第 49卷第 2期
七月 2025
Diqiu Kexue - Zhongguo Dizhi Daxue Xuebao/Earth Science Journal of China University of Geosciences
Vol. 50 No. 2
July - Dec 2025

DOI: 10.5281/zenodo. 17080297

Predicting the price of petrochemical industry stocks using price action patterns and trading board insights

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Published: 08 September2025

Accepted: 11 August 2025

Received: 09 July 2025

Abstract: Reducing transaction costs and accurately predicting stock prices are critical concerns for traders and market participants, particularly within Iran's capital market. To address these challenges, a variety of models and methods have been employed, among which market effect models—especially those capturing immediate price effects—are widely recognized. The price effect refers to the change in a stock's price following a transaction, and this study leverages such models to forecast price movements in the petrochemical sector. To achieve this, stocks within the petrochemical industry were first ranked by market value, and four representative stocks were selected using specific filtering criteria. To enhance model accuracy, transactions were categorized into buyer-initiated and seller-initiated groups. Price modeling was conducted using microstructural parameters in conjunction with temporal variables, applying the Heterogeneous Autoregressive (HAR) method. Findings indicate that the integration of time-based variables—such as days of the week—with microstructural data does not significantly improve model performance. In fact, temporal additions did not contribute to error reduction. Nonetheless, the HAR model outperforms alternatives cited in prior literature, demonstrating a meaningful decrease in prediction error on out-of-sample data.

Keywords: Price Effect, Market Microstructure, Petrochemical Industry, Heterogeneous Autoregressive Model

1. Introduction

The capital market plays a pivotal role in shaping the national economy, and the Tehran Stock Exchange—with its 52 active industries—offers a diverse and dynamic platform for investment. Among these, the petrochemical industry stands out as the second-largest sector by market value, leveraging Iran's abundant oil and gas reserves to fuel its rapid growth and strategic importance.Petrochemical products serve as essential inputs across a wide range of industries, acting as intermediaries between upstream resource extraction and downstream manufacturing. In such a volatile market environment, accurate stock price prediction is crucial. Four primary approaches are commonly employed: technical analysis, fundamental analysis, statistical modeling, and machine learning. A key concept in price forecasting is the **price effect**—both immediate and permanent—which reflects the impact of transactions on asset prices. Understanding these effects is fundamental to designing effective trading strategies. The study of **market microstructure**, which encompasses the mechanisms that promote transparency and efficiency in financial markets, is central to this endeavor. Core components such as the order book and liquidity dynamics, along with emerging practices like high-frequency and algorithmic trading, have reshaped modern market behavior. Given the rising exchange rate in Iran and the petrochemical sector's critical role in the national economy, this industry continues to attract significant attention from investors. As such, conducting targeted case studies within this sector is essential for developing more accurate models of market behavior, enhancing price prediction, and refining trading strategies. **Research Focus** This study centers on the petrochemical industry—the second-largest sector in the Iranian capital market by market value—and aims to model and predict stock prices using microstructural parameters and temporal variables. **Research Problem** Hidden transaction costs, such as price effects, often exceed explicit costs and are influenced by factors including asset type, trade volume, and market liquidity. This research seeks to model these implicit costs and analyze the price effects associated with petrochemical stock transactions.

Innovations

1. **Integrated Variable Framework**: Enhancing the forecasting model by jointly incorporating time-based and microstructure variables.
2. **Market-Specific Context**: Conducting analysis within the Iranian stock market, where price quotes are not governed by market makers—offering a unique microstructural dynamic.
3. **Asset Selection Precision**: Focusing on actively traded petrochemical stocks rather than synthetic or non-tradable indices, ensuring real-world applicability.

Research Objectives

- **Scientific Goals**:
    - Address gaps in domestic literature on price effects.
    - Employ precise oscillometric modeling techniques.

- Benchmark and compare forecasting models for robustness and accuracy.

- **Practical Goals**:
    - Develop a simplified, actionable forecasting model.
    - Minimize trading costs.
    - Empower retail and non-professional investors with better decision-making tools.

Hypotheses

1. **Microstructure Impact**: Order book parameters (e.g., bid-ask spread, depth, imbalance) significantly influence short-term price movements.
2. **Temporal Enhancement**: Incorporating time variables (e.g., time of day, duration between trades) reduces forecasting error.
3. **Model Superiority**: The proposed hybrid model outperforms existing forecasting models in terms of accuracy and cost-efficiency.

