

How does the crowd sentiment of investors affect international crude oil prices? Evidence from COVID-19 pandemic

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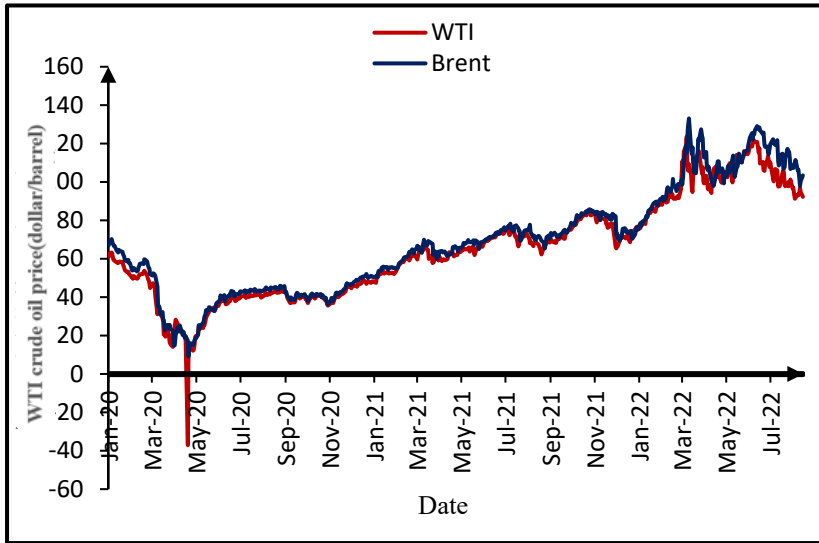
01 Introduction

02 Methodology

03 Empirical Analysis

04 Conclusions

Background



(Crude oil market)

Influence factors

Long-term trends

- Supply
- Demand

Short-term fluctuations

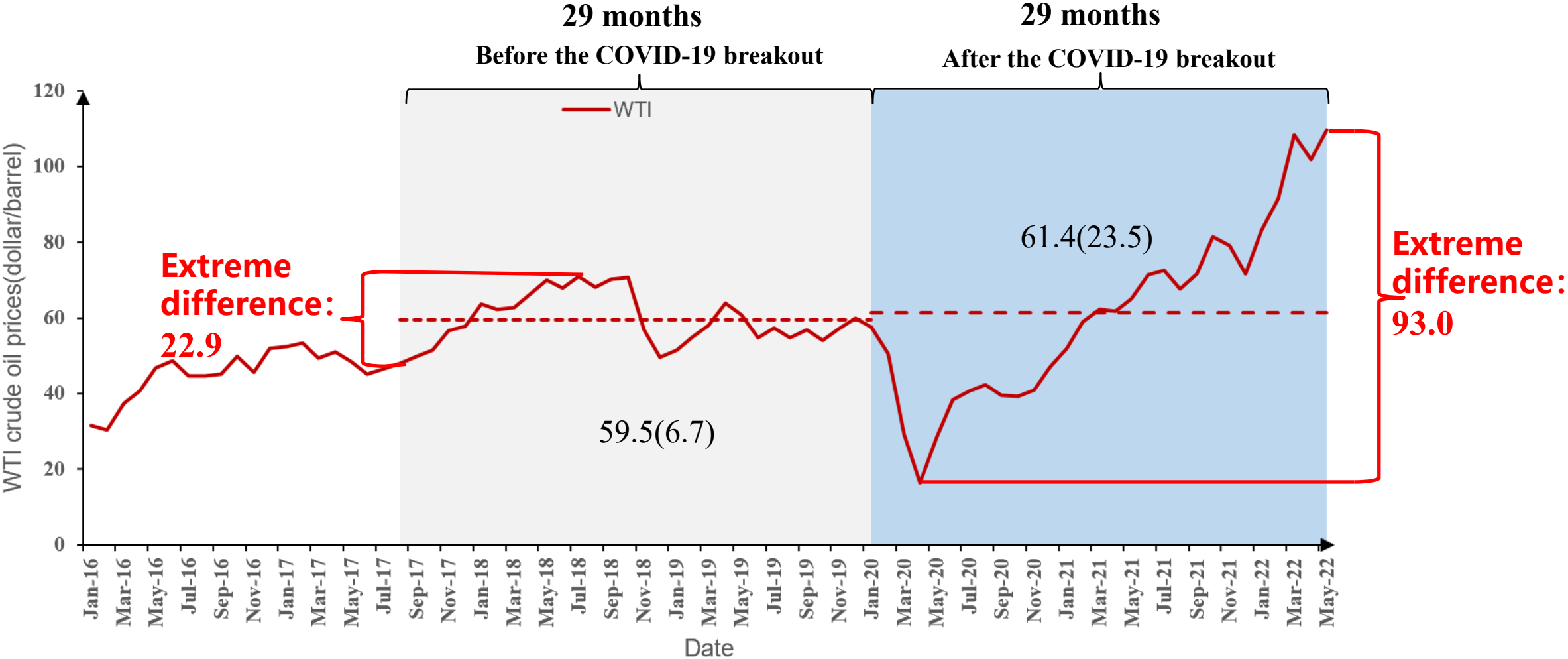
- USD exchange rate
- Big country games
- Geopolitics
- Emergency
- **Market speculation**

.....

Bullish
Bearish



Background



- ★ **Online social networks contain a large number of investment trends and play an increasingly prominent role in disseminating financial market information.**
- **Survey data:** Survey data on bullish and bearish differences of more than 130 stock commentators and consumer confidence in the market, etc. (Gregory and Michael, 2005; Lemmon and Portniaguina, 2006; Zhang et al., 2007).
- **Stock market data:** The number of IPOs, the first-day earnings volume, new account openings, closed-end fund discounts and stock turnover, etc. (Baker and Wurgler, 2006; Ljungqvist et al., 2006; Han and Wu, 2007; Yi et al., 2011).
- **Internet information:** Negative sentiment in media news, extracting investor sentiment from Yahoo stock reviews and Google search index, etc. (Das and Chen, 2007; Tetlock, 2007; Li et al., 2017; Yao et al., 2017; Wang et al., 2018).

- ★ The selection of search keywords is **subjective and one-sided**. Using the **textual term mining method** to extract search keywords can improve **the credibility of sources**.

- **Manual labeling:** Lexical annotation and hierarchical phrase extraction, etc. (Abney, 1991; Lopez et al., 2004; Kazemi et al., 2017).
 - × **Consume a lot of manpower, material resources and time, and the economic cost is high.**

- **Statistical method:** Frequency statistics, etc. (El-Kishky, 2014; Parameswaran, 2019).
 - × **The quality of the extracted phrases depends on established rules.**

- **Machine learning:** WPDV model, voting algorithm, etc. (Halteren, 2000; Shen and Sarkar, 2005).
 - × **Lack of the expansion of text corpora for different domains.**

Literature Review

★ The sentence-level sentiment analysis is not good at describing the evolution of investor sentiment. The aspect-level sentiment analysis considers the **interrelationship between aspect terms and contexts**.

Table 1. Summary of aspect-level sentiment analysis methods

Classification	Model	Characteristic	References
Sentiment lexicon	SentiWordNet	Rely on predefined dictionaries, and the accuracy is influenced by the richness of the lexicon.	Deng and Jing, 2019 Federici and Dragoni, 2016 Singh et al., 2013
	Stanford NLP		
	NTUSD		
Supervisory model	statistical method	Weak semantic understanding and poor results in aspect classification.	Alsmadi et al., 2018 Brun et al., 2016 Kumar et al., 2016
	Bayes Networks		
	Decision Trees		
Deep learning	LSTM、 Attention based LSTM	The data sample topics significantly affect the application domain of sentiment classifiers.	Hu et al., 2021 Shuang et al., 2019 Wang et al., 2016
	BPNN,RNN,CNN		

Sentence-level Sentiment Analysis

VS

Aspect-level Sentiment Analysis

Crude oil prices **rise** on OPEC Plus production **cuts**.



$$\begin{aligned} \text{sentimentScore}(\text{Sentence}) &= \text{sentimentScore}(\text{rise}) \\ &+ \text{sentimentScore}(\text{cut}) \\ &= 4.0 - 4.0 = 0 \end{aligned}$$

Topic=Search keywords="Crude oil"



$$\text{sentimentScore}(\text{Crude oil}) = 0$$



Sentence-level Sentiment Analysis

VS

Aspect-level Sentiment Analysis

tradermeetscoder @trdrmtscdr · 2020年4月13日
Crude Oil Prices Rise On OPEC Plus Production Cuts, \$30 Still Caps
tradermeetscoder.com/crude-oil-pric...



