Analysis of the Supply and Demand Mechanism of LNG Price Fluctuations in China: An Empirical Study Based on the VAR Model

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Abstract. This paper investigates the determinants of China's LNG price dynamics from a supply-demand perspective using monthly data. Employing a Vector Autoregression (VAR) model. We analyze the interrelationships among four key variables: the return of China's LNG import price, the return of Brent crude oil price, the year-on-year change in European natural gas reserves, and the year-on-year change in China's natural gas import. Impulse response analysis indicates that the impact of Brent crude oil price shock on the price of liquefied natural gas in China is relatively small and lasts for a short time. The impact of LNG import has a certain positive promoting effect on prices in the short term. The shock of natural gas reserves in Europe has shown a slight but persistent negative impact.

Keywords: VAR model, Supply and Demand, LNG Price

1 Introduction

With the rapid development of the economy, energy has become a crucial factor in national development. Compared with other energy sources, natural gas is a high-quality energy source and is increasingly being promoted by countries around the world to to promote sustainable development.

In recent years, rising geopolitical risks have led to heightened volatility in the natural gas market. Since the outbreak of the Russia-Ukraine conflict, the full suspension of the "Brotherhood" pipeline has caused Russian natural gas supplies to Europe to drop to unprecedented lows. This has not only intensified Europe's energy security crisis but also increased global competition for liquefied natural gas (LNG), further straining supply chains and exacerbating price fluctuations. At the same time, ongoing technological innovation and waves of industrial transformation are accelerating the global shift toward a green, low-carbon energy system, which also contributes to rising demand for natural gas and thus influences price trends.

As the world's second-largest natural gas consumer, China produced 246.4 billion cubic meters of natural gas in 2024, yet still remains dependent on imports. Driven by growing demand and falling gas prices, China's natural gas imports surged to a record high of 131.69 million tons, surpassing 130 million tons for the first time. Of this total,

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lower gas prices led to a 7.7% year-on-year increase in LNG imports to 76.65 million tons, accounting for approximately 58% of total imports. Pipeline gas imports rose by 13.1% year-on-year to 55.04 million tons, representing about 42% of total imports (Source: 2024 China Natural Gas Market Development and Outlook). China's external dependence on natural gas reached approximately 40.9%, up 0.9 percentage points from the previous year.

Therefore, gaining insights into the evolving dynamics of China's natural gas supply and demand is crucial for formulating effective domestic energy policies and evaluating the future trajectory of the global natural gas market.This study sorts out the factors influencing the price of imported LNG in China from the perspectives of supply and demand, and establishes a VAR model to analyze the impact of supply and demand factors on the monthly LNG price.

2 Literature Review

In recent years, research on the determinants of natural gas prices has deepened considerably, with scholars examining macroeconomic dynamics, energy substitution, geopolitical tensions, uncertainty shocks, and forecasting methodologies. Nick and Thoenes (2014), using a Structural Vector Autoregression (SVAR) model, found that short-term natural gas price fluctuations are driven primarily by temperature, storage levels, and supply shortfalls, while long-term movements are significantly influenced by crude oil prices and other alternative energy sources[1]. Chai et al. (2018) employed a Bayesian Structural Equation Model (BSEM) to identify a dual-track pricing system and reverse substitution between gas and coal, reflecting structural inefficiencies and weak market-based pricing in China's natural gas market. The findings also suggest that economic activity and demand exert the greatest influence on natural gas prices, with supply factors and alternative fuel prices playing secondary roles[2]. Chen et al. (2023) used a GARCH-MIDAS model to study how different uncertainties affect U.S. natural gas price volatility. They found that U.S. economic policy uncertainty and oil supply-demand uncertainty have strong impacts on natural gas price fluctuations[3]. Lin and Wesseh (2013) used weekly data, employ a three-state first-order Markov process and estimate the model using a Bayesian Markov Chain Monte Carlo (MCMC) method with Gibbs sampling to analyze natural gas price fluctuations. They show that natural gas prices switch between low, medium, and high volatility states, corresponding to significant market events, include supply shocks (e.g., hurricanes, production disruptions), demand changes, oil price linkages, and broader macroeconomic and geopolitical events. This highlights the importance of considering nonlinear dynamics and structural breaks in volatility modeling[4]. Jana and Ghosh (2025) developed a residual-driven machine learning model using daily natural gas futures data from the UK and US to analyze price behavior before and during the COVID-19 pandemic. Their findings show that using residuals as predictors significantly improves forecast accuracy, especially during the pandemic, highlighting the strong sensitivity of natural gas prices to supply-demand changes and short-term market fluctuations. The study underscores the importance of incorporating past volatility in price forecasting, as natural gas prices are

