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Tight oil, real WTI prices and U.S. stock returns

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ABSTRACT

Following the adoption of new techniques of shale and fracking by U.S. oil companies, a structural vector autoregression model (SVAR) complements studies on why Brent and WTI started to diverge around early-2011. Using monthly data from 2000 to 2018, we decompose oil supply into: world oil (excluding U.S.), U.S. conventional (non-tight) oil and U.S. tight oil. We examine the variance decomposition of stock returns for the aggregate market (S&P 500), the S&P Energy sector and Chevron and Exxon Mobil oil companies, and we further identify differences between two subsamples from 2000 to 2010 and 2011 to 2018, respectively. We find that supply considerations (especially due to tight oil) become more important in the subsample after 2011, not only for individual oil companies but also for the aggregate market and energy sector: Supply shocks due to tight oil explain in our benchmark model between 29% (S&P 500) and 31% (S&P Energy) of the variance in stock returns after 24 months and between 28% and 29% for oil companies. None of these are statistically significant in the pre-2011 subsample. Among impulse responses, tight oil production responds positively to disruptions in world oil, and U.S. stock returns respond positively to oil price shocks and respond negatively to tight oil shocks which is a further finding while being consistent with the literature. Copula modeling uncovers stronger tail dependences in the second subsample for the interactions during downturns and upturns among global demand, crude oil prices and stock markets.

1. Introduction

In an influential paper, Kilian (2009) proposes a structural vector autoregression (SVAR) approach to global oil supply, an index of global real demand and real oil prices. The latter are typically calculated by oil prices denominated in U.S. dollars (such as the U.S. refiner cost of oil, crude WTI or Brent oil prices) deflated by the U.S. price index. Its main message is that supply shocks are relatively less important than demand shocks, themselves captured by a global index of commodity prices, which became known as "Kilian index". Due to its impact in the academic literature, several extensions of Kilian (2009) have been developed, usually adding one series in the SVAR to consider the effects of supply and demand not only on real oil prices but also on other financial markets, including U.S. stock prices by Kilian and Park (2009), U.S. bond prices by Kang et al. (2014), exchange rates by Chen et al. (2016a), economic policy uncertainty by Kang et al. (2017) and U.S. consumer sentiment by Güntner and Linsbauer (2018). Another stream of papers has focused on misspecifications of the basic SVAR model to allow for inventories and speculative trading put forward by Kilian and Murphy (2014).

Some authors have examined the causes of why Brent and WTI started to diverge. This is very important because the two oil prices serve as major benchmarks for the world and the U.S. For example, Scheitrum et al. (2018, p. 463) aim to "explain what happened in 2011 when the spread diverged from historical levels, sending WTI to more than a $20 discount under Brent and resulting in the WTI being viewed as a broken benchmark for a time." Fig. 1a illustrates the divergence between Brent and WTI using monthly data making clear the shift in the spread after 2011 when advances in oil production became evident, as shown in Fig. 1b which compares the world (excluding U.S., right axis), U.S. non-tight and U.S. tight oil production over our sample period. Interestingly, the oil spread started diverging from historical levels at a time when U.S. tight oil production started rising. In this paper we will therefore refer to the first subsample running from 2000 to 2010 and the second running from 2011 to 2018. This paper merges the SVAR literature on real oil prices and the divergence in crude oil prices. Our contribution is not on the causes of the divergence but on the implications of this divergence for stock returns. We believe this is of interest because both academic studies and the financial press

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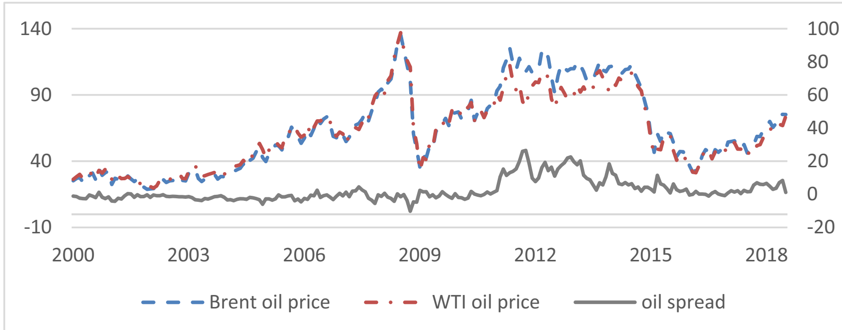

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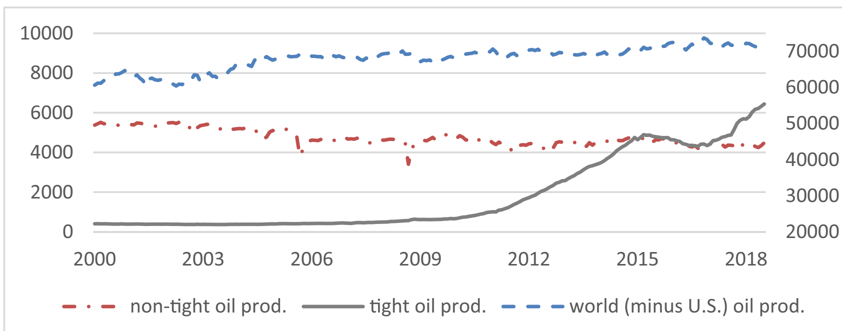

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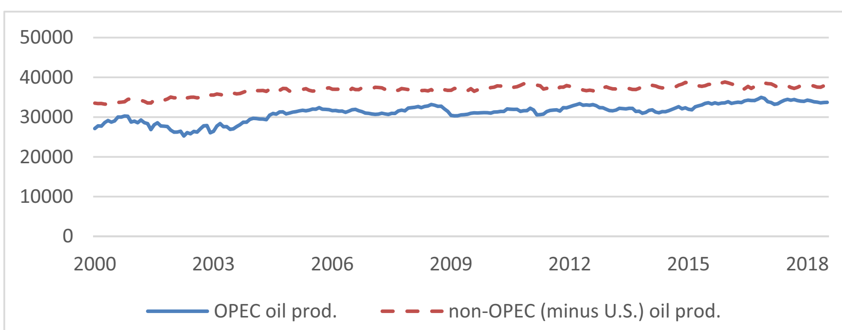

Fig. 1. a. Brent and WTI oil prices, and their spread (right axis). b. World (excluding U.S., right axis), U.S. non-tight and U.S. tight oil production. c. OPEC and non-OPEC (excluding U.S.) oil production. Notes: Fig. 1a presents how the oil spread evolves over time, along with Brent and WTI oil prices. Fig. 1b presents movements of world (excluding U.S., right axis), U.S. non-tight and U.S. tight oil production. Fig. 1c presents movements of OPEC and non-OPEC (excluding U.S.) oil production.

have suggested that the vast increase in U.S. oil production may be responsible for the divergence in oil prices, which itself may impact how oil price shocks are transmitted into the financial markets.[1]

On the one hand, there are references to the increase in U.S. oil production as the main driver of the spread in oil prices between Brent and WTI. Intuitively, if Brent prices are determined internationally, with large increases in U.S. oil production (in the absence of supply and pipeline bottlenecks) WTI will be pushed downward, thus generating a positive spread between Brent and WTI oil prices. For this mechanism to be relevant, after the U.S. oil boom one should see more effects on the financial side, such as in stock returns. Kang et al. (2016), for example, extend the Kilian (2009) and Kilian and Park (2009) SVARs to a decomposition of oil production into non-U.S. oil supply and U.S. oil supply and assume that oil prices are predetermined with respect to U.S. macro aggregates within a month. Also, they assume that non-U.S. oil production does not respond to U.S. oil supply shock within a given month and report (Kang et al. 2016, p. 179) that "… by disaggregating world oil supply into U.S. and non-U.S. oil supply shocks, demand and

[1] In late May 2018, the difference between Brent and WTI oil was approaching $ 8 as reported in The Wall Street Journal (2018a): "The two benchmarks haven't been that far apart since 2015, before U.S. crude could be freely exported." (*The Wall Street Journal*, May 22, 2018). According to the U.S. EIA report of September 12, 2018, "The United States likely surpassed Russia and Saudi Arabia to become the world's largest crude oil producer earlier this year, based on preliminary estimates in EIA's *Short-Term Energy Outlook* (STEO). In February, U.S. crude oil production exceeded that of Saudi Arabia for the first time in more than two decades. In June and August, the United States surpassed Russia in crude oil production for the first time since February 1999. Although EIA does not publish crude oil production forecasts for Russia and Saudi Arabia in STEO, EIA expects that U.S. crude oil production will continue to exceed Russian and Saudi Arabian crude oil production for the remaining months of 2018 and through 2019."

supply shocks are comparable in explaining the variation in U.S. real stock returns. In the period 1973:01–2006:12, supply shocks explain 14.1% of the variation in U.S. real stock returns, while demand shocks explain 16.8% after 60 months. Over 1973:01–2014:12, supply shocks account for 11.9% and demand shocks account for 11.6% of variations of U.S. real stock returns after 60 months. For a model in which oil production is consolidated as world oil production, supply shocks forecast 6.8% of the variation in U.S. real stock returns over 1973:01–2014:12."

Along the same lines, the increase in U.S. oil production has been accompanied by new techniques that drill oil differently than conventional techniques. These have been referred to as "fracking" and an explanation is worthwhile here, since in this paper we will decompose oil supply into three components: world oil (excluding U.S.), conventional U.S. oil and non-conventional U.S. oil. At the microeconomic level, Gong (2018) investigates whether the shale technical revolution impacts firm level efficiency using the global oilfield service market, or oil and gas service industry. See also Kleinberg et al. (2018) for an excellent review of tight oil market dynamics. Kilian (2017) refers to the term "tight oil (or shale oil)" as "commonly used by the oil industry and by government agencies to refer to crude oil extracted by certain techniques that differ from those used in conventional oil production…" These new techniques allow oil producers to "access crude oil that geologists knew about for many years, but that heretofore had been inaccessible." For more information about what tight oil is and how tight oil is extracted differently from conventional oil, see Kilian (2017, pp. 2–3).

As for demand side considerations, Bernanke (2016), Prest (2018) and others have employed financial factors as alternatives to the commonly used "Kilian index" based on commodity shipping prices. As a discussion of several indicators of economic measures of demand, Kilian and Zhou (2018, p. 70) note that "In related work, Hamilton (2014) and Bernanke (2016) recently postulated that copper prices, interest rates and the value of the dollar are good proxies for 'global demand', allowing them to estimate the global demand component of the change in oil prices or the prices of other commodities. It is important to reiterate in this context that global demand is unobservable. Indeed, their approach is not designed either to measure global demand or, for that matter, to quantify fluctuations in global real economic activity."