Crude oil **prices rise** on OPEC Plus **production cuts**.

“aspect1”

“opinion1”

“aspect2”

“opinion2”



sentimentScore(**price**)= sentimentScore(**rise**)= 4.0

sentimentScore(**production**)= sentimentScore(**cuts**)= -4.0

★ **The significant impact of investor sentiment on international crude oil prices has a rich theoretical basis.**

- **Global explanatory:** The GARCH, SVAR, and risk spillover models are used to verify that investor sentiment can significantly affect the fluctuation of crude oil prices (Baker et al., 2012; Yao et al., 2017; Su et al., 2018; Li et al., 2021).
- **Predictive validity:** Artificial intelligence forecasting models such as SVR, LSTM, and CNN have found that investor sentiment can provide new information to oil price forecasts that is not available in statistics (He and Casey, 2015; Wang et al., 2018; Li et al., 2019; Zárata and Santiago, 2019).
- **Changes in investor sentiment under the extreme events have not been considered.**

1

An **online text mining method** was designed to quantify the **aspect-level investor sentiment** of international crude oil market.

2

Using the **event study and rolling window SVAR method**, we explored the **mechanisms and time-varying effects** of investor sentiment before and after the **COVID-19 breakout**.

01 Introduction

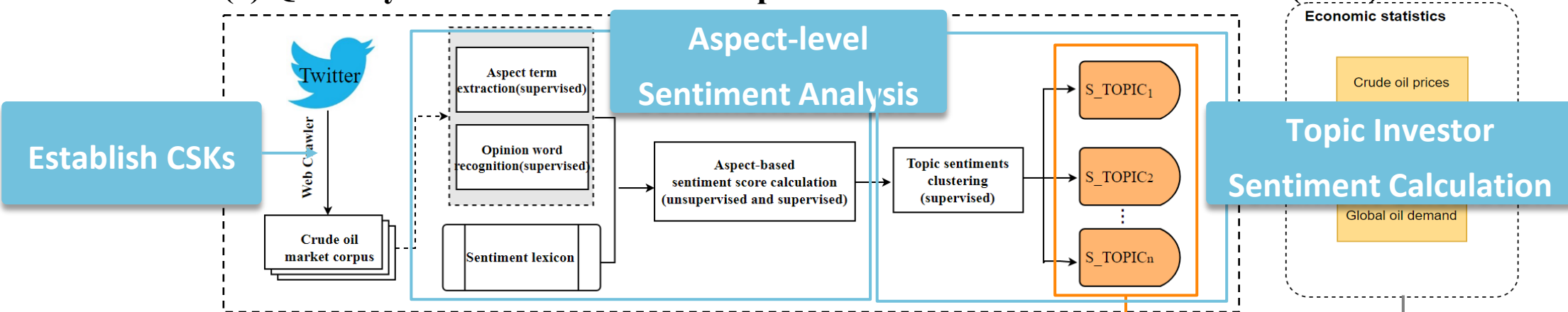


02 Methodology

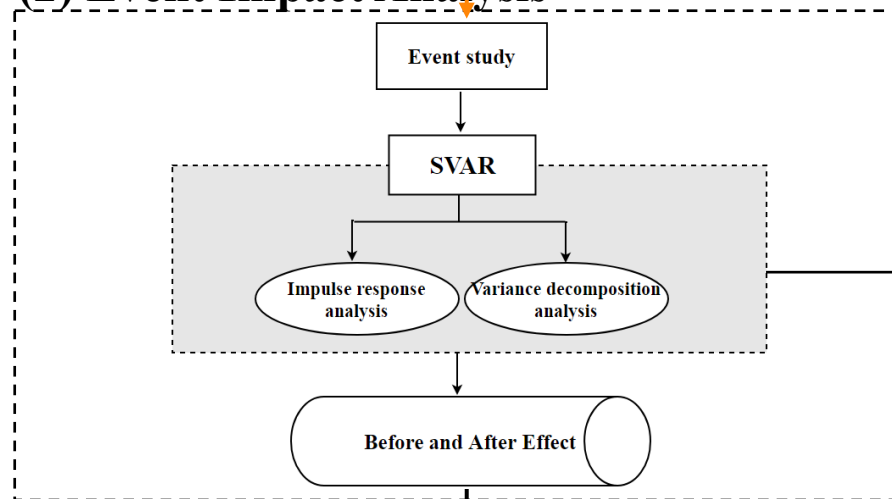
03 Empirical Analysis

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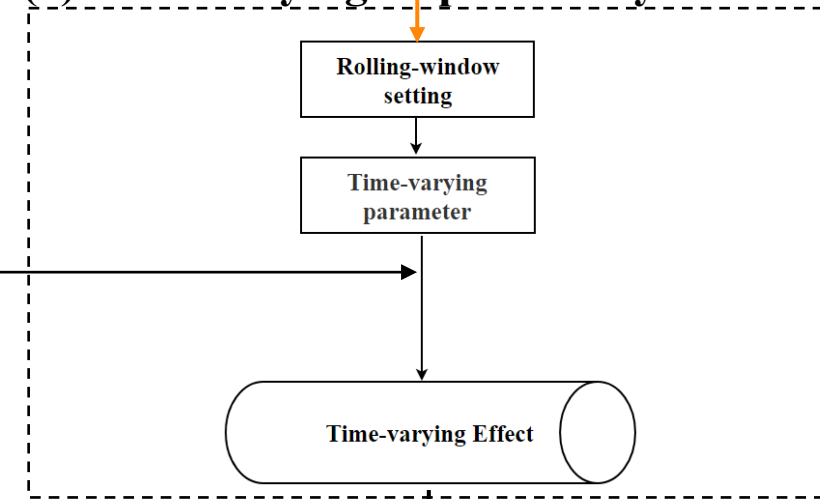
(1) Quantify Investor Sentiment—Topic-based Investor Sentiment Index (TISI)



(2) Event Impact Analysis



(3) Time-varying Impact Analysis



Conclusion

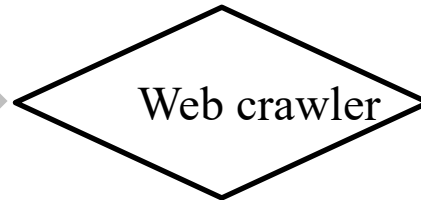
(1) Quantify Investor Sentiment

➤ Characteristic Search Keywords (CSKs) Establishment

STEP 1:
Crawl with seed keyword



"Crude oil"



Crude oil market Corpus:



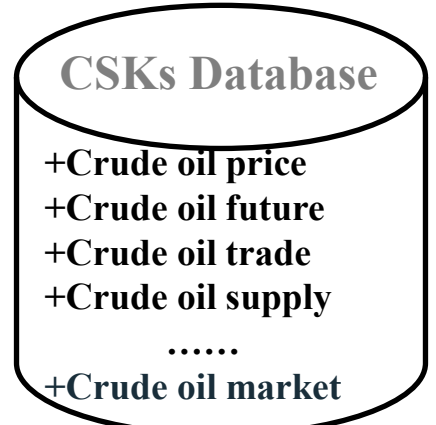
STEP 2:
Extract features and expand keywords



Statistic word frequency



$$KEYWORDS_l = \{keyword_1, keyword_2, \dots, keyword_{l_s}\}$$



l Xs keywords

Word	Frequency
Market	501
And	400
Of	300
.....



