
Volatility transmission between oil prices and banks stock prices as a new source of instability: Lessons from the US Experience

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Volatility transmission between oil prices and banks stock prices as a new source of instability: Lessons from the US Experience

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Abstract:

Linkages between oil prices and stock prices of the US banking sector have become more complex with the strong rise in the US production of shale oil. The concern is whether the exposure of the US banking sector to shale oil companies has led to volatility spillover transmission between stocks' prices of the exposed US banks and oil prices. Using stocks prices data of the four major US banks involved in oil and gas industries and the price of West Texas Intermediate crude oil, we investigate these volatility spillovers from 2006 to 2016, using a vector fractional integrated ARMA. Our results support the existence of such volatility spillovers, suggesting thus a new factor likely to trigger future turmoil on oil markets and in the banking sector.

JEL Codes: G1, Q4

Keywords: Oil, US banks stock, Realized Volatility, VARFIMA model.

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1 Introduction

In the United States (US hereafter), the extraction of shale oil¹ has grown dramatically over the last few years taking the market by surprise. In 2013, the US is estimated to have produced around 3.5 millions of barrels per day (mb/d) of shale oil, an amount three times higher than the one produced in 2010 (EIA, 2014). By 2020, US shale oil is estimated to reach 4.8 mb/d, which is about a third of total US oil supply. The growing development of the shale industry encouraged US and foreign large banks, in a context of historically low interest rates, to invest massively in this sector expected to offer a strong potential of profitability. Loans to oil and gas (O&G hereafter) companies have almost tripled in recent years, rising from 1.1 billion in 2006 to 3 trillions of US dollars in 2014 (BIS economics, July 07, 2016), much of these loans being extended to smaller oil companies, in particular those engaged in shale oil exploration and production. However, concern has risen sharply among creditors and financial markets since the recent fall in the price of oil (-60 % since June 2014). If drilling companies have shown some resistance in this lower price environment, more and more bankruptcies are yet reported. 42 companies producing O&G went out of business at the end of 2015 (Haynes and Boone LLP, December 14, 2016).² These bankrupt companies left a slate of debt to the banking sector. At the same time, stocks of the US banks, most involved in O&G industries, performed poorly on the financial market, starting with Morgan Stanley, in fall of almost 23 %, followed by Bank of America (- 21.15 %), Citigroup (-19 %) and JPMorgan (-10 %). The strengthening of the link between the banking sector and the oil market in the US has led to many debates. The concern is whether this close link could represent a new driver of a potential financial crisis. A pertinent discussion since closely linked markets are more vulnerable as negative shocks are able to propagate and proliferate more relative to weakly associated markets (Kritzman et al., 2011).

Against this background, this article aims to investigate the existence of volatility spillovers between the oil market and the US banking sector, a topic that has until now received

1. The terms shale oil or tight oil do not have a precise geological definition, but are commonly used by the oil industry and by government agencies to refer generically to crude oil produced from shale, sandstone and carbonate formations characterized by low permeability.

2. Among the failed companies, some like Samson Resources, left behind them a debt of more than 4 billion dollars.

surprisingly little attention. This issue is of central importance as the existence of such volatility spillovers could reflect the potential existence of new crisis transmission channels driven by the interactions between these two sectors. In this paper, we contribute to the empirical literature dealing with volatility spillovers between oil and stock markets³ in several ways. First, this paper adds to this literature by examining how the volatility of stock markets indexes of a specific sector – the banking sector - co-varies with the volatility of oil prices, and how this co-variance has evolved over time. Second, we assess volatility spillovers using a Vector Autoregressive Fractionally Integrated Moving Average (VARFIMA) model, a multivariate realized volatility model introduced by Chiriac and Voev (2011). This model allows us to capture the long memory characteristics found in stock and oil prices volatilities, as well as their interactive relationship. In addition, we quantify the reaction of one sector triggered by a volatility shock in the other sector, by examining volatility impulse response functions following the methodology of Chung. Finally, another contribution of this paper is to rely on an accurate estimate of the volatility by explicitly utilizing the additional information in high frequency data. The data set includes intra-day data (1-minute spot prices) of stock market indexes of the four major US banks (Bank of America, Citigroup, JP Morgan Chase and Wells Fargo) and of the West Texas Intermediate (WTI) oil price from January 2006 to June 2016. The empirical results support evidence of volatility spillovers between the oil market and the US banking sector. Moreover, impulse response functions show that a standard positive shock in the volatility of oil price has a positive impact on responses of the volatility of US banks stock prices. Responses of the volatility of oil price to a shock in the volatility of US banks stock prices are also significant. These results are more important during the period when US banks have become more involved in O&G industries.

The rest of the paper is structured as follows. Section 2 provides some empirical evidence on the increased link between the oil market and the US banking sector. Section 3 presents the data as well as the methodology used in this paper. Results are displayed in Section 4, and Section 5 concludes the paper.

3. For an extensive review of literature on this topic, see Jones and Kaul (1996); Huang et al. (1996); Sadorsky (1999); Papapetrou (2001); Hammoudeh and Aleisa; Ågren (2006); Malik and Hammoudeh (2007); Park and Ratti (2008); Apergis and Miller (2009); Malik and Ewing (2009); Fayyad and Daly (2011); Filis et al. (2011); Arouri et al. (2012); Creti et al. (2013); Souček and Todorova (2013); Mensi et al. (2013); Olson et al. (2014); Kang et al. (2015); Ewing and Malik (2016); Boubaker and Raza (2017).

2 Motivation of the paper: some stylized facts

The United States has started extracting shale oil on a large scale from 2006 although the existence of an important shale oil resource has been found for decades. With a slight slowdown due to the 2008 financial crisis,⁴ it is only after 2010 that the US shale oil production really increased creating a boom in domestic crude oil production. This boom is often referred to as the shale or fracking revolution. Figures 1 and 2 illustrate how the shale oil sector has contributed to the US oil boom. From these figures, it clearly appears that the significant growth of the overall US oil production from 2010⁵ has been driven by shale oil. Indeed, the total US oil production rose from 6.4 millions of barrels per day in 2010 to a record 11.2 millions of barrels per day in 2018, with shale oil driving more than 92 percent of the growth.⁶ The production from shale oil plays⁷ surpassed 50% of total US oil production in 2015. The growth between 2010 and 2014 – 3.2 Mbd – largely exceeds the expansion of output in the rest of the world, and as a result, the United States has become the world's largest producer of crude oil and their dependence on oil imports has collapsed.

Two main factors drove the shale revolution. The first triggering event of the fracking revolution was technological improvements in horizontal drilling and hydraulic fracturing. Indeed, the innovation of producing hydrocarbon from the source rock by combining hydraulic fracturing with horizontal drilling made oil in nonporous shale technically exploitable although the process still remains capital-intensive. The second catalyst was the 2008 financial crisis and the era of unprecedented low interest rates it ushered. As a matter of fact, US shale oil revolution has been associated with a context of historically low interest rates - due to the ultra-accommodative and unconventional monetary policies driven by the US Federal Reserve – and sustained high oil prices.

Shale oil and gas exploration and production companies are typically rated below investment grade by the rating agencies like Standard & Poor's (S&P) and Moody's, making

4. During the crisis period, crude oil prices declined from the peak of \$147 per barrel to \$32 per barrel (Gordon, 2016) and the promising future of the shale sector was called into question because low oil prices put the profitability of the sector in serious jeopardy.

5. This date certainly marks the start of fracking revolution.

6. See Energy information Administration (EIA) Drilling and Productivity Report.

7. A shale oil play refers to a geographical area suitable for shale oil production, whereas oil fields refer to areas suitable for conventional crude oil production.

their access to debt markets relatively expensive compared with investment-grade companies. In this context of low interest rates, the financing structure known as Reserve Base Lending (RBL)⁸ has been particularly instrumental in providing the sector⁹ with access to low-cost bank debt financings, allowing the rapid expansion of shale oil and gas production in the US. From 2006 to 2014, the global O&G industries' debts almost tripled, from about 1.1 billion to 3 trillion of US dollars (BIS economics, July 07, 2016) showing the increased importance of the banking system during the shale revolution.

Figure 3 depicts the ratio of credit exposure¹⁰ to O&G industries for total loans of the four most exposed US banks over the period 2006-2017 - JPMorgan Chase & Co, Bank of America Corporation, Citigroup Inc. and Wells Fargo & Company. In the years leading up to 2010, the respective amount of credit to O&G for JPMorgan Chase & Co and Bank of America averaged barely 3.27% and 2.93% of the total wholesale exposure. Wells Fargo & Company' exposure to O&G was approximately 1.14% and Citigroup's exposure amounted to 0.61% of total wholesale exposure. Exposure to the O&G portfolio increased exponentially from 2010 to 2014 and then evolved nearly at a steady pace. For instance, JPMorgan Chase & Co' O&G loan portfolio totaled \$23.322 billion, or 3.6% of total loans at December 31, 2009, compared with \$46.934 billion, or 5.46% of total loans, at December 31,2013.

The close link between the banking sector and the oil market in the US has led to many debates, especially about the fact that major US banks' exposure to O&G industries on the one hand, and on the other hand the exposure of shale oil and gas companies to low-cost bank debt financings could represent the new driver of a potential financial crisis. Indeed, in a low oil price environment, oil companies would have not only difficulties in coping with their commitment, but the value of their loans guarantees would also decrease.

8. RBL structure is a bank-syndicated revolver credit facility secured by the company's proved oil and gas reserves. As the collateral is oil and gas reserves of the company, RBL financing requires engagement of an independent reserve and production engineer to support the bank's calculations in determining the borrowing base, which is the maximum credit that could be made available to the borrower by a lender, calculated based on the company's reserves.

9. Note that unlike conventional oil and gas companies, which are traditionally deep-pocketed and largely self-financed, shale companies tend to be deeply leveraged.

10. Credit exposure is net of risk participations and excludes the benefit of credit derivatives used in credit portfolio management activities held against derivative receivables or loans and liquid securities and other cash collateral held against derivative receivables.

Figure 1: Total U.S. crude oil production (mb/d)

