International Review of Financial Analysis 78 (2021) 101953

Contents lists available at ScienceDirect

International Review of Financial Analysis

journal homepage: www.elsevier.com/locate/irfa

Do China's macro-financial factors determine the Shanghai crude oil futures market?

Boqiang Lin *, Tong Su

School of Management, China Institute for Studies in Energy Policy, Collaborative Innovation Center for Energy Economics and Energy Policy, Xiamen University, Fujian, 361005, China.

ARTICLE INFO

Keywords:
Shanghai crude oil futures (INE)
Time-varying importance
Macro-financial factors
Crude oil pricing
Dynamic model averaging
Frequency domain

ABSTRACT

Existing studies have investigated the Chinese Shanghai crude oil futures (INE) from price efficiency, cross-futures transmission, etc., but neglected the potential links with China. This paper is committed to filling this gap by conducting an initial discussion from the perspective of macro-financial factors. Applying the dynamic model averaging (DMA) approach, we examine the time-varying importance of the six potential factors that drive the INE prices. The results based on the overall conditions of all determinants and based on individual predictors both support the crucial roles of some Chinese macro-financial factors. The pricing effects of these factors almost display upward features within 6 months since the INE establishment. Thereafter, it maintains an overall stable trend, though some abnormal turmoil is found after the COVID-19 outbreak. According to the multi-scale analysis, the importance of China's macro-financial factors mainly reveals the INE market at the low-frequency components. To confirm the robustness of the estimation and the uniqueness of such effects on the INE, we utilize an alternative forecast accuracy criterion to confirm stability, accommodate the DMA estimation on the WTI and Brent oil futures prices as comparisons, and discuss the frequency domain through another decomposition procedure. These all mirror our findings.

1. Introduction

On March 26, 2018, China officially launched the Shanghai crude oil futures (hereafter, INE) that are denominated and settled in RMB. Since its establishment, INE has made terrific achievements on the market scale and the trading volume. It has exceeded the Oman crude oil, and become the largest crude oil futures contract in the Asia-Pacific, even one of the most influential crude oil prices.[1]

The background behind establishing this contract is that China imports a large amount of crude oil but has a low pricing influence on the market. This contradiction is sourced from the "Asian premium". US West Texas Crude Oil Futures (WTI) and British North Sea Brent Crude Oil Futures (Brent) jointly shape the changes in global crude oil price, but they slowly respond to the supply and demand conditions in Asia (AlKathiri, Al-Rashed, Doshi, & Murphy, 2017). Thus, there are high-risk exposures in Asian crude oil markets, ultimately triggering some premiums. The cultivation of the INE is an exploration to solve this problem (Yang & Zhou, 2020), so the INE must become an important global price benchmark and have the ability to actively respond to Chinese and Asian information. This induces a worthy research problem, does China's situation play an important role in pricing the INE crude oil futures as expected? An effective assessment of this issue would be necessary, which could be beneficial to understand whether the INE is stepping at its initial target.

Despite the outstanding significance, there remains a paucity of sufficient investigation on this issue. Most of the related research focuses on evaluating the development of INE from the perspective of its global price benchmark role. For instance, Yang and Zhou (2020) provide evidence of the initial success towards becoming a regional benchmark. Some similar researches are Huang and Huang (2020), Wang and Li (2020) and Zhu, Tang, Wei, Dai, and Lu (2020). They all assess the Shanghai crude oil futures development from the perspective of becoming a global price benchmark. Far too little attention has been paid to detecting its ability to actively respond to Chinese information. Such unclear nature further encourages the central thesis of this paper.

There are considerable variables that could describe the essential

* Corresponding author.
E-mail addresses: bqlin@xmu.edu.cn, bqlin2004@vip.sina.com (B. Lin), suyaozhicug@sina.com (T. Su).

[1] Based on the official news of Shanghai International Futures Exchange, the global market share of this contract reached 14.4% after four months of trading, far surpassing the Oman crude oil futures and becoming the world's third largest crude oil futures product (http://www.ine.cn/news/area/1486.html)

https://doi.org/10.1016/j.irfa.2021.101953
Received 29 January 2021; Received in revised form 5 October 2021; Accepted 19 October 2021
Available online 23 October 2021
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surroundings of a country including GDP, CPI, unemployment rate, etc. They undoubtedly could be treated as the underlying determinants on the INE prices, referring to the Chinese information. However, most of them are monthly or quarterly series. Limited by the short history of INE, it is difficult to obtain robust empirical results using these general economic variables. Facing this context, we, therefore, concentrates on the pricing effects of macro-financial factors that usually capture quick information changes of the fundamentals. There are two additional benefits for investigating the macro-financial factors. On the one hand, the macro-financial factors are related to inflation, the state of the economy, and even the development stages of the related industries (Asgharian, Christiansen, & Hou, 2016). We could capture the impact of fundamental information from these factors. On the other hand, macro-financial variables themselves are also significant components of Chinese information. They could reflect the situations of the financial liquidity, overall financial risk, investor sentiment, and other financial conditions of China (Morana, 2013; Wang & Li, 2020). As crude oil futures always have a high degree of financialization, Chinese information derived from the financial system is also worthy of attention. Thus, this paper estimates the pricing effects of six financial variables on INE crude oil prices, namely interest rate, exchange rate, Treasury bond rate, equity market, energy stock market, and commodity market.

Shanghai crude oil futures has undergone rapid progress since its establishment. Over time, there may be some potential changes in the pricing effects of China's macro-financial variables. With one target of the INE market as efficiently responding to China's information, detecting the changing features might be crucial for evaluating its gradual development status. Meanwhile, the COVID-19 epidemic broke out in China at the end of 2019 and then spread to the world. This black swan-like event may also cause drastic changes in the pricing effect of macro-financial factors. Based on Sharif, Aloui, and Yarovaya (2020), the COVID-19 may be firstly viewed as an economic crisis, it would shock the internal pricing structure of the commodity market. For instance, it resulted in a contagion effect in the stock markets (Okorie & Lin, 2021). Gharib, Mefteh-Wali, and Jabeur (2021) indicate the COVID-19 outbreak affects the contagion effect between oil price and other financial markets. Similar findings could be obtained in Lin and Su (2021), the cross-market links between crude oil and other commodities considerably increase during the COVID-19. Thus, it is rational to speculate the pricing effect of macro-financial factors may show some abnormal patterns, after the outbreak of COVID-19.

Therefore, we consider potential time-varying characteristics when analyzing the pricing role of Chinese macro-financial factors. Consequently, this research mainly uses the dynamic model averaging (DMA) approach to conduct the empirical estimations, which can capture the gradual changes of the pricing effects of selected variables. This approach is an extension of the original model averaging methods developed by Raftery, Kárný, and Ettler (2010) and is widely used to detect the time-varying determinants (Dong & Yoon, 2019; Kruse & Wegener, 2020; Leon-Gonzalez & Vinayagathasan, 2015; Mirestean & Tsangarides, 2016). Our estimating process mainly follows the Koop and Korobilis (2011, 2012). Since the determinants of a financial market are not always producing the same impacts for the short and long terms (Afonso, Gomes, & Rother, 2011; Strohsal, Proaño, & Wolters, 2019) and investors only concern with the market drivers corresponding to the specific investment horizon (Barunik, Krehlik, & Vacha, 2016a;(Barunik, Krehlik and Vacha, 2016b) Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018; Maghyereh, Abdoh, & Awartani, 2019). Thus, we incorporate the CEEMDAN (complete ensemble empirical mode decomposition with adaptive noise) into the estimation, which is favorable for understanding multi-scale conditions.

Our study contributes to the existing literature on commodity futures in the following ways. First, this article discusses the determinant roles of Chinese information on the INE price, with finance factors as the main perspective. It fills the existing knowledge gap in assessing the development status of the INE market. Second, the direct purpose of the establishment of the INE is to enhance the Chinese bargaining power in the crude oil trade. Exploring how it responds to Chinese information is a prerequisite for conducting studies on INE development strategies. This paper could provide some theoretical bases for related future studies. Thirdly, with the employment of the time-varying approach and considering the frequency-domain in the empirical analysis, we summarize the status of the INE towards its initial objective and obtain some details of the impact mechanisms. It expands the literature on pricing mechanisms in emerging crude oil markets. Some targeted policies and investment implications are also summarized.

The outline of the paper is as follows: Section 2 is the literature review; The third section introduces the modeling specification in this article; Section 4 summarizes our data, and we perform descriptive statistical analysis and basic metrological test analysis for the variables in this section; The fifth section is the core empirical results of this article; Section 6 provides several additional robustness tests. In the last section, we present some conclusions and recommendations.

2. Literature review

To our knowledge, few studies concentrate on the impact of Chinese financial factors on INE futures prices. Thus, we review the literature from two closely related domains, the investigations on Shanghai crude oil futures and the studies in determinants of crude oil markets, especially the financial factors.

As an emerging futures contract, Shanghai crude oil futures still lack sufficient academic exploration but are getting more and more focus. The related peer-reviewed literature mainly focuses on the financial characteristics of the INE price and its co-movements with other crude oil markets. (Ji & Zhang, 2019) first involved a financial research paradigm in this area. They use high-frequency data of INE trading to analyze the basic financial features. Eventually, the results suggest that there is an obvious jump in the market volatility. Then, Yang, Lv, Fang, and Shang (2020) studied the pricing efficiency of INE futures. The results show that this contract can respond to the fundamental information of the international crude oil supply and demand conditions, but is only a valid market in Asia. Wang, Zhang, and Broadstock (2019) considered the multifractal characteristics of INE and comparing it with the mature WTI and Brent market. The same fractal characteristic for the three futures market was obtained from the empirical analysis.

