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The inevitable role of the oil market: Does its price really matter for forestry investment in China?

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Abstract Delving into the intricate roles of oil prices holds the key to attaining sustainable growth of forestry investment in China. Utilising the full- and sub-sample approaches, this article aims to reveal the dynamically evolving relationships between oil price (OP) and forest investment (FI) in China. The quantitative outcomes underscore the complex interplay between OP and FI, highlighting favourable and unfavourable impacts. Notably, the findings indicate that a substantial surge in oil prices could potentially pose obstacles to forestry investment in China, whereas a decline in OP could serve as a stimulus. Nevertheless, it is imperative to acknowledge that this inference is not uniformly applicable when the effect turns positive, primarily influenced by sluggish economic conditions resulting from the global trade wars. Conversely, FI positively influences OP, underscoring that the decline in forestry investment in China could drive down oil prices through psychological and environmental factors. Amid escalating economic and energy uncertainties globally, essential policy suggestions will be proffered to China, aiming to ensure the robust development of the oil market and forestry investment.

Keywords: forestry investment; oil price; time-varying; China

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Introduction

The primary objective of this article is to explore the intricate relationship between oil prices and forestry investment. Furthermore, it seeks to investigate whether oil price significantly influences forestry investment in China. Oil, being a crucial source of industrial raw materials and energy, experiences fluctuations in prices that can substantially impact various economic indicators such as the price level, inflation rate, and economic growth rate (Pal et al. 2019, Xu et al. 2022, Gong et al. 2024). These price changes directly influence investors' expectations and decision-making processes, which might greatly impact their investment (Su et al. 2023b, c). Among the various investment avenues, forestry investment occupies a pivotal position since it would promote ecological construction and environmental protection, respond to global climate change and promote sustainable economic development (Liu et al. 2023, Bosch et al. 2024, Ferreira et al. 2024).

Meanwhile, oil prices might significantly influence forestry investment, playing a crucial role in shaping its dynamics. Specifically, in forestry production, from planting and rearing saplings to harvesting and transporting wood, all aspects need to rely on fuel-driven machinery and equipment and transportation (Feuerbacher et al. 2021). However, a surge in oil prices would directly inflate production and transportation costs (Li et al. 2023, Su et al. 2023a) and then reduce the overall efficiency of forestry investment. In addition, high oil prices may also exert an impact on other related industries in the forestry industry chain, such as the forestry machinery manufacturing industry, wood processing industry, forest products trade, etc. (Jin et al. 2023), which would worsen the whole environment and atmosphere of forestry investment. However, high oil prices may also boost several aspects of forestry investment. For example, it could push the forestry industry to more actively pursue alternative energy sources and energy-saving technologies to reduce production costs and improve energy efficiency. As a result, forestry investment is intricately intertwined with oil prices, a crucial aspect that remains incompletely explored. This exploration would facilitate forestry investment and ensure the market's sustained growth.

Affected by multiple factors such as the difficulty of domestic oil exploitation, slow growth of oil production and increasing demand for oil consumption, China's dependence on oil imports has shown a rising trend (Bilgili et al. 2024, Rivera-Alonso & Iglesias 2024). Thereby, the demand gap for oil is constantly expanding, which profoundly affects China's economic development (Guo et al. 2024). More specifically, an extremely high level of reliance on external energy sources can significantly impact China's energy security and economic stability, particularly during periods of volatile oil price fluctuations (Liu et al. 2022, Li et al. 2023). In this context, a thorough examination of oil prices carries crucial implications for Chinese investments, particularly those in the forestry sector.

Globally, China stands out as a country with one of the fastest-growing forest resources (Yin et al. 2024). However, China continues to be a nation with scant forest resources (Yu et al. 2023, Cheng et al. 2024) because its forest coverage falls well below the global average, and its per capita forest area and stock are merely one-third and one-sixth of the global averages. Given the backdrop of volatile oil prices, exploring effective strategies to enhance China's forestry investment and foster its sustainable development is a pertinent topic deserving of further investigation, yet it remains underexplored in current research. Moreover, previous studies have overlooked the intricate and dynamic interactions among these two elements, and we aim to address this gap in knowledge through our article.

This article makes several significant advancements. To begin with, while previous research has primarily focused on the relationships between oil price and investment (Yin & Yang 2023, Shang et al. 2024, Wang et al. 2024, Yang et al. 2024) or forestry and energy (Feuerbacher et al. 2021, Wu et al. 2023, Posadas-Paredes et al. 2024, Zhang et al. 2024), none of these studies have provided a comprehensive analysis of oil price and forestry investment in the context of China. Our study, therefore, marks a groundbreaking effort, delving deeply into the complex interactions between oil prices and forestry investment. It further explores whether oil price notably influences forestry investment in China. Moreover, it is overlooked in current research that the relationship between OP and FI could evolve over time. Given this, we conduct four stability tests on parameters to demonstrate the inadequacy of the full-sample approach. Consequently, this article innovatively employs a sophisticated sub-sample approach to reveal the evolving interplay between OP and FI.