Stop Condition: $Frequency \leq f_0$

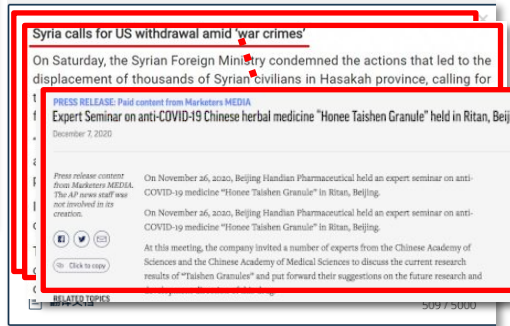
(1) Quantify Investor Sentiment

➤ Aspect-level Sentiment Analysis

STEP 3:
Label aspect terms and identify sentiment words

STEP 4:
Composite sentiment score calculation

Training set:



Preprocessing

$ASPECTs = \{a_1, a_2, \dots, a_i, \dots, a_M\}$

$POSs = \{p_1, p_2, \dots, p_j, \dots, p_N\}$

Brent crude oil price will rise.

Crude oil output will cut.



Test set:

ASPECTs

POSs

Crude oil price recoveries remain capped.

“aspect”

“opinion”

SentiWordNet



pos_score=0.6

neg_score=0.0

opinionScore(recovery)=1.0

pos_score=0.2

neg_score=0.0

opinionScore(remain)=1.0

pos_score=0.2

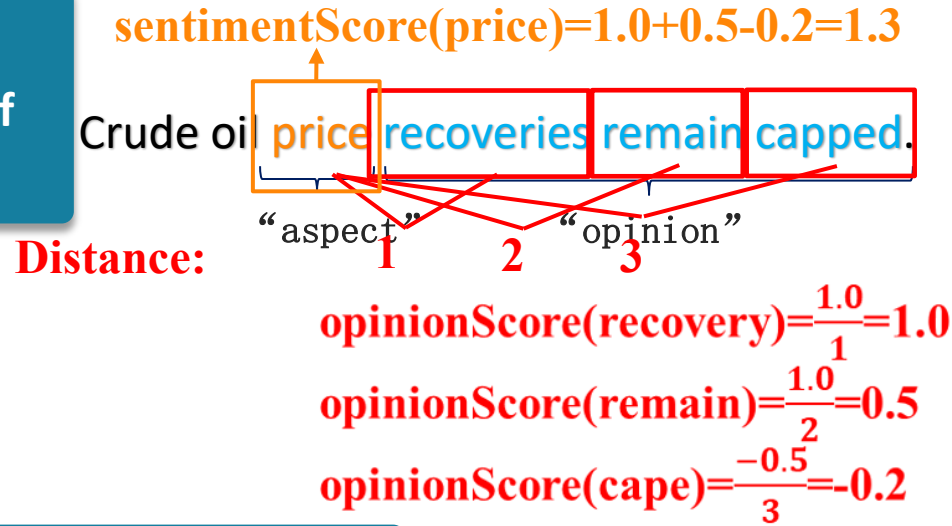
neg_score=0.6

opinionScore(cap)= -0.5

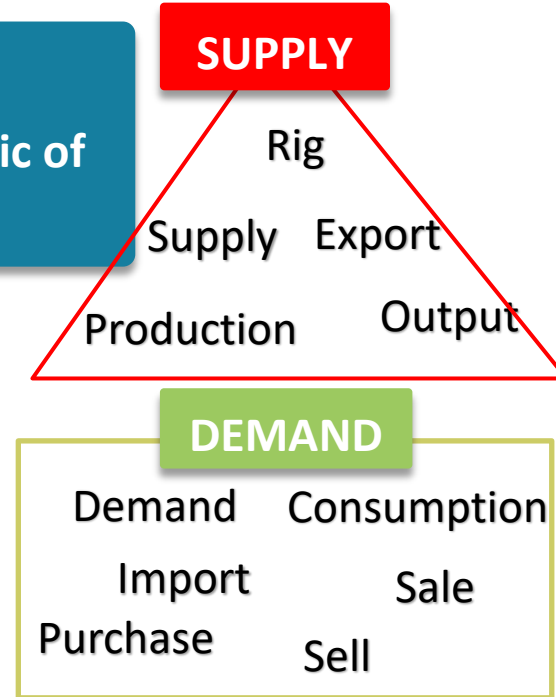
(1) Quantify Investor Sentiment

➤ Aspect-level Sentiment Analysis

STEP 5:
Calculate sentimentScore of aspect term



STEP 6:
Cluster the topic of aspect terms



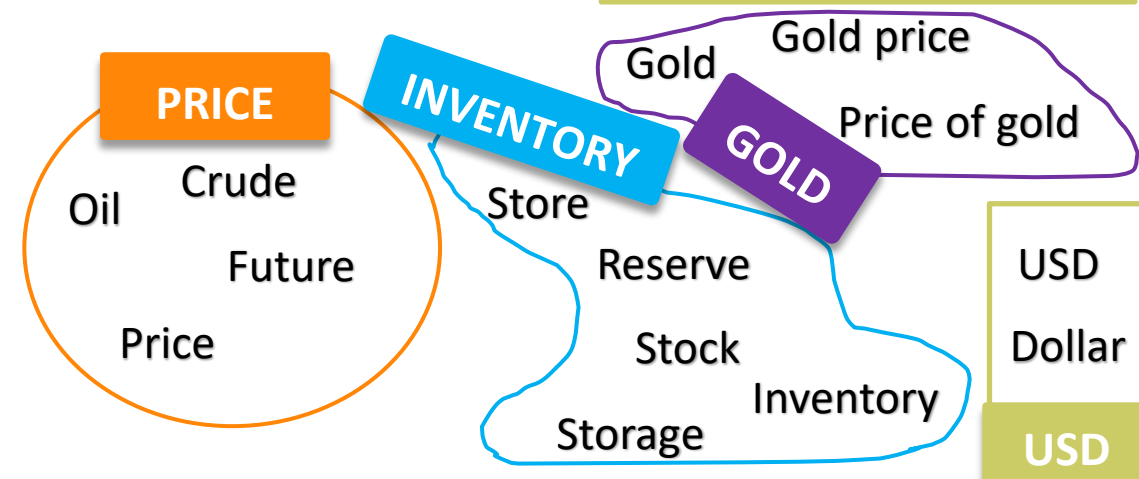
➤ Calculate TISI

STEP 7:
Calculate the **Topic-based Investor Sentiment Index (TISI)**

The **monthly sequence of TISI** is calculated as:

$$S_TOPIC_{i,t} = \frac{\sum_{a_j \in TOPIC_i} sentimentScore(a_j) \text{ on month } t}{\text{Number of tweets for } TOPIC_i \text{ on month } t}$$

where a_j is the **aspect term** in $TOPIC_i$.



(2) Event Impact Analysis

We define a SVAR model with four variables related to the **crude oil market** as:

$$\varepsilon_t = \begin{bmatrix} \varepsilon_t^{Supply} \\ \varepsilon_t^{Demand} \\ \varepsilon_t^{Senti} \\ \varepsilon_t^{Price} \end{bmatrix} = B_0^{-1} u_t = \begin{bmatrix} b_{11} & 0 & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 \\ b_{31} & b_{32} & b_{33} & 0 \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} u_t^{Supply} \\ u_t^{Demand} \\ u_t^{Senti} \\ u_t^{Price} \end{bmatrix}$$

Impulse Response Function(**IRF**):

$$IRF_{ij}^{(q)} = \frac{\partial X_{i,t+q}}{\partial u_{jt}}, q = 0, 1, 2, \dots$$

Relative Variance Contribution(**RVC**):

$$RVC_{j \rightarrow i}(\infty) = \frac{\sum_{q=0}^{\infty} (b_{ij}^{(q)})^2 \sigma_{jj}}{\text{var}(X_i)} = \frac{\sum_{q=0}^{\infty} (b_{ij}^{(q)})^2 \sigma_{jj}}{\sum_{j=1}^k \left\{ \sum_{q=0}^{\infty} (b_{ij}^{(q)})^2 \sigma_{jj} \right\}}, i, j = 1, 2, \dots, k$$

(3) Time-varying Impact Analysis

Considering the cyclical and regime changes in the crude oil market, the SVAR model is estimated at each fixed window $[k, k + h - 1]$ using a rolling window approach:

$$B_0 X_\tau = \beta + \sum_{i=1}^p B_i X_{\tau-i} + u_\tau$$

Then, the slide length is set to 1, allowing the parameter to be time-varying.