Becoming the benchmark of the global crude oil market is an important development target for the RMB-denominated crude oil futures. To evaluate the realization of this goal, Yang and Zhou (2020) conducted an in-depth analysis that investigates the correlation between INE and other international oil markets, especially detecting the return and volatility transmission across different futures markets. The estimated linkages between INE and the mature crude oil futures indicate that it will first become an Asian regional benchmark, and then gradually advance to become a global benchmark. The weak price connection between INE and international spot markets is also found in this study, which implies that the INE is still far from achieving the goal of becoming a global pricing benchmark. Through examining the effects of return and volatility spillovers among INE, WTI and Brent futures markets, Zhang & Ma, 2020 obtain similar findings. Shanghai crude oil futures market is still an obvious follower of the global crude oil futures markets. Along with similar ideas, there have been increasing outcomes in this area. For instance, Yang, Ma, Hu, Zhang, and Ji (2020) constructed upside and downside VaR connectedness networks among INE and other crude oil futures to capture the extreme risk spillover; Liu, Ding, Lv, Wu, and Qiang (2019) attempted to visit the integration of China into the world crude oil market with the utilization of the DCC-GARCH and BEKK-GARCH models; Huang and Huang (2020) combined the wavelet coherence and complex network methods to explore the evolutionary characteristics of co-movements; Jie, Huang, and Ping (2020) research on the correlation and hedge between INE futures return and the spot prices (OPEC and Oman). The above examples gain the same results that there are some strong correlations between INE and the mature crude oil futures. As they verified, the aims of the INE market launching have been partially realized, INE has effectively integrated with the global crude oil markets. Some researchers discuss the status of the INE in the global crude oil pricing mechanism. This is exemplified by the work undertaken by Lv, Yang, and Fang (2020), they explore whether the INE futures can better aid investors' risk hedging compared to WTI and Brent futures; while another example is Palao, Pardo, and Roig (2020), which studies whether the leadership of the Brent-WTI has been threatened by INE. They jointly reveal that the development of INE has not yet altered the dominant roles of WTI and Brent in crude oil pricing and the financial system, though INE has made remarkable achievements in volume and globalization.

In summary, the INE has been found to integrate with the global markets slowly over time, we speculate the importance of Chinese information may display some similar time-varying features. Understanding how Chinese factors determine INE could effectively demonstrate the authentic capability of INE in enhancing China's pricing influence and solving the problem of “Asian premium”. However, such knowledge gaps were neglected by previous researches.

Another strand of related researches is about crude oil pricing. The most crucial determinants of crude oil prices are global crude oil supply and demand (Gisser & Goodwin, 1986). Fundamental related factors therefore play crucial roles in pricing crude oil. Kaufmann, Dees, Karadeloglou, and Sanchez (2004) demonstrate OPEC production plan can directly drive the world oil price; while the OPEC announcement seems to also have a similar effect through fundamental expectations. Due to the substitution relationship between different energy varieties, the supply and demand in coal or natural gas markets will also affect crude oil prices (Bachmeier & Griffin, 2006). Kilian (2009) integrally considers the different kinds of fundamental shocks, indicating different shocks would play different roles in pricing the crude oil. Recently, the geopolitical events, US monetary policy, shale oil revolution, and even black swan events like COVID-19 have been found to affect crude oil prices through fundamental channels (Kaufmann et al., 2004; Bachmeier & Griffin, 2006; Su, Li, Chang, & Lobonţ, 2017; Amendola, Candila, & Scognamillo, 2017; Brandt & Gao, 2019; Lu, Li, Chai, & Wang, 2020;). With the acceleration of oil marketization, more external information shocks unrelated to fundamentals can be transmitted to the oil market. At first, market concerns would have a significant impact (Guo & Ji, 2013). Such as the information spillover between the crude oil market and the cryptocurrency market (Okorie & Lin, 2020). The expectations are getting more important in modeling the oil price. Byrne, Lorusso, and & Xu, B. (2019) systematically discuss the linkages among oil prices, fundamentals, and expectations. The expectations from business leaders, consumers, and markets are supported to be the crucial factors in pricing crude oil. Financial factors can always play a role in the pricing of commodities through channels such as transmitting fundamental information (Gertler & Gilchrist, 2018; Kodres & Pritsker, 2002; Lecat & Mesonnier, 2005; Okorie & Lin, 2020) and influencing market expectations (Liu et al., 2019; Chen, Zhu, & Zhong, 2019;). With the financialization of crude oil, its price changes are not only attributed to the imbalance between supply and demand but also determined by the financial factors (Boyer & Filion, 2007; Tian & Tan, 2015).

Since the driving mechanism of the financial factors is diversified and complicated, many pieces of research are devoted to this area. Hamilton (2009a) is a good illustration, which indicated that speculation leads the oil price changes dramatically. Then, Cifarelli and Paladino (2010) also obtained similar findings, oil price shifts are closely related to the stock prices and exchange rate changes due to the significant role played by speculation. Ji (2012) proposed a system analysis approach to identify the main factors driving international crude oil prices; he creatively considers the roles of financial factors. Eventually, direct or indirect contemporaneous effects are observed, especially after the financial crisis broke. Sariannidis, Galyfianakis, and Drimbetas (2015) and Karacaer-Ulusoy and Kapusuzoglu (2017) followed this research direction, contributing to the financial determinants on crude oil markets. They both verified that the American financial factors could affect the America-based oil futures price (WTI). Miao, Ramchander, Wang, and Yang (2017a, 2017b) identified influential factors in crude oil price forecasting and also found a significant effect of US interest rate, exchange rates, stock market, and commodities price index on WTI crude oil futures price. Some articles also tried to introduce financial variables when analyzing the relationship between the crude oil market and national factors (see Liu et al., 2019; Wen, Zhang, Deng, Zhao, & Ouyang, 2019). They provide direct evidence that financial factors could exert a significant impact on the oil futures price, as well as the underlying time-varying characteristics should be concerned when analyzing this effect. Overall, previous studies support our speculation that the Chinese financial variables may be the potential determinants in pricing the INE oil futures.

3. Methodology

This article aims to explore the determining role of China's macro-financial factors on the Shanghai crude oil futures market. Motivated by the discussions in the previous sections and related literature. The importance of these factors may vary over time, which retires a variety of general econometric models (Bork & Møller, 2015; McCormick, Raftery, Madigan, & Burd, 2012; Yuan, 2019). To allow the pricing effects to vary over time, our main empirical estimation uses the dynamic model averaging (DMA) approach, which could estimate the changing importance of variables in shaping prices. In specific, the DMA approach, developed by Raftery et al. (2010), introduces time-varying parameters into the basic model averaging method (BMA). It considers time-varying parameters of the inclusion probabilities of variables; the corresponding results would effectively capture the gradual changes in the driving effects of determinants. We contemporarily select multiple time series to represent the Chinese macro-financial factors, while the DMA approach based on the Bayesian procedure could lighten the pressure in estimation. These advantages illustrate that the DMA approach fits the needs of the empirical analysis of this article.

We construct the DMA framework from a TVP model, whose standard specification is written as:

$$Y_t = X_t\theta_t + \varepsilon_t \tag{1}$$

$$\theta_t = \theta_{t-1} + \tau_t \tag{2}$$

Where Y_t for $t = 1, \ldots, T$ is a vector of the dependent variable, X_t is a $1 \times m$ vector of financial factors for underlying driving the INE. Thus, the θ_t is the estimated parameters, $\varepsilon_t \sim i.\ i.\ d.\ N(0, H_t)$ and $\tau_t \sim i.\ i.\ d.\ N(0, Q_t)$ are the errors that are assumed to be mutually independent at all leads and lags.

The TVP model effectively extends the traditional constant parameter approaches, dealing with structural instability in the majority of the series and avoiding the window size problem in the alternative recursive estimated methods. However, there is still a large concern that the same set of explanatory variables is assumed to be relevant at all points in time, thereby neglecting the differences in the importance of driving factors. The extensions of the TVP model to the TVP-VARs (time-varying vector auto regressions) could not still resolve such a problem. Groen, Paap, and Ravazzolo (2013) extend the TVP models as involving a treatment of predictor uncertainty thus modifies the specifications to be:

$$Y_t = \sum_{j=1}^{m} s_j X_{j,t}\theta_{j,t} + \varepsilon_t \tag{3}$$

Where $s_j \in \{0, 1\}$ allows the factors to either be included (if $s_j = 1$) or excluded (if $s_j = 0$), all other items indicate the same implications as the Eq. (1). Since s_j does not vary over time, such measurement is still hard to capture the gradually changing importance of the factors.

Raftery et al. (2010) thus present the DMA approach that allows the standard econometric methods for state-space models to change over time while, at the same time, allowing for coefficients in each model to evolve. In other words, this expansion could examine the changing importance of influential factors in time. This procedure supposes there are K models are characterized by having different subsets of X_t as predictors, denoted by the $X_t^{(k)}$ for $k = 1, 2, \ldots, K$. Thus the Eq.(1) and (2) are written as:

$$Y_t = X_t^{(k)}\theta_t^k + \varepsilon_t^{(k)}, \varepsilon_t^{(k)} \sim i.i.d.N\left(0, H_t^{(k)}\right) \tag{4}$$

$$\theta_t^{(k)} = \theta_{t-1}^{(k)} + \tau_t^{(k)}, \tau_t^{(k)} \sim i.i.d.N\left(0, Q^{(k)}\right) \tag{5}$$

Where Y_t, $X_t^{(k)}$, θ_t^k, $\varepsilon_t^{(k)}$ and $\tau_t^{(k)}$ represents the same with the Eq.(1) and (2), and the superscript (k) indicates the conditions on the Kth model. Let $L_t \in \{1, 2, \ldots, k\}$ denote the kth model that applies at time t, $\Theta_t = (\theta_t^{(1)\prime}, \theta_t^{(2)}, \ldots, \theta_t^{(k)\prime})'$ and $Y^t = (Y_1, Y_2, \ldots, Y_t)'$, the DMA could both allow the time-varying parameters and forecasting model. Thus, using the DMA to forecast is the process of calculating the probabilities $Pr(L_t = k|y^{t-1})$ for $k = 1, 2, \ldots, K$ and then weighting average the results from different models. Notably, DMS while only selects the single model for a prediction that has the highest value for probabilities $Pr(L_t = k|y^{t-1})$.