Materials and Methods

Full-sample technique

Consistent with Sims (1980), a vector auto-regressive (VAR) system is established to investigate the intricate relationships among diverse series. Nonetheless, the selected sequences and the VAR process must adhere to the standard normal distributions. Failing to comply with this requirement, we must refrain from employing the VAR model to discern relationships among variables, as its reliability remains uncertain (Su et al. 2024a). Subsequently, Shukur and Mantalos (1997) addressed this issue by introducing a critical value derived from the residual bootstrap (RB) technique. Employing this method for causality testing enables variables and the VAR model to accommodate skewed distributions, even in the case of small samples (Qin et al. 2024a, c). Additionally, they enhanced the likelihood ratio (LR) method, adapting it to accommodate size and power considerations (Shukur & Mantalos 2000). This article employs the RB-based revised-LR technique to investigate the Granger causal relationship among chosen series. The following formula represents the VAR (s) process.

$$Z_t = \phi_0 + \phi_1 Z_{t-1} + ... + \phi_s Z_{t-s} + \vartheta_t \qquad (1)$$

In this context, the optimal lag order, denoted by s, is determined using the SIC. This selection process ensures the identification of the most appropriate lag order for the VAR model. Utilising specific variables, we represent Z as Z_t = (FI$_t$, OP$_t$)' , leading to reforming the previous formula into Equation (2).

$$\begin{bmatrix} \text{FI}_t \\ \text{OP}_t \end{bmatrix} = \begin{bmatrix} \phi_{10} \\ \phi_{20} \end{bmatrix} + \begin{bmatrix} \phi_{11}(L) & \phi_{12}(L) \\ \phi_{21}(L) & \phi_{22}(L) \end{bmatrix} \begin{bmatrix} \text{FI}_t \\ \text{OP}_t \end{bmatrix} + \begin{bmatrix} \vartheta_{1t} \\ \vartheta_{2t} \end{bmatrix} \qquad (2)$$

We construct the VAR (s) system using the formula as a foundation. Our initial assumption is straightforward: there is no significant Granger causality between FI and OP. If no evident influence is observed from OP to FI ($\chi_{21,j}$=0 =0, $j \in [1,s]$), the hypothesis is upheld; otherwise, it is rejected.

Stability test of parameters

The full-sample technique assumes a fixed set of parameters in the VAR system, an assumption that might not be universally applicable (Su et al. 2024b). When the coefficients experience structural alterations, utilising this approach may yield inaccurate estimations. Therefore, to refine the precision of our estimations, we integrate the *Sup-F*, *Ave-F*, and *Exp-F* techniques into the article, as introduced by Andrews (1993) and Andrews and Ploberger (1994). The *Sup-F* technique identifies structural changes in the chosen sequences and the VAR (s) model, whereas the *Ave-F* and *Exp-F* methods evaluate whether the coefficients undergo gradual variations over time. Furthermore, we employ the L_c statistics, initially proposed by Nyblom (1989) and Hansen (1992), to ascertain if the parameters exhibit a random walk pattern. When structural alterations occur in the chosen sequences or the VAR (*s*) process, the correlation between FI and OP becomes contingent upon time. In conclusion, the full-sample approach may carry biases, and it is recommended that this article adopt a sub-sample one to capture the dynamic relationship among the selected sequences accurately.

Sub-sample technique

The sub-sample technique, as advocated by Balcilar et al. (2010, 2013), is utilised to identify the varying nature of the relationship between FI and OP. Subsequently, it is necessary to divide the entire sequences into smaller segments using a predefined rolling window width and gradually shift them from the start to the end. However, choosing an appropriate width is not straightforward, as a wider window reduces the analysis frequency, while a narrower one may lead to inaccurate conclusions.

Pesaran and Timmermann (2005) addressed this challenge by demonstrating that when the VAR (s) model parameters exhibit time-varying characteristics, the recommended width should be at least 20 or greater. The concrete procedure involves the following steps: Firstly, we assume that the total length of the sequences is *E* and the rolling window width is *r*. Then, it determines the endpoints of each section as *r*, *r+1*, ..., and *E*. In the second step, we employ the *RB*-based revised-*LR* technique to identify the interrelationship within each segment. The third step involves acquiring the estimates of the sub-sample technique by sequentially computing the *LR* statistics and p-values. The mean values $N_b^{-1}\sum_{k=1}^{s}\hat{\phi}_{21,k}^{*}$ and $N_b^{-1}\sum_{k=1}^{s}\hat{\phi}_{12,k}^{*}$ signify the influence of OP on FI, as well as the reciprocal effect of FI on OP. Furthermore, the research factors in the 90% confidence interval encompassed the upper boundary defined by the ninety-fifth quantile and the lower boundary defined by the fifth quantile.

Results and discussions

Literature review

Relationship between oil price and investment

Previous studies have delved into the linkage between oil prices and investment from diverse angles. Dutta et al. (2020) highlight that the influence of crude oil prices on environmental investment appears to be statistically insignificant, albeit often positive. One potential explanation for this observation is that the dependency on oil is primarily confined to eco-friendly enterprises. Maghyereh and Abdoh (2020) demonstrate that the adverse impact of uncertainty surrounding crude oil price returns on investments exhibits asymmetry. Specifically, it could be observed that investments are more significantly curtailed in response to the volatility of positive oil price changes than to that of negative ones, which is particularly evident in smaller firms.