Methodology

- **Approach**: Quantitative research using correlation analysis and predictive modeling.
- **Objective**: Forecast future prices of petrochemical stocks during the fiscal in 2022.
- **Techniques**: Time-series modeling, microstructure variable extraction, and performance benchmarking.

Statistical Population

Sample Selection:

- Applied three trading filters to identify eligible petrochemical stocks.
- Categorized stocks into four groups based on market capitalization.
- Randomly selected one representative company from each category to ensure diversity and reduce selection bias.

Model Structure

- **Model Framework**: The study employs the *Heterogeneous Autoregressive (HAR)* model, originally proposed by Corsi (2009), which is well-suited for capturing dynamics in high-frequency financial data by incorporating multiple time horizons.
- **Estimation Technique**: Parameters are estimated using *Ordinary Least Squares (OLS)*. The dataset is partitioned into *in-sample* and *out-of-sample* segments to evaluate model performance and generalizability.
- **Trade Classification**: Individual transactions are categorized as either *buyer-initiated* or *seller-initiated*, based on trade direction and order book dynamics—enabling microstructure-level analysis of price formation.

__Table 1.__ Model variables

Variable Type	Description and calculation method
Dependent	Stock price changes: Logarithm of the median of the buy and sell quotes before and after the trade
Trading Volume	Ratio of the trade volume to the average of the volume before and after; normalization for smoothing
Market Value	Product of the number of shares of the company by the median of the quotes
Share Volatility	Standard deviation of the quotes from the first trade price to before the trade in question
Daily Transactions	Dummy variables for days of the week to examine time effects
Price Averages	Average price changes in the previous n periods to account for short-term time horizons

Proposed average price model

$$\overline{\Delta p}_{t-n} = \frac{1}{n}\sum_{j=1}^{n} \Delta p_{t-j}$$

Key Points

- Trading volume is a critical predictor of price movements, often reflecting informed trading activity or underlying information asymmetry in the market.
- Company size influences investor behavior; smaller-cap stocks may attract attention due to perceived growth potential, inefficiencies, or behavioral biases.
- Incorporating both microstructural features (e.g., bid-ask spread, order flow) and temporal dynamics (e.g., lagged returns, volatility clustering) significantly improves model accuracy and reduces prediction error.
- Historical price averages help capture time-based effects and behavioral memory, enabling the model to reflect past market conditions and investor sentiment.

Numerous studies in the field of trade price effect show that this phenomenon is influenced by various factors such as trading time, order volume and type, market liquidity and trader behavior. The research results indicate that:

• Reducing the time interval between trades increases the price effect and the speed of information adjustment (Dafour, 2000).

• Trader behavior can increase trading costs (Stanzel, 2002).

• Smaller companies with low market capitalization experience a greater price effect (Lima, 2005; Zhou, 2012).

• Trading volume has a direct relationship with price changes and large orders should be executed gradually (Jin, 2009; Lampreir, 2011).

• Order imbalance has a linear relationship with price changes that is inversely related to market depth (Rama Kant, 2011).

• Analytical models such as power-law, logarithmic, and depth-of-trade indices play an important role in predicting price impact (Barabazan, Jiang, Pham).

• Hidden and algorithmic trading have a gradual and normalizable impact on price (Maru, Dong).

• The herd behavior of institutional investors is more intense in selling than buying, causing asymmetric fluctuations (Fang, 2017).

Overall, accurate understanding and scientific modeling of the price impact of transactions can help optimize trading strategies and reduce hidden costs in financial markets.

2. Method

In this study, various sources have been used to examine the price effect of transactions in the petrochemical industry. The theoretical part and background of the research were compiled using scientific articles, theses, and specialized books, and the required data were collected from reliable sources such as the Tehran Stock Exchange Technology Management website and the Stock Exchange Library. Data extraction and processing were performed using Python software, and Excel was used to sort and integrate the data. Then, econometric modeling and analysis were performed using Python and Iviews software to provide an accurate database for analysis. The statistical population of this study includes companies active in the petrochemical industry on the Tehran Stock Exchange and the Iranian OTC in the fiscal year 2022. After applying three trading filters (share open rate, number of transactions, and whether the buy/sell queue is locked), the companies were divided into four groups based on market value, and one company was randomly selected from each group: Jam (83 trillion Tomans), Kermasha (23 trillion Tomans), Shekam (3.9 trillion Tomans), and Sheleab (1.06 trillion Tomans).