To obtain the changing importance of different macro-financial factors on a specific futures market, the key procedure is the estimation of the $Pr(L_t = k|y^{t-1})$. A common way of selecting the suitable predictors in time is through the transition matrix $P = p_{i,j} = Pr\ (L_t = i| L_{t-1} = j)$, for $i, j = 1, \ldots, K$ $i, j = 1, \ldots, K$. If the number of independent variables is n, there are a total of $K = 2^n$ model permutations that can be used to describe the Y_t and P is a $K \times K$ matrix. Thus, allowing the forecasting models to change over time would causing a drawback that considerable numbers of coefficients need to be estimated as the K is getting large. It would bring a huge computational burden and take a long time for the overall process. Consequently, a fully Bayesian approach to DMA can be quite difficult (Koop & Korobilis, 2012).

We follow Raftery et al. (2010) to utilize an approximate solution involving the two forgetting factors, α and λ. They are the numbers slightly below the one and such approximation is computationally simple and has sensible properties (Koop & Korobilis, 2012). In specific, the first step is utilizing the standard state-space model to obtain the θ_t, with the Kalman filtering given the values of H_t and Q_t:

$$\theta_t|Y^{t-1} \sim N\left(\widehat{\theta}_{t-1}, \Sigma_{t-1|t-1}\right) \tag{6}$$

Where $\Sigma_{t-1|t-1} = \Sigma_{t-1|t-1} + Q_t$ and it could be replaced by the $\Sigma_{t-1|t-1} = \frac{1}{\lambda}\Sigma_{t-1|t-1}$ to simplify the estimation procedure. That is, $Q_t = (1 - \lambda^{-1})\Sigma_{t-1|t-1}$ where $0 < \lambda \leq 1$. This forgetting factor λ denotes how rapidly the forecasting model and parameters evolve. The smaller the value λ, the faster it is to bring unstable models. With such replacement, we merely need to simulate the H_t.

Estimation in the one-model case is then completed by the updating equation:

$$\theta_t|Y^t \sim N\left(\widehat{\theta}_t, \Sigma_{t|t}\right) \tag{7}$$

Where $\widehat{\theta}_{t|t} = \widehat{\theta}_{t|t-1} + \Sigma_{t|t-1}X_t'\left(H_t + X_t\Sigma_{t|t-1}X_t'\right)^{-1}\left(Y_t - X_t\widehat{\theta}_{t-1}\right)$ and $\Sigma_{t|t} = \Sigma_{t|t-1} - \Sigma_{t|t-1}X_t'(H_t + X_t\Sigma_{t|t-1}X_t')^{-1}X_t\Sigma_{t|t-1}$.

Then, expanding the above single model case to the multiple model case. Let Θ_t denote the vector of all the parameters in Eq. (3), for model k, the estimated parameters could be obtained from:

$$\Theta_t|L_t = k, Y^t \sim N\left(\widehat{\theta}_t^{(k)}, \Sigma_{t|t}^{(k)}\right) \tag{8}$$

Where $\widehat{\theta}_t^{(k)}$ and $\Sigma_{t|t}^{(k)}$ are same as the $\widehat{\theta}_t$ and $\Sigma_{t|t}$ in Eq. (7), both from the Kalman filtering, but (k) superscripts are added to denote the cases of model k.

Hereafter, still following the Raftery et al. (2010), we need to involve another forgetting factor α to extend the conditional prediction on $L_t = k$ to the unconditional situation. The analogous result of Eq. (8) for unconditional prediction is given by:

$$P\left(\Theta_{t-1}, L_{t-1}|Y^{t-1}\right) = \sum_{k=1}^{K} p\left(\theta_{t-1}^{(k)}|L_{t-1} = k, Y^{t-1}\right) Pr\left(L_{t-1} = k|Y^{t-1}\right) \tag{9}$$

Where $p(\theta_{t-1}{}^{(k)}|L^{t-1} = k, Y^{t-1})$ can be gained from Eq.(8) that denotes the probabilities of the kth model. If we set $\pi_{t|s,\phi} = Pr\ (L_t = \phi|\ Y^s)$, the right side of Eq.(9) is $\pi_{t-1|t-1,k}$. Using the forgetting factor α ($0 < \alpha \leq 1$), the model prediction equation is eventually consisted as:

$$\pi_{t|t-1,k} = \frac{\pi_{t-1|t-1,k}^{\alpha}}{\sum_{l=1}^{K}\pi_{t-1|t-1,\phi}^{\alpha}} \tag{10}$$

The model updating equation in the Kalman filter is defined as follows:

$$\pi_{t|t,k} = \frac{\pi_{t|t-1,k}p_k\left(Y_t|Y^{t-1}\right)}{\sum_{\phi=1}^{K}\pi_{t|t-1,\phi}p_\phi\left(Y_t|Y^{t-1}\right)} \tag{11}$$

Where $p_\phi(Y_t|\ Y^{t-1})$ is the evaluated forecasting density for the model ϕ evaluated at Y_t. Subsequently, the estimated probability of the model k can be measured as $\pi_{t|t-1,k}$.

This function estimates the probabilities that all the considered factors determine the dependent variable. It should be noted that the estimated results of the DMA model are sensitive to the different settings of the forgetting factors α and λ. To ensure accuracy, this article refers to the method of Drachal (2016) conducting a grid search over 121 combinations of different forgetting factors, ranging from 0.9 to 1 at increments of 0.1. We calculate and compare the root mean square error (RMSE) criteria of the prediction result of the DMA model under different forgetting factors, then selecting the parameters setting that minimizes the RMSE value. Note that mean absolute error (MAE) is also used for selecting the forgetting factors, we display the corresponding empirical results in the section of robustness.

4. Variables and data

We select the variables based on the theoretical deduction. Based on previous studies (Liu, Ding, Lv, et al., 2019; Miao et al., 2017a, 2017b; Wen et al., 2019), the potential mechanisms of macro-financial factors driving the crude oil prices lie in two aspects. (1) Bridge channel: financial factors are the bridges that transmit fundamental information to the crude oil futures (Galariotis, Rong, & Spyrou, 2015). For instance, the interest rates imply information about the adjustments of Chinese monetary policy and the official assessment of the future economy. Such released signals from macro-financial factors would influence the expectations of investors on RMB-based assets and crude oil demand, and ultimately the INE crude oil price. (2) Macro-financial factors may also drive the crude oil price from the channel inside the financial system (market channel). It is sourced from the financialization of crude oil (see, Adams & Glück, 2015; Tang & Xiong, 2012). In specific, investing in commodities has become an important way for producers to hedge against risks (Basu & Miffre, 2013; Erb & Harvey, 2016). Capital holders are also keen to participate in the commodity futures market for arbitrage. When other closely related Chinese financial markets change, investors will adjust their positions in the INE futures due to the potential rebalance of the opportunities or risks, which will ultimately drive the price of crude oil futures.

To comprehensively cover the underlying influence mechanisms, we consequently consider two kinds of financial factors in this study, namely the monetary financial factors and market financial factors. They respectively reflect the two channels of macro-financial factors pricing the INE crude oil. The monetary financial factors contain the interest rate, exchange rate, and Treasury bond interest rate while the overall equity market status, energy industrial stocks conditions, and the composite commodities price constitute the variables for the financial market. All these variables have been already verified to determine the crude oil prices by some literature (see, Alquist & Gervais, 2013; Asgharian et al., 2016; Ji, 2012; Miao et al., 2017a, 2017b; Wen et al., 2019), which provide complementary evidence for the selection of these variables as China's macro-financial factors.

This article uses daily data and selects the sample period from the day after the listing of Shanghai crude oil futures to September 18, 2020. Such interval covers as much data as possible since the establishment of INE, consisting of 603 observations for each variable. The data of the INE crude oil futures price is from the Wind database (the closing price) and the precise references and sources of the considered macro-financial factors are given in Table 1.

Then, we calculate the log-difference form for all variables as the final series for the estimation; Table 2 shows the descriptive statistics of these time series. As displayed in this table, the mean values of all the variables are around 0, of which CP is the largest, and INE is the smallest. IR is relatively higher than the others in terms of the standard deviation while the ER is the most stable time series during the sample period. Besides, the INE price changes are negatively skewed, similar to the SHCI, EI, and CP. All the series are excess kurtosis and fat-tailed. According to the Jarque-Bera test results, the null hypothesis could be rejected by all the selected time series, illustrating they are not normally distributed. The last column in Table 2 is the ADF test results, it could be found that all series are stationary.