highly sensitive to their own historical volatility and short-term market dynamics[5]. Wang et al. (2022) use a dynamic model averaging (DMA) approach to analyze the time-varying drivers of China's LNG import price from 2008 to 2020, finding that gas consumption, weather, and industrial growth—are the main contributors to price volatility and premium. Their results suggest China's LNG import price is more influenced by domestic market conditions and Japan's pricing mechanism than by international crude oil prices[6].

On the modeling and forecasting frontier, Ambya et al. (2020) analyzed daily natural gas prices from 2009 to 2019 to build a reliable forecasting model. They concluded that while the ARIMA(1,1,1) model had limited predictive ability, the AR(1)-GARCH(1,1) model provided a better fit for capturing natural gas price volatility, which showed strong performance with high accuracy and significance[7]. Guan et al. (2022) considered that political events, supply and demand changes, and climate factors could affect natural gas price volatility. They extracted news text embeddings from natural gas-related news using BERT-Base to reflect these factors. By combining an attention model and a BiLSTM module, they built a fused network with a transformer to predict natural gas price trends. They finally achieved high prediction accuracy[8]. Pei et al. (2023) proposed a new model based on a Temporal Convolutional Network (TCN) with a dynamic learning rate to more accurately forecast natural gas spot prices for the next two weekdays[9].

Collectively, these studies suggest that natural gas prices are shaped by a complex interplay of macroeconomic conditions, energy market linkages, institutional mechanisms, and uncertainty shocks, while increasingly sophisticated econometric and machine learning techniques offer more accurate and adaptive tools for modeling and forecasting price behavior. However, relatively few have analyzed the influencing factors from a supply and demand perspective. Regarding forecasting research, most efforts have concentrated on modeling daily price predictions.

3 Methodology and Data

3.1 Econometric Model Specification

To achieve the research objectives, this study adopts a Vector Autoregression (VAR) model as the primary analytical framework. The VAR model is well-suited for capturing dynamic interrelationships among multiple time series variables without imposing a predetermined causal structure. By incorporating representative variables from both the supply and demand sides, based on monthly data, the model facilitates an in-depth analysis of the short-term impacts and shock responses on LNG import prices.

The study employs a Vector Autoregression (VAR) model of the following form:

$$\boldsymbol{Y_t} = \boldsymbol{\alpha} + \sum_{\mathrm{i}}^{\mathrm{p}} A_i \boldsymbol{Y_{t-i}} + \in_{\mathrm{t}} \tag{1}$$

Where Y_t is a four-variable vector, including the month-on-month return of China's LNG import price (MOM_PRICE), the month-on-month return of Brent crude oil price (MOM_BRENT), the year-on-year change rate of European natural gas reserves

(YOY_RESERVE), and the year-on-year change rate of China's natural gas imports (YOY_IMPORT). is the coefficient matrix, is the constant vector, and is the residual vector.

3.2 Data Description

When studying the factors influencing China's LNG prices, this paper mainly relies on the following key factors: supply side, demand side, and alternative energy sources.

From the demand-side perspective, China's natural gas imports are a direct indicator of domestic demand. Higher import volumes typically reflect growing consumption needs, which can exert upward pressure on LNG prices.