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(1) Data and Description

Oil market data

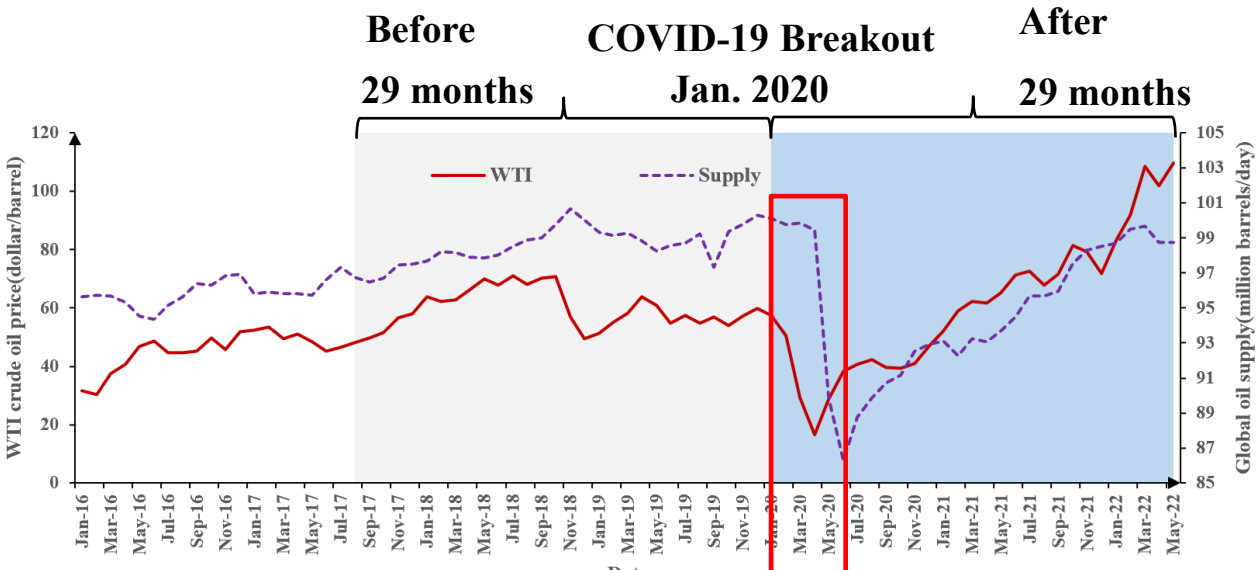


Fig. Trend of WTI crude oil price and global oil supply.

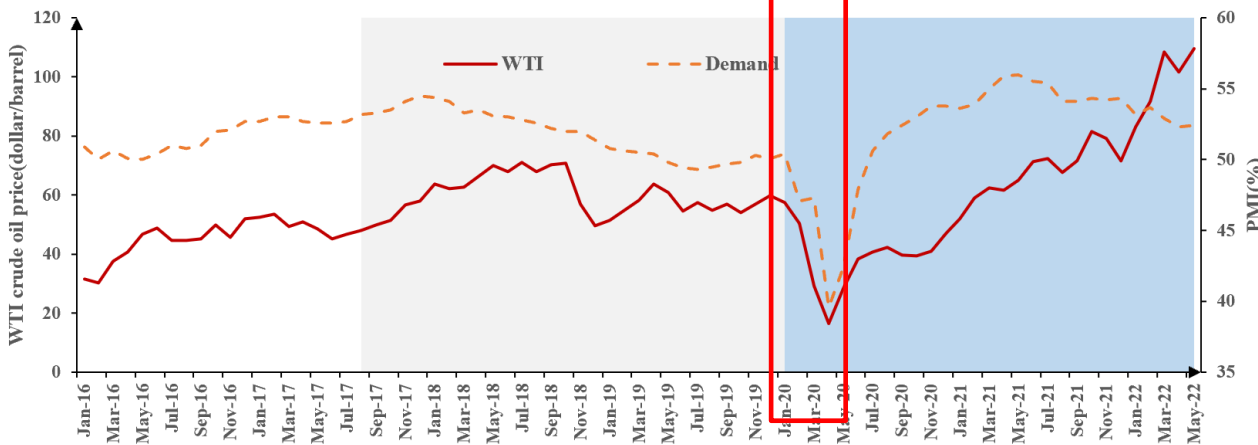


Fig. Trend of WTI crude oil price and global oil demand.

Table 3. Descriptive statistic.

	WTI Spot price	Supply Global oil production	Demand PMI
Mean	67.0417	94.6229	51.6232
Median	59.8800	95.1400	51.8000
Max	109.5500	100.6400	56.0000
Min	16.5500	86.2900	39.6000
Std.	22.9817	3.5970	2.2168
Skewness	0.3122	-0.1107	-1.7790
Kurtosis	1.9169	1.7377	10.6387

Data source: Wind

*Monthly data from Jan. 2012 to May. 2022

(1) Data and Description

➤ Proxy variables for investor sentiments

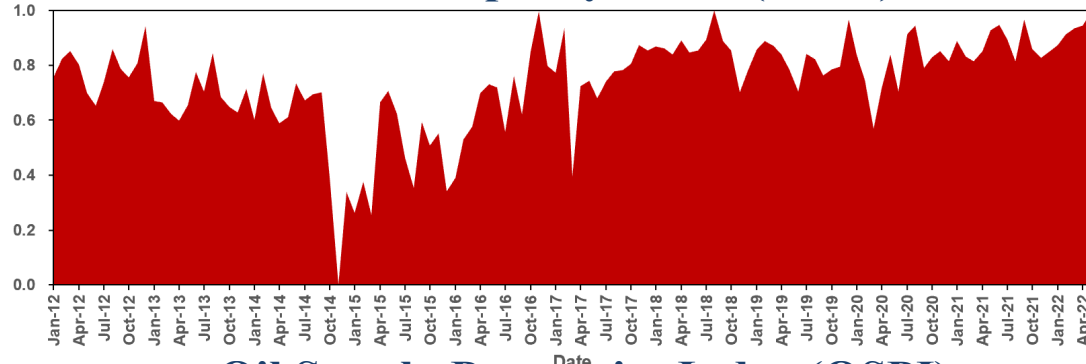
Table 4. Description of investor sentiment proxy variables.

Name	Meaning and Calculation	Data Source
BW	A composite sentiment index is constructed based on six basic sentiment indicators.	http://people.stern.nyu.edu/jwurgler
AAII	The sentiment is calculated as the spread between the percentage of bullish investors and that of bearish investors.	http://www.aaii.com
CCI	Indicators reflecting the development of household consumption and future savings are constructed based on perceptions of the expected financial position of U.S. households, general economic conditions, unemployment, and the ability to save.	https://data.oecd.org/leadind/consumer-confidence-index-cci.htm
DHI	About 10% of daily tweets posted on Twitter are randomly selected for a happiness rating of 1-9.	http://hedonometer.org/index.html
OVX	Presented by the Chicago Board Options Exchange (CBOE), it captures the uncertainty of market participants about the future volatility of oil prices.	http://www.cboe.com
VIX	Proposed by the Chicago Board Options Exchange (CBOE) to measure market expectations of the near-term volatility implied by stock index option prices.	http://www.cboe.com
TEU	A standardized measure of the number of tweets on Twitter containing keywords related to "uncertainty" and "economy".	http://www.policyuncertainty.com/twitter_uncert.html
TMU	A standardized measure of the number of tweets on Twitter that contain keywords related to "uncertainty" and "market".	http://www.policyuncertainty.com/twitter_uncert.html
GS	It is weighted by the Google search volume of 11 related keywords whose correlation coefficient with "crude oil price" is greater than 0.9.	https://trends.google.com/trends