We implement a SVAR approach to capture these developments linking oil supply, world real economic activity (demand), real oil price returns and real stock returns. On stock returns, in particular, we investigate effects at the aggregate market (S&P 500), at the S&P Energy sector and at two large oil companies: Chevron and Exxon Mobil. We also apply copula methods to uncover tail dependences. Examination of tail dependences in bivariate pairs will reinforce our findings obtained by SVAR approaches when modeling oil supply, world demand, real oil prices and stock markets.

Our SVAR approach is based methodologically on Kilian and Park (2009) for stock returns, Güntner (2014) on the responses of oil producers (OPEC versus non-OPEC members) to demand shocks triggered by the price of oil during 1975–2011, Chen et al. (2016b) for political risk and OPEC, Kang et al. (2016) for U.S. oil production and Güntner and Linsbauer (2018) for extensions to U.S. consumer sentiment. Earlier works on the topic of oil prices and stock returns include the present value approach of future earnings by Chen et al. (1986), linear projections by Nandha and Faff (2008) and the unrestricted VARs by Park and Ratti (2008). Alternative models include GARCH models by El-Sharif et al. (2005), MGARCH by Mollick and Assefa (2013), bivariate GARCH-in-mean estimation by Elder and Serletis (2010) between real oil price and real GDP on how oil price uncertainty affects economic activity, as well as Alsalman (2016). Moreover, Bampinas and Panagiotidis (2017) examine bivariate oil and stock markets through local Gaussian correlations. Our copula modeling is based on Nelsen (2006). In the process of selecting copula families, the White test proposed by Huang and Prokhorov (2014) or the Kendall test investigated by Genest and Rivest (1993) and Wang and Wells (2000) are mainly applied, as detailed in Section 3.

We find that supply considerations (especially due to tight oil) become more important in the subsample after 2011, not only for individual oil companies but also for the aggregate and energy sector stock markets. Supply shocks due to tight oil alone explain in the model with Kilian index - after 24 months – a substantial part of the variance of stock returns: between 29.42% (S&P 500) and 30.80% (S&P Energy) and between 27.78% and 29.15% for oil companies. None of these were statistically significant in the pre-2011 period. A few impulse responses are discussed in detail, along with the tail dependence identification.

Section 2 introduces the data used in this work, Section 3 reviews the methodologies adopted in this paper, and Section 4 contains our results and interpretations. Section 5 summarizes the main findings of this paper.

2. The data

Data are of monthly frequency. Oil prices and other commodity prices (such as copper) change more frequently, but oil supply series are only available at monthly frequency. In particular, given the focus of this paper on developments of U.S. tight oil supply, we have to consider a shorter time span (2000 onwards) than others who have examined global oil production from the mid-1970s onwards. As described below in this section, our sample period includes the global financial crisis with significant changes in oil prices and stock markets. The U.S. CPI deflator to deflate nominal prices of commodities and stocks is also available monthly. This makes us adopt the monthly frequency, which happens to be the frequency used by Kilian (2009), Kilian and Park (2009) and Kang et al. (2016).

The sources of all data are as follows. Brent and WTI oil prices, S&P 500 Composite and S&P 500 Energy indices, Chevron and Exxon Mobil stock prices and London Metal Exchange (LME) copper grade A prices are downloaded from *Datastream*. World oil production, U.S. total oil production and U.S. tight oil production are downloaded from the U.S. Energy Information Administration (EIA). U.S. non-tight oil production is calculated by subtracting U.S. tight oil production (originally available at the level of U.S. regions) from U.S. total oil production. One of the anonymous reviewers suggested that it should be interesting to add OPEC supply variables to see if our results and conclusions change. OPEC oil production and non-OPEC oil production are also downloaded from EIA. Fig. 1c presents movements of OPEC and non-OPEC (excluding U.S.) oil production. The U.S. CPI deflator is the consumer price index for all urban consumers, seasonally adjusted, downloaded from the Federal Reserve Economic Data (FRED) database. Kilian index is the updated and corrected version (Kilian, 2019) of the index of global real economic activity in industrial commodity markets proposed by Kilian (2009) and downloaded from the website of Dr. Lutz Kilian.

A comparison of returns of asset prices across subsamples is presented in Table 1. In the first subsample, the aggregate S&P 500 index is the only one with negative mean returns (−0.28 with standard deviation of 5.13). Commodity price returns are higher and with higher standard deviation than stock returns. Copper has higher mean returns (1.07) compared to oil (0.74 in Brent and 0.69 in WTI), but lower standard deviation (8.47 versus 11.45 in Brent and 11.09 in WTI). This pattern changes in the second subsample with downturns in commodities when copper prices have lower mean returns (−0.64) compared to oil (−0.40 in Brent and −0.43 in WTI) and lower standard deviation (5.95 versus 8.86 in Brent and 8.83 in WTI).

There are some very interesting observations in the correlation patterns in subsamples shown in Table 2. In the first subsample, correlation coefficients between copper and oil vary from 0.41 with Brent oil to 0.44 with WTI and between WTI and Brent oil is 0.94. In the second subsample, correlation coefficients between copper and oil vary from 0.24 with Brent oil to 0.28 with WTI, lower than in the earlier subsample. Correlation coefficients between copper and energy sector move, however, from 0.43 in the first subsample to 0.51 in the second subsample. The increase in correlation in the second subsample extends to all stock

Table 1
Descriptive statistics for the two subsamples.

	Mean	Median	Minimum	Maximum	Std. dev.	Sharpe ratio	Skewness	Kurtosis
Period from Feb 2000–Dec 2010 ($N = 131$)								
ret_Brent	0.74	2.65	−49.19	27.17	11.45	0.07	−1.05	5.82
ret_WTI	0.69	2.18	−51.51	25.47	11.09	0.06	−1.41	8.27
ret_copper	1.07	0.94	−39.47	22.83	8.47	0.13	−0.59	6.03
ret_S&P 500	−0.28	0.27	−16.58	14.51	5.13	−0.05	−0.58	4.28
ret_S&P 500 Energy	0.48	0.66	−20.60	12.28	6.37	0.08	−0.81	4.23
ret_CVN	0.40	0.46	−23.06	20.49	6.57	0.06	−0.34	4.61
ret_XOM	0.24	−0.06	−19.18	14.97	5.39	0.05	−0.46	4.29
Period from Jan 2011–Jul 2018 ($N = 91$)								
ret_Brent	−0.40	−0.21	−26.02	25.65	8.86	−0.04	−0.17	3.76
ret_WTI	−0.43	0.00	−25.73	18.23	8.83	−0.05	−0.44	3.12
ret_copper	−0.64	−0.28	−27.05	16.19	5.95	−0.11	−0.89	6.62
ret_S&P 500	0.73	1.51	−9.45	10.10	3.54	0.21	−0.60	4.10
ret_S&P 500 Energy	−0.04	0.29	−15.98	15.65	5.67	−0.01	−0.29	3.70
ret_CVN	0.20	0.62	−11.79	19.14	5.52	0.04	0.15	3.78
ret_XOM	−0.06	−0.03	−16.98	14.01	5.04	−0.01	−0.29	3.99

Notes: This table presents descriptive statistics for the monthly data used in this study for the two subsamples defined in the paper. All series in the table are in real terms: Brent and WTI oil price returns, copper price returns, S&P 500 and S&P Energy sector stock index returns, and Chevron (CVN) and Exxon Mobil (XOM) stock returns. That is, we deflate commodity prices, stock indices and stock prices (all measured in U.S. dollars) by the U.S. CPI index, and then take returns. Sharpe ratio measures the risk-adjusted performance of returns and is calculated by dividing the mean return by its associate standard deviation.

returns. The only other visible decline in correlation coefficients is between Brent and WTI oil from 0.94 to 0.87 across subsamples, which can be explained by the divergence in oil prices as already documented in Fig. 1. Additional correlation coefficients with Kilian index and others and those for the whole sample appeared in earlier versions of this paper.

As displayed in Fig. 2a correlation coefficients in Table 2 between aggregate stock market and WTI returns move from 0.14 to 0.33, together with an overall increase in correlation between energy stock returns and returns of commodities, moving from 0.37 in first subsample to 0.51 in the second subsample. Fig. 2b shows the same trends for oil company stock returns and oil: moving from 0.28 in the first subsample to 0.51 in the second subsample for Chevron, and moving from 0.18 in the first subsample to 0.37 in the second subsample for Exxon Mobil. This confirms that correlation coefficients between all stock market returns and oil price returns move up across subsamples. Fig. 2c displays the movement of stock returns for the aggregate market and energy sector, whose correlation increases from 0.68 to 0.75 with energy stock returns fluctuating more than the aggregate market. Fig. 3 shows the movements of WTI price returns and copper price returns in real terms, in which WTI price returns move more than copper.

Fig. 4 reports Kilian index in levels, constructed as growth of shipping rates of commodities (grain, oilseeds, coal, iron ore, fertilizer and scrap metal) by Kilian (2009) and updated and corrected by Kilian (2019). Fig. 4 shows an abrupt decline during the global financial crisis in 2008 and comparatively more fluctuations to the downside in the second subsample, especially after the late 2014 fall in oil prices. Fig. 5a shows the monthly changes in world (excluding U.S.) oil production. It is apparent that there are more substantial changes in the earlier part of the sample. Fig. 5b shows monthly changes in two types of U.S. oil production over time: non-tight and tight oil. Tight oil production is very stable in the first subsample and starts to outpace non-tight oil in the end of the second subsample. In the beginning of the second subsample when oil prices were around $ 100 a barrel, U.S. tight oil production was on a steady upward trend while non-tight oil fluctuated in many instances to the downside. Fig. 5c shows monthly changes in OPEC and non-OPEC (excluding U.S.) oil production over time.

How does some type of oil production respond to the other type of oil production? How does the stock market at different levels respond to tight oil production and to WTI oil prices? The subsequent sections provide some answers.