5. Empirical results

In this section, we present and discuss the main empirical results. There are three subsections. The first subsection concentrates on the expected size of the models, namely investigating the number of significant predictors' change over time; Then, the probabilities that each considered factor is a significant determinant of the INE price are displayed one by one in the second subsection, thereby obtaining the specific evidence for each macro-financial factors' effects and illustrating the heterogeneous pricing effects among selected financial variables; Thirdly, we compare the time-varying importance of the Chinese macro-financial factors for different frequency scales of the INE futures to understand the influence mechanisms. Since the statistical initialization effects might contaminate the estimated DMA results (Broadstock & Filis, 2020; Wang, Ye, & Wu, 2019), we employ a burn-in period of the 40 observations to eliminate this concern. According to previous research (Wang, Zhang, & Broadstock, 2019), we use 50% (0.5) as the threshold to judge whether the underlying factor is a significant determinant.

Table 1
Definition of Chinese financial factors and data sources.

Class	Factors	References	Data sources
Monetary financial factors	Exchange Rate (ER)	Ji, 2012; Alquist & Gervais, 2013;	Wind Database (The central parity rate of the US dollar against RMB)
	Interest Rate (IR)	Ji, 2012; Asgharian et al., 2016;	Wind Database (Shibor RMB Interbank Offered Overnight Rate)
	Treasury Bonds Rate (TR)	Hamilton (2009b); Hammoudeh, Mensi, Reboredo, & Nguyen, 2014; Miao et al., 2017a, 2017b	Wind Database (3-month Treasury bond rate)
Financial markets variables	Overall equity market (SHCI)	Ji, 2012; Miao et al., 2017a, 2017b; Wen et al. (2019);	Wind Database (Shanghai Composite Index)
	Energy Industry stock market (EI)	Henriques & Sadorsky, 2008; Elyasiani, Mansur, & Odusami, 2011	Wind Database (CSI Energy Index)
	Commodities market (CP)	Ji, 2012; Belousova & Dorfleitner, 2012	Wind Database (Nanhua commodity Index)

5.1. The analysis based on the expected number of predictors

We start our analysis with the aggregated results for the overall circumstance that Chinese macro-financial factors determine the INE market. Treating the considered six factors as an entirety, we estimate the average number of these factors included in the INE crude oil futures forecast model at different points in time. The results are derived from the following equation,

$$E(Number_t) = \sum_{k=1}^{K} \pi_{t|t} Number_{k,t} \tag{12}$$

Where the $Number_{k,\ t}$ indicates the estimated number of factors in model k at time t, $\pi_{t|t}$ is the probabilities in Eq. (11). Thus the $Number_t$ is calculated as the weighted sum of $Number_{k,\ t}$ for different models.

Fig. 1 provides the corresponding results. It can be seen from this figure that the time-varying importance of China's macro-financial factors on Shanghai crude oil futures return can be roughly divided into three stages, which have been painted in different background colors. Before 2019, there are always only one to two factors that could significantly predict the INE futures price, but the trend of the time-varying characteristic is particularly striking. What stands out in the rising curve is that, in the first stage, the pricing effects brought by China's macro-financial factors have become more and more obvious over time. For the second stage, the estimated size of the models has always remained relatively stable, around three predictors. This stage mainly exists throughout 2019, reflecting the pricing effects of the considered macro-financial factors that have moved to a stable state after the rapid development in the first stage. After the beginning of 2020, especially around March 2020, the curve in Fig. 1 displays some new patterns. The realistic background of this period is that the COVID-19 epidemic broke out in China at the beginning of 2020, and then it spread to the whole world, bringing a huge impact on the international crude oil market. We choose the timing of the COVID-19 warning issued by the World Health Organization (WHO) as the boundary (March 11, 2020) for the second and third stages. Strong evidence of a structural change is found comparing the two stages. After this date, the expected number of the significant predictors rose to a high point and peaked around 5 macro-financial factors in mid-April, then this number fell back to around 3 at the end of September 2020. In other words, China's macro-financial factors' capability to drive the Shanghai crude oil futures price rose rapidly after the global spread of the COVID-19 epidemic, and then gradually declined. This strange trend is quite instructive. Though COVID-19 has caused violent turmoil in the international crude oil futures (Dutta, Das, Jana, & Vo, 2020; Gharib, Mefteh-Wali, & Jabeur, 2021), this black swan incident objectively caused a positive effect for improving the pricing effects of the Chinese macro-financial factors in a short time. It is worth noting that the upward phenomenon did not last. As the epidemic gradually normalized, the importance of macro-financial factors also returned to a similar state as the second stage.

In summary, the detection of the average number of Chinese macro-financial factors included in the forecast model reveals the pricing effects of these factors have obvious phased characteristics. Since the beginning of this futures contract, the role of macro-financial factors has gradually increased and reached a stable level after the end of 2018. This stable pricing influence could have been sustained, but the global spread of COVID-19 and the subsequent global crude oil market turmoil pulled up the importance of China's macro-financial factors. This structural change may attribute to the low uncertainty of China's fundamentals. That is, the continuous spread of COVID-19 in China was effectively prevented and controlled under some strong governance measures, the corresponding predictable demand strongly guiding the investors'

Table 2
The statistical summary of the main variables.

	Mean	Max.	Min	St.Dev.	Skewness	Kurtosis	J.B.	ADF
INE	−0.073	9.732	−11.203	2.265	−0.35	6.667	350.148***	−8.135***
ER	0.011	0.898	−0.711	0.221	0.017	4.721	74.453***	−7.764***
IR	−0.024	104.952	−41.985	12.843	1.554	12.627	2571.198***	−10.148***
TR	−0.044	18.303	−13.388	2.459	0.111	12.117	2089.848***	−7.109***
SHCI	0.009	5.554	−8.039	1.282	−0.577	7.808	614.29***	−8.565***
EI	−0.049	6.074	−8.052	1.359	−0.465	6.954	414.501***	−8.532***
CP	0.019	2.566	−5.651	0.791	−0.808	7.816	648.533***	−7.327***

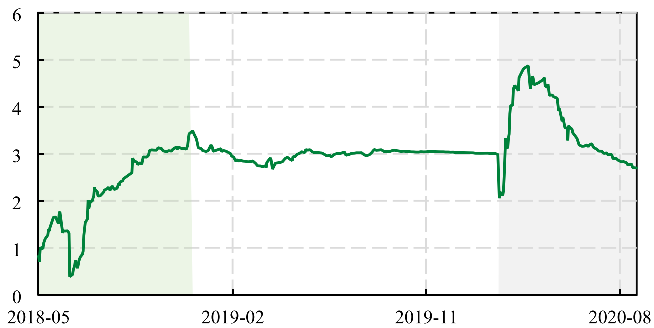

Fig. 1. The expected number of predictors in forecasting INE return.

judgments on the crude oil price. Another potential mechanism might be information contagion (Gharib et al., 2021; Klein, 2018). After a significant emergency, investors will be more at panic and irrational, leading to more information transmission. As the epidemic has gradually been effectively understood and spread speed becomes stable, the rational judgment on COVID-19 gains the upper hand (Lin & Su, 2021), driving down the pricing effects of the Chinese macro-financial factors. If we do not consider the impact of the epidemic, it could be implied that the capacity of China's macro-financial factors determining the INE price has gone from a gradual rise to a long-term plateau.

5.2. *The analysis based on posterior model-inclusion probabilities*

The nature of the importance for each factor remains unclear and results in Fig. 1 are unable to encompass the specific time-varying features for all the considered factors. What follows is an account of these issues.

We estimate the posterior inclusion probabilities of every considered Chinese macro-financial factor that drives the INE return series at all-time points in the sample period, and then plot the time-varying trend in Fig. 2 to show the dynamic importance of these factors. It should be noted that we add a shaded area for the time-varying importance map of each factor to distinguish between before and after the global outbreak of the COVID-19. For each of the posterior inclusion probabilities plots, we draw an exponentially smooth curve as a visual contour of the trend.