This research aims to accurately model the price effect of transactions in the petrochemical industry and examines three main hypotheses:

1. The significant relationship between order book parameters and stock price changes

2. The role of qualitative time variables in reducing forecast error

3. Comparison of the performance of the proposed model with existing models such as HARt, LFM1 and LX

Proposed model features:

• A combination of microstructural, time and price averages

• Inspired by heterogeneous autoregressive (HAR) models

• Using ordinary least squares and rolling regression

• Evaluation with MSE and MAE criteria for out-of-sample data

• Including variables such as trading volume, market value, volatility, trading days and price averages of the last five and ten transactions

Theoretical and methodological points:

• Based on the heterogeneous market hypothesis: traders have different time horizons

• The HAR model with daily, weekly, and monthly horizons performs better than the GARCH and ARCH models

• Investigating the stationarity of time series with unit root tests (such as Dickey-Fuller)

• In case of non-stationarity, using cointegration methods such as Engel-Granger, Durbin-Watson, and Johansen to analyze long-term relationships

In summary, this research leverages high-quality data and multi-layered modeling to develop an advanced framework for stock price prediction in the Iranian capital market, while also contributing to a more precise analysis of transaction-induced price effects.

3. Findings

Four stocks were selected as a sample from the studied population, and the transactions of each of these stocks were divided into two types: initial buyers and initial sellers. As pointed out in Pham and Anderson (2020) and other studies, purchase and sale transactions do not have the same effect on price, so to examine this effect and prevent bias in the results, the data were divided into two groups. So, it can be said that eight samples were evaluated for models and variables simultaneously, and finally, using the results obtained, comments were made about each of the variables and then the model. It should be noted that for convenience, each of these data samples is called a data group. The data of the present study is divided into two groups in all sample stocks, in-sample and out-sample, so that 80% of the data is considered as in-sample data and 20% of the data is considered as out-sample data. We have trained and estimated the model coefficients on the in-sample data and then used them to predict out-of-sample data. However, since we are primarily looking for the immediate price effect and, on the other hand, considering the volume of data and the structural changes in the market in the year under study, we have used the rolling window technique or rolling regression to reduce the error of our predictive model.Next, we have compared our model with other models in this field in recent years, using our data, and finally, the model with the lowest prediction error has been selected as the optimal model.

Hypothesis 1: "The parameters in the order book have a significant relationship with stock price changes."

This hypothesis has been tested in all past studies in the field of price effect, because as previously stated, the issue of price effect is an implicit issue and finding the variables that affect this issue is very important and complex, which is why all studies in this field have examined this hypothesis. In this study, the proposed research model has been used for testing to examine this relationship. It should be noted that this test was performed on the data within the sample, i.e. 80 percent of the total data, and its results for all stocks can be seen below.

Table 2. *Interpretation of the 'Jam' Symbol: Indicates Buyer Presence at Market Open*

Probability of significance	*t-statistic*	*Coefficient*	*Variable*
0	30.4	0.033	M
0.17	-1.3	-4.52E-06	V
0	5.3	0.049	Σ
0.00	*Probability of F-statistic*	299	*F-statistic*

Table 3. *Interpretation of the 'Jam' Symbol: Indicates Seller Presence at Market Open*

Probability of significance	*t-statistic*	*Coefficient*	*Variable*
0	28	0.023	M
0	4.9	1.29E-05	V
0.17	-1.34	-0.00933	Σ
0.00	*Probability of F-statistic*	257	*F-statistic*

Table 4. *Interpretation of the 'Kermasha' Symbol: Indicates Buyer Presence at Market Open*

Probability of significance	*t-statistic*	*Coefficient*	*Variable*
0	21	0.012	M
0.11	-1.57	-2.88E-06	V
0.01	2.4	0.017	Σ
0.00	*Probability of F-statistic*	270	*F-statistic*

Table 5. *Interpretation of the 'Kermasha' Symbol: Indicates Seller Presence at Market Open*

Probability of significance	*t-statistic*	*Coefficient*	*Variable*
0	22.4	0.008	M
0.07	2.2	4.55E-09	V
0	3.6	0.012	Σ
0.00	*Probability of F-statistic*	322	*F-statistic*

Table 6. *Interpretation of the 'Shekam' Symbol: Indicates Buyer Presence at Market Open*

Probability of significance	*t-statistic*	*Coefficient*	*Variable*
0	6.4	0.018	M
0.012	-2.4	-3.68E-05	V
0.11	-1.81	-0.0025	Σ
0.00	*Probability of F-statistic*	19	*F-statistic*

Table 7. *Interpretation of the 'Shekam' Symbol: Indicates Seller Presence at Market Open*