3. Methodologies: the SVAR models and copula modeling

Unrestricted VAR models of oil price shocks and stock returns include Cologni and Manera (2008), Park and Ratti (2008) and Cunado and Perez de Gracia (2014). We implement a structural VAR model following Kilian and Park (2009) and Kang et al. (2016), who extend the

Table 2
Correlation coefficients of asset prices in returns.

	ret_Brent	ret_WTI	ret_copper	ret_S&P 500	ret_S&P 500 Energy	ret_CVN	ret_XOM
Period from Feb 2000–Dec 2010 (N = 131)							
ret_Brent	1.00						
ret_WTI	0.94	1.00					
ret_copper	0.41	0.44	1.00				
ret_S&P 500	0.17	0.14	0.41	1.00			
ret_S&P 500 Energy	0.38	0.37	0.43	0.68	1.00		
ret_CVN	0.29	0.28	0.29	0.58	0.87	1.00	
ret_XOM	0.19	0.18	0.24	0.51	0.85	0.80	1.00
Period from Jan 2011–Jul 2018 (N = 91)							
ret_Brent	1.00						
ret_WTI	0.87	1.00					
ret_copper	0.24	0.28	1.00				
ret_S&P 500	0.31	0.33	0.48	1.00			
ret_S&P 500 Energy	0.43	0.50	0.51	0.75	1.00		
ret_CVN	0.44	0.51	0.42	0.68	0.88	1.00	
ret_XOM	0.32	0.37	0.33	0.68	0.83	0.78	1.00

Notes: This table presents correlation coefficients for the monthly data used in this study for the two subsamples defined in the paper. See Notes to Table 1 for more information.

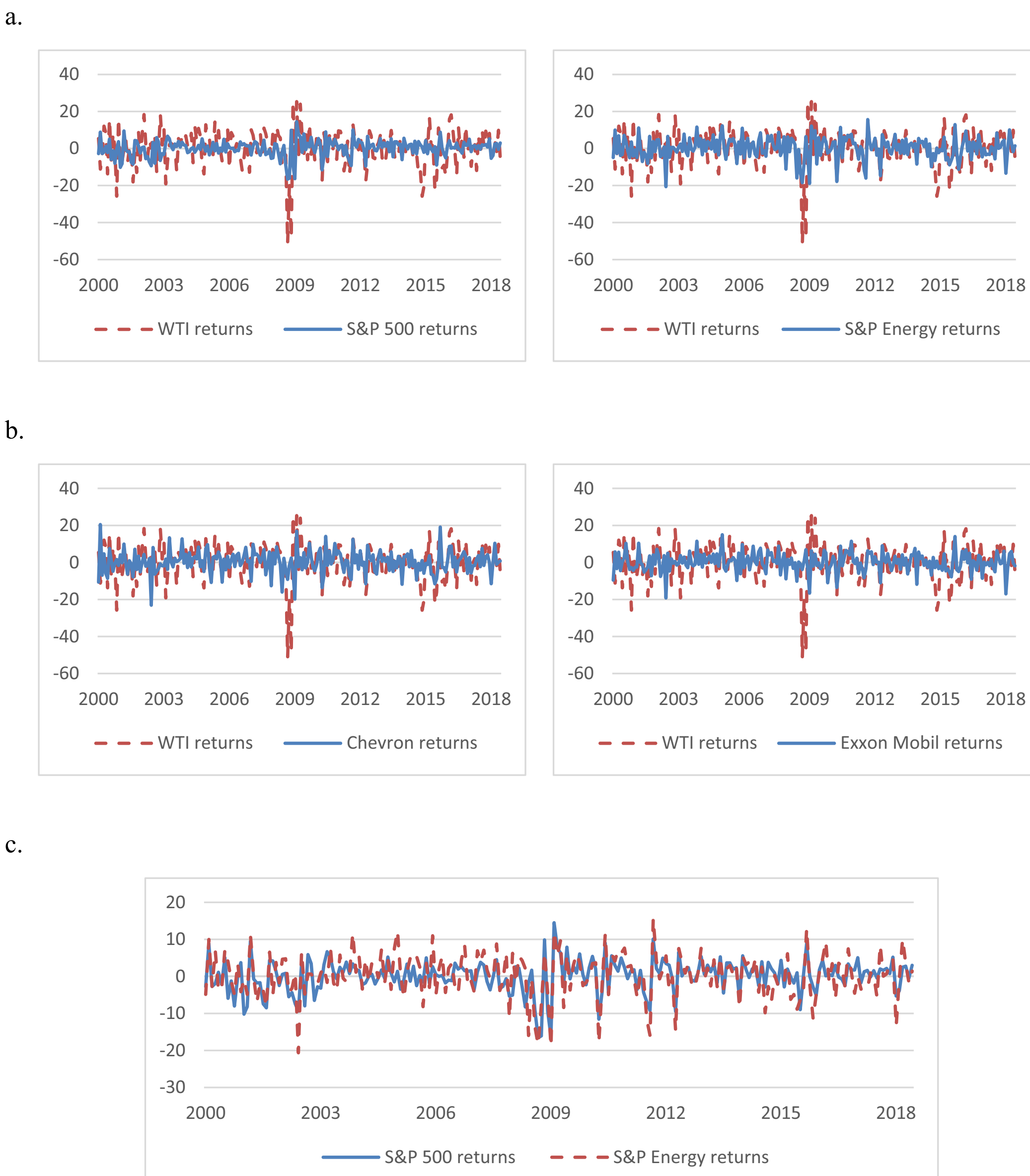

Fig. 2. a. Stock returns (S&P 500 and S&P Energy) and WTI returns. b. Stock returns (Chevron and Exxon Mobil) and WTI returns. c. Stock returns: S&P 500 and S&P Energy. Notes: Figs. 2a, 2b and 2c present movements between real stock index returns (S&P 500 and S&P Energy) and WTI real returns, individual companies' stock real returns (Chevron and Exxon Mobil) and WTI real returns, and S&P 500 and S&P Energy real returns, respectively.

original model by Kilian (2009) to stock returns. The framework herein has therefore supply decomposed into three types: world oil (excluding U.S.), conventional U.S. oil and non-conventional U.S. oil. We also look at real global demand in two ways: either by Kilian index or by another measure. Following Kilian and Park (2009) and Kang et al. (2016), supply and demand are followed in the vector by real WTI oil price returns and stock returns, which are in turn the aggregate market (S&P 500), the energy sector (S&P Energy) and two individual oil companies: Chevron and Exxon Mobil. The causal ordering with minimum identifying assumptions goes from supply (an exogenous factor

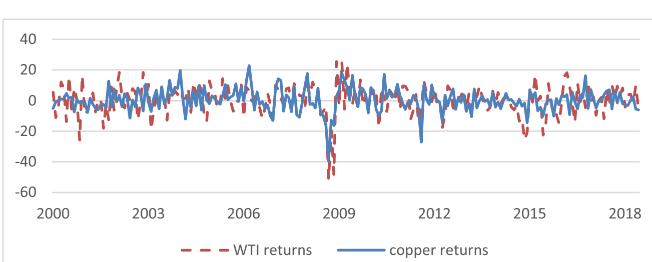

Fig. 3. Returns of real WTI versus real copper prices. Notes: This figure presents movements of WTI price returns and copper price returns in real terms.

Fig. 4. Kilian index. Notes: This figure presents how Kilian index evolves over time.

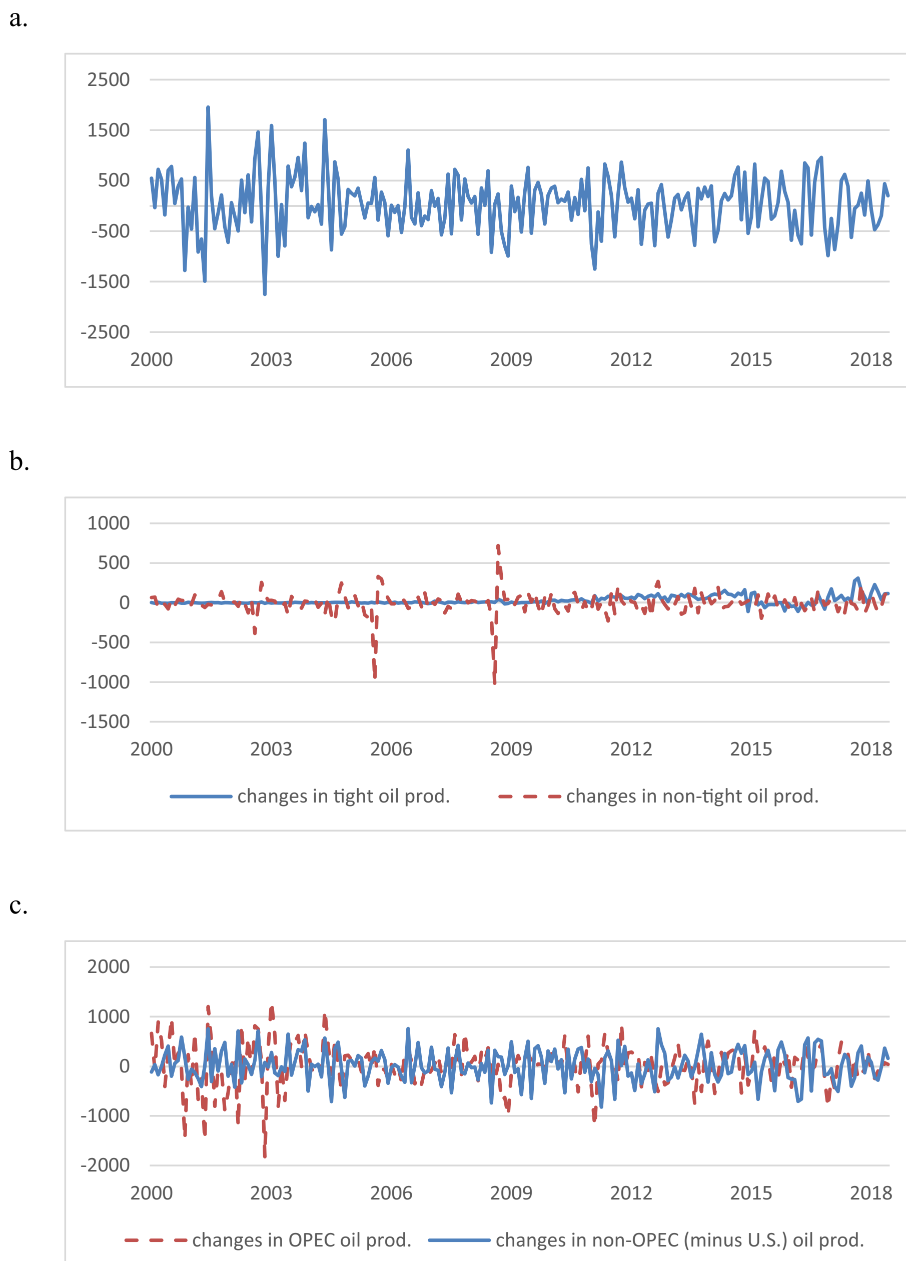

Fig. 5. a. Changes in world (excluding U.S.) oil production. b. Changes in U.S. oil production: non-tight and tight oil. c. Changes in OPEC and non-OPEC (excluding U.S.) oil production. Notes: Figs. 5a, 5b and 5c present movements of changes in world (excluding U.S.) oil production, U.S. types of oil production, and OPEC and non-OPEC (excluding U.S.) oil production, respectively.

determined by global oil supply, excluding U.S., followed by U.S. conventional oil and then U.S. tight oil) to demand (either by Kilian index with "commodity shipping" only or by copper price returns) and then to real oil price returns and stock returns.