Ilyas et al. (2021) evidence that the negative impact of oil price uncertainty is more significant in oil-producing nations than oil-consuming countries. Wu and Wang (2021) show that the correlation between oil prices and corporate investment expenditure is negative. However, this relationship undergoes a shift when market conditions are factored in. In unfavourable market conditions, the negative correlation persists. Conversely, in favourable market conditions, corporate investment expenditure also rises as oil prices increase.

Relationship between forestry and energy

Researchers have also zeroed in on exploring the correlation between forestry investment and energy. Feuerbacher et al. (2021) find that fuelwood, one of the forestry resources, remains the principal energy source for heating and cooking purposes in rural regions. However, the overexploitation of forest resources for fuelwood would lead to deforestation and degradation of the environment, affecting the sustainability of energy. Wu et al. (2023) suggest that natural resources manifesting as forest rents could exacerbate energy insecurity.

Forest rents typically refer to the economic returns derived from utilising and exploiting forest resources, including timber sales, logging rights, and other forms of exploitation. While these rents may provide temporary economic gains, they often come with long-term costs that would have profound implications for energy security. Posadas-Paredes et al. (2024) propose that by harmoniously integrating the development of energy infrastructure with incentives for reforestation, the Mexican electricity sector can not only strive to fulfil its escalating energy demands but also take substantial steps towards environmental preservation. Zhang et al. (2024) emphasise that constructing solar farms over forested areas or at the cost of deforestation does not improve energy efficiency compared to using open land. Therefore, such practices should be approached with utmost caution or avoided altogether.

The case of China

From the perspective of China, Wang et al. (2017) underline that uncertainty surrounding oil prices has a detrimental effect on corporate investment spending, and this negative impact is particularly notable for non-state-owned listed companies in contrast to state-owned listed companies. Yin and Yang (2023) reveal that the returns on oil prices possess a statistically and economically noteworthy negative predictive capacity for a company's fixed investment. The inconsistencies in this impact across different industries and their hierarchical structures exhibit a distinct "production pattern". Shang et al. (2024) provide evidence that the fluctuation in crude oil prices has a detrimental impact on investment expenditure while concurrently improving the investment efficiency of enterprises.

During significant events such as the global COVID-19 pandemic and the Russia-Ukraine conflicts, there is a substantial increase in crude oil price uncertainty, leading to reduced enterprise investment expenditure and improved enterprise investment efficiency. Wang et al. (2024) point out that upward trends in international crude oil futures prices tend to constrain the investment scale of Chinese manufacturing enterprises, whereas price volatility exhibits a stimulatory effect. Yang et al. (2024) underscore that oil price uncertainty has a negative impact on inefficient investment and identify a shortened debt maturity structure as one of the underlying mechanisms. Additionally, this adverse influence is more pronounced in state-owned enterprises, companies facing higher financing constraints, and those with lower ownership concentration.

Research gaps

Unlike previous research, which mainly examines the relationship between oil prices and investment or between forestry and energy, our work focuses specifically on the relationship between oil prices and forestry investment in China. It provides a comprehensive analysis of this connection, exploring whether oil prices significantly affect forestry investment. A key innovation of our study is the use of the cumulative growth rate of forestry fixed assets as a measure of forestry investment in China. Additionally, our research challenges the assumption that the relationship between oil prices and forestry investment remains stable over time. To address this, we apply a sub-sample approach, demonstrating that the relationship evolves and that a full-sample analysis is inadequate. Based on these insights, we offer policy recommendations aimed at promoting the growth of both the oil and forestry sectors in China.

Data

The main focus of this article is on monthly data, ranging from January 2004 to December 2023, to elucidate the intricate relationship between oil price and forestry investment. Additionally, it aims to investigate whether oil price significantly influences forestry investment in China. In 2004, global oil prices rose sharply, increasing from 31.28 dollars per barrel in January to 49.78 dollars per barrel in October. This phenomenon is attributed to reduced production and imports in the Gulf of Mexico due to Hurricane Ivan, the threat of strikes by the Nigerian oil workers' union, and tensions in the Middle East. Since then, oil prices have been subject to economic factors (economic policy uncertainty, such as the U.S.-China trade conflicts), political factors (geopolitical risks, such as the Russia-Ukraine war), climatic factors (natural disasters, such as cyclones), and epidemiological factors (such as COVID-19).

Brent crude oil, a key commodity traded primarily on the London Commodity Futures Market, is the pricing benchmark for most crude oil transactions worldwide (approximately

70%). Therefore, this article utilises the Brent crude oil price (OP) in U.S. dollars to reflect it, with the data being sourced from the U.S. Energy Information Administration. At the same time, owing to the steady progress of six key forestry projects, such as protecting natural forests and returning farmland to forests and grasslands, China has achieved remarkable progress in forestry investment and development.