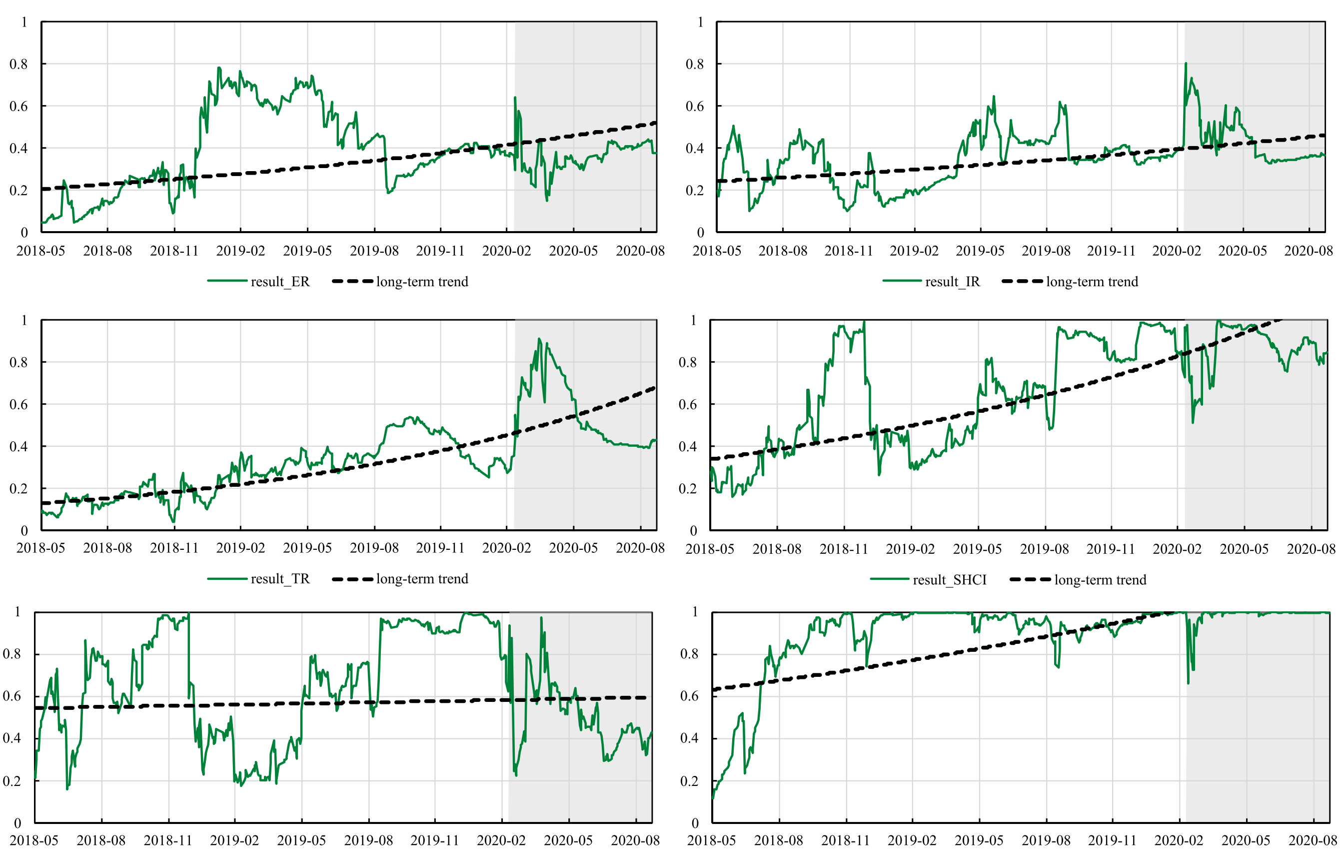

Fig. 2. The time-varying importance for each Chinese macro-financial factor as a predictor.

It is apparent from Fig. 1 that very few factors could not synthesize an obvious upward trend for its time-varying importance on INE futures price. This mirrors the findings in the last subsection, the pricing influence of Chinese macro-financial factors on the Shanghai crude oil futures were getting an increase on the whole. During the period after the global spread of COVID-19, the pricing effect of most factors showed a trend of rapid growth first and then a gradual decline. This once again provides evidence that the shock of the COVID-19 epidemic is objectively beneficial to the independent quotes for INE, namely responding more actively to the Chinese factor during this period.

The most noteworthy aspect of the corresponding results in Fig. 2 is the traits for different kinds of selected macro-financial factors. There is a total of six variables are considered, which roughly represent two channels of financial factors pricing the INE. Treating the 0.5 as the boundary of the significance of a factor determining the INE futures, it can be seen from the figure that the three monetary financial factors (ER, IR, and TR) display a similar gradual upward pattern and are significant for only seldom. In contrast, since 2019, the market financial factors (SHCI, EI, and CP) are always important for predicting the INE futures return. Combining the results in Fig. 1, we could suggest that market financial factors dominate the pricing influence for macro-financial factors in the first and second stages. In the third stage, the COVID-19 caused an abnormal change in the importance of monetary financial factors, thereby forming a new pricing influence situation.

What stands out in the different characteristics between two kinds of macro-financial factors is the mechanism through which Chinese factors or Chinese information pricing the Shanghai crude oil futures price. In specific, the monetary financial factors are always the bridges that transmitting fundamental information to commodity markets (Albagli, Ceballos, Claro, & Romero, 2019; Buch, Bussiere, Goldberg, & Hills, 2019). Three monetary financial factors exceed the significant level only a few times, which indicates the pricing influence is not mainly generated through transmitting the Chinese fundamentals. Interest rates and exchange rates are both closely related to the attractiveness of RMB assets to foreign capital. Regarding their weak driving effects, it could be implied that China cannot effectively shape the Shanghai crude oil futures price by influencing capital flows among different crude oil markets yet. On the other hand, the results of Fig. 2 provide some evidence that the financial market channel is the crucial mechanism that China's macro-financial factors determine the INE price. The financialized crude oil assets are often included in the portfolios of investors and hedgers, and so is INE. Thus, the changes in the price of related assets (eg, other commodities and equities of the downstream industries) may affect the value judgments to the crude oil futures, ultimately the price. What is behind this mechanism is the capital flows brought about by information transmissions across different financial assets (Chevallier, Nguyen, Siverskog, & Uddin, 2018; Portes, Rey, & Oh, 2001; Wen, Wang, Ma, & Zhang, 2020). The different effects of the two channels suggest a remarkable development shortcoming of the Shanghai crude oil futures in reality. In specific, few foreign investors are participating in this market. Domestic financial markets might drive the INE price through the cross-market co-movements while the factors reflecting the fundamentals of RMB assets are not important for pricing the INE. Correspondingly, the bargaining power of China's factors overall reaches a bottleneck stage after 2019 as the importance of market financial factors reaches a peak.

Among the considered variables, CP is the most important predictor of the INE price while EI has the least obvious trend of its curve for posterior inclusion probability. CP represents the overall price conditions of the domestic commodity price. Its continuous large importance provides evidence that Chinese crude oil futures not only effectively integrate with the global crude oil markets, but also become a component of the overall commodity markets in China. While the possible rationale behind EI's irregular trend is the two-way effects between the crude oil and stocks of the related industry. EI proxy the stocks in the energy industry, it always closely correlated with the crude oil futures and the two influence each other. Who occupies the pricing power is often determined by the amount of information on both sides (Filis, 2010; Ritter, 2003). Therefore, EI might show a weak pricing influence on the INE futures when oil price receives a huge information shock, this is exemplified in the declining importance of EI during the period of global crude oil turmoil after the COVID-19 global spread.

5.3. The analysis based on different frequency components

Based on some literature (Faria & Verona, 2018; Risse, 2019; Xu, Jin, & Jiang, 2020), important predictors or determinants of financial asset prices may be different in the short-term and long term. The importance of a single factor could also not produce the same pricing effect for different time scales. Thus, we furtherly construct a combination of the frequency domain analysis with the DMA method to obtain the different pricing effects in various frequency domains. We employed the CEEMDAN (complete ensemble empirical mode decomposition with adaptive noise) method (Torres, Colominas, Schlotthauer, & Flandrin, 2011) to decompose the oil price returns.

We determine the $IMFs\ number = Ceiling(log_2(xsize)) - 1$ (Wu, Huang, Long, & Peng, 2007), where *xsize* represents the ensemble size 603. Following this rule, a total of eight IMFs were extracted from the original data series. To efficiently representing the short-, medium-, and long-term changes of the INE return sequence, we classify the components obtained from the CEEMDAN process by k-means algorithm clustering the frequencies (Xu, Shang, & Lin, 2016; Zhu, Liu, Wu, Chen, & Zhou, 2019).

The main procedure of the CEEMDAN method and the clustering results are available in Figure A.1. At last, we set the high-frequency component as the IMF1; the second group is IMF2 + IMF3, representing the medium-frequency component; while the sum of the remaining IMFs and residue is defined as the low-frequency component. Similar to the previous sections, we further applied the DMA method to understand how these decomposed frequency components responding to the Chinese macro-financial factors.

The results obtained from the DMA specification are in Fig. 3, which shows at least how many a number of the considered factors are included as the significant variables to forecast INE price return. In general, the expected size of the forecast models for three frequency components always differs over time and is increasing. The rising numbers of predictors provide further evidence that the pricing effects of Chinese macro-financial on INE futures have been improving, namely this emerging futures contract was developing towards the set goals.

The differences between the three frequency components are obvious. Strong evidence can be found that the predicting capability of Chinese macro-financial factors on high-frequency components is overall larger than the other frequency components. Thereupon, Chinese macro-financial factors produce the most influence on the short-term frequency components when pricing the INE crude oil futures. The most striking result to emerge from the figure is that Chinese macro-financial factors are more efficient to predict the low frequency of INE price return than the medium-frequency component. This unanticipated finding illustrates that the bargaining power of the Chinese macro-finance does not always decrease with the extension of the time horizon. The larger pricing effects on low-frequency INE prices might attribute to its underlying economic meaning. Considering the time-spans of different frequency components, the low-frequency component tends to be of a large time scale of approximately a monthly period. Such fluctuations always indicate worldwide supply-demand shocks (Chen, Liao, Tang, & Wei, 2016; Xu, Tan, He, & Liu, 2019). As the largest crude oil importer, China could determine the enduring trend of crude oil price thereby displaying good pricing effects of the macro-financial factors.

Note: For this figure, A yellow point (brown, red, black) indicates several included predictors is above 1 (2, 3, 4), while there is no color point if the expected number of predictors is less than 1.

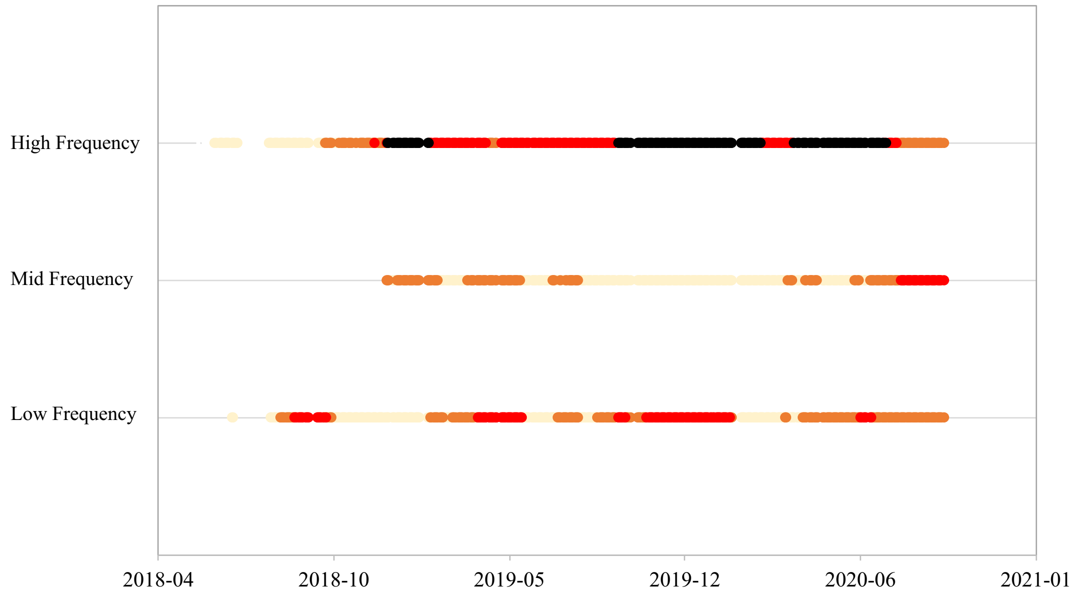

Fig. 3. The expected number of predictors in forecasting decomposed frequency components of INE.