The SVAR is written compactly by:

$$A_0 Z_t = c + \sum_i = 1^{12} A_i Z_t - i + \varepsilon_t. \tag{1}$$

In model (1), $Z_t = (\Delta S_{\text{world-U.S.}}, \Delta S_{\text{conventional}}, \Delta S_{\text{tight}}, \text{REA}, \text{ret\_WTI}, \text{ret\_r})$, where $\Delta S_{\text{world-U.S.}}$, $\Delta S_{\text{conventional}}$ and ΔS_{tight} denote the first difference in world oil supply (excluding U.S.), U.S. conventional oil supply and U.S. tight oil supply, respectively, REA is the world real economic activity (demand) Kilian index, ret_WTI represents returns of real WTI oil prices, and ret_r represents returns of real stock prices, for which we use in turn S&P 500, S&P Energy, Chevron and Exxon Mobil stock returns. Of the series in vector Z_t, REA is stationary in levels[2] since it is already in growth rate of shipment cargos and then detrended, and other series are also stationary in either first-differences (oil production) or in returns (commodity price returns and stock returns). We include 12 lags in the model following Hamilton and Herrera (2004) and Güntner and Linsbauer (2018), who recommend a sufficient number of lags to account for seasonality and for the usual lagged responses of macro variables to oil prices. Kilian and Park (2009) use 24 lags for a longer time span. We also test for serial correlation in the residuals using the likelihood ratio (LR) form of the Breusch-Godfrey Lagrange multiplier (LM) test with an Edgeworth expansion correction, under the null that

[2] A previous version of this paper had the VAR with REA in first-differences (ΔREA) and has been revised following suggestions from an anonymous reviewer.

there is no serial correlation.[3] In (1), c is a 6×1 vector of constant terms, A_o is a 6×6 matrix of unknown coefficients, and ε_t is a vector of errors with the white noise properties for orthogonal innovations. For the whole monthly period from January 2000 to July 2018 (as well as for the first subsample) we will follow the tradition in the literature to account for business cycles and include a dummy variable which takes value 1 for crisis months as identified by NBER, i.e., from March to November 2001 and from December 2007 to June 2009, and 0 otherwise.

Vector Z_t contains the three supply forces first in the causal ordering: world oil supply (excluding U.S.), followed by U.S. conventional oil and then U.S. tight oil. The three rows of supply are followed further by the demand: Kilian index or copper price returns as discussed below. The combination of supply and demand determine real oil price returns, which then affects stock returns: aggregate stock market (S&P 500), energy sector (S&P Energy) or one of the two oil companies Chevron and Exxon Mobil. The recursive assumptions on the shocks are used, following Kilian (2009), Kilian and Park (2009), Kang et al. (2016) and Güntner and Linsbauer (2018). It follows that U.S. tight oil responds to shocks in U.S. conventional oil but not vice versa. This block recursive structure for the identification strategy has the world oil market as contemporaneously predetermined with respect to other shocks. In the first row of the 6×6 matrix A_o, only shocks to the world supply curve affect world crude oil production contemporaneously. Being last, stock returns will respond to the three supply shocks, the demand shocks, the real oil price shocks and its own shocks. Variance decompositions are generated by factor decompositions using recursive factorization (A unit triangular and B diagonal), and impulse responses are associated with one-standard error innovation of the structural shocks with corresponding confidence bands computed using 5000 Monte Carlo replications.

A modification of (1), suggested by an anonymous reviewer, has vector Z_t decomposed further into four supply forces in the causal ordering: OPEC oil supply, non-OPEC oil supply (excluding U.S.), U.S. conventional oil supply and U.S. tight oil supply. In this modification, inspired by Ratti and Vespignani (2015) VAR with OPEC and non-OPEC oil production and the global economy, the four rows of oil supply are followed by the demand: Kilian index or copper price returns. Note that in their system U.S. oil production is not decomposed further, nor does it have real stock returns appearing last in the vector. Applying this suggestion into (1) will extend the VAR to 7 variables. The main changes in results will be discussed in Section 4.[4]

Scheitrum et al. (2018) explore the divergence between oil prices and conclude that the segmentation in the crude oil market is unlikely to reoccur. Performing a supremum Wald test for a structural break of WTI estimated on a constant and Brent, they report a breakpoint on January 6, 2011 which is consistent with other studies, such as Chen et al. (2015). We will adopt this breakpoint and examine two subsamples for our SVARs separately: one until the end of 2010 and the other from 2011 to 2018.[5] The second subperiod has substantial divergence in oil prices, which has coincided with the expansion of U.S. oil production, presumably because of tight oil and innovation in drilling techniques. When we estimate the first subsample we will follow the tradition to account for business cycles and include a dummy variable which takes value 1 for crisis months and 0 otherwise as defined above. The second subsample had subpar economic growth but no recessions as identified by NBER and therefore does not have the dummy variable as exogenous variables in the SVAR estimation.

Our SVAR identified above will help us determine a few important research questions. First, as outlined in Section 2, would the stock returns of U.S. major oil companies respond to increases in tight oil? And is there any significant increase in explaining the variance in U.S. stock markets by supply factors? Second, do U.S. stock market returns respond to innovations in tight or non-tight oil? Third, how do stock markets respond to positive shocks in real WTI price returns? One would expect the energy sector and individual companies to respond by more than the overall S&P 500 market, but by how much? Fourth, are the SVAR results sensitive to the use of alternative measures of demand (copper price returns) instead of the widely adopted global index of commodities (Kilian index)? We verify for that matter an alternative SVAR model with real copper price returns instead of Kilian index and comment on the main changes.[6]

In copula modeling, for each pair of variables that we are interested in, we first select from a pool of forty copulas based on AIC and then apply a formal goodness-of-fit test, i.e., the White test proposed by Huang and Prokhorov (2014) or the Kendall test investigated by Genest and Rivest (1993) and Wang and Wells (2000), considering that both tests are subject to some restriction(s).[7] If a copula selected by AIC does not pass an appropriate goodness-of-fit test, we select again among all available copulas using the criteria of Vuong (1989) and Clarke (2007). Our copula modeling will help us identify lower and upper tail dependences, i.e., the dependence during downturns and upturns.

Suppose X and Y are different continuous random variables representing the global demand, real crude oil price returns or stock returns. Let F and G be their cdf's, respectively. The lower (upper) tail dependence λ_L (λ_U) is the limit (if it exists) of the conditional probability that Y is less than or equal to (greater than) the 100t-th percentile of G given that X is less than or equal to (greater than) the 100t-th percentile of F as t approaches 0 (1). That is,

$$\lambda_L = \lim_{t \to 0^+} \Pr\left[Y \le G^{(-1)}(t) | X \le F^{(-1)}(t)\right], \tag{2}$$

$$\lambda_U = \lim_{t \to 1^-} \Pr\left[Y N G^{(-1)}(t) | X N F^{(-1)}(t)\right]. \tag{3}$$

It can be shown (see, e.g., Nelsen, 2006) that Eqs. (2) and (3) can be re-

[3] An anonymous reviewer suggested we not only refer to the literature but also use our own dataset to decide on lag-length. Following this suggestion, we also checked AIC and SIC for the VAR system in selecting lag-lengths. For the VAR with S&P 500 for the second subsample, AIC suggested 12 lags, and SIC suggested 1 lag. Implementing residual serial correlation LM tests, we do not encounter problems for either 1 lag or 12 lags for the second subsample. However, for the first subsample AIC suggested 4 lags, and SIC suggested 1 lag. When we use the longer lag length of 12 for the first subsample we do not reject the null, which makes us prefer using the VARs with longer 12 lags in both subsamples. Diagnostics for residual serial correlation LM tests are included in Tables 3 and 4 below.

[4] Since we have now a 7-variable VAR system, we revise the long lag approach with 12 lags. Based on AIC and SIC, together with residual LM tests, we select 6 lags except for Exxon Mobil, in which case 3 lags are used.

[5] Our analysis in this paper is from the viewpoint of returns of assets (commodity and stock market returns), together with monthly changes in economic conditions (the three supply factors). This is because SVAR models require that all variables in the system should be stationary. If we implement formal sequential breakpoint tests on returns of WTI against returns of Brent, there are no identified breaks. For this reason, we take the breakpoint as identified by as Chen et al. (2015) and Scheitrum et al. (2018) on the two series of oil prices in levels.

[6] The robustness check with copper price returns instead of Kilian index is simpler to implement due to both the nature of the recursive factorization and for computational reasons. In OLS regressions, Bernanke (2016) and Prest (2018) use three factors when explaining changes in oil prices: copper prices, U.S. yields and the value of the U.S. dollar. Employing these three factors in the VAR framework is not straightforward due to extending too much the dimension of the vector, which may violate the recursive orderings or cause computational problems. In principle, one should use copper prices before U.S. interest rates (or the change in the yield curve, Δyield) in Z_t since commodity prices may induce inflation and thus affect fixed income securities. However, using both series in the vector (instead of Kilian index, REA) would lead to a 7-variable SVAR instead of the 6-variable SVAR above. Another possibility is to use copper prices together with a trade-weighted index of the U.S. dollar against broad or major currencies, in which case the value of the USD should precede copper given that commodities are denominated in U.S. dollars. Using only changes in yield instead of Kilian index leads to – in some cases – first or second order conditions not being met.

