0.032</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GOLD</td>
<td>0.205</td>
<td>–0.039</td>
<td>0.053</td>
<td>–0.273</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GAS</td>
<td>0.093</td>
<td>0.0855</td>
<td>–0.006</td>
<td>0.032</td>
<td>0.04</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>WHEAT</td>
<td>0.115</td>
<td>–0.089</td>
<td>–0.138</td>
<td>–0.153</td>
<td>0.088</td>
<td>0.064</td>
<td>1</td>
</tr>
</tbody>
</table>

Panel A shows that the average of return series are positive over our sample period. S&P 500 equity VIX has the highest mean return of about 1.35%.

The unconditional volatility, as measured by standard deviations, is the highest for S&P 500 equity VIX that exhibits the highest volatility (17.86%), in addition of getting the highest return. By comparison, exchange rates are the least volatile (1.66%) and display the lowest return (0.7%). The results confirm that high (resp. low) levels of risk are typically associated with high (resp. low) potential returns.

With negative skewness coefficients and kurtosis coefficients above three, the distributions are typically asymmetric, and the probability of observing large negative returns is higher than that of a normal distribution. The Bera-Jarque test statistic strongly rejects the hypothesis of normally distributed returns, except for exchange rates.

Panel B reports unconditional correlations between the return series. There are more positive values than negative ones. Therefore, potential diversification opportunities exist, because some correlations are negative and low.

Moreover, the highest correlation is between gold and WTI and about 20.5%. The lowest one is –27.3% between gold and exchange rates. Thus, gold is sensitive to variations.
Besides, we implement information criteria for lag selection and take the optimal lag according to the Bayesian Information Criterion (BIC) since we estimate our model using Bayesian techniques. The optimal number of lags retained is $p = 13$. This choice confirms the one made by Bernanke et al. (2005), indicating that the series are very persistent. The residuals are found to be white noise when the lag length is 13.$^3$

4 Empirical results

We estimate the BVAR model to examine the relationship between commodities and financial key variables. The estimation is implemented using Gibbs sampling procedure.$^6$ More precisely, we use the MCMC method$^7$ with 10,000 iterations, the first 2000 of which were discarded to minimise the effects of initial conditions.$^8$ To assure convergence of the algorithm, we imposed proper Minnesota priors on the parameters, as explained in the methodology section.

To get a visual inspection of the links between “liquid commodities” and key financial variables, we rely on impulse response functions.

We follow Stock and Watson (2005) and Bernanke et al. (2005), and divide the variables into two categories: slow and fast-moving variables. This distinction is crucial because it implies that slow-moving variables do not respond contemporaneously to an initial shock. This hypothesis is equivalent to ranging the variable in an exogeneity order. In our case, slow-moving data are commodity variables (WTI, wheat, gold and gas) and fast-moving ones are exchange rates, Federal Reserve rates, and S&P 500 equity VIX.

Figure 3 draws the posterior median impulse response functions when simulating a shock on one variable to evaluate its impacts on other included variables.

A WTI shock significantly impacts all liquid commodities in addition to key financial variables. Thus, crude oil has a negative relationship with wheat, gold (Filis et al., 2011) but also with FRR, exchange rates and the S&P 500 equity VIX. This finding confirms that exchange rates are considered as primary channel through which the fluctuations of oil prices are transmitted to the real economy and financial markets as stated by Reboredo (2012). Exchanges rates can influence commodities prices through several conduits (Manera et al., 2013).

According to the literature, there is no a unique consensus on the relationship between oil and gold prices: many authors claim two-way feedback relationships (Wang et al., 2010). But in all cases, literature suggests a strong correlation between the prices of oil and gold (e.g. Zhang and Wei, 2010).

The same for wheat, the relationship is not clear in the literature. According to our empirical results, a shock on wheat leads to significant impulse responses. In all cases, an increase happens but is more pronounced for exchange rates by comparison to the other variables.

Besides, the exchange rates are impacted significantly by shocks on commodities: crude oil, gas, gold, and wheat (Bai and Ng, 2004), but insignificant to an FRR shock.

Another finding is that a shock on commodities prices significantly impacts the FRR and vice versa. In fact, high Fed interest rates reduce the price of storable commodities because high interest rates increase the incentive for extraction today rather than
On the relationship between liquid commodities and financial variables

tomorrow and thus, decrease firms’ desire to carry inventories. Also, it encourages
speculators and investors to shift out of commodity contracts. Therefore, monetary policy
is a major driver of global asset prices Hammoudeh et al. (2015). It drives the movement
of commodity prices in addition of key financial variables.