Together these results provide important insights into the time-varying importance of the Chinese macro-financial factors on INE price return. Since the high-frequency component responds the most from the Chinese macro-financial factors, we further display the time-varying importance for each factor as a predictor of the short-term INE price fluctuations in Fig. A.2. These corresponding results reveal the pricing influence of Chinese macro-financial factors was roughly increase continuously. Such a time-varying trend similar to the case of the original series reconfirms that the pricing power of China's macro-financial factors mainly dominates in the short term. The lower pricing effects of monetary financial factors compared to the market financial factors could still be observed in this figure. It strengthens the deduction to the essential mechanism of which China's macro-financial factors determine the INE price might be the contagions inside the financial system.

6. Robustness check

In this section, we present some robustness tests to respond to any concerns induced by different forgetting factors, synergy trends of global crude oil futures, and unreasonable frequency decomposition.

6.1. The results based on RMSE criteria

The DMA specification needs appropriate forgetting factors to provide precise results. To confirm the robustness, we apply another widely used criterion mean absolute error (MAE) to set the forgetting factors. The results are displayed in Fig. B.1. Comparing it with Fig. 2, we find that the results based on two criteria for selecting the forgetting factors are largely consistent with each other. Thus, we could confirm our estimation is robust.

6.2. The results based on WTI and Brent data

Crude oil futures markets are always the typical representatives for the globalization of the commodity market. There are lots of studies that have provided evidence for the integration among different global crude oil futures contracts (Ji & Fan, 2016). It is reasonable to speculate the pricing effects of Chinese macro-financial factors on INE might be merely the particular projection of their influence on the global crude oil market. In other words, whether the estimated pricing effects are unique to INE remains to be discussed. To solve this potential concern, we further estimate the posterior inclusion probabilities for each Chinese macro-financial variable as a predictor of crude oil prices in WTI and Brent futures contracts, as the comparison.

The price data of these two crude oil futures were sourced from the EIA website,[2] and they are converted to RMB denominated to eliminate the biases from currency exchange. We display the time-varying importance of Chinese factors on WTI and Brent futures price return in Fig. B.2 and Fig. B.3, respectively. To omit space, we only present the results based on selected forgetting factors minimizing the RMSE criteria. From the results based on WTI and Brent crude oil futures, the DMA probabilities of all considered factors always fluctuate around 0.4, and which cannot present the obvious trend over time. They combinedly mirror the unique pricing effects for Chinese macro-financial factors on INE futures contracts.

6.3. The frequency analysis based on wavelet decomposition

There might be still a question that does the scale differences always exist for other decomposition methods? To answer this question, we rerun our estimation by using an alternative method to decompose the original price returns series of INE futures contracts, traditional wavelet decomposition (Gençay, Selçuk, & Whitcher, 2001; Percival & Walden, 2000).

With the specification of the wavelet method, we still decompose the original INE futures price return sequence into the 9 wavelets. After the clustering process, these wavelets could reconstruct three components to represent the high frequency, mid-frequency, and low frequency of the INE price fluctuations. The subsequent DMA estimation on the three frequency components confirms the findings of the previous section that INE price would receive the large pricing effects from the Chinese macro-financial factors in the short-term, and INE has been developing towards the aim of responding to more Chinese information.[3] In general, all the findings by wavelet decomposition provide strong evidence for the robustness of our results.

[2] https://www.eia.gov/dnav/pet/hist/RCLC1D.htm

[3] Due to the length of the article, we do not present the corresponding results, it is available if request.

7. Conclusions

This article aims to initially understand how the INE responds to China's information by analyzing the driving role of macro-financial factors. With the dynamic model averaging (DMA) specification, we conduct our main empirical analysis from three perspectives, the expected numbers of significant factors, the time-varying importance of each macro-financial factor, and the discussion with considering the frequency domain. Eventually, we reveal the following findings.

(1) The pricing influence of Chinese macro-financial factors on the Shanghai crude oil futures increased during the sample period. It did develop towards its initial goal of responding to more Chinese information. In specific, the time-varying importance of China's macro-financial factors can be roughly divided into three stages, taking 2019 and the COVID-19 global spread as the boundary. The first stage is an evolutionary process of increasing the pricing importance of Chinese macro-financial factors; then such effects kept stable in the second stage; while the turmoil caused by COVID-19 dramatically rises and then declines the pricing effects, representing the third stage. After assessing the characteristics of the three stages, we could suggest that the capability of INE futures contracts responding to Chinese information has entered into a bottleneck period.

(2) The main channel of Chinese macro-finance pricing the INE futures contract is the contagion inside the financial system. Based on the distinct time-varying importance for predicting the INE crude oil price return, we find monetary financial factors display less pricing influence than the market financial factors. Such discoveries suggest a shortcoming of INE futures that there are still not many foreign investors in this market, ultimately causing the fundamentals of RMB assets are not important for pricing the INE. Attracting more participation from overseas investors and traders might be crucial to breaking this situation.

(3) Chinese macro-financial factors produce the most influence on the short-term frequency component of INE crude oil futures. Thus, more efforts should be applied to improve its capability to respond to Chinese information in the med and long-term periods to realize the original mission of China's crude oil futures contracts. This result also suggests that INE price seems like a shadow of the mature crude oil futures, and it cannot form an independent long-run trend based on regional supply and demand conditions.

Overall, the cultivation of the Shanghai crude oil futures contract provides new possibilities for solving "Asian premiums". However, the INE is still far away from forming a stable and consistent regime as expected, and the responsiveness improvement has been slowing down. Thus, it is significant to find new momentum for developing the INE to break through the bottleneck. According to our findings, Chinese information lacks a strong bridge channel for affecting the INE futures price changes. This confirms the practical shortcomings of this new futures market, international investors and traders rarely participate. To overcome this defect, a gradual progression would be appropriate for China. Firstly, guiding domestic enterprises to preferentially use the INE for pricing or settlement, then strengthening its role in the process of signing long-term agreements and importing crude oil. The increased utilization in proceeding international trades would generate more overseas investors and eventually increase the influence of China's information. Besides, a more open futures management mechanism should be implemented, the policymakers need to further liberalize the access restrictions for foreign investors, and it is also crucial to guide and manage RMB value expectations to stabilize the market's confidence. The above steps may attract investors to pay more attention to Chinese fundamentals when investing in the RMB-based crude oil futures.

At last, our findings could also provide some implications for crude oil investors. The role of Chinese macro-financial in pricing the futures price has been verified increasing, which implies the more important role of Chinese information in this market. Thus, the investors in this market should pay full attention to China's economic policy adjustments, RMB exchange rate expectations, and the market conditions of crude oil-related RMB assets but not only focus on the information spillover from the other mature crude oil futures. The significant increase in the importance of Chinese financial factors during COVID-19 indicates that investors should consider hedging the exposure to Chinese regional risk, especially when similar global black swan events occur. Since the pricing effects of macro-financial factors differ in the short-term through to the long-term, investors should be cognizant of the importance of the time horizon in their capital allocation on INE futures. The rapid changes in Chinese information may only require special attention from investors engaged in short-term high-frequency trading.

Declaration of Competing Interest

None.

Acknowledgments

This paper is supported by National Natural Science Foundation of China (Key Program， No 72133003).

Appendix A. The main steps of CEEMDAN decompositions

Huang et al. (1998) proposed that all-time series signals are composed of oscillating fluctuations of different scales, so it is possible to extract the intrinsic mode functions (IMFs) from the original signal sequence to obtain the signal situation at different frequencies. Based on this view, the Empirical mode decomposition (EMD) method was developed and gradually applied to analyze the periodic fluctuations and spectrum characteristics of financial markets. However, this method is prone to modal aliasing, so that the precipitated price signal cannot reflect the real market conditions.

Thus, Torres et al. (2011) developed an alternative CEEMDAN approach that adds noise to residuals from previous iterations so that avoiding the modal aliasing. To sum, there are two advantages of this method: (1) This method is an extension of the empirical mode decomposition (EMD), thereby enable decomposing of nonlinear time series signals and avoiding the defects of the wavelet decomposition approach that requires the predefined mother wavelets when decomposing a sequence. (2) The CEEMDAN is an adaptive method. During the process of decomposing a signal, it adds the white noise component to the residual of the previous iteration at each iteration, so that no additional input is created for the original signal. The adaptive noises solve the problem of mode mixing caused by the EMD method and have an efficiency advantage over the ensemble empirical mode decomposition (EEMD) method whose reconstructed signal may appear to residual noise.

The specification of CEEMDAN is constructed as the following steps.