[7] Both the White and Kendall tests are subject to some restriction(s). For example, the Kendall test does not apply to Student t copula and its code running for some copula(s) is time-consuming, while the White test does not apply to BB copulas. Therefore, we apply the White test for Student t copula and Kendall test for BB copulas. For other copulas, we apply both the White and Kendall tests to make sure that our selected copulas pass both tests.

written, respectively, as

$$\lambda_L = \lim_{t} \rightarrow 0^{+} \frac{C(t,t)}{t}, \tag{4}$$

$$\lambda_U = \lim_{t} \rightarrow 1^{-} \frac{1-2t+C(t,t)}{1-t}, \tag{5}$$

where C is the copula of X and Y. Eqs. (4) and (5) suggest that tail dependence can be determined by copula only. Therefore, we are able to calculate tail dependence for each copula selected.

4. Results

For illustrative purposes, we replicate the SVAR in (1) with supply factors aggregated as one, i.e., combining world (excluding U.S.) oil production and both U.S. non-tight and tight oil production, as in Kilian (2009) and Kilian and Park (2009). The results of the baseline SVAR with one aggregate world oil supply are available upon request. Among the results, for the S&P 500 supply factors explain 14.30% (insignificant) of the variance in stock returns after 24 months in the first subsample and 21.19% (significant) in the second subsample. Kilian index and real oil prices explain considerably less, and shocks to real stock returns explain about 65.44% of the variance in stock returns in the first subsample and 55.58% in the second subsample after 24 months. For comparison, Kilian and Park (2009, p. 1274) use value weighted market portfolio from CRSP from 1973 to 2006 and find that "oil supply shocks only account for about 6% of the variability of returns." For two types of oil supply - world and U.S. - Kang et al. (2016) report about 10% of value weighted market portfolio from CRSP at 24-month horizon from 1973 to 2014.

Table 3 presents forecast error variance decompositions of the four stock returns (S&P 500, S&P Energy, Chevron and Exxon Mobil) to the structural shocks identified with factorizations applied to (1). We report in Table 3 the variance decomposition at 1-month and 24-month forecast horizons. We highlight in bold and with "*" the statistically significant variance decompositions at 5% significance level with standard errors calculated using 5000 Monte Carlo replications. In the first subsample, shocks to non-tight oil, shock 2 (to $\Delta S_{\text{conventional}}$) explain – after 24 months – 13.74% and 20.40% of the variance in S&P 500 and S&P Energy stock returns, respectively. For individual companies, these shocks explain 16.67% of the variance in Chevron stock returns (not statistically significant) and 19.60% for Exxon Mobil. Meanwhile, shocks to tight oil in (shock 3) explain 11.44% and 12.68% of the variance in the aggregate market and energy sector, respectively, and from 10.33% to 11.23% in company stock returns. In all cases, for the earlier subsample none of the responses to innovations in tight oil supply are statistically significant. Shocks to real WTI returns explain from 15.57% of the variance in the energy sector stock returns after 1 month to 13.31% after 24 months of the shock. In S&P 500, Chevron and Exxon Mobil shocks to real economic activity explain from 10.21% to 13.09% of the variance in stock returns after 24 months but these are not statistically significant. Interestingly, the amount of real stock returns explained by its own shocks after 24 months range between 41.60% (in S&P Energy) to 50.65% (in Chevron), with aggregate market and Exxon Mobil in between, suggesting strong self-dependence in the stock market at all levels during the first subsample.

In the second subsample, after 24 months, shocks to tight oil (shock 3) explain a larger amount (29.42%) of the variance in S&P 500 stock returns, followed by the energy sector (30.80%) and individual oil companies (between 27.78% and 29.15%). Also, shocks to WTI oil price returns explain a little over one quarter of the variance in returns of S&P Energy (about 28.33%), Chevron (24.76%) and Exxon Mobil (18.23%), but insignificant in the aggregate market. Overall, after 24 months in the second subsample a much smaller fraction of variance in stock returns are explained by their own shocks, indicating that stock returns do not have much interpretation of their own. What follows from Table 3 is that tight oil supply consideration becomes more important than conventional oil in the second subsample, not only for individual oil companies but also for the aggregate market and energy sector. In all four cases, innovations in tight oil are statistically significant after 2 years of the shock! We also note an increase in explaining the variance of stock returns by WTI price returns, reaching around 28.33% in the case of energy sector - after 24 months - or close to 25% for Chevron.

Table 3
Forecast error variance decompositions of SVAR for U.S. stock returns using Kilian Index.

VDs across months ↓	Innovations in supply					
	Shocks in $\Delta S_{\text{world-U.S.}}$	Shocks in $\Delta S_{\text{conventional}}$	Shocks in ΔS_{tight}	Shocks in REA	Shocks in ret_WTI	Shocks in ret_r
Period from Feb 2000–Dec 2010 with recessions dummy						
ret_S&P 500						
1	1.87	0.82 (1.94)	2.18	0.10	5.74	**89.29***
	(2.72)		(2.83)	(1.21)	(3.98)	(**5.59**)
24	7.69	**13.74***	11.44	8.05	13.09	**46.00***
	(7.48)	(**6.68**)	(6.77)	(6.92)	(6.90)	(**9.37**)
LM = **37.79*[0.39]**						
ret_S&P Energy						
1	0.22	0.01 (1.20)	0.91	0.41	**15.57***	**82.88***
	(1.47)		(2.02)	(1.59)	(**5.86**)	(**6.39**)
24	5.89	**20.40***	11.68	7.12	**13.31***	**41.60***
	(7.74)	(**8.94**)	(8.54)	(6.51)	(**6.53**)	(**10.73**)
LM = **23.79*[0.94]**						
ret_CVN						
1	0.20	1.44 (2.41)	0.00	1.51	8.51	**88.34***
	(1.43)		(1.20)	(2.36)	(4.76)	(**5.70**)
24	5.20	16.67 (8.60)	11.23	6.04	10.21	**50.65***
	(7.46)		(8.10)	(6.35)	(6.52)	(**9.31**)
LM = **29.07*[0.79]**						
ret_XOM						
1	0.55	1.27 (2.30)	0.22	0.79	4.55	**92.62***
	(1.83)		(1.44)	(1.89)	(3.55)	(**4.89**)
24	5.43	**19.60***	10.33	11.27	11.40	**41.97***
	(7.38)	(**8.96**)	(9.32)	(7.06)	(6.63)	(**7.84**)
LM = **22.02*[0.97]**						
Period from Jan 2011–Jul 2018						
ret_S&P 500						
1	5.39	**19.69***	**17.40***	5.61	**13.46***	**38.46***
	(4.74)	(**7.34**)	(**6.17**)	(3.56)	(**4.70**)	(**6.25**)
24	13.72	14.76	**29.42***	13.92	10.94	**17.25***
	(12.60)	(14.80)	(**11.20**)	(9.40)	(8.17)	(**8.09**)
LM = **29.64*[0.76]**						
ret_S&P Energy						
1	0.19	0.11 (1.68)	3.78	0.04	**67.12***	**28.75***
	(1.85)		(3.97)	(1.52)	(**6.14**)	(**4.98**)
24	9.78	12.00	**30.80***	7.27	**28.33***	11.81
	(11.67)	(13.08)	(**12.47**)	(8.45)	(**11.93**)	(8.53)
LM = **37.74*[0.39]**						
ret_CVN						
1	3.67	1.22 (2.61)	0.28	0.09	**59.21***	**35.53***
	(4.12)		(1.77)	(1.52)	(**6.67**)	(**5.74**)
24	13.95	16.40	**29.15***	4.94	**24.76***	10.80
	(11.84)	(13.34)	(**12.91**)	(7.32)	(**11.60**)	(8.07)
LM = **37.82*[0.39]**						
ret_XOM						
1	7.41	0.45 (2.01)	9.16	0.40	**31.1***	**51.49***
	(5.36)		(5.49)	(1.66)	(**7.25**)	(**7.24**)
24	13.50	11.66 (9.04)	**27.78***	10.23	**18.23***	18.59
	(11.12)		(**11.13**)	(10.14)	(**9.25**)	(9.57)
LM = **40.85* [0.27]**						

Notes: This table reports the variance decompositions associated with SVAR models with structural factorization using Monte Carlo 5000 replications, with standard errors in parentheses. Numbers of lag-length used in these VAR models are 12, except for Exxon Mobil (XOM) in the second subsample when 11 lags were used. VAR residual serial correlation LM tests are applied, and the testing results show that we fail to reject the null of no serial correlation at any lags. We report in this table only the test statistics at lag 12 with corresponding p-values in square brackets. Statistical significance at the 5% level is highlighted in bold and marked with *.

These results are preserved in our robustness check using real copper price returns instead of Kilian index. As shown in Table 4, in the second subsample after 24 months, shocks to tight oil (shock 3) explain up to 39.41% of the variance in S&P 500 stock returns, followed by 33.41% in the energy sector and a little less in Exxon Mobil around 30.46%. Similar amount for Chevron returns is 27.88%. Shocks to WTI oil price returns (shock 5), however, explain 12.42% of the variance in stock returns only for the energy sector in the first month, and insignificant for others. Compared to the earlier subsample in Table 4, there are visible increases as shocks to copper price returns explain more of the variance in stock returns than Kilian index earlier at least on impact (in one month): 23.50% for S&P 500, 48.80% for S&P Energy, 57.70% for Chevron and 39.56% for Exxon Mobil. In Table 4, tight oil supply consideration continues to become more important than conventional oil in the second subsample, not only for individual oil companies but also for the aggregate stock market (39.41% of the variance) and energy sector stock market (33.41%). We find that shocks to copper price returns have larger effects on oil company stock returns than Kilian index, while the role of shocks to WTI is reduced in the second subsample.