Probability of significance	*t-statistic*	*Coefficient*	*Variable*
0	8.58	0.016	M
0.09	1.486	1.48E-05	V
0.12	-1.14	-0.002	Σ
0.00	*Probability of F-statistic*	35	*F-statistic*

Table 8. *Interpretation of the 'Sheleab' Symbol: Indicates Buyer Presence at Market Open*

Probability of significance	*t-statistic*	*Coefficient*	*Variable*
0	26	0.01	M
0	-9	-4.41E-05	V
0.14	1.7	0.007	Σ
0.00	*Probability of F-statistic*	230	*F-statistic*

__Table 9.__ Interpretation of the 'Sheleab' Symbol: Indicates Seller Presence at Market Open

Probability of significance	*t-statistic*	*Coefficient*	*Variable*
0	28	0.013	M
0.0063	2.73	9.32E-06	V
0.12	-1.51	-0.017	Σ
0	*Probability of F-statistic*	334	*F-statistic*

As shown in the tables, the majority of order book variables exhibit statistically significant relationships at the 5% level. A smaller subset of variables across different categories are significant at the 10% and 20% levels, which remains acceptable given the research objectives. Notably, the F-statistic is significant at the 5% level across all models, indicating that each model is generally well-specified.

Since the primary aim of this study is to identify an optimal price effect model for stock price prediction—and given that the tables already contain sufficient information to assess variable relationships—further detailed examination of these relationships has been intentionally limited.

It is well established that when both in-sample and out-of-sample data are available, out-of-sample evaluation provides a more reliable basis for model comparison. In-sample metrics can be misleading, as they are susceptible to overfitting (Horwich and Tassie, 1990). For instance, goodness-of-fit measures may overstate model performance and are therefore not ideal for comparative analysis.

Accordingly, the subsequent analysis relies on out-of-sample results to assess the remaining assumptions and compare model performance. This includes evaluation using mean squared error (MSE) and mean absolute error (MAE), both of which quantify the deviation between predicted and actual values.

Hypothesis 2: *Incorporating time variables qualitatively into the model reduces forecast error.*

To test this hypothesis, we first applied the rolling regression method and computed the average forecast error. As discussed in Chapter 2, prior research (e.g., Zhou, 2017; Fam & Anderson, 2020) has demonstrated that combining time variables with microstructural parameters enhances forecast accuracy and reduces error.

In this paper, we examine this effect by qualitatively incorporating weekday variables into the model. Since trading behavior and price dynamics likely vary across weekdays—for instance, transactions on the final trading day of the week may differ in impact from those on the first—weekday effects are modeled using dummy variables. These categorical indicators allow us to capture potential asymmetries in price behavior across the trading week. The corresponding variables are presented in the table below.

__Table 10.__ Weekday Variables

Virtual variable	Saturday	Sunday	Monday	Tuesday	Wednesday
D1	1	0	0	0	0
D2	0	1	0	0	0
D3	0	0	1	0	0
D4	0	0	0	1	0
D5	0	0	0	0	1

We know that to examine the dummy variables in the model, all of these variables cannot be entered into the model at the same time; because due to the existence of the origin in the model, it causes severe collinearity (most of the time complete collinearity), so according to past knowledge, these variables have been entered into the model in a controlled manner and the last day variable has been removed. The model and its effects are applied based on their changes in the origin, and as a result, the model does not suffer from complete collinearity. It should be noted that this is not related to the existence of collinearity among the independent variables of the model; but rather arises due to the incorrect use of the variables.

According to the descriptions, the models used to test the present hypothesis are as follows:

HAR:

$$\Delta P_t = c + \alpha * (V) + \beta * (M) + \gamma\sigma_t + \Phi_1(\Delta P_{t-1}) + \Phi_5(\overline{\Delta p}_{t-5}) + \Phi_{10}(\overline{\Delta p}_{t-10}) + \varepsilon_t$$

HARt:

$$\begin{aligned}\Delta P_t = {} & c + \alpha * (V) + \beta * (M) + \gamma\sigma_t + \delta_1 d_1 + \delta_2 d_2 + \delta_3 d_3 + \delta_4 d_4 + \delta_5 d_5 \\ & + \Phi_1(\Delta P_{t-1}) + \Phi_5(\overline{\Delta p}_{t-5}) + \Phi_{10}(\overline{\Delta p}_{t-10}) + \varepsilon_t\end{aligned}$$

$LFM1$:

$$\Delta P_t = \epsilon_t * (\frac{v_t}{\bar{v}_t})^{\alpha} * \frac{1}{M_t^{\beta}} + \varepsilon_t$$

LX :

$$\Delta P_t = c + \alpha * (V) + \beta * (M) + \gamma\sigma_t + \varepsilon_t$$

The following tables display the magnitude of forecast errors across models evaluated against the proposed framework.