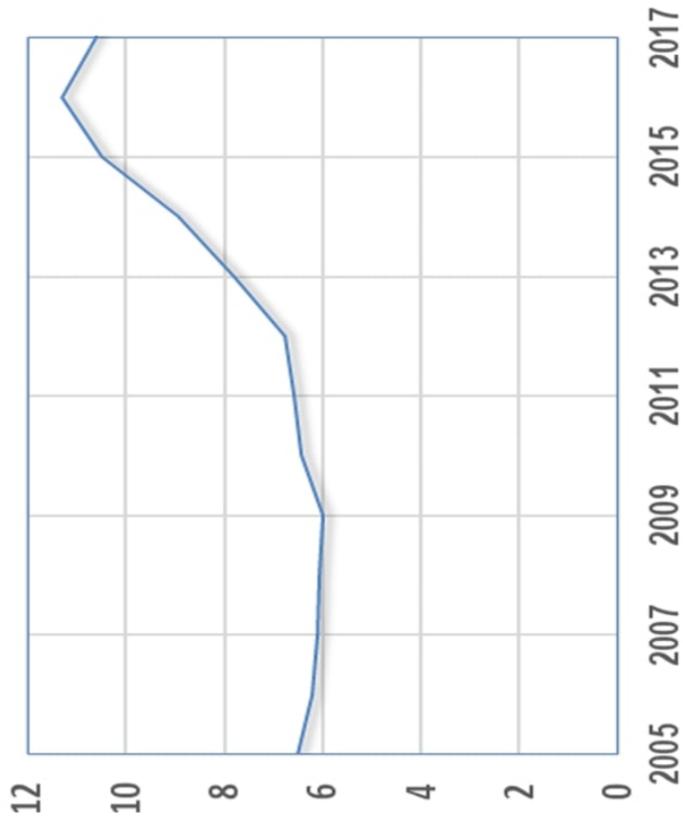
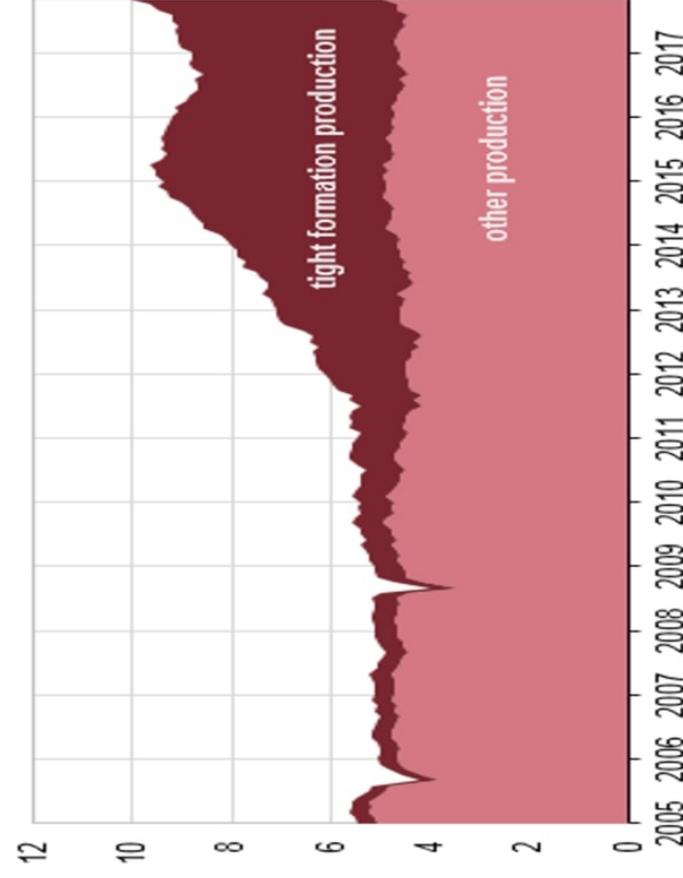
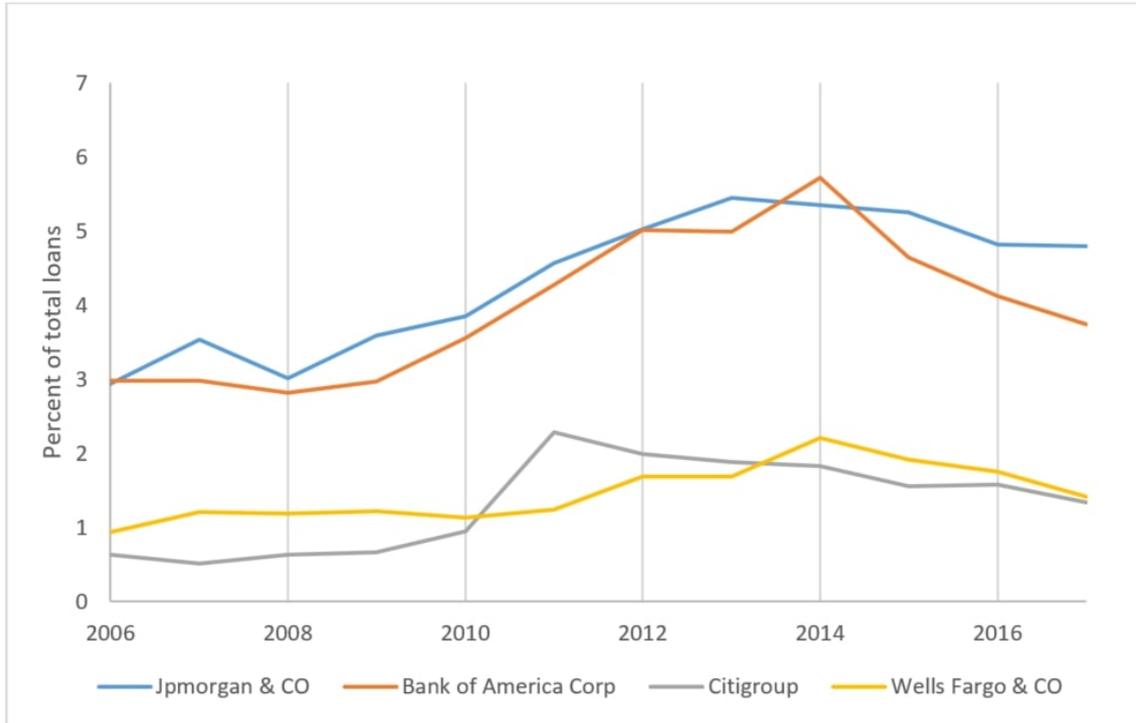


Figure 2: Estimates of U.S. shale oil production (mb/d)



Source: Official US. Energy Information Administration (EIA) estimates derived from state administrative data collected by DrillingInfo Inc.

Figure 3: Ratio of credit exposure to O&G industries, 2006 to 2017.



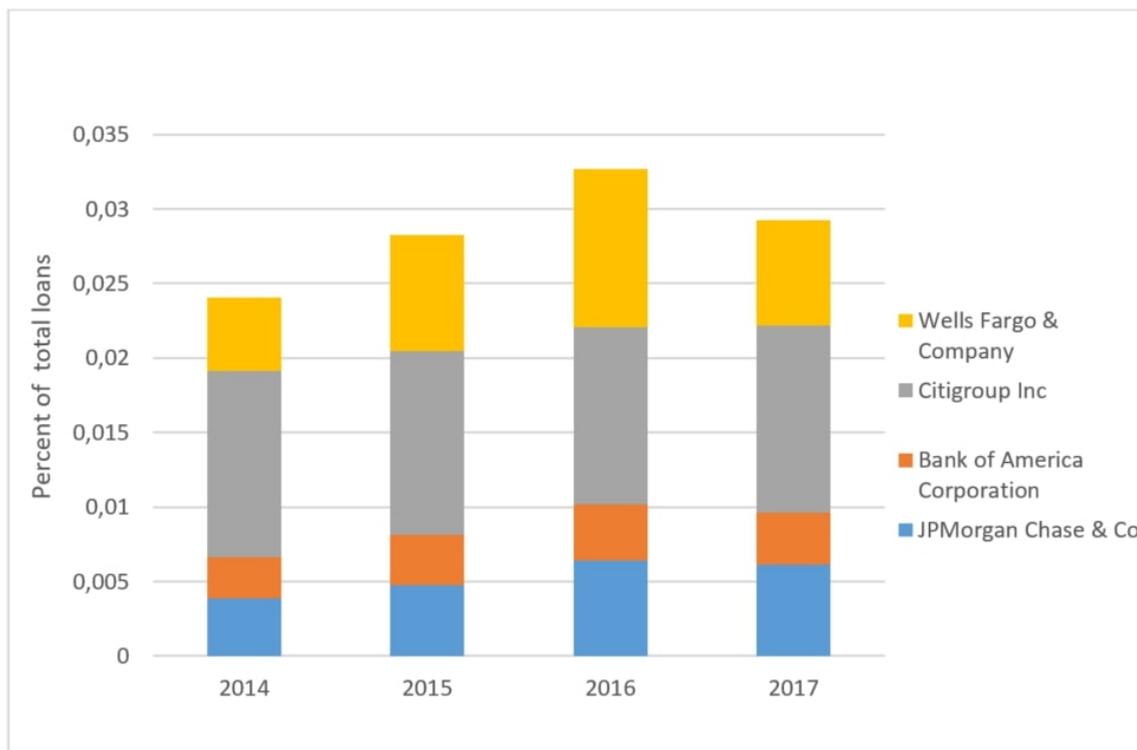
Source: Companies annual reports. *Notes:* The data used to draw this chart are extracted from Companies annual reports from 2006 to 2017. Vertical axis: Calculated as the amount of credit exposure to O&G industries divided by total loans multiplied by 100. Credit exposure is net of risk participations and excludes the benefit of credit derivative hedges and collateral held against Derivative receivables or Loans.

As the banks use the oil reserves as collateral for the loans, defaults in the oil sector could in turn impact negatively the banking sector, a sequence similar in part to the one that led to the subprime crisis one.¹¹

On the other, given the capital-intensive and bank financing dependence nature of the shale oil extraction process, it can be expected that the declining lending from US banks will impact drilling companies. Indeed, if US banks withdraw completely from O&G sectors, companies of the heartlands of the shale revolution will drown. It would follow a decline in US oil production leading to inevitable repercussions on the global oil market.

11. Indeed, one of the roots of the subprime crisis was the US house « bubble » since the US banks used the house as collateral for the housing loans.

Figure 4: Provision for loans losses, 2014 to 2017.



Source: Companies annual reports. *Notes:* The data used to draw this chart are extracted from Companies annual reports from 2014 to 2017. Vertical axis: Calculated as the total provision expenses divided by total loans.

Nevertheless, no crisis has occurred despite a huge volatility of oil price and the prolonged period of low oil price since 2014. The price of oil declined dramatically and unexpectedly in the second half of 2014, breaking through the level many oil producers needed to maintain profitability. If drilling companies have shown some resistance to this lower price environment, more and more bankruptcies have been however reported. Many companies producing shale oil and gas failed at the end of 2015 and left a slate of debt to the banking sector (Haynes and Boone LLP, December, 2016). How do banks have coped with these losses?

Firstly, as Figure 4 shows, the four most exposed US banks increased the provision expenses for loans losses after the oil price decline. The deterioration in the O&G sector, due to the oil shock of 2014, was probably a factor in increased provision expenses in order to cope with these losses. Secondly, as showed by Bidder, Krainer, and Shapiro (2018), following the dramatic decline in oil prices in 2014, banks with high exposure to

O&G extracting industries made significant adjustments to their balance sheets. They tightened credit supply to O&G companies and expanded other types of lending and asset holdings with a bias towards less risky securities.

3 Data and Methodology

In this section, we describe the data and the empirical strategy used in our analysis.

3.1 *Data*

Our data set of prices begins in January 3, 2006,¹² ends in June 30, 2016, is sampled at a high frequency (1-minute) from 9:30 until 16:00 and is quoted in US dollars. The use of spot prices is important when analyzing volatility, because these prices are the underlying asset upon which derivatives are based (Vivian and Wohar, 2012) and furthermore, their use allows to dodge issues related to rollover of futures contracts.

We use spot prices of West Texas Intermediate (WTI) crude oil sourced from Tick data market. Assessing risk on shale oil activity using WTI is relevant as the projected flow of shale oil production depends not only on the stock of recoverable shale oil below the ground, but also on crude oil prices. The sharp decline in the price of WTI crude oil from \$106 in June 2014 to \$47 in January 2015, followed by a recovery to \$60 by June and another drop below \$50 in August 2015, serves as a reminder that the shale oil industry is vulnerable to downside crude oil price risk (Kilian, 2016). To assess banking sector vulnerability, we also consider the S&P 500 stock market index of the following four major US banks sourced from QuandQuote: Bank of America, Citigroup, JP Morgan Chase and Wells Fargo. Two criteria have guided this choice: (i) the four selected banks have been the most exposed to O&G sectors over the recent period;¹³ (ii) they are recurrently identified as global systemically important banks by the Financial Stability Board,¹⁴ so, they are likely to destabilize the whole financial system in case of bankruptcy.

12. Since the US has started to extract shale oil on a large scale from 2006.

13. See the company (banks) annual reports.

14. The Financial Stability Board publishes at the end of each year, the list of global systemically important banks using previous year's data and an assessment methodology designed by the Basel Committee on Banking Supervision.