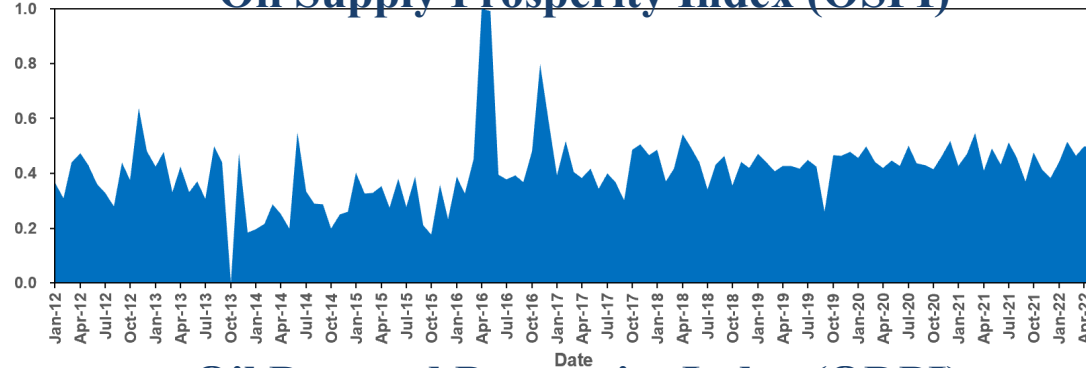
(2) Calculate the TISIs (Topic-based Investor Sentiment Index)



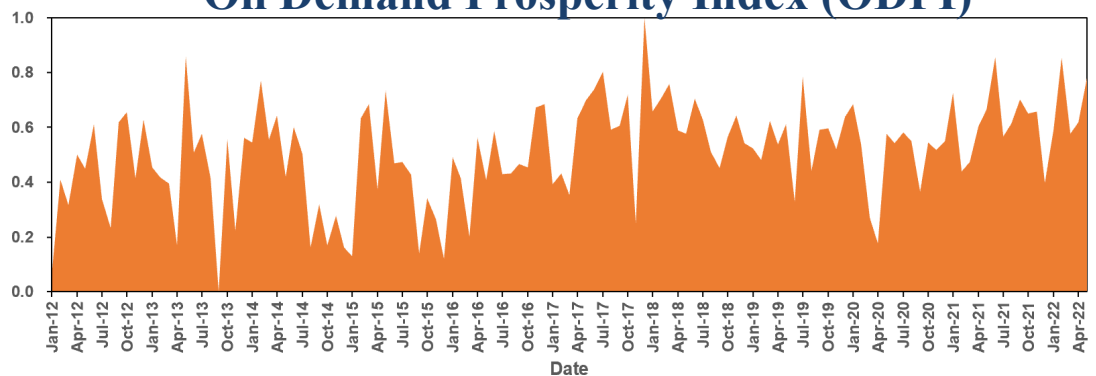
Oil Price Prosperity Index (OPPI)



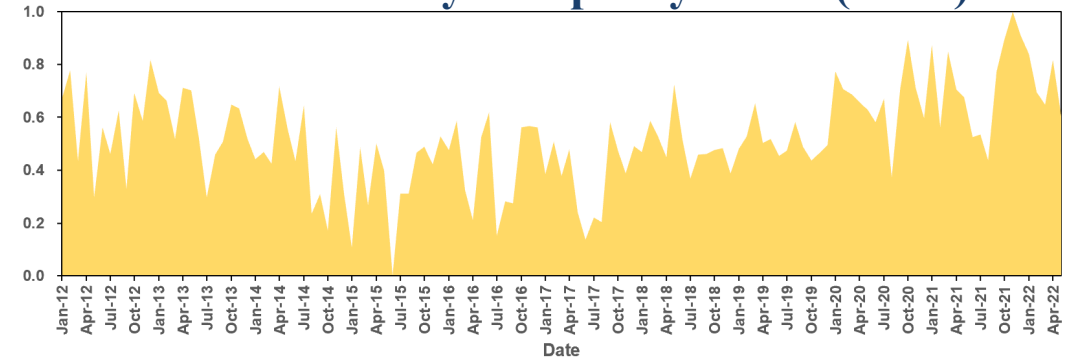
Oil Supply Prosperity Index (OSPI)



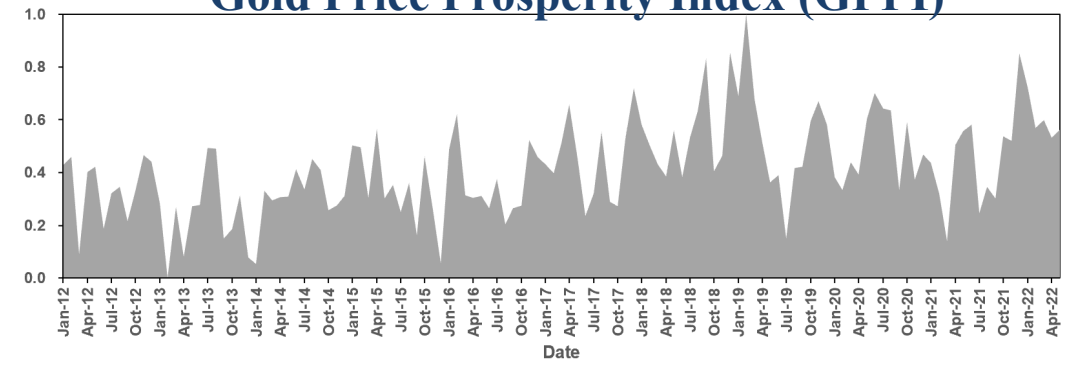
Oil Demand Prosperity Index (ODPI)



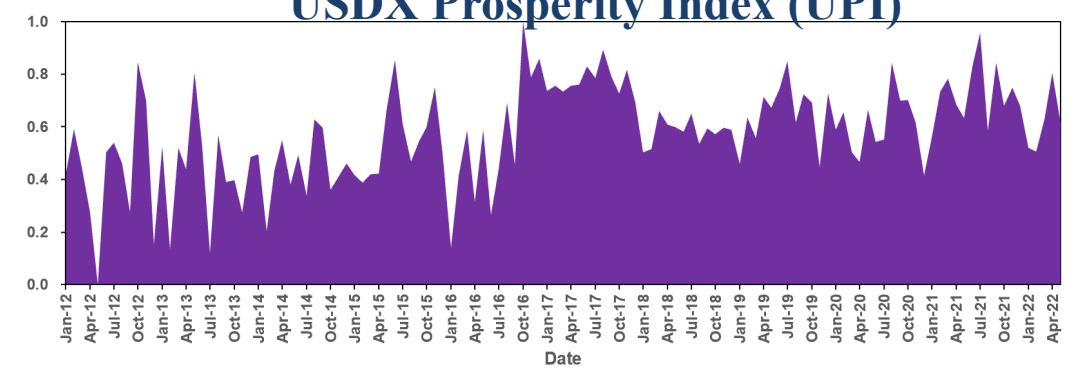
Oil Inventory Prosperity Index (OIPI)



Gold Price Prosperity Index (GPPI)



USDX Prosperity Index (UPI)



(3) How does TISIs affect crude oil prices?

The impulse response results of crude oil prices to one standard deviation of **OPPI, OSPI, ODPI, OIPI, GPPI and UPI shocks** based on a four-variable SVAR model are shown as follows:

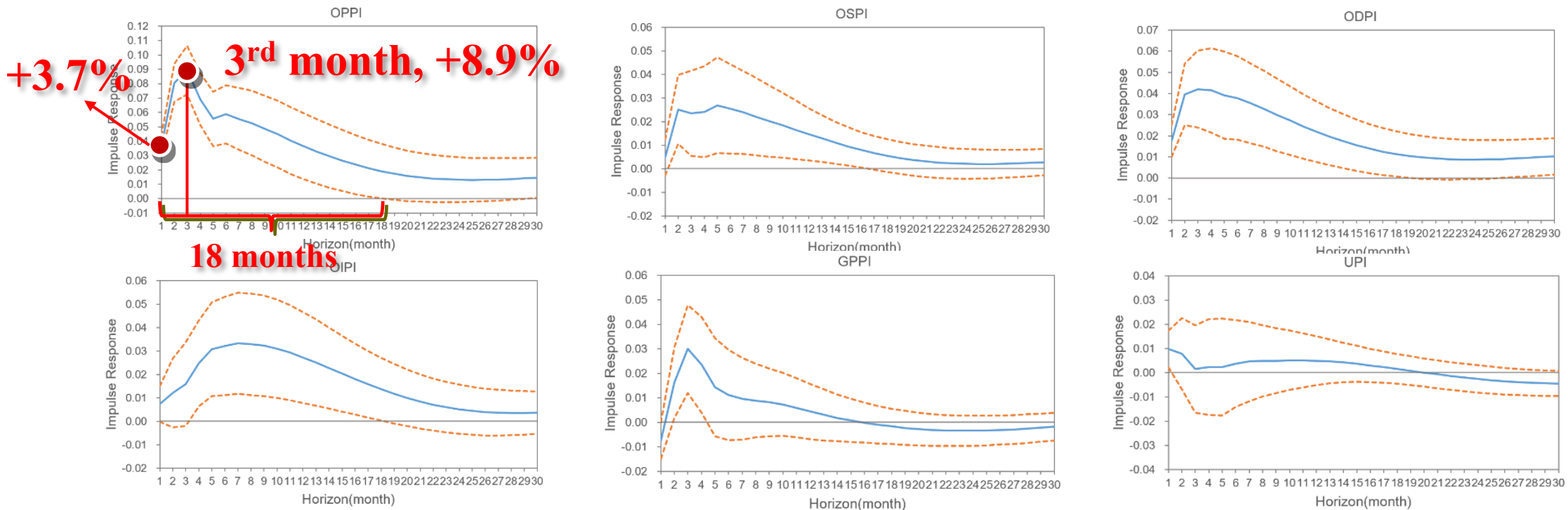


Fig. Responses of WTI crude oil prices to different shocks.

◆ The impact of **price-topic investor sentiment index** on crude oil prices is the **great effective, high timely and long-term correlated.**

(3) How does TISIs affect crude oil prices?

The impulse response results of WTI crude oil prices to one standard deviation of **OPPI, OSPI, ODPI, OIPI, GPPI and UPI shocks** based on a four-variable SVAR model are shown as follows:

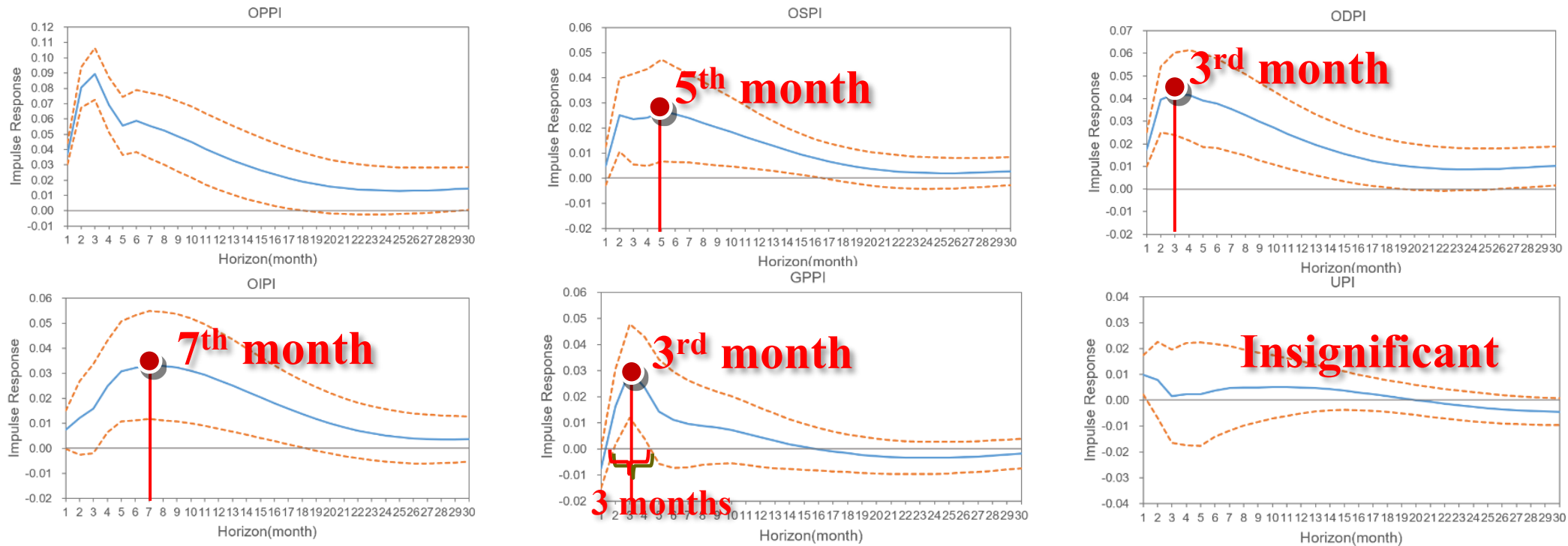


Fig. Responses of WTI crude oil prices to different shocks.

◆ **TISIs about fundamental factors (Supply, Demand and inventory) have a stronger impact on oil prices than the other factors (Gold price and USDX).**

(3) How does TISIs affect crude oil prices?

➤ Compare with supply and demand factors

◆ OPPI can explain the **longer term of oil price fluctuations** and has a **stronger effect** than supply and demand factors.