Between 1998 and 2004, the six key forestry projects were consecutively carried out, encompassing a total afforestation area spanning 25.329 million hectares, and the cumulative investment amounted to 126.363 billion yuan. Therefore, this article employs the cumulative growth rate of investment in forestry fixed assets as a metric to assess forestry investment (FI). This data will be sourced from the National Bureau of Statistics of China. This indicator signifies the increase in the overall investment allocated towards forestry fixed assets during a designated time frame compared to the preceding period. In the realm of forestry, this encompasses diverse aspects, including the development of forested land, planting of trees, construction of forestry-related facilities, and research and development in forestry science and technology. Moreover, it is a gauge to assess the vitality and upward trend of forestry fixed asset investment efforts. A higher FI signifies more significant progress, while a lower FI indicates less progress. Consequently, the focal point of this article lies in investigating the correlation between OP and FI. We utilise natural logarithm and first difference to transform OP to simplify the computational procedures and mitigate the impact of significant fluctuations. Additionally, Figure 1 visually represents the trends associated with these indicators.

As depicted in Figure 1, the directions of FI and OP do not always align; thus, the intricate interrelationship between them is not static but instead dynamic and continuously evolving. In light of this, the traditional full sample technique, which assumes a constant relationship across the entire dataset, cannot effectively capture the subtleties of this Granger causal relationship. While applicable in many contexts, the full-sample approach fails to account for the time-varying nature of the FI-OP relationship, which can shift depending on the specific period or subset of data being analysed. To address this challenge, the sub-sample technique offers a more sophisticated and reliable approach. This technique allows for a more detailed analysis of the FI-OP relationship by dividing the data into smaller subsets. Each subset will be analysed separately, revealing patterns and trends that may be obscured or averaged out in a full-sample analysis, which is particularly useful in capturing time-dependent relationships.

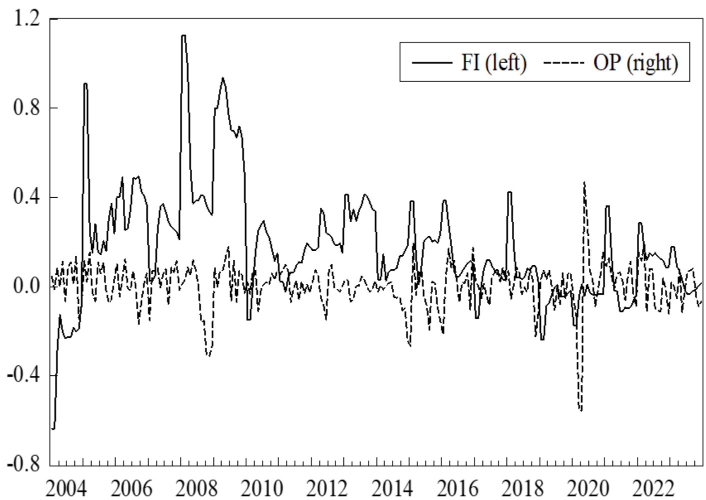

Figure 1 The trends of FI and OP. Notes: The solid line depicts the trend of FI, indicated on the left axis, while the dashed line illustrates the trend of OP, represented on the right axis.

Table 1 displays descriptive statistics for the variables FI and OP. The average values for the variables FI and OP are 0.176 and 0.004, respectively, suggesting

Table 1 Descriptive statistics for FI and OP.

	FI	OP
Observations	240	240
Mean	0.176	0.004
Median	0.141	0.017
Maximum	1.128	0.469
Minimum	-0.637	-0.555
Standard Deviation	0.261	0.108
Skewness	0.869	-1.141
Kurtosis	5.229	9.632
Jarque-Bera	79.863 ***	491.891 ***
Probability	0.000	0.000

Notes: *** is the significance at a 1% level.

that the distribution of their values tends to cluster around these two central points. However, the notable disparities between the maximum (1.128 and 0.469) and minimum (-0.637 and -0.555) values for each variable indicate that FI and OP have undergone substantial variations over time. The skewness value for FI being positive indicates a right-skewed distribution, where the bulk of the data is clustered towards the left, and the minimum values are relatively isolated towards the right side of the distribution. But OP exhibits a negative skewness, indicating that its distribution is left-skewed. In relation to kurtosis, FI and OP exhibit a leptokurtic pattern, which is evident from their kurtosis value surpassing 3. Thicker tails and sharper peaks than a standard normal distribution distinguish this pattern. Additionally, the Jarque-Bera test, conducted at a significance level of 1% for FI and OP, rejects the null hypothesis that these two variables follow a normal distribution. Consequently, given that the data does not adhere to a normal distribution, using the Granger causal relationship test within the VAR system is inappropriate. Therefore, this article opts for the RB-based revised-*LR* technique to overcome the challenge posed by the skewed distributions of FI and OP. Moreover, we adopt the sub-sample approach to detect any potential variations in the transmission mechanisms between FI and OP as they evolve over time.