3.2 *Realized measures of volatility and co-volatility*

A variety of models has been developed to measure volatility. These models include ARCH model (Engle, 1982), GARCH model (Bollerslev, 1986), EGARCH model (Nelson, 1991), fractionally integrated GARCH model (Baillie, 1996), and stochastic volatility specifications (Taylor, 1994). The performance of these models has also been evaluated exhaustively.¹⁵

Researches initiated by Andersen and Bollerslev (1998) suggest that intradaily returns are more precise than daily returns to construct estimates of volatility on daily returns. These authors have proposed a new approach more commonly known as "realized" volatility that exploits the information in high-frequency returns. Indeed, if the sample path of volatility is continuous, then increasing the sampling frequency yields arbitrarily, although accurately estimates of volatility at any given point in time (Merton, 1980). As volatility becomes "observable", it can be modeled directly rather than being treated as a latent variable. Basically, the realized volatility approach¹⁶ consists in estimating volatility by summing the squares of returns sampled at very short intervals. Unlike previous models of volatility, this approach is a non-parametric one, and therefore does not rely on the assumption that the data come from any particular distribution. In addition, realized volatility appears to be log normally distributed and exhibits long-memory dynamics or strong persistence, a prominent characteristic of volatility that parametric models fail to describe in an adequate manner. Subsequently, a large number of related estimators have been proposed in the literature¹⁷ to deal with problems inherent to the use of high-frequency data such as nonsynchronous trading, market microstructure frictions or noise and the eventual presence of jumps. The multivariate extensions of realized volatility was developed by Barndorff-Nielsen and Shephard (2004a) and, as in the univariate case, robust estimators to noise and/or asynchronous observations have been proposed by Hayashi et al. (2005), Voev et al. (2007), Griffin and Oomen (2011),

15. See Silvennoinen and Teräsvirta (2009) and Asai, McAleer, and Yu (2006) for their multivariate extension.

16. See McAleer and Medeiros (2008) for a review on realized volatility approach.

17. See Barndorff-Nielsen and Shephard (2004b) (realized power and bipower variation robust to jumps), Barndorff-Nielsen et al. (2008) (realized kernels estimator in presence of noise), Zhang et al. (2006) (Multiscale approach in presence of noise), Jacod et al. (2009) (pre-averaging estimators), Hansen and Horel (2009) (Quadratic Variation by Markov Chains dealing with microstructure noise) and references therein.

Christensen et al. (2010) and Barndorff-Nielsen et al. (2011).

In this paper, we rely on the multivariate kernel estimator introduced by Barndorff-Nielsen et al. (2011) that has the double advantage of dealing with noise and asynchronous issues and of guarantying the covariance matrix to be positive semi-definite. The authors assumed that the observed price process encompasses a latent efficient or true price process plus a finite activity jump process. Their analysis suggests that rather than being viewed as an issue, jumps are associated to market information. As a result, the realized kernel estimator does not deal with the issue of jumps. In our study we consider jumps as macroeconomic or market news.

We study a d -dimensional log price process $P = (P^{(1)}, P^{(2)}, \dots, P^{(d)})'$. These prices are observed irregularly and are nonsynchronous over a generic interval $[0, 1]$, which we think of as a day. The observation times are written for the i -th asset as $t_1^{(i)}, t_2^{(i)}, t_3^{(i)}, \dots$, which could correspond to trades or quote updates. Hence, the database of prices at hand is $P^{(i)} t_j^{(i)}$, for $j = 1, 2, \dots, N_{(t)}^{(i)}$ and $i = 1, 2, \dots, d$. Here $N_{(t)}^{(i)}$ is the number of distinct data points available for the i -th asset up to time t . The observed price process P , is assumed to be driven by P^E , the efficient price modeled as a Brownian semimartingale plus a finite activity jump process. The refresh time of Barndorff-Nielsen et al. (2011)¹⁸ is applied to deal with the non-synchronicity of the data. The authors define refresh time as $\tau_1 = \text{Max}(t_1^{(1)}, t_1^{(2)}, \dots, t_1^{(d)})$, and then subsequent refresh times as $\tau_{j+1} = \text{Max}(t_{\tau_{j+1}}^{(1)}, t_{\tau_{j+1}}^{(2)}, \dots, t_{\tau_{j+1}}^{(d)})$. The resulting refresh time sample size in N , while we write $n^i = N^{(i)}$. So τ_1 is the elapsed time until all the assets has traded, i.e. all the posted prices have been updated. τ_2 is the first time when all the prices are again refreshed. Once defined the common time clock, τ_{j+1} , the vector of returns series in which the multivariate realized kernel will be based on can now be built.

Let $n, m \in N$, with $n - 1 + 2m = N$, and define the vector observations P_0, P_1, \dots, P_N as $P_j = P_{j+m}$, $j = 1, 2, \dots, n-1$, and $P_0 = \frac{1}{m} \sum_{j=1}^m P(\tau_j)$ and $P_n = \frac{1}{m} \sum_{j=1}^m P(\tau_{N-m+j})$. P_0 and P_n are constructed by jittering initial and final time points.¹⁹ The high-frequency vector of returns for a asset i is given by: $r_i = P_j - P_{j-1}$.

18. Refresh time was used in a cointegration study of price discovery by Harris et al. (1995).

19. For more details about jittering, see Barndorff-Nielsen et al. (2011).

The class of positive semi-definite multivariate realized Kernel (rK), takes the following form:

$$K(P) = \sum_{h=-n}^n k\left(\frac{h}{H}\right)\Gamma_h \quad (1),$$

where $\Gamma_h = \sum_{j=h+1}^n r_j r_{j'-h}$, for $h \geq 0$ and the h-th realized autocovariance $\Gamma_h = \Gamma_{-h}$.

r_i is the 5-minute return of stock i and k is a non-stochastic weight function. Following Barndorff-Nielsen et al. (2011), $k(\cdot) : \mathbb{R} \rightarrow \mathbb{R}$, will be taken to be a Parzen form. In particular, that means that:

$$k(r) = \begin{cases} 1 - 6r^2 + 6r^3 & \text{if } 0 \leq r \leq 1/2, \\ 2(1-r)^3 & \text{if } 1/2 \leq r \leq 1, \\ 0 & \text{if } r > 1. \end{cases}$$

Let Y_t the resulting realized covariance (n,n) dimension matrix obtained, where n represents the numbers of assets considered. The Cholesky decomposition of the matrix Y_t is given by the upper triangular matrix P_t , for which $P_t' P_t = Y_t$. Let $X_t = \text{vech}(P_t)$ be the m x 1 vector obtained by stacking the upper triangular components of the matrix P_t in a vector, where $m = \frac{n(n+1)}{2}$. X_t contains the realized volatilities and covolatilities.

3.3 Multivariate model of volatility: A trivariate VARFIMA

To investigate volatility spillovers transmission between Oil and US Banking markets, we use a Vector Autoregressive Fractionally Integrated Moving Average VARFIMA (p,d,q) model introduced by Chiriac and Voev (2011). The parsimonious version²⁰ of the original VARFIMA (p,d,q) model is defined as follows:

$$\Phi(L)D(L)X_t = \Theta(L)\epsilon_t, \quad \epsilon_t \hookrightarrow iid(0, \Sigma_t) \quad (2)$$

where $D(L) = \text{diag} \{ \Delta^{d_1}, \dots, \Delta^{d_m} \}$, where d_1, \dots, d_m are degrees of fractional integration of each elements of X_t , with $\Delta^d = (1 - L)^d$ the fractional difference operator and L the lag operator.

20. By parsimonious we mean model without constant and/or others exogenous variables.

$\Phi(L) = I_m - \Phi_1 L - \Phi_2 L^2 - \dots - \Phi_p L^p$, $\Theta(L) = I_m - \Theta_1 L - \Theta_2 L^2 - \dots - \Theta_q L^q$ are matrix lag polynomials with Φ_i , $i=1,2,\dots,p$ and Θ_j , $j=1,2,\dots,q$ the AR and MA coefficient matrices. $\Phi(L)$ and $\Theta(L)$ are assumed to be outside the unit circle and X_t is stationary if $d_i < 0.5$, for all $i=1, \dots, m$. If any $0.5 < d_i < 1$, the process is not covariance stationary, but still mean reverting, that's to say it takes a long time for mean reversion.

To evaluate volatility transmission between the oil market and stock returns of the US banking sector, we implement, for each US bank, one trivariate VARFIMA(1,d,0)²¹ models that can be expressed as:

$$\Delta^{d_B} X_{1,t} = \alpha_1 \Delta^{d_B} X_{1,t-1} + \beta_1 \Delta^{d_O} X_{2,t-1} + \gamma_1 \Delta^{d_{OB}} X_{3,t-1} + e_{B,t} \quad (3)$$

$$\Delta^{d_O} X_{2,t} = \alpha_2 \Delta^{d_B} X_{1,t-1} + \beta_2 \Delta^{d_O} X_{2,t-1} + \gamma_2 \Delta^{d_{OB}} X_{3,t-1} + e_{O,t} \quad (4)$$

$$\Delta^{d_{OB}} X_{3,t} = \alpha_3 \Delta^{d_B} X_{1,t-1} + \beta_3 \Delta^{d_O} X_{2,t-1} + \gamma_3 \Delta^{d_{OB}} X_{3,t-1} + e_{OB,t} \quad (5)$$

The equations (3), (4) and (5) describe how volatility and co-volatility are transmitted over time across the oil market and stock returns of each US bank considered.

$X_{1,t}$ and $X_{2,t}$ represent the realized return volatilities of respectively the US bank stock prices and oil price. $X_{3,t}$ is the realized return co-volatility between the two series, which measures the correlation between their realized return volatility.

d_O , d_B and d_{OB} take into account the persistence or long-run dependency of volatility series. $e_{O,t}$, $e_{B,t}$ and $e_{OB,t}$ refer to the volatility and covolatility innovations.

The parameters of interest are first α_1 , β_2 and γ_3 which capture the direct effects of past (co) volatility series on the current (co)volatility. β_1 and α_2 account respectively for volatility spillovers or interdependencies from oil price to the US banks stock prices and from the US banks stock prices to oil price. γ_1 and γ_2 measure the impact of past oil-bank co-volatility respectively on the volatilities of the US banks stock prices and oil price. Finally, α_3 and β_3 capture the effects exerted by volatilities of the US banks stock prices and oil price on the co-volatility of the two series.

21. Note that we implemented two models: a VARFIMA (1, d,1), the workhorse of Chiriac and Voev (2011) empirical study and a VARFIMA (1, d,0) as alternative model following the study of Sela and Hurvich (2009). We retained the last one, because it outperforms the first in terms of information criterion.

The VARFIMA model allows to capture strong persistence in volatility series as well as short-range dependence dynamics and to take into account volatility spillovers between series. Additionally, by using such a model, we are able to generate functions to examine impulse responses, one of the interests of this study.

Estimation of all the parameters of the model is carried out using the conditional Gaussian likelihood Durbin-Levinson (CLDL) algorithm of Tsay (2010). In order to examine how the strengthening of the link between the oil market and the US banking sector affects their dynamic interrelationships, we divide our sample period into two sub-periods according the upward trend of US shale oil production and of US banks involvement in O&G industries from 2010, estimate our model for the whole period and for each sub-period and test for Granger causality between the two series of volatility. Finally, to complete our empirical analysis, we generate volatility impulse response functions (VIRF) based on Chang's methodology.

4 Empirical results and discussions

4.1 *Dynamics of volatility and co-volatility*

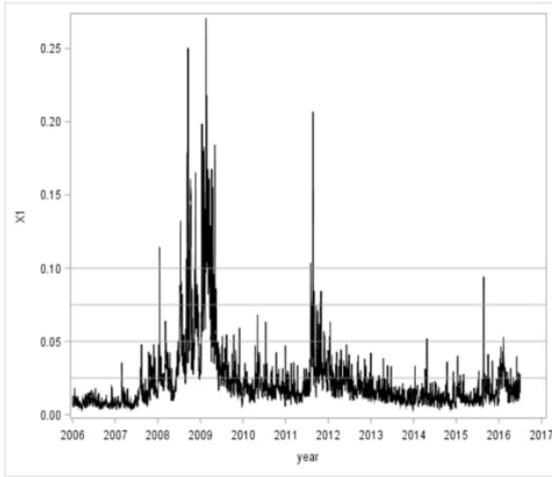
Before presenting the estimation results, we first show the dynamics of the volatility series (Figure 5) and then, the covolatility series (Figure 6).

As shown in Figure 5, oil prices are characterized by a very high volatility over the whole period, with a break in trend identified during the 2007–2008 global financial crisis. Indeed, between March and August 2008, crude oil price has more than doubled from \$US 71 to \$US 147 before going back, to around \$ 40 at the end of the year.