We turn next to selected SVAR impulse responses associated with one-standard error innovation of the shocks with the corresponding confidence bands generated by 5000 Monte Carlo replications. We are particularly interested in how tight oil responds to other types of oil supply and also how stock returns respond to shocks in tight oil and in oil price returns. For S&P stock returns, we find in Fig. 6 - for the second subsample - at month 1 a positive and statistically significant response of changes in tight oil to one-standard deviation structural shock to world (excluding U.S.) oil production (shock 1): in response to unexpected structural innovations to world (excluding U.S.) oil supply, U.S. tight oil produces more oil. The response of changes in tight oil to non-tight U.S. oil production is not statistically significant for the aggregate stock market and is not shown in Fig. 6. Also shown in Fig. 6 is a negative and statistically significant response of the aggregate market (−1.33 with standard deviation of 0.28) to unexpected disruptions in U.S. tight oil production (shock 3): as disruptions to U.S. tight oil increase, the aggregate stock market falls which is consistent with responses along the lines of Kang et al. (2016). It is interesting to note that, while the response of the aggregate stock market to shocks in U.S. tight oil production is *negative* and significant, its response to shocks in U.S. non-tight oil production is *positive* and significant (1.42 with standard deviation of 0.31). Kang et al. (2016, p. 178) find negative response of stock returns to shocks in U.S. oil production. In this paper, by decomposing U.S. oil production further into non-tight and tight oil production, we find that this negative response can be attributed to tight oil. Also statistically significant in the second subsample is the positive response of the aggregate market to shocks to oil price returns (shock 5) at the bottom chart: 1.17 (standard deviation of 0.22).

Fig. 7 reports – also for the second subsample – responses of energy sector stock returns to two shocks, preceded by the response of changes in U.S. tight oil to a one-standard deviation structural shock in world (excluding U.S.) oil production at month 1 as positive and statistically significant response of 23.55 (standard deviation of 7.44). We interpret Fig. 7 as follows. As disruptions to world supply increase, U.S. tight oil production increases significantly on impact, therefore supplying the

Table 4
Forecast error variance decompositions of SVAR for U.S. stock returns using real copper price returns.

VDs across months ↓	Innovations in supply					
	Shocks in $\Delta S_{\text{world-U.S.}}$	Shocks in $\Delta S_{\text{conventional}}$	Shocks in ΔS_{tight}	Shocks in ret_copper	Shocks in ret_WTI	Shocks in ret_r
Period from Feb 2000–Dec 2010 with recessions dummy						
ret_S&P 500						
1	0.00 (1.23)	0.67 (1.81)	9.52 (5.00)	1.85 (2.39)	**13.55***(**5.38**)	**74.41***(**6.80**)
24	10.46 (7.70)	**15.5*** (**8.02**)	**15.10***(**7.04**)	9.83 (7.62)	**11.78***(**5.88**)	**37.27***(**7.22**)
LM = **44.13*[0.17]**						
ret_S&P Energy						
1	0.26 (1.45)	0.98 (2.07)	4.06 (3.51)	**16.80***(**5.91**)	7.96 (4.16)	**69.94***(**6.91**)
24	7.12 (6.84)	**22.52***(**7.51**)	11.63 (7.32)	**14.59***(**6.68**)	9.74 (5.61)	**34.42***(**7.48**)
LM = **43.75*[0.18]**						
ret_CVN						
1	0.01 (1.25)	1.25 (2.30)	1.20 (2.24)	**12.01***(**5.34**)	5.19 (3.57)	**80.34***(**6.44**)
24	5.58 (7.10)	**18.55***(**7.63**)	11.15 (7.13)	12.46 (6.52)	9.03 (5.57)	**43.23***(**7.48**)
LM = **41.51*[0.24]**						
ret_XOM						
1	0.35 (1.58)	0.08 (1.25)	0.02 (1.16)	3.01 (3.12)	0.14 (1.28)	**96.40***(**3.93**)
24	7.55 (6.73)	**18.12***(**7.52**)	12.14 (7.29)	9.27 (6.01)	7.43 (5.07)	**45.49***(**7.70**)
LM = **40.11*[0.29]**						
Period from Jan 2011–Jul 2018						
ret_S&P 500						
1	**14.29***(**6.69**)	**14.74*** (**6.41**)	3.99 (3.51)	**23.50*** (**6.44**)	0.42 (1.14)	**43.00***(**6.51**)
24	21.50 (12.35)	7.88 (9.72)	**39.41***(**13.36**)	10.43 (10.51)	5.84 (8.77)	14.94 (10.63)
LM = **37.98*[0.38]**						
ret_S&P Energy						
1	0.66 (2.39)	2.10 (3.24)	4.80 (4.30)	**48.80***(**7.41**)	**12.42***(**4.35**)	**31.22***(**5.39**)
24	9.26 (11.27)	11.21 (12.36)	**33.41***(**13.67**)	15.01 (10.72)	11.75 (8.48)	19.36 (12.40)
LM = **40.74*[0.27]**						
ret_CVN						
1	6.88 (5.20)	3.75 (3.93)	3.58 (3.69)	**57.70*** (**7.09**)	3.05 (1.94)	**25.03***(**4.46**)
24	18.66 (12.46)	11.77 (11.96)	**30.46***(**13.94**)	20.69 (11.45)	6.52 (8.53)	11.90 (8.31)
LM = **45.27*[0.14]**						
ret_XOM						
1	0.02 (1.62)	0.00 (1.59)	1.84 (3.07)	**39.56***(**7.66**)	0.01 (0.90)	**58.57***(**7.58**)
24LM = **39.01*[0.34]**	17.25 (11.79)	5.74 (11.56)	**27.88***(**12.26**)	20.90 (11.69)	6.36 (9.22)	21.87 (11.73)

Notes: This table reports the variance decompositions associated with SVAR models with structural factorization using Monte Carlo 5000 replications, with standard errors in parentheses. Numbers of lag-length used in these VAR models are 12, except for Exxon Mobil (XOM) in the second subsample when 11 lags were used. VAR residual serial correlation LM tests are applied, and the testing results show that we fail to reject the null of no serial correlation at any lags. We report in this table only the test statistics at lag 12 with corresponding *p*-values in xsquare brackets. Statistical significance at the 5% level is highlighted in bold and marked with *.

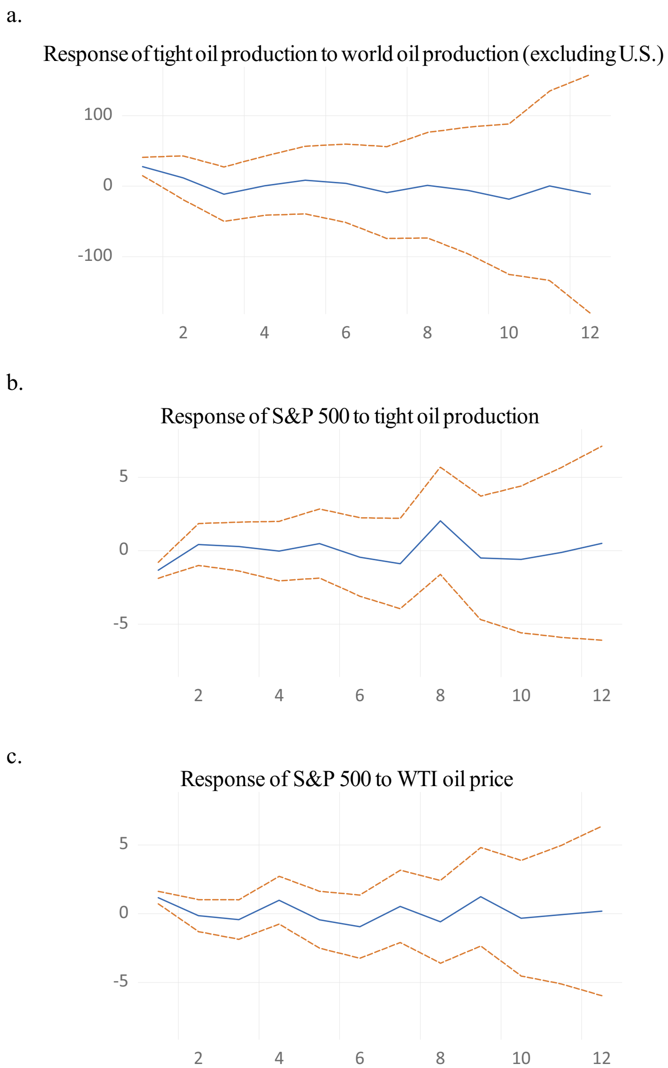

Fig. 6. Impulse responses of SVAR with real S&P 500 returns: the second subsample. Notes: This figure presents the impulse responses, with plus/minus two standard error bands, of SVAR with real S&P 500 returns in the second subsample for structural factorization with 5000 Monte Carlo replications. The first graph shows responses of changes in U.S. tight oil production to shocks in changes in world oil production (excluding U.S.), and the second and third show responses of S&P 500 stock returns to shocks in changes in U.S. tight oil production and to shocks in real WTI oil price returns, respectively.

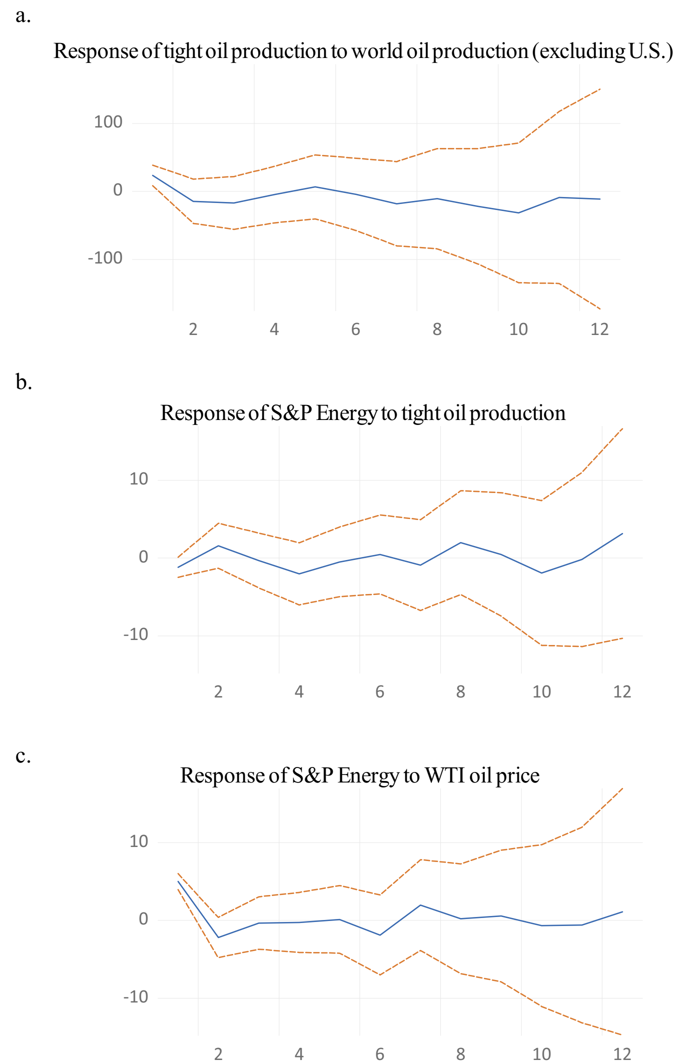

Fig. 7. Impulse responses of SVAR with real S&P Energy stock returns: the second subsample. Notes: This figure presents the impulse responses, with plus/minus two standard error bands, of SVAR with real S&P Energy stock returns in the second subsample for structural factorization 5000 Monte Carlo replications. The first graph shows responses of changes in U.S. tight oil production to shocks in changes in world oil production (excluding U.S.), and the second and third show responses of S&P Energy stock returns to shocks in changes in U.S. tight oil production and to shocks in real WTI oil price returns, respectively.

unavailable oil. There is also a negative but close to not statistically significant response of the energy sector −1.18 (standard deviation of 0.62) to one-standard deviation structural shock to U.S. tight oil production. However, the response of the energy sector to real WTI returns is larger than the S&P 500 aggregate market in the bottom chart of Fig. 7: as shocks to U.S. real WTI increase, so does the energy stock market on impact in the bottom chart of Fig. 7: 4.99 (standard deviation of 0.50).