Quantitative evaluations and deliberations

To ascertain the absence of unit roots in FI and OP, we apply the ADF (Dickey & Fuller 1981), PP (Phillips & Perron 1988), and KPSS (Kwiatkowski et al. 1992) tests. The outcomes of these unit root assessments are presented in the ensuing table. Our observations reveal that, at the 1% significance level, FI and OP reject the null hypothesis of a unit root in the first two tests. Besides, OP upholds the presumption of stationarity in the final test, whereas FI refutes this supposition at a 5% level. Consequently, we deduce that FI and OP are devoid of unit roots. Therefore, this article proceeds with subsequent analysis utilising these two stationary series.

Table 2 The results of unit root tests.

	ADF	PP	KPSS
FI	-6.112 (1) ***	-5.031 [10] ***	0.679 [10] **
OP	-10.591 (1) ***	-11.033 [15] ***	0.100 [7]

Notes: The numbers enclosed in parentheses represent the optimal lag order determined through the application of SIC. The numbers enclosed in brackets represent the bandwidth selected using the Newey-West technique. *** and ** are the significance at 1% and 5% levels.

Using Equation (2) as a foundation, this article establishes the VAR (s) model to carry out comprehensive sample discussions. This approach enables us to capture the unwavering interrelationship between FI and OP. Based on SIC criteria, the optimal lag order is determined to be 1, and the bootstrap repetitions are set to 10000. The pertinent results are summarised in Table 3. It is evident that OP exhibits a significant Granger causality relationship with FI, whereas the converse relationship is absent. Nevertheless, these findings contrast with those reported in prior research (Dutta et al. 2020, Feuerbacher et al. 2021, Wu et al. 2023, Yin & Yang 2023, Shang et al. 2024, Posadas-Paredes et al. 2024).

During the full-sample analysis, we postulate that the coefficients of the VAR (*s*)

Table 3 The outcomes of the bootstrap full-sample method.

H_0: OP is not the Granger cause of FI		H_0: FI is not the Granger cause of OP	
Statistic	*p*-value	Statistic	*p*-value
0.070	3.180 *	0.460	0.511

Notes: The research calculates p-values through the employment of 10000 bootstrap repetitions. * is the significance at a 10% level.

model remain constant, indicating that a single Granger causality should be observed throughout the entire time span. However, this assumption may not hold true if the selected series and coefficients within the VAR (*s*) model undergo structural shifts. Such structural mutations indicate a dynamic and evolving interrelationship between FI and OP. Therefore, to assess the suitability of the full-sample technique, this article employs the *Sup-F*, *Ave-F*, *Exp-F*, and L_c statistics, summarising the outcomes in Table 4.

As evident in Table 4, the *Sup-F* method indicates that they refute the initial assumption at varying significance levels: 5% for FI, 10% for OP, and 1% for the VAR (*s*) system. This underscores the existence of structural variations in the variables and parameters employed in the VAR (*s*) model. The *Ave-F* approach suggests that FI and the coefficients in the VAR (*s*) model reject the original assumption at the 5% and 10% significance levels, whereas they refute it at 5% and 1% levels in the *Exp-F* technique. This confirms that the selected sequences and parameters within the VAR (*s*) process change over time. However, OP fails to demonstrate concordance in the outcomes of these two tests. Furthermore, the L_c statistics confirm the acceptance of the alternative hypothesis at a significance level of 1%, thereby establishing that the VAR (*s*) system does not adhere to a random walk. Hence, the tests demonstrate that the relationship between FI and OP is constantly evolving and dynamic in nature. Consistent with these findings, the study employs the sub-sample methodology to explore the intricate conduction mechanism between FI and OP. To enhance the precision of our estimations, this article follows the suggestion of Pesaran and Timmermann (2005) and adopts a width of 24 months. Subsequently, we will be able to ascertain whether the alternative hypothesis that OP (FI) Granger causes FI (OP) holds true or is rejected at a significance level of 10%. Additionally, we can clarify the directional impact of OP (FI) on FI (OP), providing a deeper understanding of their interaction.

Figures 2 and 3 offer an extensive breakdown of the relationship between FI and OP, highlighting the p-values and parameters involved. Notably, from March 2015 to December 2017, March 2019 to December 2019, and January 2023 to April 2023, there are significant Granger causalities from OP to FI at a 10% significance level. Furthermore, it is evident that during these three periods, the impact of OP on FI varies. Specifically, there are instances of positive influence (March 2019 to December 2019) and examples of negative impact (March 2015 to December 2017 and January 2023 to April 2023).

The adverse effects of OP on FI underscore that high oil prices could hamper forestry investment in China. From March 2015 to December 2017, OP initially diminished due to the oversupply of oil (e.g., the surge in shale oil production and OPEC's refusal to cut production), followed by a subsequent increase due to dollar depreciation, production cuts (e.g., OPEC and its non-OPEC counterparts reached an agreement to limit crude oil production in late 2016) and natural disasters (e.g., fires in Canada and Hurricane Harvey). The fundamental reasons underlying this negative effect on FI are explained in the following manner.

Firstly, forest resources, particularly logs and wood-based products, frequently necessitate transportation across vast distances via road, rail, or waterway (Liu et al. 2023). Consequently, elevated OP will

Table 4 The results of unit root tests.