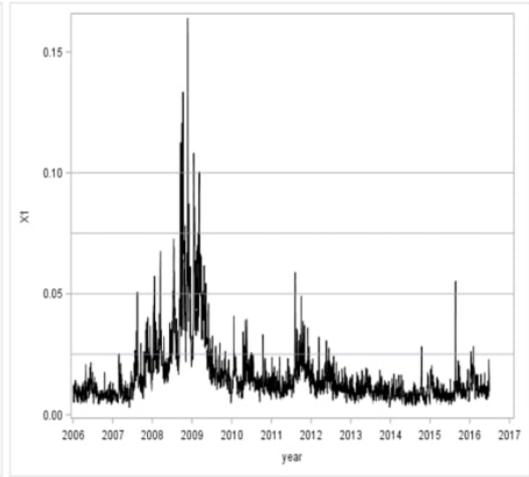
Volatilities of stocks prices of the US banks share some common features. US banks stocks prices have been weakly volatile before 2007. High volatility persistence is then identified between 2007 and 2010. This period was marked by an excessive volatility of US banks securities due to their heavy cumulative accounting losses and the environment of uncertainty that prevailed at that time. From 2010, the volatility appears to be lower but slightly more important than that of the pre-crisis period.

Figure 5: Realized volatilities of oil prices and of US banks' stocks price

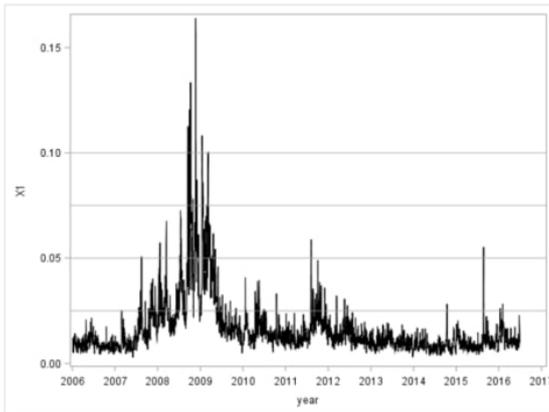
Bank of America



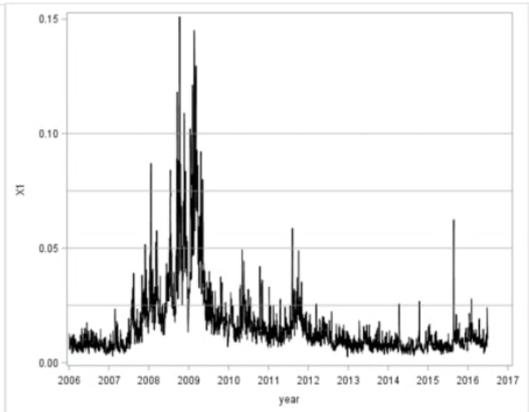
JPMorgan



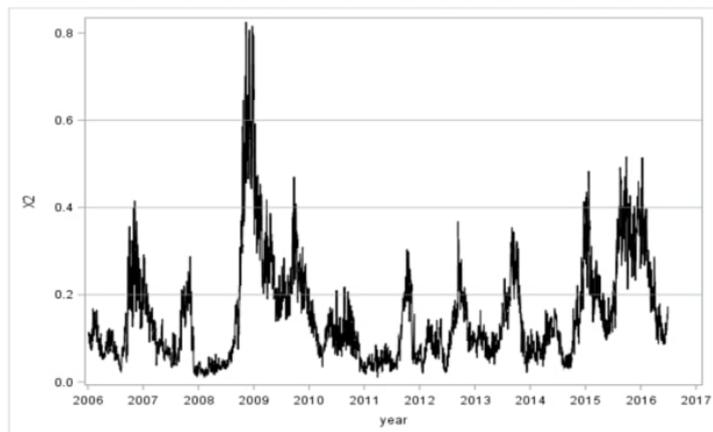
Citigroup



Wells Fargo

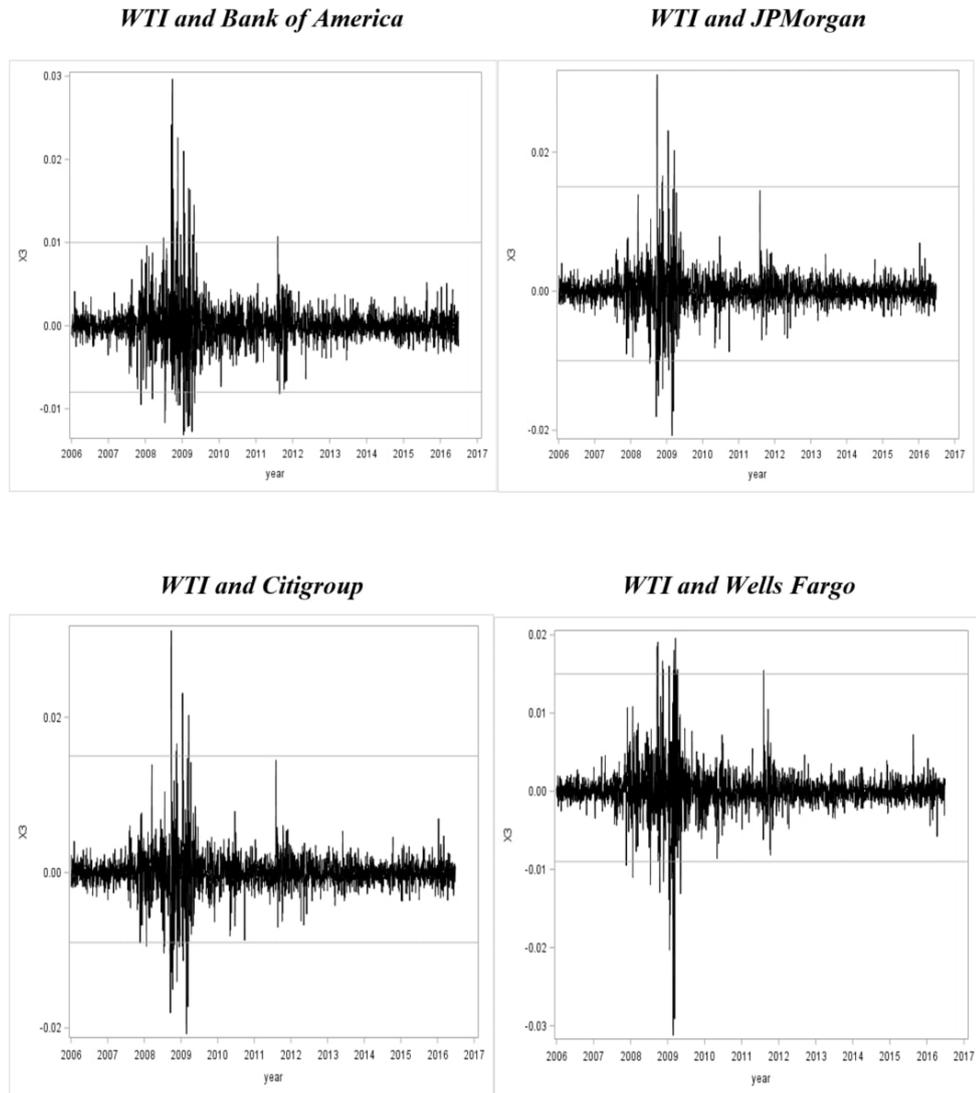


WTI



Source: Author's calculations

Figure 6: Realized Co-volatilities between oil prices and US banks' stocks



Source: Author's calculations

Looking at Figure 6, the following characteristics of co-volatilities between the oil price and US banks' stock prices can be highlighted. Co-volatilities were close to zero before the 2007 and after 2010 and were very high at the heart of the financial crisis until 2010. In term of variability, relatively to the pre-crisis period, the correlation between oil price and US banks' stock prices volatilities has increased from 2010, showing an increased link between the oil market and the US banking sector due to the strong implication of the banking sector in the shale industry.

4.2 *Estimation results*

Tables 1 and 2 report the estimation results of each trivariate VARFIMA (1, d ,0) model for the whole period, as well as for the two sub-periods: the pre oil exposure of US banks (Jan 3, 2006–Dec 31, 2009) and the post oil exposure (Jan 4, 2010–June 30, 2016).

Results reveal in all cases (i.e., for each model and for the whole period, as well as for the two sub-periods) that volatilities of the oil price and US banks stock prices are significantly affected by their own past volatilities, as evidenced by the significance at the 5% level of the coefficients α_1 and β_2 . In addition, volatilities of each series are indirectly affected by the past volatility of the other, as indicated by the significant coefficients of β_1 and α_2 and the results of the Granger-causality test. In other words, when unexpected changes in oil prices occur, US banks stock prices become more volatile and vice versa. These findings are in line with those found by previous studies which evidence significant volatility spillovers between oil price and equity markets.²² Focusing on the value of coefficients, it appears that this transmission effect is more important over the second period, i.e. when banks became more exposed to the oil shale sector, meaning that the oil price and US banks stocks price have become more sensitive to each other. However, the volatility response of US banks stock prices to a shock in oil price volatility remains weak.

No significant effect of past covolatility on oil price volatility as well as on US banks stock prices volatilities is evidenced. We also find that the correlation between the volatility of the oil price and the volatility of US banks stock prices does not significantly depend on its previous value. In some cases, (on the whole period and after exposure for JPMorgan and Bank of America), the covolatility is positively related to the past volatility of US banks stock prices. This result can be explained by the effect of US banks stock prices volatility on oil price volatility which has become sufficiently large after banks' exposure to O&G industries to influence the correlation between the two volatilities series.

22. See Jones and Kaul (1996); Huang et al. (1996); Sadorsky (1999); Papapetrou (2001); Hammoudeh and Aleisa; Ågren (2006); Malik and Hammoudeh (2007); Park and Ratti (2008); Apergis and Miller (2009); Malik and Ewing (2009); Fayyad and Daly (2011); Filis et al. (2011); Arouri et al. (2012); Creti et al. (2013); Mensi et al. (2013); Olson et al. (2014); Kang et al. (2015); Ewing and Malik (2016); Boubaker and Raza (2017).

Table 1: Estimates of trivariate VARFIMA (1, d, 0) models on the whole period.

<i>Parameters</i>	JPM	BAC	CITIG	WFC
α_1	0.89795***	0.89574***	0.84956***	0.90549**
β_1	0.00820***	0.00858**	0.01623**	0.00784**
γ_1	0.09642	0.04243	0.38314	0.09823
α_2	0.39003***	0.34127***	0.22983***	0.28801***
β_2	0.94100***	0.94498***	0.94855***	0.94963***
γ_2	0.29624	-0.49218	-0.33761	-0.02680
α_3	0.00889***	0.00865*	-0.00042	0.00438
β_3	-0.00055	-0.00043	0.00055	-0.00017
γ_3	0.01858	0.04432	-0.00713	-0.02230
d^B	-0.4476**	0.4777*	0.4738***	0.5372***
d^O	0.4738***	0.4738***	0.4738***	0.4738***
d^{OB}	0.00835*	0.0118***	0.0136*	-0.02665***
Granger-causality Test (H0):				
X_1 does not granger cause X_2	0.0001	0.0001	0.0001	0.0001
X_2 does not granger cause X_1	0.0001	0.0001	0.0001	0.0001

Notes : ***, ** and * denote rejection of the null hypothesis of non-significance at 1%, 5% or 10% critical level. JPM = JPMorgan Chase & Co; BAC = Bank of America Corporation, CITIG = Citigroup Inc and WFC = Wells Fargo & Company. Reported values for Granger-causality test are *P*-values.

Table 2: Estimates of trivariate VARFIMA (1, d, 0) models by sub-period.