On the supply side, several factors come into play. First, changes in crude oil prices reflect cost pressures on the supply side. An increase in oil prices typically indicates tightening upstream energy supply or rising production costs, which in turn drives up the supply price of natural gas. Since China's LNG imports mainly originate from regions such as the Middle East, Australia, and Russia—where pricing is often linked to Brent crude oil—fluctuations in Brent crude prices significantly affect the cost of imported LNG and consequently influence domestic LNG market prices. Second, natural gas production and reserves have a direct impact on the supply side. Global natural gas production and reserves directly determine the available natural gas resources for export. If production increases or reserve expectations rise, market supply is sufficient, and international LNG prices may decline. Conversely, supply shortages will push prices up. Therefore, this study uses European gas storage to reflect natural gas production and reserves.The descriptive statistics of the variables are presented in Table 1.

Table 1. Data description

	variables	definition	source	Time(monthly)
LNG Price	MOM_PRICE	Month-on-month return of China's LNG import price	ICIS Database	2013/01-2024/06
Supply	MOM_BRENT	Month-on-month return of Brent crude oil price	ICIS Database	2013/01-2024/06
Supply	YOY_RESERVE	Year-on-year change rate of European natural gas reserves	ICIS Database	2013/01-2024/06
Demand	YOY_IMPORT	Year-on-year change rate of China's natural gas imports	ICIS Database	2013/01-2024/06

As shown in Table 2, the descriptive statistics of the variables show that the MOM return of LNG import prices shows a small positive mean (0.173%) and median (2.111%), but with substantial volatility (standard deviation of 22.151%) and extreme fluctuations, indicating significant short-term price instability. Similarly, Brent crude oil price returns (MOM_BRENT) exhibit moderate average growth (0.558%) with notable monthly variability (standard deviation 9.812%). The year-on-year change in European natural gas reserves (YOY_RESERVE) demonstrates a positive trend (mean 16.151%) with considerable seasonal and cyclical variation (standard deviation 26.155%), underscoring supply-side fluctuations. Demand side, proxied by the year-

on-year growth of China's natural gas imports (YOY_IMPORT), also shows upward movement (mean 2.763%) accompanied by high variability (standard deviation 24.350%), reflecting evolving domestic consumption patterns.

Table 2. Descriptive Statistics of Variables

	MEDIAN	MEAN	MAXIMUM	MINIMUM	STD. DEV.
MOM_PRICE	2.111	0.173	127.197	-59.447	22.151
MOM_BRENT	0.250	0.558	42.900	-46.950	9.812
YOY_RESERVE	18.036	16.151	89.341	-28.934	26.155
YOY_IMPORT	5.433	2.763	73.428	-44.685	24.350

As shown in Table 3, it is the correlation coefficient matrix of the variable. Focusing on LNG Price Return, its correlations with Brent Oil Return (0.073) and Gas Reserves Change (0.050) are weakly positive. Meanwhile, LNG Price Return exhibits a slightly stronger negative correlation (-0.166) with LNG Import Change, suggesting that increases in import volumes may exert downward pressure on LNG price returns in the short term. Examining the other variables, Brent Oil Return and Gas Reserves Change show a modest positive correlation (0.166), while their correlations with LNG Import Change remain weakly negative (-0.058 and -0.113 respectively).

Table 3. Correlation coefficient matrix

	MOM_PRICE	MOM_BRENT	YOY_RESERVE	YOY_IMPORT
MOM_PRICE	1.000	0.073	0.050	-0.166
MOM_BRENT	0.073	1.000	0.166	-0.058
YOY_RESERVE	0.050	0.166	1.000	-0.113
YOY_IMPORT	-0.166	-0.058	-0.113	1.000

Given these low contemporaneous correlations, simple linear analysis may be insufficient to capture the dynamic interactions between these variables. Therefore, the use of a Vector Autoregression (VAR) model is justified to explore their lagged and feedback effects over time. The VAR framework allows for a more comprehensive investigation of the supply-demand mechanisms driving LNG price fluctuations in China. Furthermore, impulse response analysis based on the VAR model provides valuable insights into the temporal propagation of shocks within the system.

4 Empirical Analysis Results

4.1 Estimation of the VAR Model

The ADF test was conducted and all variables were found to be stationary and the VAR model could be directly constructed. Through the test of the lag order of the model, the SC criterion determines that the optimal lag order of VAR is the first order. The model fitting results are shown in Table 4 as follows.