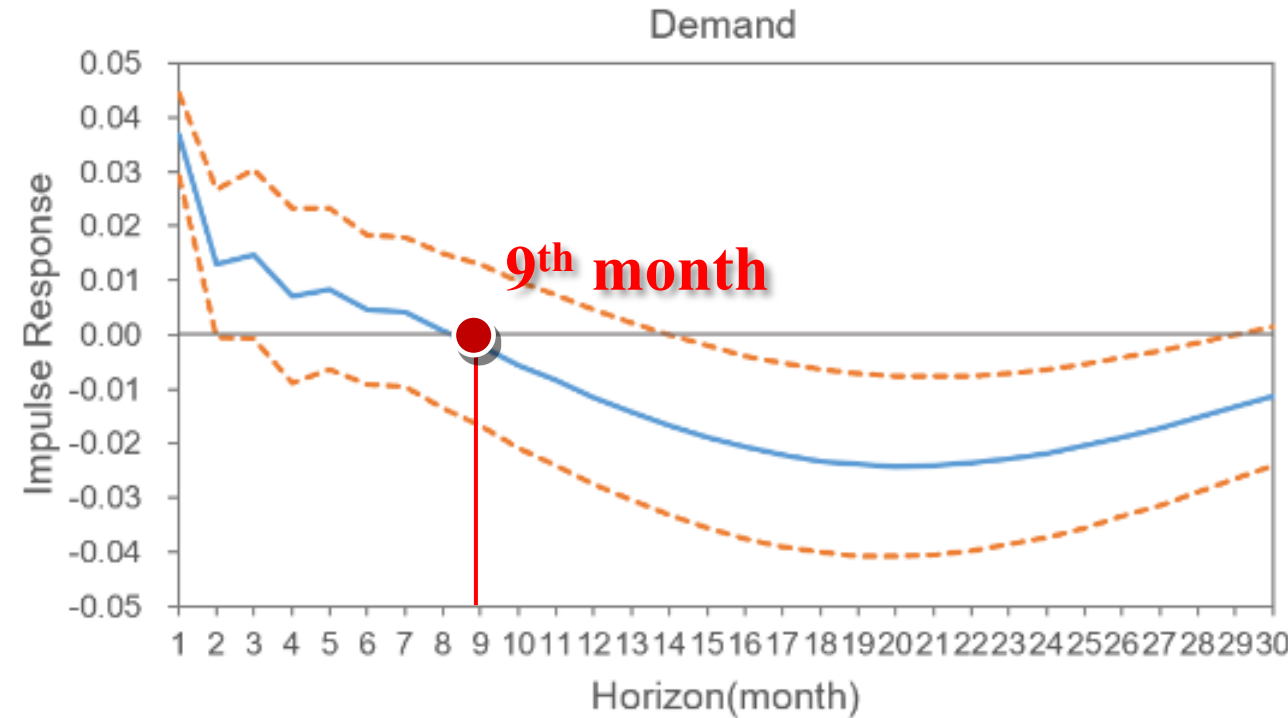
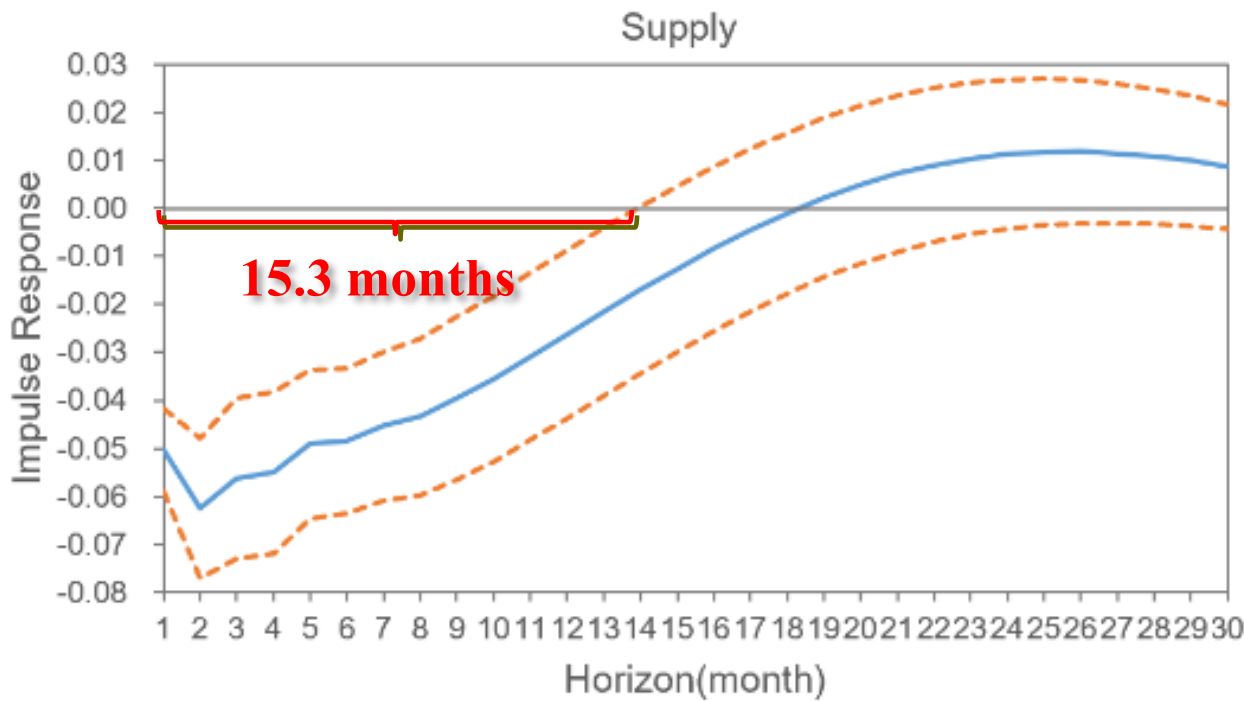
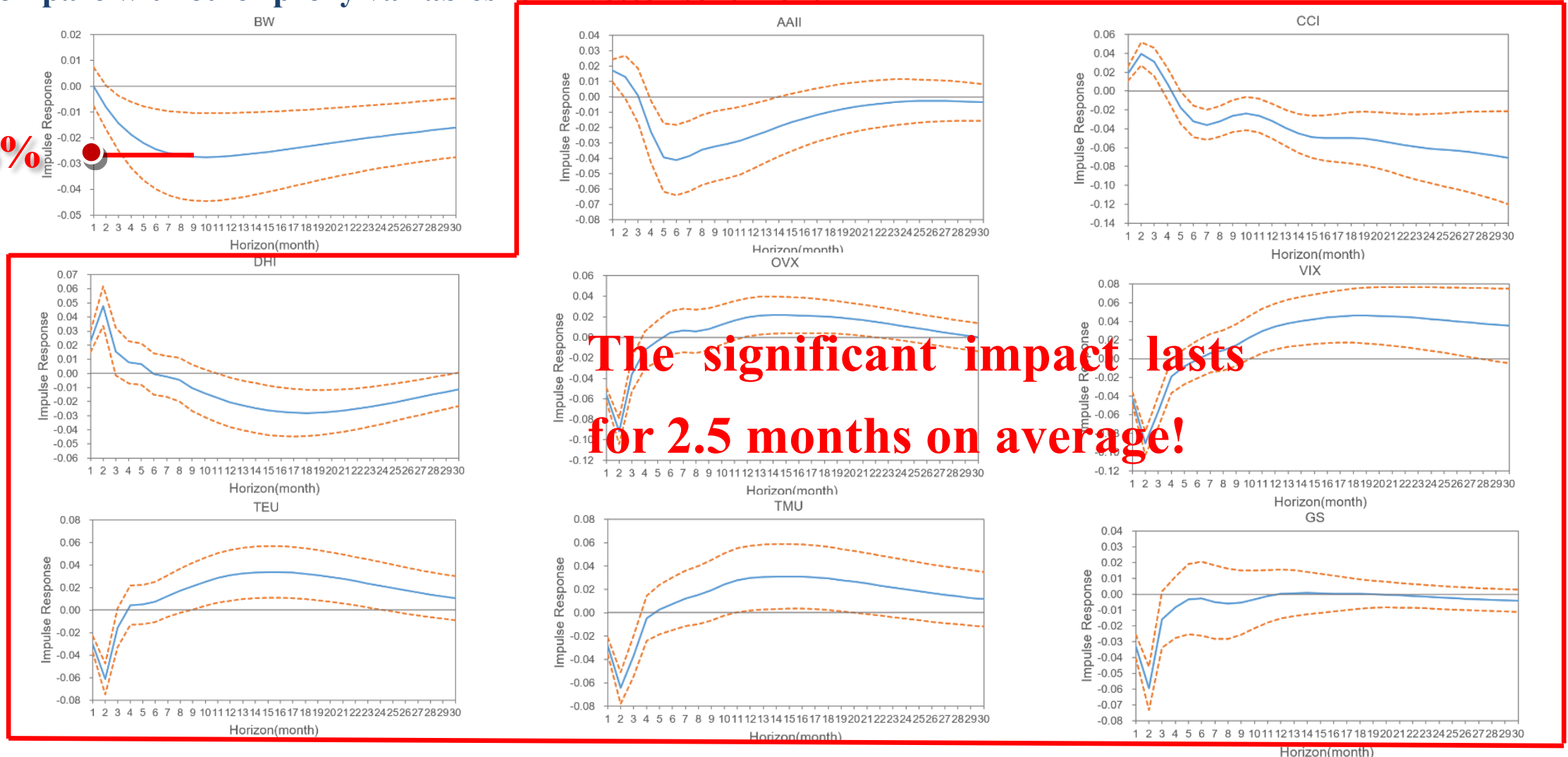


Fig. Responses of WTI crude oil prices to supply and demand shocks.

(3) How does TISIs affect crude oil prices?

➤ Compare with other proxy variables for investor sentiment

-2.8%



The significant impact lasts for 2.5 months on average!

Fig. Responses of WTI crude oil prices to other investor sentiment shocks.