(1) Decompose the synthesized series into the intrinsic modes from the procedure of EMD;

(2) Let $E_j(\cdot)$ be the operator that produces the jth mode obtained by EMD, and let Let w^i be white noise with $N(0,1)$.

(3) Define the original signal for the INE futures return as the y(t) and ε_0 is a noise coefficient, we could decompose each $y_i(t) = y(t) + \varepsilon_0 w^i$ by EMD

to extract the first IMF, where i = 1, 2, …, I. The first mode function is $\overline{IMF}_1 = \frac{1}{I}\sum_{i=1}^{I} IMF_{i1}$.

(4) Calculate the corresponding residue as $r_1(t) = y(t) - \overline{IMF}_1$

(5) Thus, the second mode function could be calculated from decomposing the residue in the last step as $r_1(t) + \varepsilon_1 E_1(w_i(t))$, that is $\overline{IMF}_2 = \frac{1}{I}\sum_{i=1}^{I} E_1(r_1(t) + \varepsilon_1 E_1(w_i(t)))$.

(6) Repeat Steps 3 to 5 until the obtained residue is no longer feasible to be decomposed, then we obtain the all IMFs.

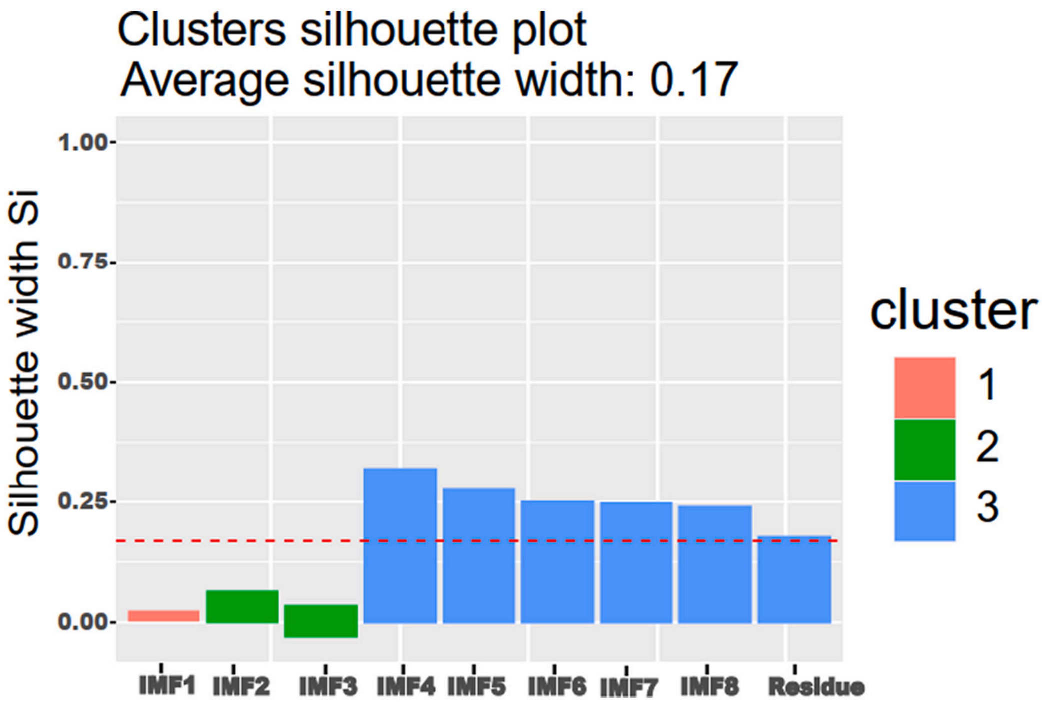

Fig. A.1. The results for the clustering algorithm.

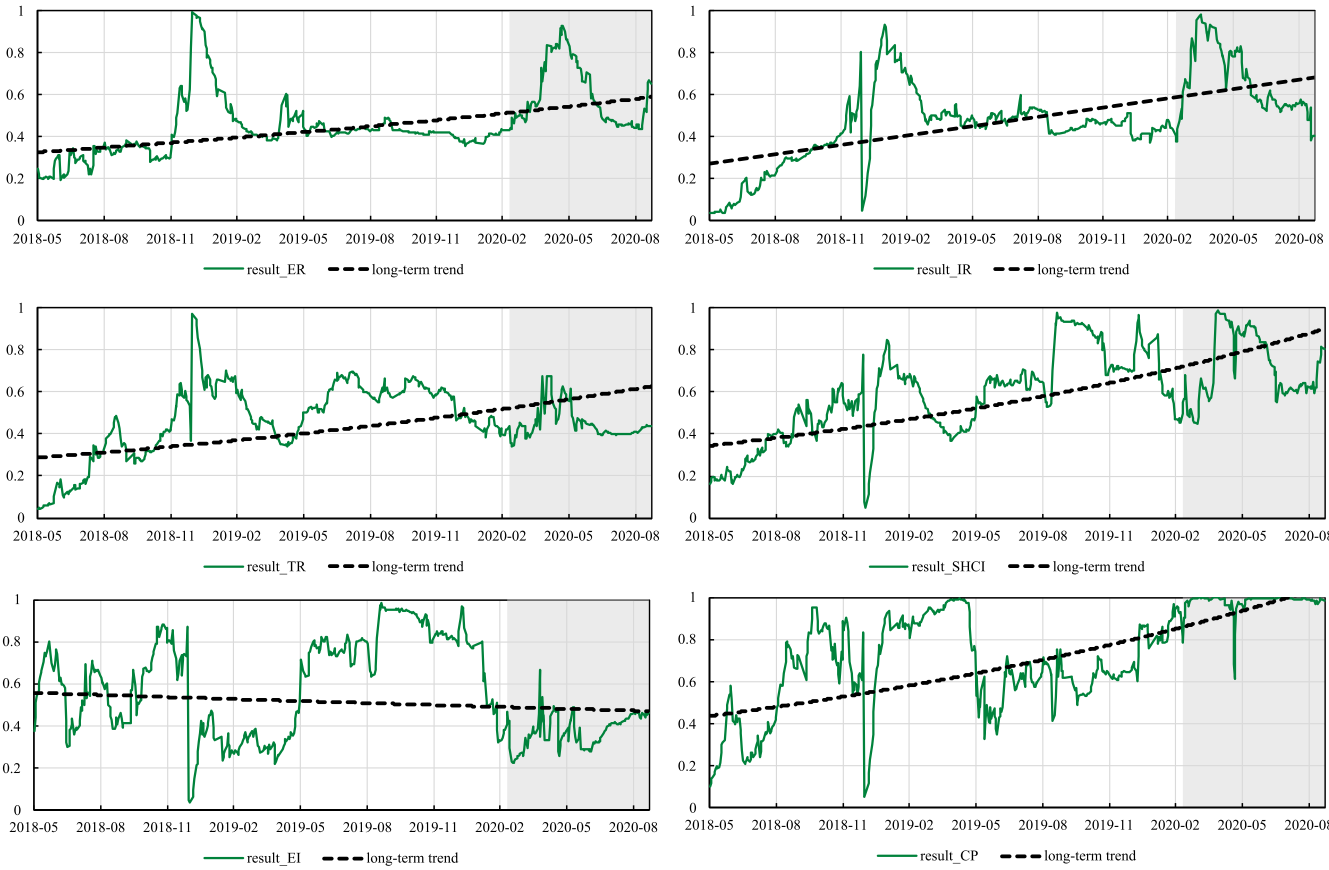

Fig. A.2. The posterior inclusion probabilities for each Chinese macro-financial variable as a predictor for the low-frequency components of INE futures.