Table 4. Estimation of the VAR model

	MOM_PRICE	MOM_BRENT	YOY_RESERVE	YOY_IMPORT
MOM_PRICE(-1)	0.090	-0.018	-0.015	0.023
	(0.087)	(0.038)	(0.088)	(0.075)
MOM_BRENT(-1)	0.018	0.133	0.017	-0.164
	(0.197)	(0.086)	(0.199)	(0.169)
YOY_RESERVE(-1)	0.038	0.054	0.539	0.015
	(0.074)	(0.032)	(0.075)	(0.064)
YOY_IMPORT(-1)	-0.109	-0.046	0.007	0.639
	(0.080)	(0.035)	(0.081)	(0.068)
C	1.619	-0.443	8.210	1.945
	(2.417)	(1.054)	(2.443)	(2.071)

4.2 Impulse Response Analysis

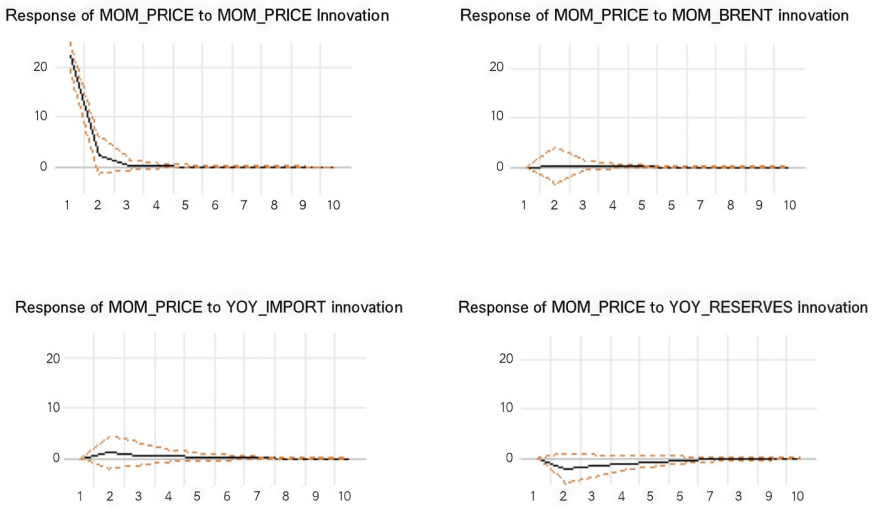

Fig. 1. Impulse response analysis

Impulse response analysis based on the VAR model is conducted, and the results are shown in Figure 1. It can be found that the positive impact on MOM_BRENT led to a small increase in MOM_PRICE, but it dissipated rapidly. It indicates that the impact of crude oil prices on the price of liquefied natural gas in China is limited and temporary, possibly due to partial price linkage or the rigidity of liquefied natural gas market contracts. The impact on imports will have a positive response to the price of liquefied natural gas, reaching a peak in the second stage, then declining and approaching zero after seven cycles. This means that the increase in imports may slightly raise the short-term price level, reflecting the pressure on demand. By contrast, the impact on

YOY_RESERVES will initially cause a slight negative reaction to MOM_PRICE, which means that the increase in natural gas reserves in Europe may temporarily relieve the supply pressure in the global liquefied natural gas market, thereby reducing China's import prices.

5 Conclusion

In summary, this study employs a VAR model and impulse response analysis to investigate the dynamic relationship between China's LNG import price and supply-demand factors. The empirical results reveal that: The Brent crude oil price was subject to a shock, causing a slight positive change in the price of liquefied natural gas in China, which quickly disappeared. The growth of reserves in Europe will rapidly ease the price of natural gas and gradually recover. The growth of China's LNG imports often leads to a rapid increase in LNG prices at the same time, and then the impact gradually disappears.

The price of LNG in China is jointly determined by multiple mechanisms, and the influence of a single variable on it is often relatively weak. Furthermore, monthly data may not be sufficient to capture high-frequency shocks or micro-mechanism changes. Overall, the study offers valuable insights into the drivers of LNG price volatility in China and provides a foundation for further research and policy design concerning energy price stability and supply security.

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