(4) How does the COVID-19 affect the OPPI's performance

➤ Price Response

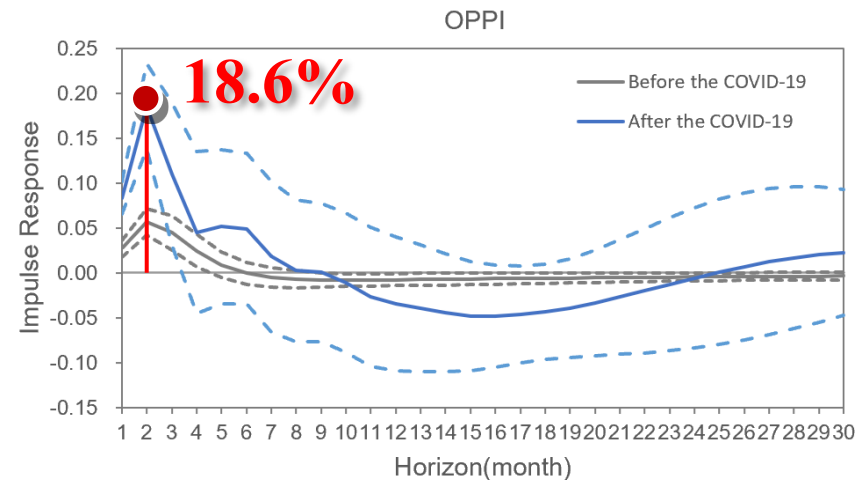
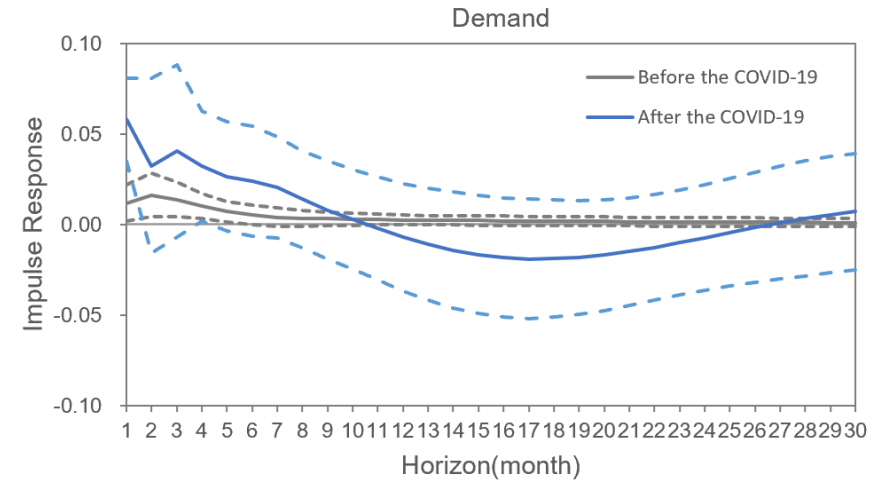
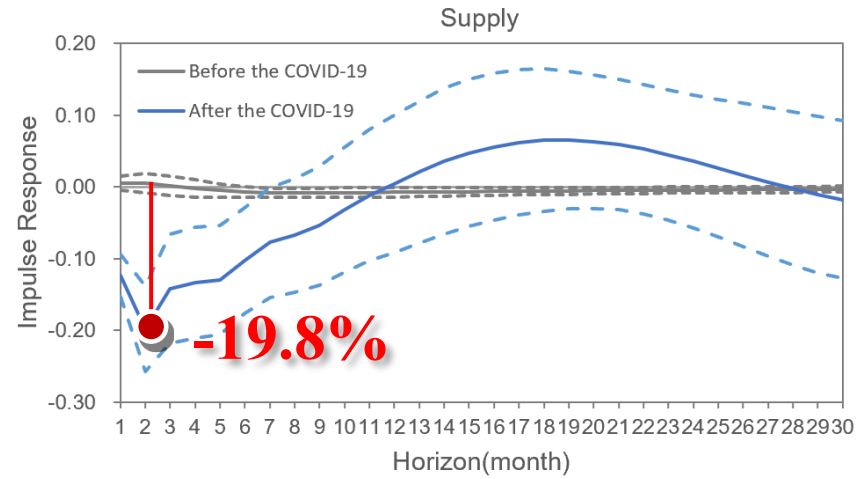


Fig. Responses of WTI crude oil prices to different shocks before and after the COVID-19 breakout.

(4) How does the COVID-19 affect the OPPI's performance

➤ Price Response

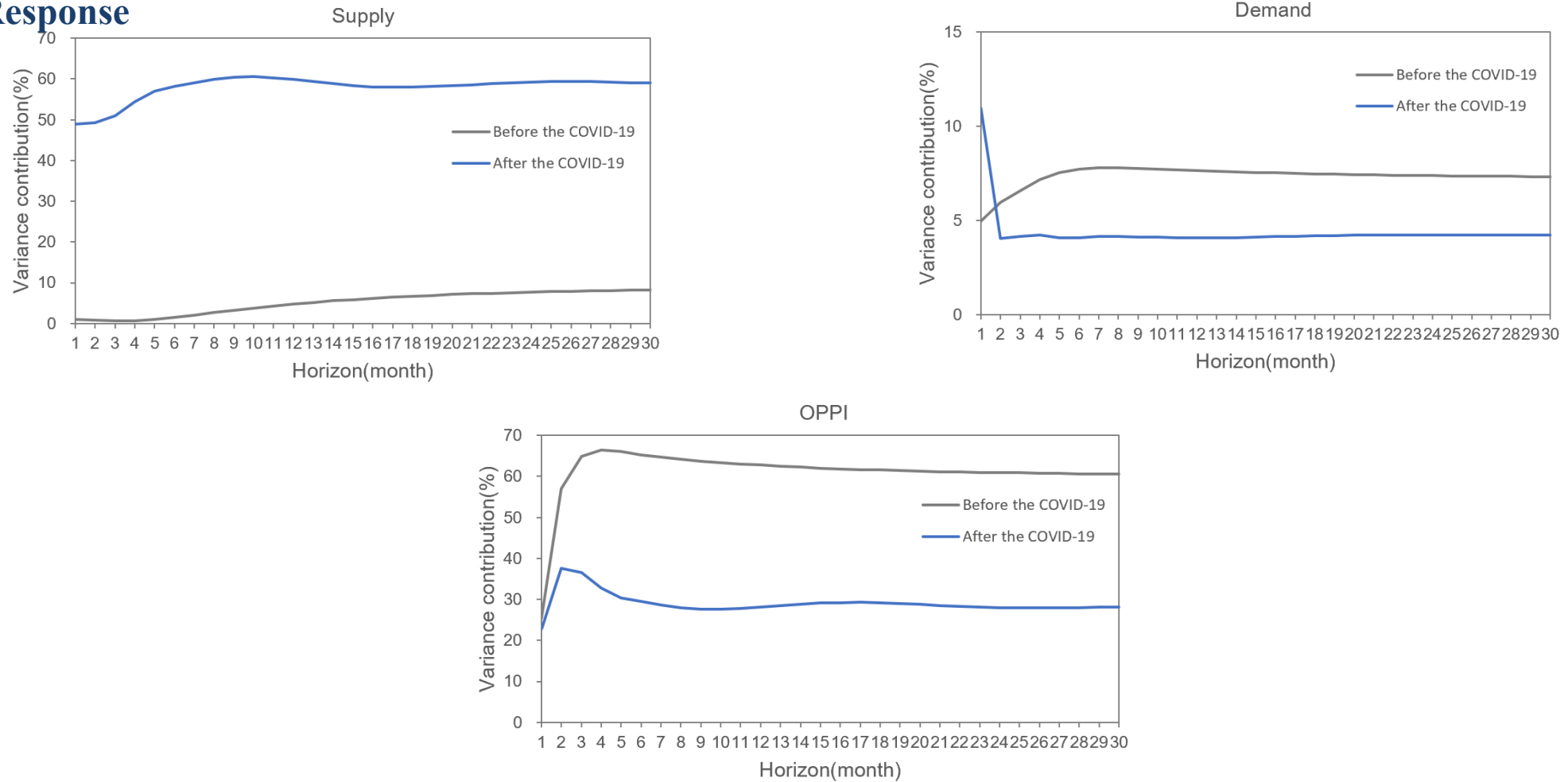


Fig. Contribution of different shocks to WTI crude oil price fluctuations before and after the COVID-19 breakout.

★ WTI crude oil prices were more **closely related to fundamental supply-and-demand factors** during **the COVID-19 pandemic**

CONTENTS

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01

Based on the **keyword screening rules**, we constructed **a crude oil market corpus**. A fine-grained **aspect-level sentiment analysis method** was developed to quantify investor sentiment, and the **oil price prosperity index (OPPI)** was constructed. The empirical results showed that it had **a strong, significant and sustained impact** on crude oil prices.

02

During the COVID-19 epidemic, the significant positive impact of OPPI on oil prices **emerged rapidly** with **enhanced timeliness and significant short-term effects**, but the **long-term relationship became weak**.

The maximum impulse response of the WTI crude oil price to OPPI shocks increased from **5.7% to 8.3%**, and the speed shortened from **3.3 months to 2.0 months**. Although OPPI's ability to explain WTI crude oil price fluctuation has weakened, it can still explain **29.4% of oil price fluctuations**.

03

Sharp fluctuations of international oil prices triggered market panic, contributed to short-term irrational speculation, and further amplified oil price fluctuations. **The changes in investor sentiment would be reasonably guided**. The online public opinion on social media platforms would react and be regulated in time to promote the stable and healthy development of the market.



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THANKS !

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