<i>Parameters</i>	Before banks' oil exposure January 3, 2006–December 31, 2009				After banks' oil exposure January 4, 2010–June 30, 2016			
	JPM	BAC	CITIG	WFC	JPM	BAC	CITIG	WFC
	α_1	0.88626***	0.90272***	0.91057***	0.90069**	0.89354***	0.88430***	0.81619***
β_1	0.00713***	0.00591***	0.00676***	0.00585**	0.01039***	0.01197***	0.02549***	0.01109**
γ_1	0.10504	0.10289	-0.06615	-0.03355	0.09216	0.02510	0.51255	0.13217
α_2	0.38686***	0.33304***	0.22593***	0.27880**	0.52087***	0.51956***	0.36492***	0.41003**
β_2	0.94294***	0.94378***	0.94843***	0.95155**	0.93150***	0.93643***	0.93985***	0.93943**
γ_2	-0.96757*	-0.94239	-0.13810	0.12455	0.76790*	-0.31183	-0.41009	-0.05438
α_3	0.00126	-0.00249	0.00891	0.00013	0.01137*	0.01069**	-0.00401	0.00524
β_3	-0.00014	0.00004	-0.00031	-0.00001	-0.00075	-0.00044	0.0012	-0.00017
γ_3	0.04223	0.04062	0.05602	0.07287	0.00911	0.04294	-0.02875	-0.04915
d^B	0.4504**	0.4357**	0.4754***	0.47545**	0.5256**	0.4720***	0.4828***	0.5315**
d^0	0.48735***	0.48735***	0.48735***	0.48735**	0.48735***	0.48735***	0.48735***	0.48735**
d^{0B}	0.02215	0.0117***	0.0361*	0.0292***	0.002169	0.0054	0.1181	0.04665***
Granger-causality Test (H0):								
X_1 does not granger cause X_2	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
X_2 does not granger cause X_1	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0004	0.0003

Notes : ***, ** and * denote rejection of the null hypothesis of non-significance at 1%, 5% or 10% critical level. JPM = JPMorgan Chase & Co; BAC = Bank of America Corporation, CITIG = Citigroup Inc and WFC = Wells Fargo & Company. Reported values for Granger-causality test are *P*-values.

4.3 *Impulse response functions*

To support our finding of significant spillovers between the oil market and the US banking sector, we also conduct an impulse response analysis by investigating volatility impulse response functions (VIRFs) over the two sub-periods for a 100 days' horizon. These VIRFs, displayed in Figures A.1 to A.8 in appendix, allow us to examine the response of oil price volatility to a volatility shock from US banks' stock prices (and inversely) and how quickly does these volatility shocks dissipate.

Two main findings emerge from the analysis of volatility impulse response functions. Firstly, results are very similar among the four US banks considered. Secondly, over the first sub-period, a shock on oil price volatility seems to have a negligible effect on the volatility of the US banks stock prices. On the contrary, over the second sub-period, oil price volatility significantly, although weakly, influences the volatility of US banks stock prices. Indeed, following the shock, volatilities of the US banks returns move away from their expected value (the horizontal line at 0.00) and dissipate back after 80 days approximately. Moreover, this effect is more pronounced in the second sub-period when banks have become more involved in O&G sectors. Turning now to volatility spillover from the US banking sector to the oil market, it appears that a volatility shock of the US banks stocks prices alters the expected value of oil return volatility in the two sub-periods. Particularly, the shock effect dissipates more slowly (after 100 days) and in terms of magnitude, the response during the second sub-period is greater than before. These results suggest that because of the strong implication of the banking sector in the shale industry, the major US banks, and therefore the US financial system, have become more sensitive to a shock on oil price volatility and inversely.

4.4 *Discussion*

One plausible explanation for this transmission of volatility from the oil market to the US banking sector is that a shock on oil price volatility could reflect higher risk from the perspective of investors. In fact, investors know that shale companies have been heavily indebted to the US banks. So according to them, a volatility shock of oil price is synonym of a potential risk of bankruptcy for specialized companies as was ascertained after the

recent decline in oil prices (Kilian, 2016). These risks of default, by sending a wrong signal, can imply deterioration in the value of the banks' portfolio assets, leading investors to make massive withdrawals; further weakening the balance sheets of banks. Additionally, because the most exposed banks are systemic, they could be more disruptive to the financial as it was the case during the subprime crisis. Thus, our results evidence a new potential banking crisis transmission channel. It should be noted that if the effect of a volatility shock of oil price on the banking system is weak, it is certainly due to the cutting back on loans granted to O&G companies (Bidder et al., 2018) as well as the increase of the provision expenses for loans losses following the dramatic decline in oil prices. As a result, the potential banking crisis transmission channel is ever more relevant with the recent rise in oil prices insofar as banks tend to minimize risk during the flourishing period.

Further, a shock on the volatility of the banks stock prices has an immediate effect on their assets prices which become valued below their fundamental value. To address the uncertainties around the value of assets they held, banks are forced to urgently restructure their balance sheets in order to cope with spiraling downside liquidity. This process can lead to a considerable decrease in the amount of granted loans and a hasty rise of interest rates by banks (Bidder et al., 2018). This situation will be a challenge to funding future drilling and production during a low oil price environment, particularly for small and midsize companies due to the capital-intensive nature of shale. The worst-case scenario for US oil producers would be a drop in oil price coupled with a gradual increase in interest rates. As a result, a decline in the US oil production will occur and undoubtedly affect the total oil production and thus oil prices volatility, since the US is now one of the largest oil producers. In the facts, following the dramatic decline in oil prices in 2014, banks with high exposure to O&G extracting industries made significant adjustments to their balance sheets. They tightened credit supply to O&G companies and expanded other types of lending and asset holdings with a bias towards less risky securities. However, the rise in oil prices, although still remaining below standard (barrel price under \$ 50) and highly volatile, has prompted banks to reopen credit to O&G industries after falling for two years. More than 34 drilling companies have seen their credit lines revalued by an average of 5% since autumn 2017, according to the data collected by Reuters.

The fall of breakeven costs could partly explained the fact that no crisis occurred after this episode despite huge volatility and a low price environment. Nevertheless, we can not exclude the possibility of a crisis in a scenario where the price of oil would fall below the breakeven point. A shock on the volatility of stock price of the US banking sector therefore appears as a potential root cause and catalyst for turmoil in the oil market.

These results have policy implications as they suggest that specific macro-prudential policies are needed in order to prevent or limit these potential systemic risks. We highlighted that the exposure of shale oil companies to bank interest-rate fluctuations is tied to their form of financing. Therefore, shale oil companies should diversify their source of funding. More particularly as conventional oil and gas companies must reduce the bank facility in favor of self-financing. On the banks' side, measures to reduce their exposure to shale oil sector, and more generally to energy sector, should be taken. For this purpose, banks should become more efficient and selective in oil and gas exploration and productions companies lending. In addition, we can also refer to the first proposal of the plan outlined by the Federal Reserve to limit Wall Street bets on the energy sector given the exposure of the banking sector to the shale sector. This plan includes some measures which consists in making investment in energy sector costlier in capital by forcing exposed banks to hold more capital against such investments (Reuters, 2016 September 23th), therefore potentially less profitable.

5 Conclusion

Since the strong implication of the banking sector in the shale industry, the question of volatility spillovers between the oil market and the US banking sector has become a matter of great concern for bank regulators as well as investors for many reasons. First, billions of dollars of debt have been accumulated in the banks' portfolio. Second, the drop in oil prices made the fluorescence of shale industry uncertain, deferring the debts held by the oil companies. This strengthening link between the US oil and banking markets could thus make another major financial crisis more likely. To provide clearer insights into this issue, we investigate in this paper the relationship between the volatilities of the oil market and of stock prices of the four US banks most oil exposed from January 3,

2006 to June 30 2006-2016 period by estimating several trivariate VARFIMA models.

On the whole, our results support evidence of significant volatility transmission across oil market and the US banking sector. These findings are in line with some previous studies that revealed the existence of volatility spillovers between oil price and equity markets. More particularly, over the period during banks have become more exposed to the oil shale sector, we evidence an increased, although weak, volatility response of US banks stock returns to a shock on oil return volatility, highlighting therefore a new potential banking crisis transmission channel by a greater exposure of banks to oil shale industry. Moreover, the response of oil return volatility to a shock on the volatility of US banks stock returns is significant, suggesting that a crisis on oil market could stem from a volatility shock on the US banking sector.

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Appendix

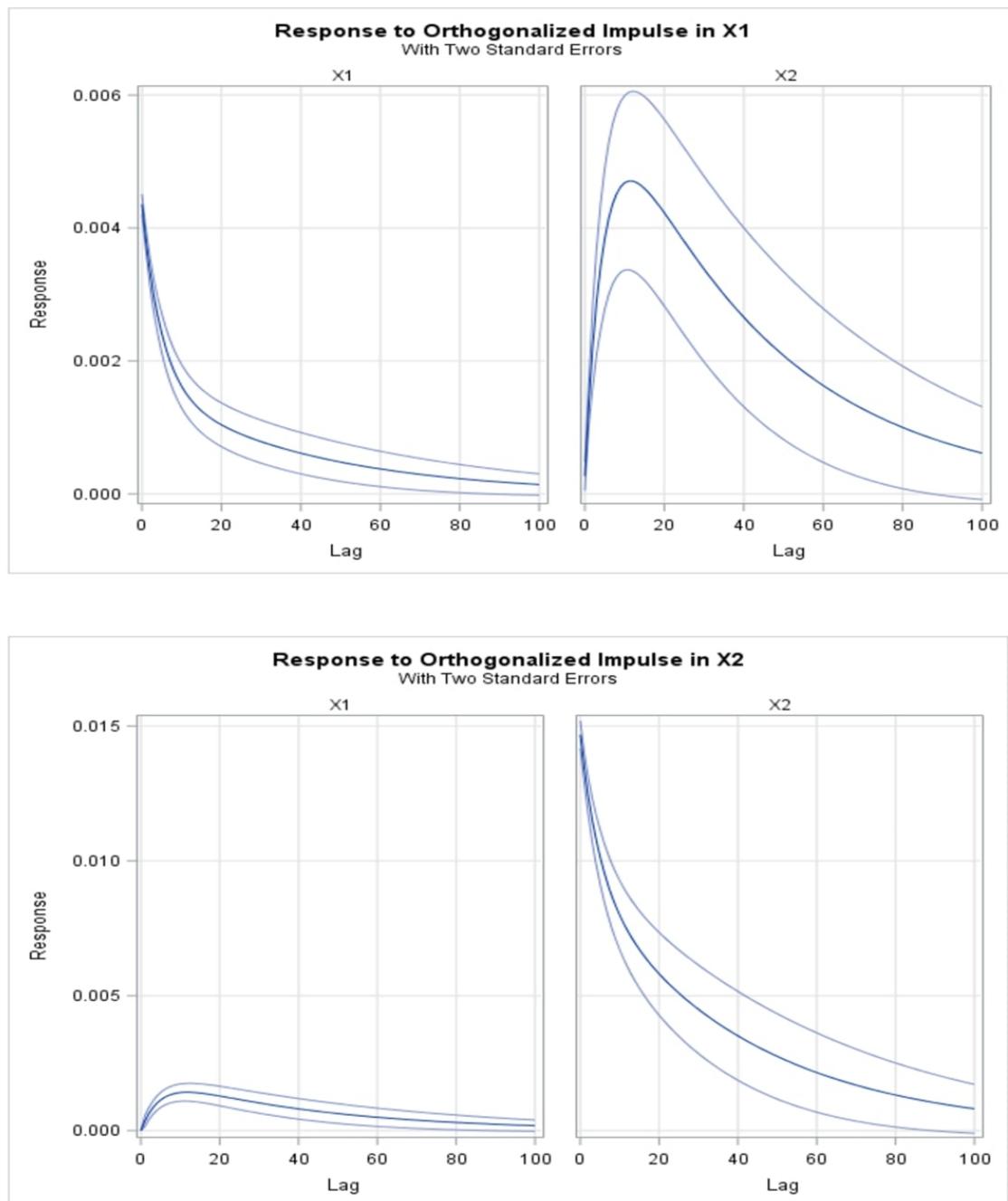


Figure A.1: Orthogonalized VIRFs of oil price and JP Morgan before exposure. Notes: As a reminder, $X_{1,t}$ and $X_{2,t}$ represent the realized return volatilities of respectively bank stock price and oil price. Bold line is the orthogonalized impulse response and the two light lines build the 95% confidence interval.