Figs. 8 and 9 report the impulse responses for the SVARs of the two oil companies. The graphs of tight oil responding to world oil production (excluding U.S.) are not displayed since changes in U.S. tight oil are measured for the whole U.S. economy (and also for the Energy sector), already shown in Figs. 6 and 7, and we do not have company specific amounts of change in tight oil. Interestingly, in Figs. 8 and 9, Chevron and Exxon Mobil stock returns respond differently to increases in U.S. tight oil production (shock 3): there are large standard errors for Chevron with its −0.29 point estimate (standard deviation of 0.58) and declines for Exxon Mobil (as in the energy sector) with point estimate of −1.57 (standard deviation of 0.52). Recall from Table 1 that, in the second subsample, mean returns are negative for Exxon Mobil (−0.06) and positive for Chevron (0.20). However, the responses of the stock returns of both companies to real WTI returns are much larger than the S&P 500 aggregate market: as shocks to U.S. real WTI increase, so do the stock returns of oil companies on impact: 4.31 (standard deviation of 0.47) for Chevron and 2.89 (standard deviation of 0.45) for Exxon Mobil.

For the SVAR model with copper prices (instead of Kilian index), the impulse responses are not reported for space constraints and are found to respond in the same way in the aggregate market and energy sector. For Chevron, the negative point estimate of the impulse response becomes marginally significant (−1.15 with standard error of 0.60) and for Exxon Mobil it becomes insignificant, which means that both companies continue to have their stock returns responding differently to innovations in tight oil production.

As noted in Section 3, we modify (1) by decomposing world (excluding U.S.) oil production further into OPEC and non-OPEC oil production, following Ratti and Vespignani (2015) who estimate SVAR with OPEC and non-OPEC oil production, global GDP in U.S. dollars and real oil

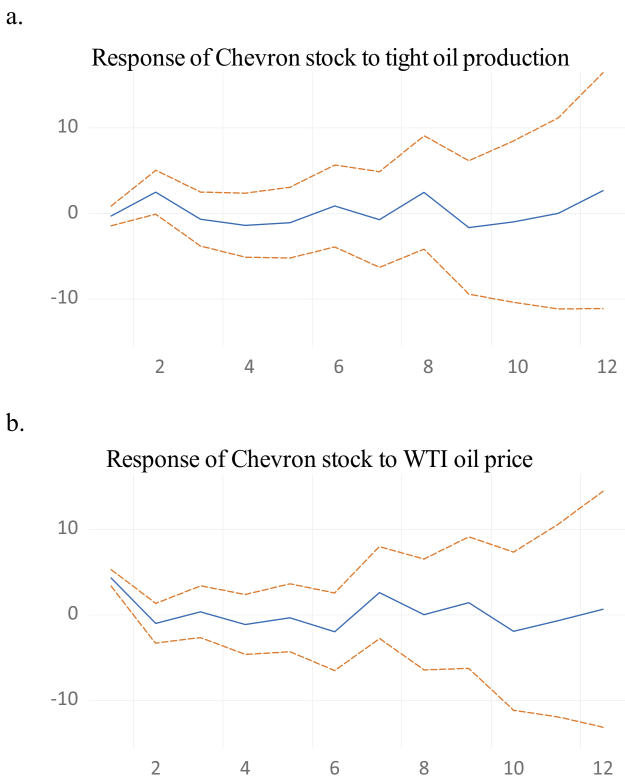

Fig. 8. Impulse responses of SVAR with real Chevron stock returns: the second subsample. Notes: This figure presents the impulse responses, with plus/minus two standard error bands, of SVAR with real Chevron stock returns in the second subsample for structural factorization with 5000 Monte Carlo replications. The first and second graphs show responses of Chevron stock returns to shocks in changes in U.S. tight oil production and to shocks in real WTI oil price returns, respectively.

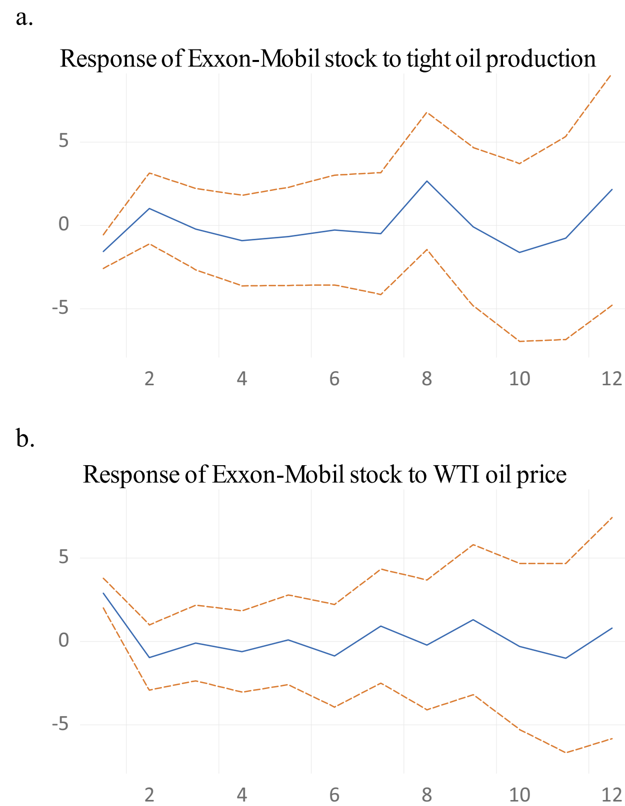

Fig. 9. Impulse responses of SVAR with real Exxon Mobil stock returns: the second subsample. Notes: This figure presents the impulse responses, with plus/minus two standard error bands, of SVAR with real Exxon Mobil stock returns in the second subsample for structural factorization with 5000 Monte Carlo replications. The first and second graphs show responses of Exxon Mobil stock returns to shocks in changes in U.S. tight oil production and to shocks in real WTI oil price returns, respectively.

prices (4-variable SVAR). Based on AIC, SIC and residual serial correlation tests, we report SVARs with 6 lags for the stock returns of the aggregate market, energy sector and Chevron, and 3 lags for Exxon Mobil. The results reveal that impulse response functions obtained by structural factorization do not show statistically significant responses of changes in tight oil to shocks in OPEC production, non-OPEC production and U.S. non-tight oil production. Real stock returns (in S&P 500 and Chevron cases) have no statistically significant responses to innovations in U.S. tight oil, but S&P Energy sector (marginally significant) and Exxon Mobil (estimate at −1.36 with standard error of 0.49) continue to show negative impulse responses. This decomposition of world oil suggests that the changes in U.S. tight oil do not respond to any structural innovations in supply.[8] Responses of energy sector or company stock returns to real WTI returns are larger than the S&P 500 aggregate market: as shocks to real WTI increase, so do stock returns of oil companies on impact: 3.25 (standard deviation of 0.51) for Chevron; 1.92 (standard deviation of 0.46) for Exxon Mobil; 3.20 (standard deviation of 0.56) for S&P Energy sector; versus 1.17 (standard deviation of 0.34) for S&P 500.

Corresponding to Tables 3 and 4, Tables 5 and 6 report the copula modeling results for real asset price returns. The copula families selected are reported in Table 5, with the *p*-values of a goodness-of-fit test for copulas in parentheses. The results indicate that all *p*-values are larger than 5%, suggesting that the selected copula families are appropriate. Our purpose of copula modeling is to uncover the tail dependences. Therefore, from the copula families selected, we further examine the corresponding tail dependences which are presented in Table 6. We find that, during downturns, copper price returns and all stock returns depend on each other significantly for both subsamples. In the second subsample, WTI oil price returns and Exxon Mobil stock returns depend on each other significantly during the downturns. We also find significant dependences in the second subsample between Brent oil price returns and Exxon Mobil as well as the aggregate stock returns during downturns, and between Brent oil price returns and Chevron stock returns during upturns. The energy sector is leading the fluctuations of the aggregate stock market during downturns for both subsamples (lower tail dependences of 0.48 and 0.55, respectively). Chevron is leading the aggregate stock market in both downturns and upturns for the first subsample but only in downturns for the second subsample, and it is leading the energy sector in both downturns and upturns for the second subsample. Exxon Mobil is leading the fluctuation of the whole market during downturns and leading the energy sector during both downturns and upturns in the first subsample. In addition, Exxon Mobil and Chevron comove during both downturns and upturns for the first subsample, but only during downturns in the second subsample. Overall, the level of tail dependence varies but is generally higher in the second subsample for copper and stock returns and also for oil and stock returns.

5. Concluding remarks

A growing literature, including Kolodziej et al. (2014), Adams and Glück (2015) and Chen et al. (2017), links the co-movements of commodities and equities spurred by investors' decisions to hold assets and take risks. This paper investigates tight oil production with risk-

[8] Recall that in our benchmark 6-variable SVAR model (1), responses of changes in tight oil to innovations in world oil production (excluding U.S.), which in that case represent both OPEC and non-OPEC, are estimated to be always positive: increases in tight oil production in response to positive innovations to world oil production.

Table 5
Copula families selected for returns of real asset prices.