Appendix B. Appendix

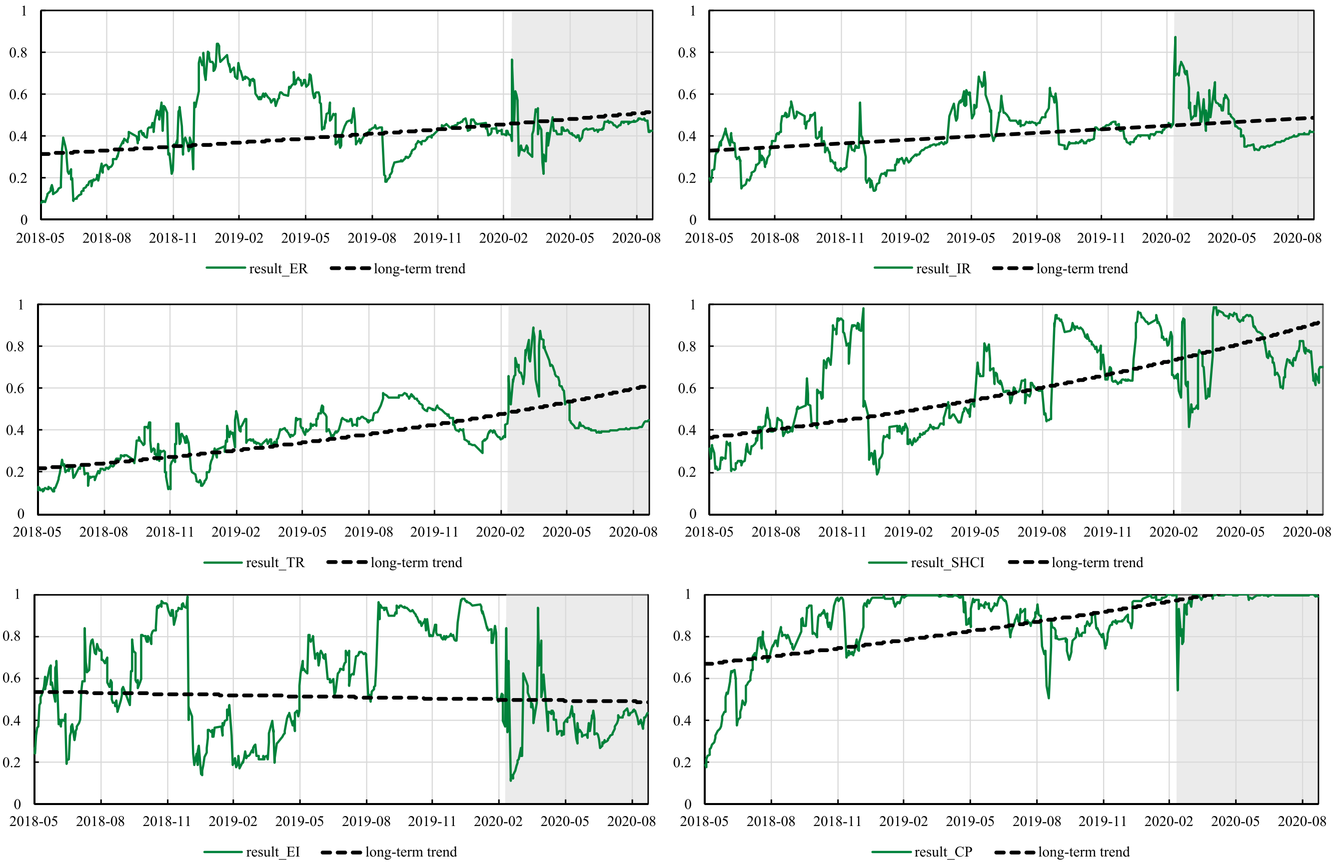

Fig. B.1. The posterior inclusion probabilities for each Chinese macro-financial variable as a predictor (MAE criteria).

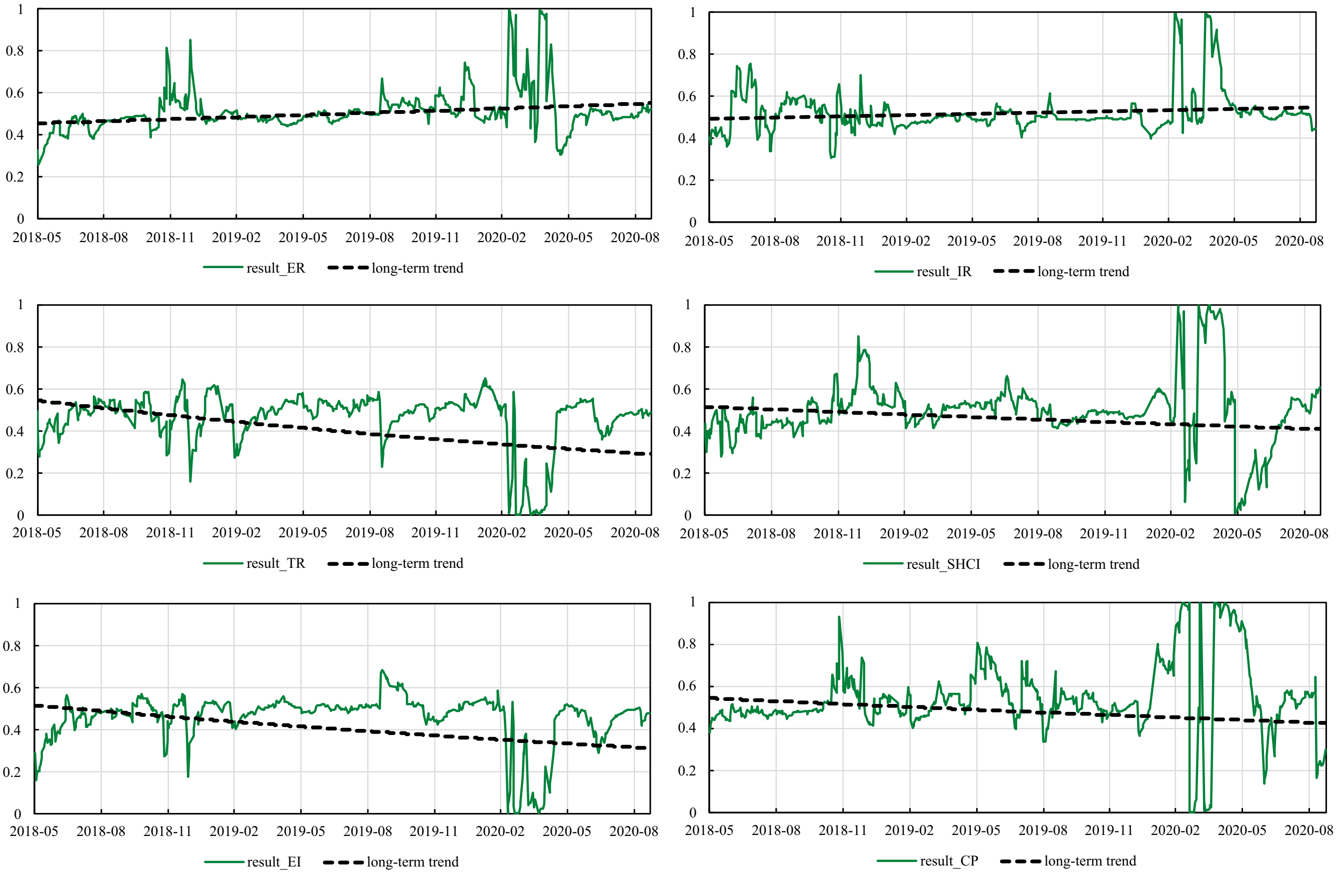

Fig. B.2. The posterior inclusion probabilities for each Chinese macro-financial variable as a predictor of WTI prices.

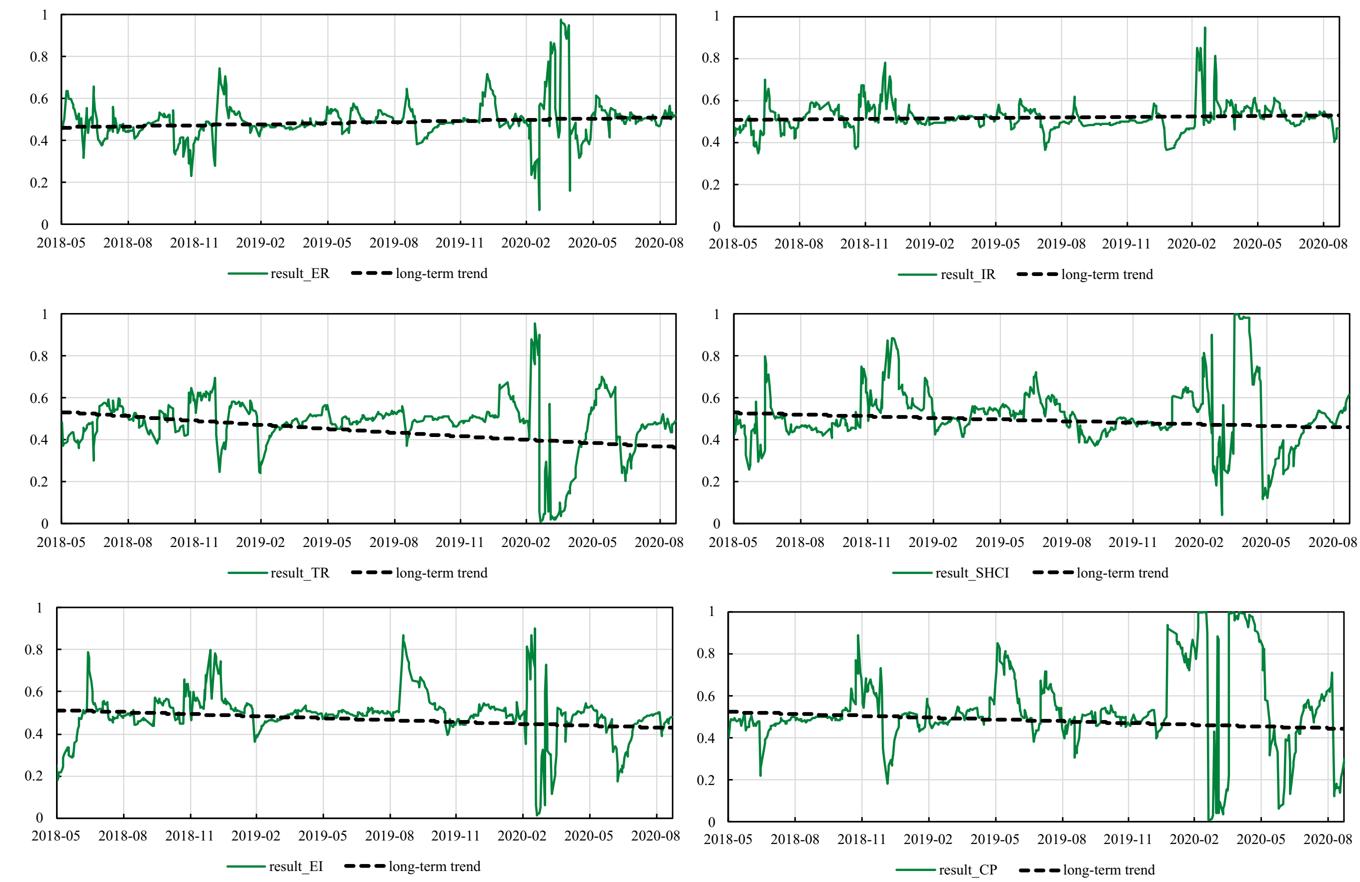

Fig. B.3. The posterior inclusion probabilities for each Chinese macro-financial variable as a predictor of WTI prices.

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