Figure 3  Impulse response functions
The results reveal that S&P 500 equity VIX has an insignificant response only when responding to an FRR shock. It comforts our choice of including the S&P 500 equity VIX as a variable in our Bayesian VAR and confirms the interaction of VIX with liquid commodities and financial variables, with the exception of FRR. Those findings are in concordance with those of Mensi et al. (2013). In fact, the authors point out that past volatility and unexpected volatility shocks to the S&P 500 have significant effects on oil and gold.

All responses are positive and mainly significant. Moreover, the impact for all shocks is immediate and is not quickly absorbed. In fact, mainly it exceeds sixty months, thus suggesting long-term effects.

Understanding these shocks transmission among commodities and financial variables is crucial for investors and policy-makers, helping in their decisions and even for portfolio allocation. In fact, the empirical results hold considerable implications for policy-makers: decreasing liquid commodity prices can provide a negative signal on financial markets, inducing rising levels in volatility and Federal reserve rate.

5 Conclusion

The idea of the paper is to explore the relationship between liquid commodities and key financial variables (S&P 500 equity VIX, exchange rates, and interest rates). In order to account for nonlinearities, we use a Bayesian VAR framework. There are many reasons why liquid commodities may influence financial variables and vice versa.

The empirical results suggest significant relationships between the commodities and financial variables. Typically, there are inverse relationships between the value of the liquid commodities and financial variables.

Mainly, the empirical findings emphasise that positive relationships exist between energy prices (crude oil and gas) and both gold and wheat; and even between gold and wheat.

The FRR has a significant relationship with each commodity or financial variable. In fact, high Fed interest rates reduce the price of storable commodities because high interest rates increase the incentive for extraction today rather than tomorrow and thus, decrease firms’ desire to carry inventories. Also, it encourages speculators and investors
to shift out of commodity contracts. Hence, monetary policy is a major driver of global asset prices. It drives the movement of commodity prices in addition of key financial variables.

Besides, exchange rates and S&P 500 equity VIX can influence liquid commodities via several ways as stated by Reboredo (2012) and Manera et al. (2013).

All the significant responses are immediate and exceed sixty-months. These results suggest that the markets are responding immediately and may emphasise the shocks, referring to what happened during the 2007–2008 global economic and financial crisis.

Our results may be used to improve accuracy in liquid commodities and financial variables forecasting.

To put forward of this work, a study of the transmission channels would be interesting. Therefore, an extension of this study could be through the implementation of factor augmented VAR models and why not quantifying the transmission channels impacts on a wider database.

Another avenue of future would be increasing the number of data, since the literature illustrates that there is a relationship between the economic activity and both financial and commodity prices.

References


On the relationship between liquid commodities and financial variables


Notes

1 For a complete review of the various methods for the settlement of priors, the reader can refer to Koop (2010), Koop and Korobilis (2010) and Korobilis (2016). In addition, Koop and Korobilis (2009) present the results of a BVAR model estimated using different priors and argue that different priors provide similar empirical results. Lenza et al. (2010) test different priors in BVARs with different sizes (SMALL, MEDIUM and LARGE) and recommend the Minnesota priors.
2 Litterman (1986) and other researchers at the University of Minnesota developed priors for VAR coefficients, which are known as the Minnesota priors. For a review of all the different methods for the settlement of priors, the reader can refer to the work of Koop and Korobilis (2010).
3 The ADF and PP tests are based on the null hypothesis of a unit root, while the KPSS test considers the null of no unit root. The obtained results can be given on request.
4 Interest rates variables are differenced, whereas activity variables are logarithmised as in the literature.
5 Diagnostic residual tests are not reported in this paper for the sake of brevity but are available on request.
6 Therefore, we resort to the MCMC method, which is appropriate because of the intractability of the likelihood function and offers the possibility of inference for the state variables with the uncertainty of the unknown parameters. This method allows also the estimation of the function of the parameters, such as an impulse response function, with the uncertainty of the unknown parameters.
7 As stated by Primiceri (2004) and Copy (2011), MCMC yields smoothed estimates of the parameters of interest based on the entire available set of data.
8 No problems were experienced in achieving convergence, and both alternative starting values and the use of 20,000 iterations produced essentially the same results.