	Shocks in ret_WTI	Shocks in ret_Brent	Shocks in ret_copper	Shocks in ret_S&P 500	Shocks in ret_S&P Energy	Shocks in ret_CVN	Shocks in ret_XOM
Period from Feb 2000–Dec 2010							
ret_S&P 500	**Independence*** (**0.65**)	**Independence*** (**0.77**)	**SBB7 *** (**0.25**)	–	**SGumbel*** (**0.72**)	**BB7*** (**0.74**)	**SGumbel*** (**0.66**)
ret_S&P Energy	**Gaussian*** (**0.71**)	**Gaussian*** (**0.67**)	**SGumbel*** (**0.42**)	**SGumbel*** (**0.72**)	–	**Gaussian*** (**0.40**)	**Student *t**** (**0.17**)
ret_CVN	**Frank*** (**0.43**)	**Frank*** (**0.12**)	**SGumbel*** (**0.64**)	**BB7*** (**0.74**)	**Gaussian*** (**0.40**)	–	**BB1*** (**0.26**)
ret_XOM	**Gaussian*** (**0.89**)	**Frank*** (**0.22**)	**SGumbel*** (**0.90**)	**SGumbel*** (**0.66**)	**Student *t**** (**0.17**)	**BB1*** (**0.26**)	–
Period from Jan 2011–Jul 2018							
ret_S&P 500	**Gaussian*** (**0.84**)	**SGumbel*** (**0.62**)	**Clayton*** (**0.44**)	–	**SGumbel*** (**0.71**)	**Clayton*** (**0.70**)	**SBB8*** (**0.62**)
ret_S&P Energy	**Gaussian*** (**0.92**)	**Gaussian*** (**0.84**)	**Clayton*** (**0.44**)	**SGumbel*** (**0.71**)	–	**SBB7*** (**0.12**)	**Frank*** (**0.76**)
ret_CVN	**Gaussian*** (**0.53**)	**Gumbel*** (**0.26**)	**Clayton*** (**0.35**)	**Clayton*** (**0.70**)	**SBB7*** (**0.12**)	–	**SGumbel*** (**0.59**)
ret_XOM	**SGumbel*** (**0.68**)	**SJoe*** (**0.17**)	**SGumbel*** (**0.83**)	**SBB8*** (**0.62**)	**Frank*** (**0.76**)	**SGumbel*** (**0.59**)	–

Notes: This table reports the copula families selected with the *p*-values of a goodness-of-fit test for copulas in parentheses. Statistical significance at the 5% level is highlighted in bold and marked with *.

taking decisions by firms operating new drilling technologies. Are these decisions rewarded in the market? Does innovation in drilling techniques in the U.S. (tight oil) complement conventional forms of oil production: U.S. non-tight oil and non-U.S. oil production? The figures show that tight oil has increased substantially in recent years with effects on stock returns, matching evidence (The Wall Street Journal, 2018b) that "… global oil companies including Exxon, Chevron, BP PLC, Royal Dutch Shell PLC, Occidental Petroleum Corp. and ConocoPhillips made almost $5 billion in the quarter from their North American drilling units, up from a $373 million loss …" Investment in new technologies of oil drilling is rewarded in the stock market within the month.

Our paper quantifies this proposition using SVARs based on Kilian and Park (2009) and its recent extensions by Chen et al. (2016a, 2016b), Kang et al. (2016, 2017) and Güntner and Linsbauer (2018). Our major results can be summarized as follows. For the variance decomposition of stock returns of the aggregate market (S&P 500), the energy sector (S&P Energy) and two individual U.S. oil companies (Chevron and Exxon Mobil), supply considerations (especially due to tight oil) become more important in the second subsample, no matter which measure to use for the demand (Kilian index or copper). Supply shocks associated with tight oil production explain - after 24 months - between 27.78% and 30.80% of stock returns compared to lower and always insignificant explanations in the first subsample for the benchmark model with Kilian index. Figures of stock returns explained by shocks in tight oil for the SVAR with copper prices are between 27.88% and 39.41% in the second subsample versus 15.10% for S&P only in the first subsample. On the impulse responses, we find that changes in tight oil production respond meaningfully to disruptions in oil production: innovations to world oil production lead to more tight oil production in the U.S. We also find negative responses of stock returns to disruptions in U.S. tight oil production, but positive responses to shocks in U.S. non-tight oil production. Kang et el. (2016, p. 178) find negative response of stock returns to shocks in U.S. oil production. By decomposing U.S. oil production further into non-tight and tight, we find that the negative responses can be attributed to tight oil. Overall, these responses reflect domestically recent developments in world oil production: U.S. production fell between 2015 and 2016 with major

Table 6
Tail dependence for returns of real asset prices.

	Shocks in ret_ Brent	Shocks in ret_WTI	Shocks in ret_copper	Shocks in ret_S&P 500	Shocks in ret_S&P Energy	Shocks in ret_CVN	Shocks in ret_XOM
Period from Feb 2000–Dec 2010							
ret_S&P 500	–	–	**0.24***, 0.14 (**0.10**, 0.09)	–	**0.48***, – (**0.05**, –)	**0.27***, **0.38*** (**0.11**, **0.10**)	**0.41***, – (**0.05**, –)
ret_S&P Energy	–	–	**0.30***, – (**0.06**, –)	**0.48***, – (**0.05**, –)	–	–	**0.56***, **0.56*** (**0.12**, **0.12**)
ret_CVN	–	–	**0.22***, – (**0.06**, –)	**0.27***, **0.38*** (**0.11**, **0.10**)	–	–	**0.58***, **0.44*** (**0.08**, **0.08**)
ret_XOM	–	–	**0.22***, – (**0.07**, –)	**0.41***, – (**0.05**, –)	**0.56***, **0.56*** (**0.12**, **0.12**)	**0.58***, **0.44*** (**0.08**, **0.08**)	–
Period from Jan 2011–Jul 2018							
ret_S&P 500	**0.25***, – (**0.11**, –)	–	**0.32***, – (**0.10**, –)	–	**0.55***, – (**0.06**, –)	**0.54***, – (**0.06**, –)	–
ret_S&P Energy	–	–	**0.42***, – (**0.08**, –)	**0.55***, – (**0.06**, –)	–	**0.75***, **0.73*** (**0.04**, **0.05**)	–
ret_CVN	–, **0.44*** (–, **0.06**)	–	**0.41***, – (**0.09**, –)	**0.54***, – (**0.06**, –)	**0.75***, **0.73*** (**0.04**, **0.05**)	–	**0.54***, – (**0.06**, –)
ret_XOM	**0.36***, – (**0.08**, –)	**0.29***, – (**0.10**, –)	**0.26***, – (**0.10**, –)	–	–	**0.54***, – (**0.06**, –)	–

Notes: This table reports the lower (left) and upper (right) tail dependences with corresponding standard errors in parentheses. Statistical significance at the 5% level is highlighted in bold and marked with *.

declines in oil prices (−0.31% in the U.S. oil versus increases of 1.02% in OPEC members and 0.21% in Russia), and U.S. production rose between 2016–17 and 2017–18 when prices recovered (0.82% and 2.18% in the U.S., respectively, versus decreases of −0.11% and −0.18% in OPEC members and mixed growth in Russia: −0.04% and 0.16%). In sum, when oil prices are firmer (e.g., closer to $ 70 than to $ 40 a barrel), overall U.S. oil production growth rates are positive and growing, most of which is due to tight oil production.[9]

In addition, we find that U.S. stock returns respond positively in the first month to positive shocks in real oil prices. This supports the view that the whole economy benefits with higher oil prices, which was not the case when the U.S. imported oil. Foroni et al. (2017) show that the sign of the relation between real oil returns and real U.S. stock returns has changed over time, and that in the recent period this relation has turned positive since early 2007. See also Mollick and Assefa (2013) for GARCH-type approach to stock returns. Another interpretation involves efficiency considerations (The Wall Street Journal, 2018c): "That is because the shale production is far less speculative, and far more efficient, than it was a few years ago. Even though the U.S. is pumping much more crude now than when production peaked in 2015, the oil industry accounts for a smaller share of overall capital spending. It also employs fewer people. As of last month, there were 153,200 oil-and-gas extraction jobs in the country, according to the Labor Department, which compares with 200,700 jobs four years earlier."

Based on copula modeling, we uncover the interaction during the downturns and upturns among the global demand, crude oil prices and various levels of the stock market. We find that WTI and Brent oil price returns affect stock market differently during the extremes. Significant tail dependences are found between oil prices and stock returns in the second subsample but not in the first. Finally, we identify the interaction among asset prices during the downturns and upturns.

We list a few extensions for further work. First, it is interesting to explore the SVAR in this paper to financial factors (U.S. dollar versus major or broad currencies or U.S. 10-year interest rates), following Bernanke (2016), Prest (2018) and Kilian and Zhou (2018). Our preliminary attempts in this direction face computational problems in some specifications with the yield curve. Second, the role of OPEC on oil price determination, allowing for conventional and tight U.S. oil production, could be further investigated along the lines of Ratti and Vespignani (2015) with real oil price returns at the end of SVAR. With Russia and Saudi Arabia more recently leading groups forming the so-called "OPEC+ alliance", the OPEC categorization may be more tenuous than ever. This is particularly relevant given the size of Russian oil production, which compounds the changing composition of OPEC with countries joining or leaving the organization. Third, subject to data availability, we will examine stock returns in other areas undergoing developments of shale-oil production and other microeconomic regularities reviewed by Kleinberg et al. (2018). Kryukov and Moe (2018) report that the Russian oil sector is dominated by big companies, which face infrastructure conditions different from the U.S. and have different risk-taking behavior and a regulatory framework.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2019.104574.

[9] According to the *Short-Term Energy Outlook* of the U.S. EIA, November 2018, the data of world crude oil and liquid fuels production are as follows: in 2015, OPEC with 38.38 million barrels per day, U.S. with 15.14, and Russia with 11.03 for a total of 96.50 million barrels per day; in 2016, OPEC with 39.40 million barrels per day, U.S. with 14.83, and Russia with 11.24 for a total of 97.03 million barrels per day; in 2017, OPEC with 39.29 million barrels per day, U.S. with 15.65, and Russia with 11.20 for a total of 97.71 million barrels per day; and in 2018 (forecast), OPEC with 39.1 million barrels per day, U.S. with 17.83, and Russia with 11.36 for a total of 100.09 million barrels per day.

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