	FI		OP		VAR (*s*) process	
	Statistics	***p*-values**	**Statistics**	***p*-values**	**Statistics**	***p*-values**
Sup-F	24.294 **	0.022	20.272 *	0.085	41.730 ***	0.004
Ave-F	12.335 **	0.034	7.318	0.387	20.309 *	0.051
Exp-F	9.065 **	0.018	5.438	0.250	15.756 ***	0.009
L_c					3.971 ***	0.008

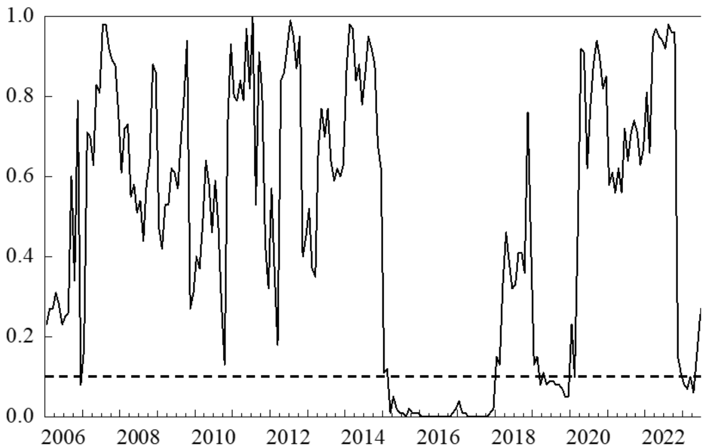

Figure 2 Examining the null hypothesis that FI is not a Granger cause of OP. Notes: The research calculates *p*-values through 10000 bootstrap repetitions. The solid line signifies the bootstrap *p*-values, whereas the dashed line denotes a *p*-value of 0.1.

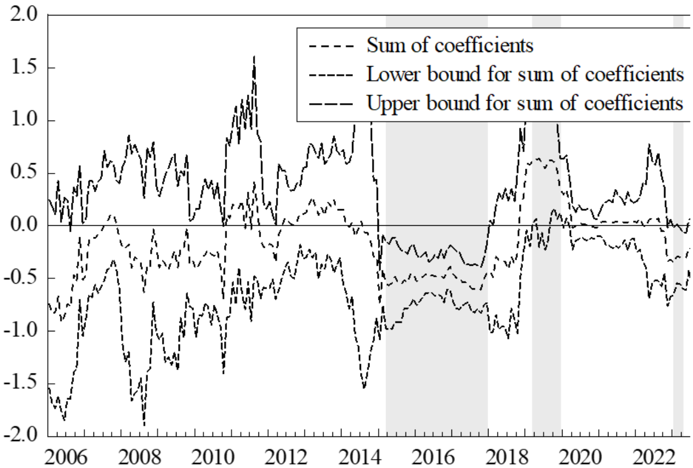

Figure 3 The coefficients of the influence from FI to OP. Notes: The shaded area depicts the interval during which FI exhibits significant Granger causality towards OP.

inevitably result in escalated transportation expenses, subsequently hiking the production costs of forestry goods (Li et al. 2023, Su et al. 2023a). For investors in the forestry sector, such a cost surge may potentially diminish their projects' anticipated profitability, thereby rendering the investment less lucrative and appealing.

Secondly, high OP could decrease consumer purchasing power in China, especially for energy-intensive products (Pal & Mitra 2019, Su et al. 2023b). As an essential raw material for construction, furniture manufacturing and other industries (Baul et al. 2022, Zou et al. 2023), the demand for wood might be affected by the decline in consumer purchasing power. Decreased market demand will negatively influence both the sales volume and pricing of forestry products, ultimately leading to a detrimental effect on FI.

Thirdly, rising OP may prompt the public to look for alternative energy sources and raw materials to reduce their dependence on fossil fuels (Qin et al. 2023a, b). Bioenergy, for example, is likely to receive more attention and investment as a renewable energy source in China (Fang et al. 2024).

This causes a shift in the use of forestry resources from traditional wood to bioenergy production. However, this transition could require significant capital and technology investment (Song et al., 2023), which is a challenge for forestry investors.

Fourthly, high OP might give rise to heightened economic uncertainty in China (Li et al. 2023, Gong et al. 2024), subsequently influencing the risk evaluation of FI. Consequently, investors may adopt a more cautious approach and demonstrate reduced willingness to finance forestry projects. Moreover, fluctuations in OP would potentially undermine the stability and profitability of industries associated with forestry, further escalating investment risks. Conversely, a decline in OP would produce the opposite effects. Therefore, it can be verified that the adverse impact of OP on FI during the period from March 2015 to December 2017 is evident.