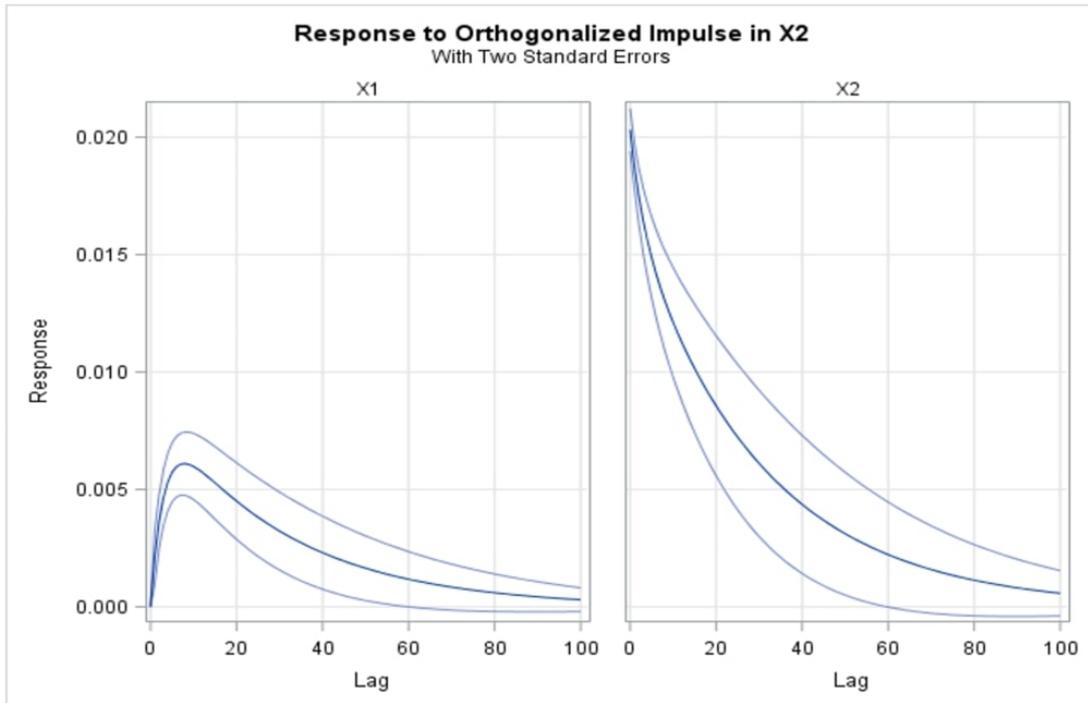
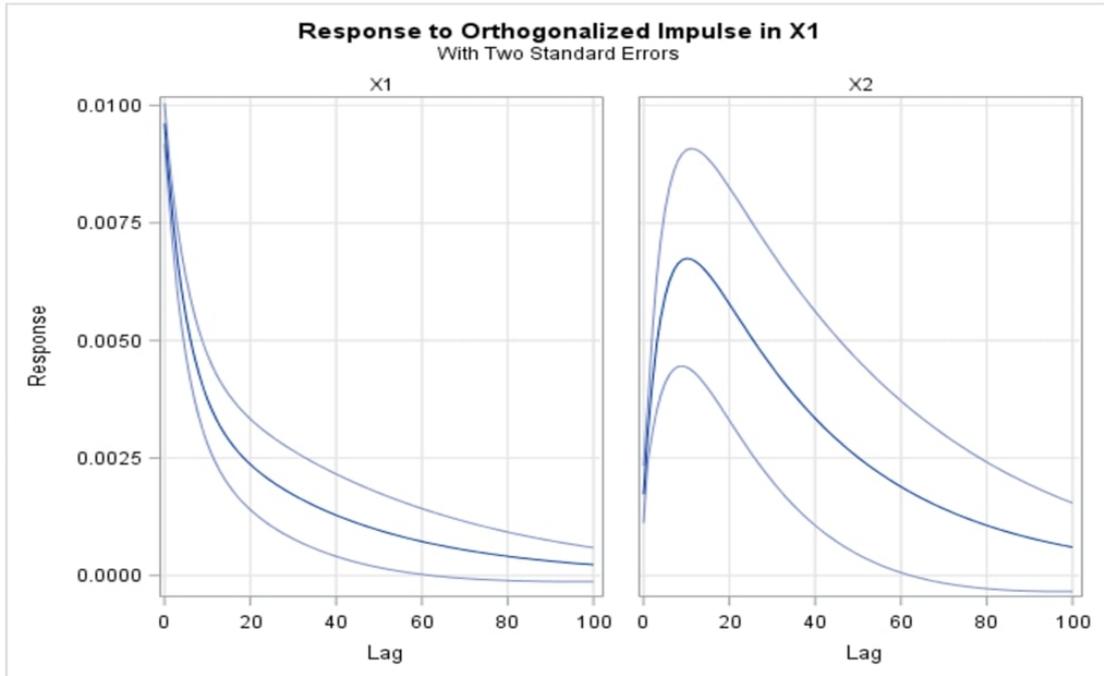


Figure A.2: Orthogonalized VIRFs of oil price and JP Morgan after exposure. Notes: As a reminder, $X_{1,t}$ and $X_{2,t}$ represent the realized return volatilities of respectively bank stock price and oil price. Bold line is the orthogonalized impulse response and the two light lines build the 95% confidence interval.

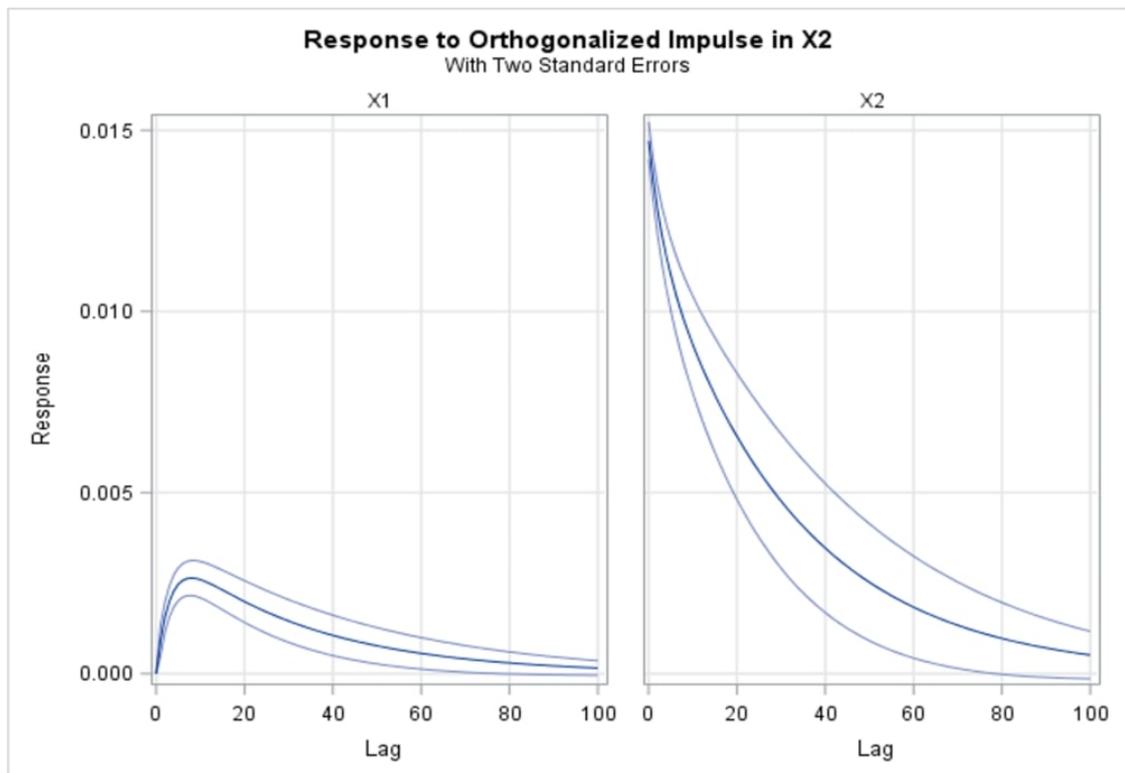
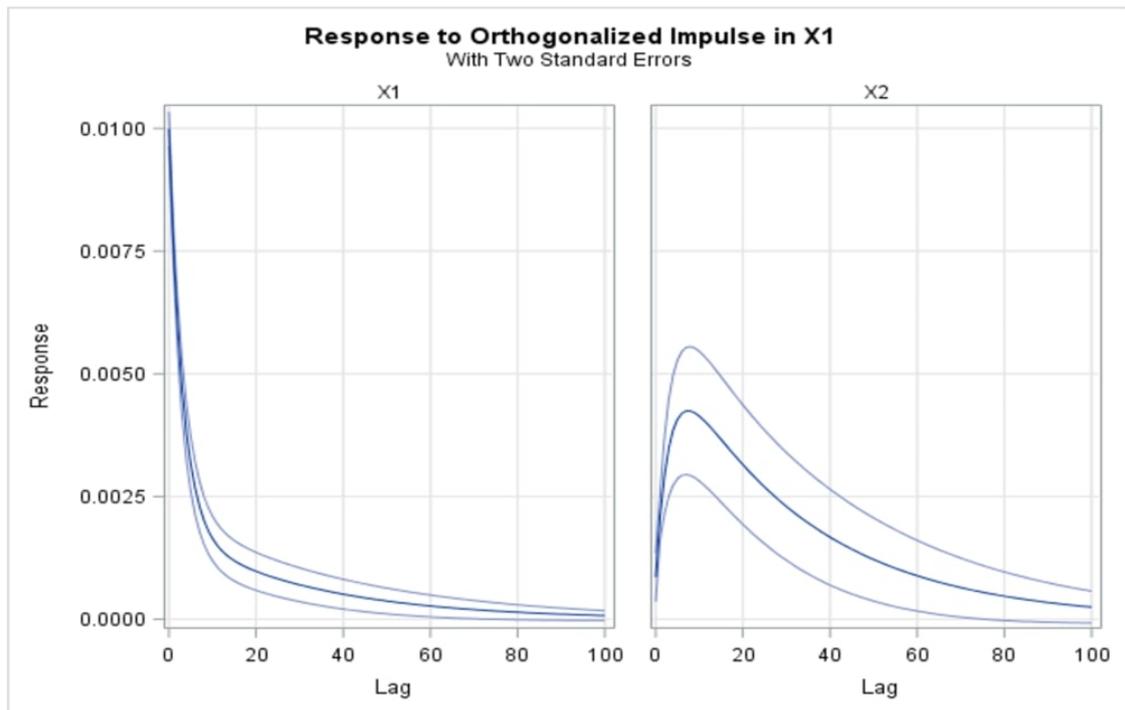


Figure A.3: Orthogonalized VIRFs of oil price and Bank of America before exposure. Notes: As a reminder, $X_{1,t}$ and $X_{2,t}$ represent the realized return volatilities of respectively bank stock price and oil price. Bold line is the orthogonalized impulse response and the two light lines build the 95% confidence interval.