Table 11. Comparison of Forecast Errors in Literature Models of Price Effect – Initial Seller Transactions

Sell		HAR	HARt	LX	Lmf1
Kermasha	Mse	3.56E-07	3.56E-07	3.60E-07	3.71E-07
	Mae	0.000251065	0.000251	0.000284	0.000247
Sheleab	Mse	6.99E-07	7.00E-07	7.04E-07	7.14E-07
	Mae	0.000400056	0.000399	0.000462	0.00046
Jam	Mse	6.07E-07	6.09E-07	6.30E-07	6.30E-07
	Mae	0.000330912	0.000331	0.000391	0.000381
Shekam	Mse	1.39E-06	1.40E-06	1.41E-06	1.43E-06
	Mae	0.000478795	0.000473	0.000604	0.000586

Table 12. Comparison of Forecast Errors in Literature Models of Price Effect – Initial Buyer Transactions

Buy		HAR	HARt	LX	Lmf1
Kermasha	Mse	4.71E-07	4.71E-07	4.76E-07	4.76E-07
	Mae	0.000259336	0.000259	0.000289	0.000286
Sheleab	Mse	1.60E-06	1.60E-06	1.64E-06	1.65E-06
	Mae	0.000466839	0.000466	0.000548	0.000569
Jam	Mse	9.21E-07	9.28E-07	9.58E-07	9.58E-07
	Mae	0.000412399	0.000412	0.000487	0.000505
Shekam	mse	1.85E-06	1.85E-06	1.86E-06	1.86E-06
	Mae	0.000483813	0.000479	0.000645	0.000616

The results indicate that the proposed model in this study outperforms existing models, demonstrating lower prediction errors across the two primary evaluation criteria. This suggests that the model offers a more accurate and reliable framework for price forecasting. A key distinction of this research, relative to prior studies in the field, lies in its finding that weekday time variables do not exert a significant influence on price behavior. Consequently, their inclusion does not enhance model performance.

4. Conclusion

This paper explores the role of capital markets in fostering economic development and optimizing liquidity across national economies. By absorbing excess liquidity and facilitating enterprise financing, capital markets contribute to production growth and the execution of economic plans. Achieving these objectives requires a market characterized by depth, transparency, and robust infrastructure. One of the key instruments for enhancing market efficiency is the analysis of its microstructure.

Accordingly, this research aims to deepen the understanding of capital market performance through microstructural analysis and to propose actionable strategies for its improvement.

The study is structured around two primary axes:

1. The relationship between transaction-induced price effects and market variables
2. The influence of time variables (i.e., weekdays) on stock price prediction

Key Findings:

- **Model Performance:** The proposed model demonstrates superior predictive accuracy compared to existing models—including nonlinear approaches—particularly within the Tehran Stock Exchange.
- **Buyer vs. Seller Transactions:** The price effect is more pronounced in buyer-initiated transactions than in seller-initiated ones. This finding contrasts with international studies that typically report stronger selling effects. The discrepancy is attributed to the absence of short-selling mechanisms and the unique conditions of the Iranian market following the collapse of the aggregate index.
- **Market Value Sensitivity:** The intensity of the price effect is inversely related to the market value of shares. Stocks with lower market capitalization exhibit stronger price effects. For mid-cap stocks, share flotation may also contribute to observed differences.
- **Time Variables:** Weekday-based time variables did not significantly influence price effects. This may be due to deliberate trading behavior by large market participants and the limited depth of the market during the study period.

In sum, the proposed model—by integrating structural and price-based variables—offers a more precise framework for analyzing price effects. However, time variables appear to have limited explanatory power in the context of the Iranian capital market. The price effect remains a complex phenomenon, shaped by market structure, regulatory constraints, and trader behavior.

Summary of findings

Table 13. *Summary of Research Hypothesis Evaluation*

No.	Approval or disapproval	Description of the hypothesis
Hypothesis 1	The hypothesis is supported.	There is a significant relationship between limit order book parameters and stock price changes.
Hypothesis 2	The hypothesis is not supported.	Using time variables qualitatively in the model reduces prediction error.
Hypothesis 3	The hypothesis is supported.	The proposed model has better performance compared to similar models.

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