Between January 2023 and April 2023, OP presents a downward trend, primarily stemming from the gradual deceleration of inflation in Europe and the U.S. The Federal Reserve and the European Central Bank have persisted in hiking interest rates, which has generated adverse economic impacts, making global oil demand prospects bleak. The underlying reasons for this negative impact on FI are explained as follows:

i) In the forestry industry, whether it is the harvesting and transporting of wood or the processing and sales of forestry products, considerable fuel oil needs to be used. Decreasing OP means lower fuel costs for these activities (Li et al. 2023, Su et al. 2023a), which increases the profitability of forestry enterprises and raises the economic attractiveness of FI. Besides, with lower OP, the cost of forestry products is reduced, making their prices more competitive, thus helping to expand market share and attract more investment in China.

ii) According to the National Bureau of Statistics, China's dependence on crude oil imports will rise 72.99% in 2023. Lower OP indicates consumers and enterprises would save some of their energy bills, which could translate into more consumption and investment (Xu et al. 2022, Zhang et al. 2022). On the one hand, consumers have witnessed a remarkable surge in their purchasing power (Su et al. 2023b), potentially leading to a boost in the demand for forestry products. On the other hand, enterprises have more economic space to try and adopt new technologies and methods to improve production efficiency further and reduce production costs (He et al. 2022, Yang & Song 2023). The development and application of these new technologies, in turn, may attract more FI.

iii) Lower OP might shift energy consumption patterns, potentially leading individuals to prefer petroleum products over more eco-friendly alternatives. This could result in a surge in greenhouse gas emissions and air pollution, exerting an adverse impact on the environment and climate (Su et al. 2023c, 2024c).

Given China's ambition to achieve carbon neutrality, the government actively encourages forestry investments to accomplish this goal (Qin et al. 2023a, b). As a vital area, forestry is expected to witness a surge in investment from FI, thereby contributing to the nation's environmental sustainability efforts. Consequently, it is evident that the negative influence of OP on FI is pronounced from January 2023 to April 2023.

However, the positive impact of OP on FI does not support the perspective above, which indicates that low oil prices would also hinder forestry investment in China. From March 2019 to December 2019, OP remains at a relatively low level; here are the primary reasons for this decline:

i) The significant increase in the production of shale oil in the U.S. has exerted downward pressure on OP (Wang et al., 2023).

ii) Despite attempts by OPEC to stabilise OP through production cuts, the organisation's efforts fell short.

iii) Fears of a potential global economic slowdown have loomed large over the oil market, which erodes investor confidence in this sector, subsequently affecting OP (Su et al. 2023c).

Meanwhile, FI is also on a downward trend, and there are two perspectives from which we can elucidate this. On the one hand, fluctuations in the global economic situation impact FI. In 2019, the global economy faces many uncertainties, including trade wars (e.g., the Sino-U.S. trade disputes), geopolitical tensions (e.g., a military coup in Sudan), and slowing growth in major economies (e.g., the real GDP growth in the U.S. amounted to 2.29%, while in the European Union, it reached 1.8%). These external factors make Chinese investors cautious about investing in national and overseas markets (Zhong et al., 2023), which in turn affects the scale of FI. On the other hand, slowing domestic economic growth and reduced liquidity in China are also important factors affecting FI. In the context of slowing economic growth, corporate profitability and investor confidence have been affected to a certain extent, affecting investment willingness (Bissoondoyal-Bheenick et al. 2022, Bouteska et al. 2024). Also, reduced liquidity limits the financing capacity of enterprises, making it difficult for forestry projects to obtain sufficient financial support. Indeed, there is ample evidence to support the positive impact of OP on FI from March 2019 to December 2019.

Figures 4 and 5 illustrate the *p*-values and parameters ranging from FI to OP. Between December 2017 and January 2018, FI exhibits a notable Granger causality towards OP at a significance level of 10%. Additionally, during this period, a positive impact was observed in FI and OP. This is mainly because FI might also psychologically affect the energy markets (including the oil market). Investors who invest less in forestry and have pessimistic expectations about its future development may expect this to increase dependence on fossil fuels (especially oil). Then, oil suppliers would increase the oil supply, resulting in a decline in OP. In addition, the decrease in FI also leads to a fall in forest protection and restoration activities, which may have a certain negative impact on the global ecological environment, and oil extraction would continue to increase, further reducing OP. Whereupon the unfavourable influence of FI on OP between December 2017 and January 2018 is evident.

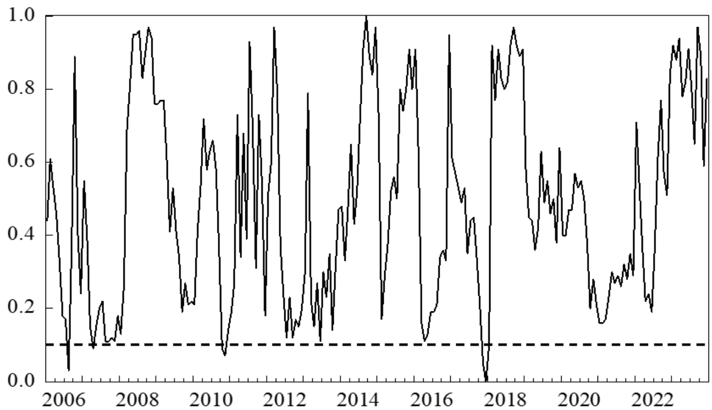

Figure 4 Examining the null hypothesis that OP is not a Granger cause of FI. Notes: The research calculates *p*-values through 10000 bootstrap repetitions. The solid line signifies the bootstrap *p*-values, whereas the dashed line denotes a *p*-value of 0.1.