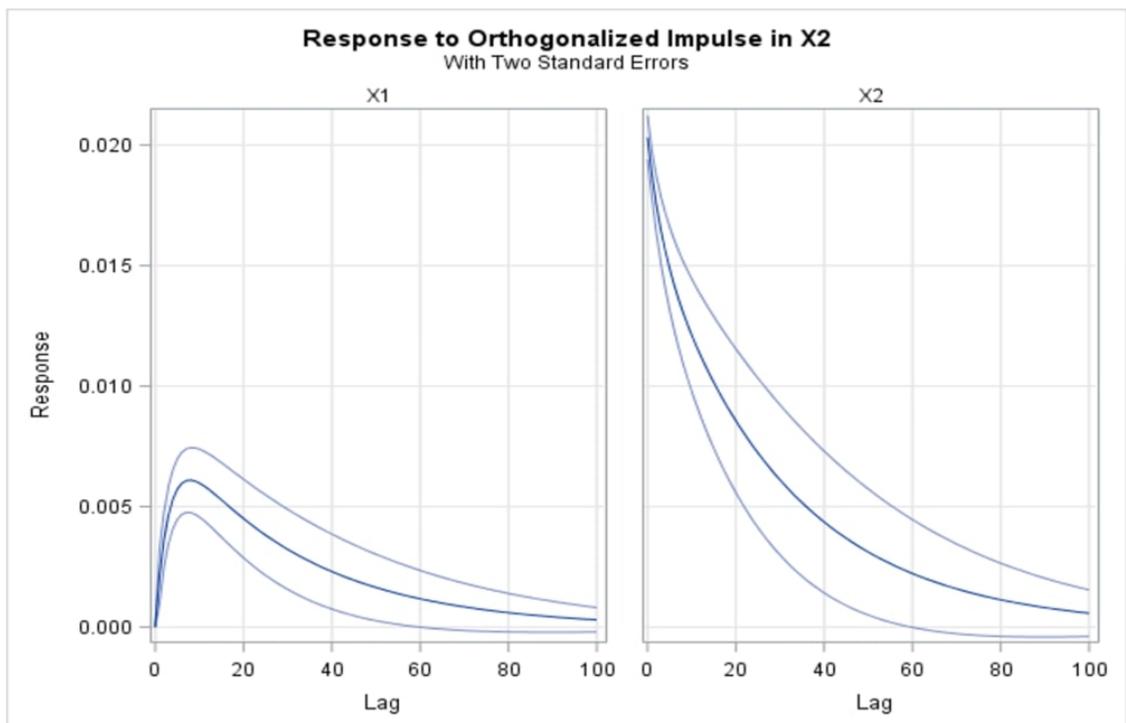
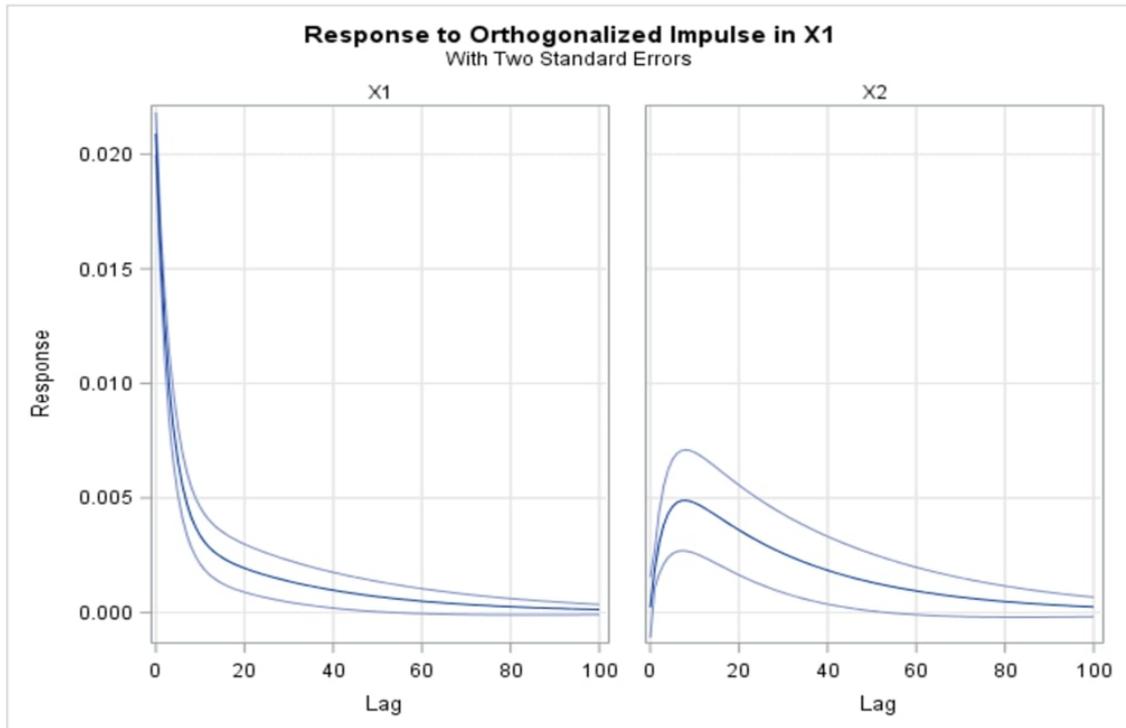


Figure A.4: Orthogonalized VIRFs of oil price and Bank of America after exposure. Notes: As a reminder, $X_{1,t}$ and $X_{2,t}$ represent the realized return volatilities of respectively bank stock price and oil price. Bold line is the orthogonalized impulse response and the two light lines build the 95% confidence interval.

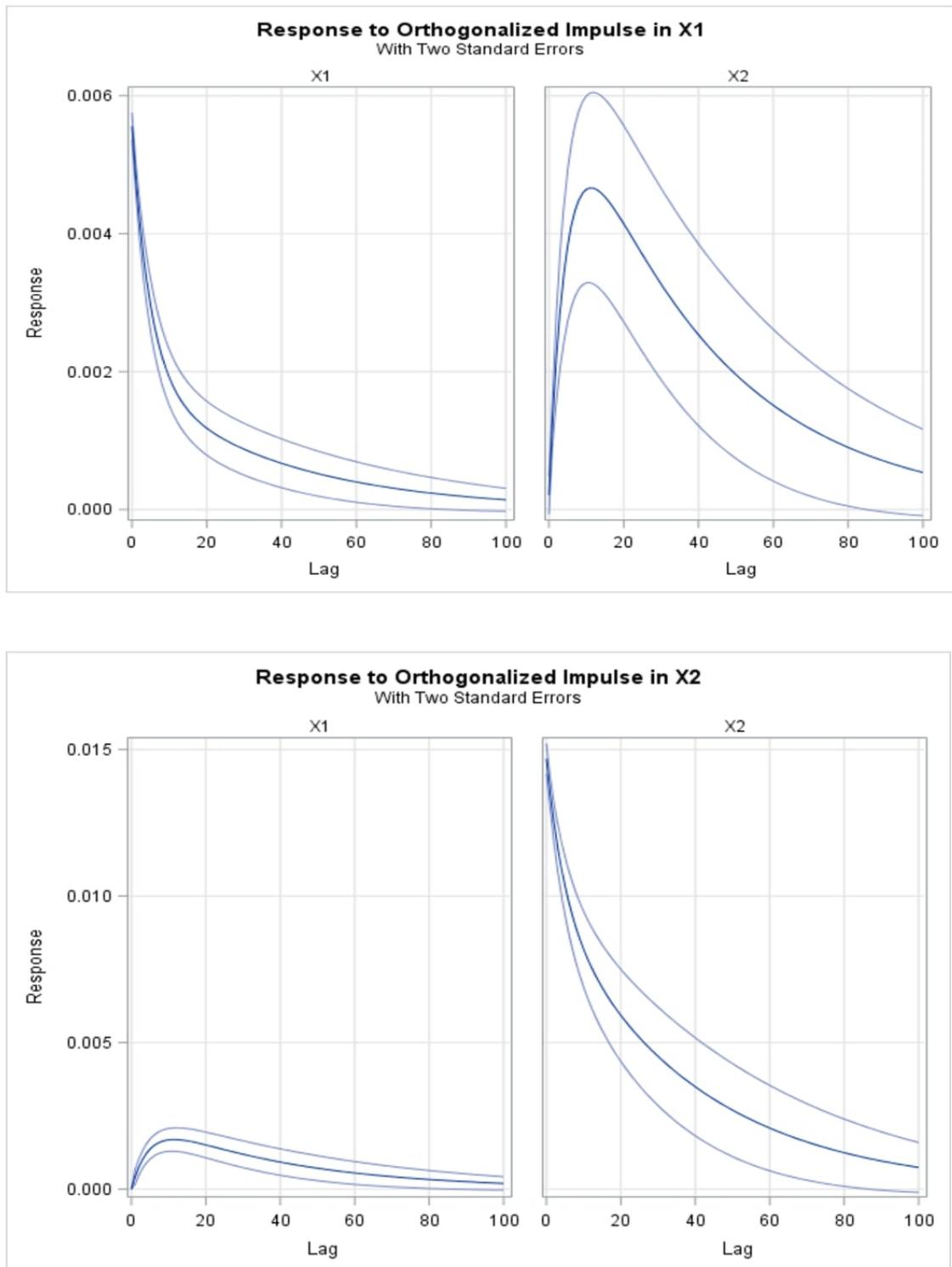


Figure A.5: Orthogonalized VIRFs of oil price and Citigroup before exposure. Notes: As a reminder, $X_{1,t}$ and $X_{2,t}$ represent the realized return volatilities of respectively bank stock price and oil price. Bold line is the orthogonalized impulse response and the two light lines build the 95% confidence interval.

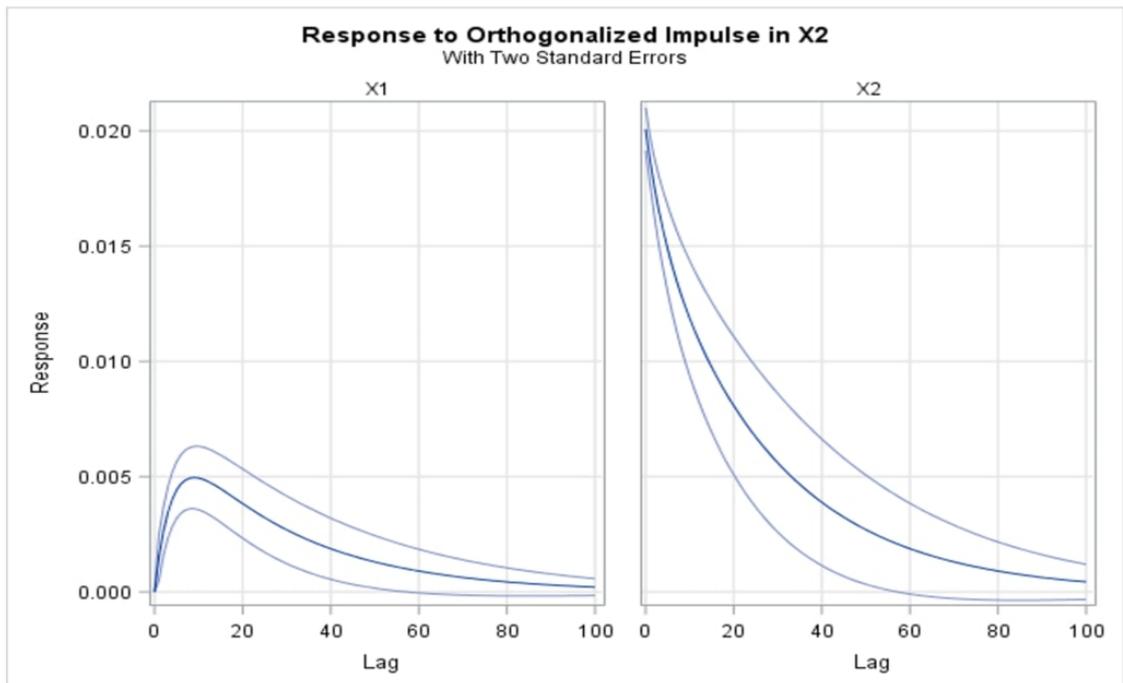
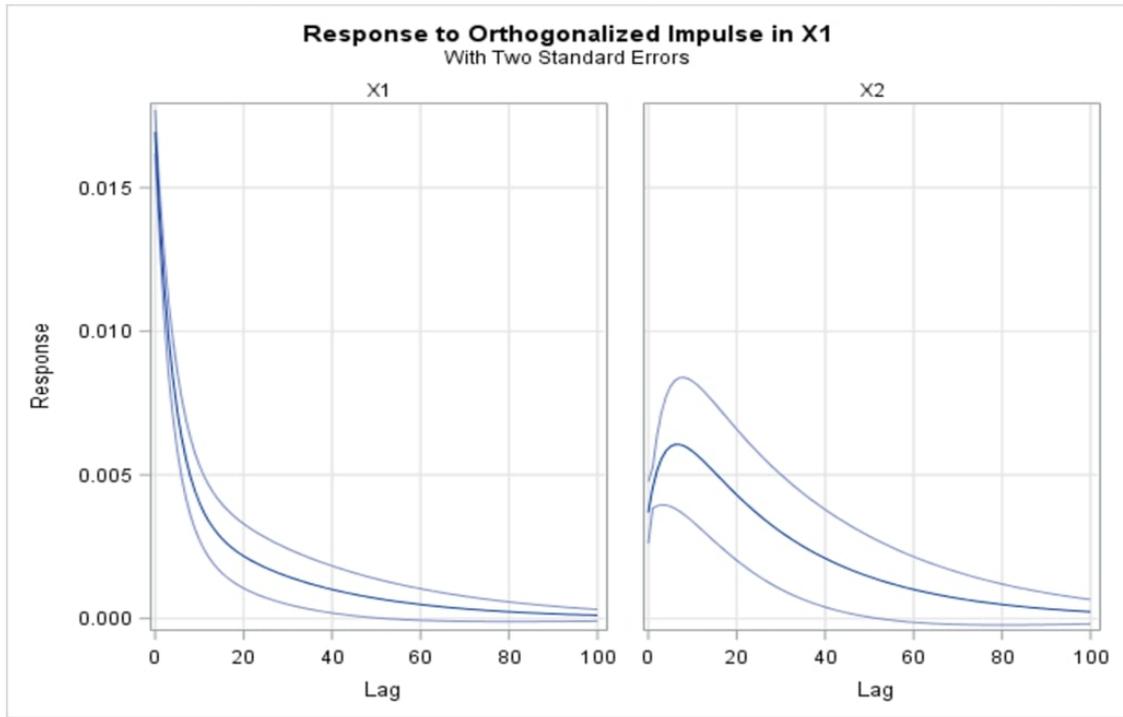


Figure A.6: Orthogonalized VIRFs of oil price and Citigroup after exposure. Notes: As a reminder, $X_{1,t}$ and $X_{2,t}$ represent the realized return volatilities of respectively bank stock price and oil price. Bold line is the orthogonalized impulse response and the two light lines build the 95% confidence interval.

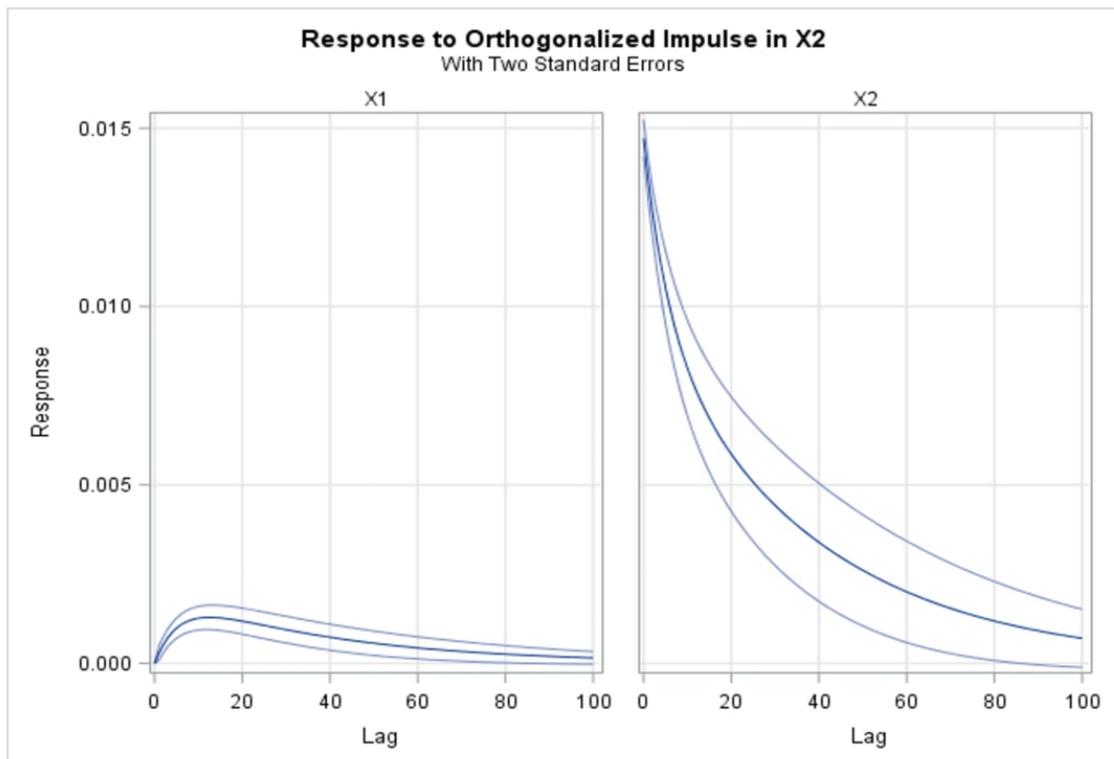
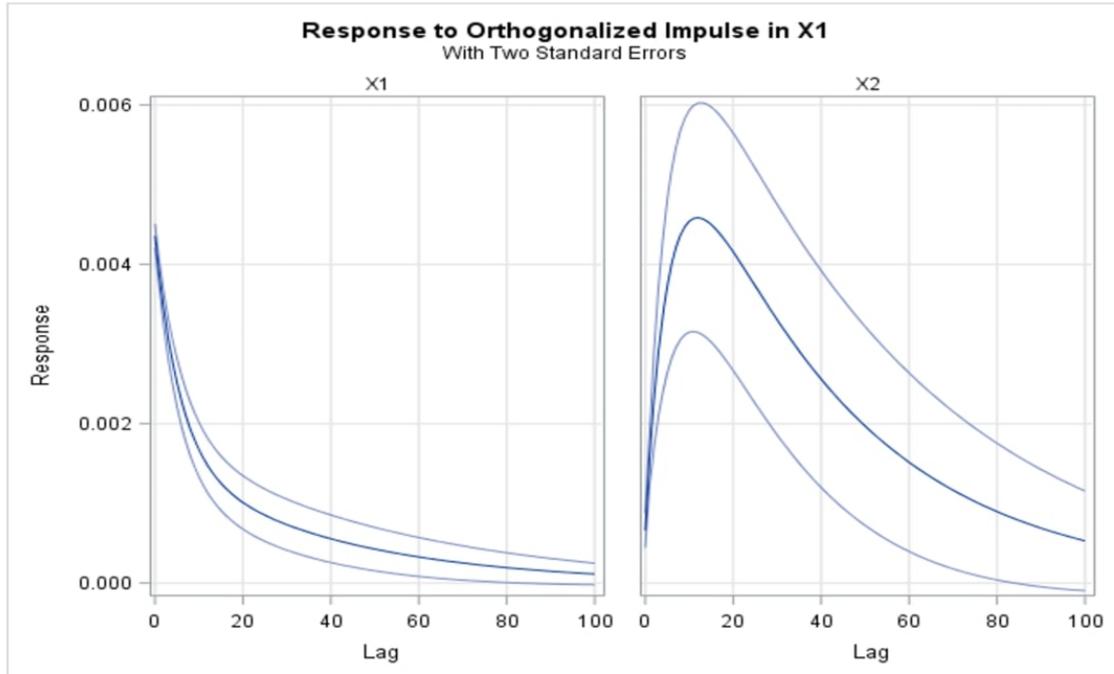


Figure A.7: Orthogonalized VIRFs of oil price and Wells Fargo & Co before exposure. Notes: As a reminder, $X_{1,t}$ and $X_{2,t}$ represent the realized return volatilities of respectively bank stock price and oil price. Bold line is the orthogonalized impulse response and the two light lines build the 95% confidence interval.

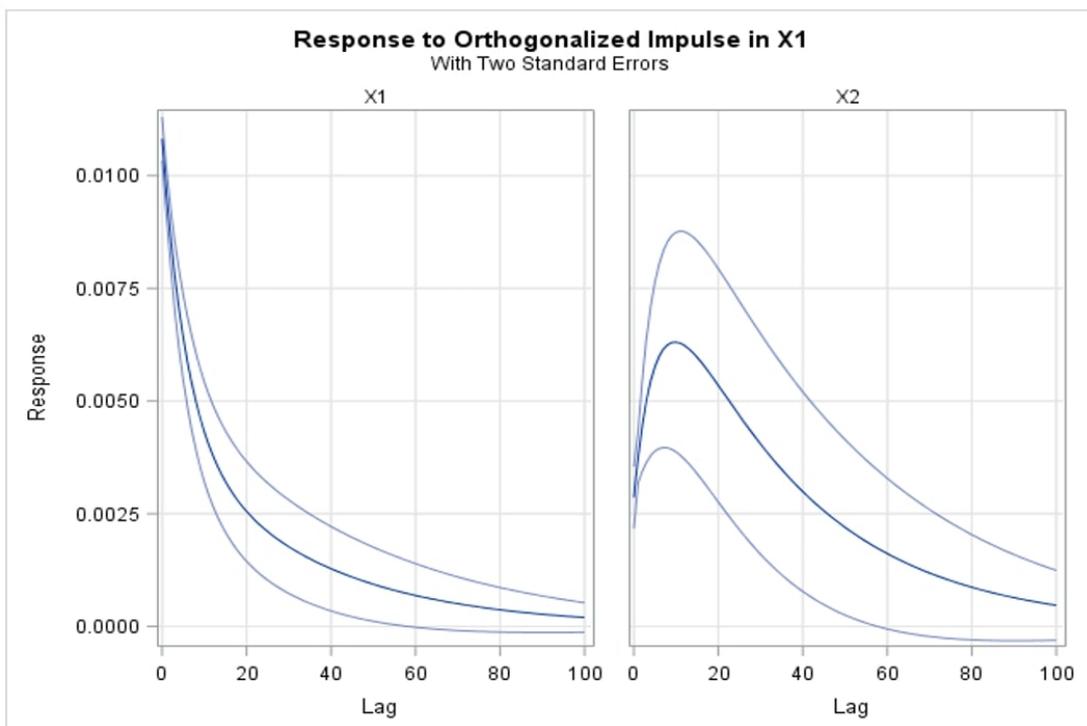
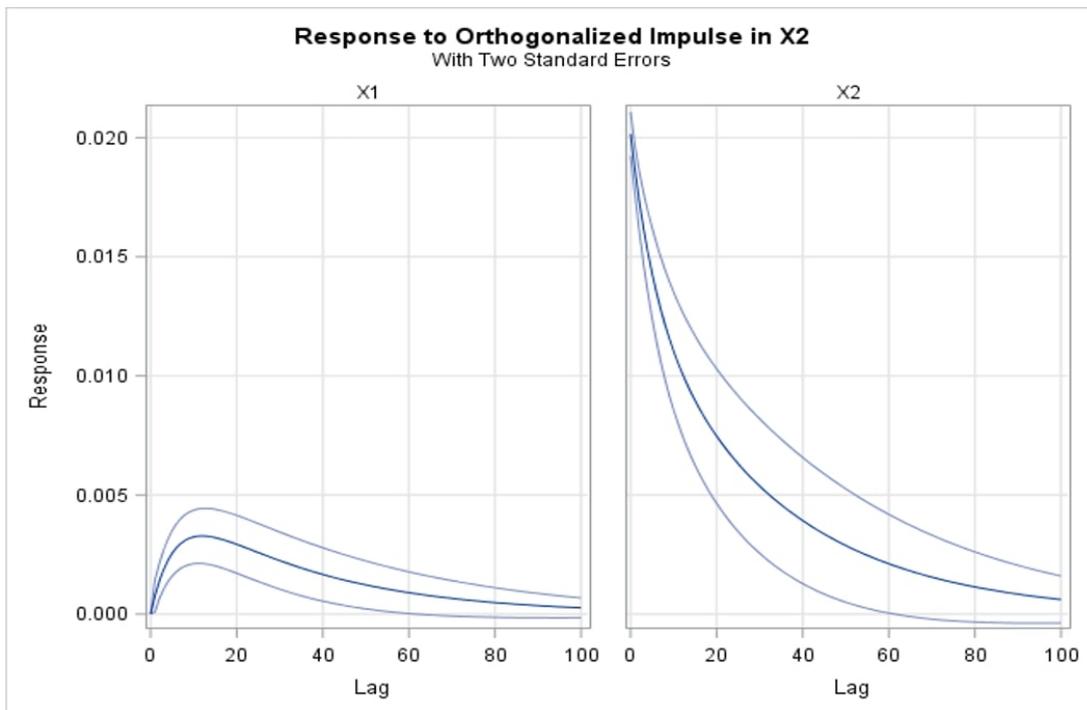


Figure A.8: Orthogonalized VIRFs of oil price and Wells Fargo & Co after exposure. Notes: As a reminder, $X_{1,t}$ and $X_{2,t}$ represent the realized return volatilities of respectively bank stock price and oil price. Bold line is the orthogonalized impulse response and the two light lines build the 95% confidence interval.

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