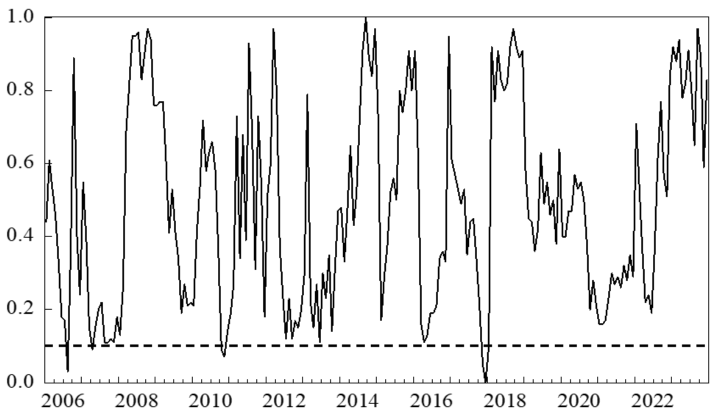

Figure 5 The coefficients of the influence from OP to FI. Notes: The shaded area depicts the interval during which FI exhibits significant Granger causality towards OP.

Summary

Employing the full-sample methodology, our investigation reveals that OP demonstrates a notable Granger causality with FI, whereas the opposite causality is nonexistent. However, this finding contradicts previous research, and relying solely on a full sample may be untrustworthy given the constantly fluctuating coefficients within the VAR

(s) model. Given the considerations above, our article employs four techniques to assess the stability of parameters and capture time-varying characteristics, ultimately revealing the existence of structural mutations within FI, OP, and the VAR (s) model. Following this, we determine that the full-sample methodology is not dependable. Consequently, this article adopts the sub-sample method to discern the dynamic interaction between the chosen series. The quantitative outcomes of this sub-sample analysis underscore both beneficial and detrimental impacts exerted by OP on FI. Notably, the negative effects indicate that a surge in oil prices could impede forestry investment in China. Nevertheless, this conclusion is not always sustained, primarily because of the poor economic performance. On the contrary, FI positively influences OP, which is attributed principally to psychological and environmental considerations.

Conclusions and policy recommendations

This article delves into the intricate linkage between oil price and forestry investment, seeking to unravel their conduction mechanism. Furthermore, it endeavours to ascertain the significance of oil prices in shaping forestry investment decisions in China. Afterwards, we utilise comprehensive and subsample techniques to explore the complex interplay between OP and FI. The sub-sample analysis's quantitative results emphasise the dual nature of OP's impact on FI, revealing both advantageous and disadvantageous effects. Specifically, the adverse outcomes suggest a significant increase in oil prices could hinder forestry investment in China. However, it's worth noting that this conclusion is not consistently upheld, primarily due to the economy's sluggish performance. Conversely, FI positively impacts OP, which is mainly influenced by psychological and environmental factors. Through examining the dynamically evolving interconnectedness between OP and FI, it is established that oil price plays a significant part in shaping forestry investment decisions in China.

Consistent with the previously mentioned findings, vital policy recommendations will be put forward for China to guarantee the healthy development of oil and forestry markets. On the one hand, both high and low oil prices are likely to discourage investment in forestry; thus, it is crucial to stabilise the crude oil market:

i) China's crude oil market will be affected by international oil price fluctuations. To stabilise China's crude oil market, enhancing political and economic collaborations with other significant crude oil reserve-holding nations is crucial to maintaining stability in the international crude oil trade market for China.

ii) Is it necessary to actively respond to changes in the international political and economic situation, including geopolitical conflicts, trade frictions and other factors on? The impact of international oil prices. In addition, a diversified crude oil trading system should be established to reduce the dependence on a single source of crude oil supply.

iii) The related authorities should issue a series of policies to promote the development of the crude oil industry, such as strengthening the reserve capacity of energy resources such as crude oil, expanding the scale of oil and gas reserves, as well as improving the organic combination of government reserves and corporate social responsibility reserves. These policies will help strengthen the ability to maintain a stable energy supply and manage risks to provide a strong guarantee for the stability of the crude oil market.

iv) It is necessary to strengthen scientific and technological innovation, which is beneficial to improve the level of crude oil extraction and processing technology, reduce production costs, and enhance the efficiency of crude oil utilisation.

On the other hand, strengthening investment in forestry is also significant:

i) It is imperative for the government to establish and refine regulations and policies that are conducive to forestry investment, thus providing investors with a stable, transparent, and foreseeable business environment. Additionally, the policy publicity should be strengthened to improve the social awareness and attractiveness of forestry investment.

ii) The government could bolster financial investment in forestry, support infrastructure construction, promote scientific and technological advancements, and foster personnel training, all of which would contribute to enhancing the overall competitiveness of forestry development.

iii) The relevant authorities should actively steer social capital towards forestry, broadening financing avenues for the sector through the establishment of forestry investment funds, issuance of forestry bonds, and other means, which ensures a steady stream of funding for forestry development.

Compliance with ethical standards

Conflict of interest

The authors declare that they have no conflict of interest.

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