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Research Article

Adaptive Polynomial Regression Analysis for Predicting Indonesian Stock Exchange Movements With R-Square Optimization and Trading Channel Construction

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ABSTRACT

Stock price movements in financial markets often reflect rapid macroeconomic shifts and liquidity-driven volatility. This is particularly evident in large-cap, highly liquid stocks within the Indonesian LQ45 index. Traditional deep learning models often struggle with this market's unique volatility, suffering from overfitting, lack of transparency, and look-ahead bias. To address these issues, this study proposes an adaptive rolling polynomial regression (APR) framework for non-linear trend filtering and automated trading signal generation. The method uses a sliding window with endpoint locking to prevent look-ahead bias. At each step, it finds the best lookback window by optimizing a local OLS polynomial regression and filtering out noisy market regimes using a strict R-squared threshold. The resulting trends are converted into trading signals (BUY, SELL, HOLD, CLOSE) through dynamic Z-score volatility channels. When evaluated on daily historical data from 2015 to 2024 for five LQ45 stocks ANTM, ASII, BBCA, PTBA, and TLKM the framework shows an excellent fit, with R-squared values between 0.9881 and 0.9966. Backtesting indicates that the strategies yield positive returns and profit factors above one for all assets. ASII performed best, with a total return of 2680.16%. Despite low win rates (<10%), the long-term profitability was maintained as large trend-following gains offset small losses. This study highlights that simple, interpretable mathematical models can provide effective, computationally efficient systematic trading options in emerging equity markets.

Keywords: Adaptive Polynomial Regression, Trend Filtering, LQ45 Index, Quantitative Trading

1. INTRODUCTION

Stock price movements in financial markets often mirror quick macroeconomic changes, shifting market sentiment, and diverse investor behaviors. In Indonesia, these effects are especially noticeable among large-cap, highly liquid stocks in the LQ45 index, a key benchmark watched by both local and international investors (Clarissa & Priatmodjo Koesrindartoto, 2024). Because these assets are highly responsive to local regulations and global liquidity patterns, their volatility often leads to rapid noise, making traditional predictive models more challenging to apply (Sergi et al., 2025). Much of the current machine learning and quantitative finance research focuses on statistical accuracy using metrics like Root Mean Squared Error without assessing whether these predictions translate into real economic gains or risk-adjusted benefits (Indra et al., 2025). Moreover, complex non-linear architectures often introduce structural issues such as overfitting and look-ahead bias, which can weaken automated trading strategies in emerging markets (Saputra et al., 2025). To overcome these challenges, this study introduces an adaptive rolling polynomial regression framework that employs non-linear trend modeling to produce reliable, actionable trading signals (Cohen, 2024). By separating trend detection from noise-sensitive point estimation, this approach enables a more stable evaluation of market movements in the volatile LQ45 landscape (Bhatter, 2024).

By using dynamic Z-score channels, we develop a framework that emphasizes mean-reversion detection and structural stability rather than transient price swings that are prone to noise (Wingdes & Ferdi, 2025). This method helps prevent the degradation seen in traditional models during shifts in market regimes or during periods of liquidity-driven volatility. As a result, it improves the reliability of entry signals by minimizing the impact of class imbalances and labeling inconsistencies common in Indonesian blue-chip stock data. Overall, our approach seeks to balance the high-frequency volatility of the Indonesian market with the need for stable, long-term capital strategies (Jonathan & Saputra, 2025).

This structural refinement offers a practical alternative to traditional deep learning models, which often struggle with the unique volatility of the Indonesian equity market (Dwiandiyanta et al., 2025), (Hidayat & Ade Putra Prima Suhendri, 2025). By prioritizing structural interpretability over opaque black-box models, this study presents a method that connects quantitative alpha generation to liquidity management constraints in the LQ45 index (Friday et al., 2026). Specifically, it assesses how effective the proposed regression-based indicators are at reducing forecast accuracy loss, a common issue in complex deep learning architectures (Marakub & Zarlis, 2026).

Furthermore, it shows that straightforward, understandable mathematical frameworks can effectively operate in non-stationary financial settings, where conventional high-parameter models often suffer from overfitting and declining performance (Adedoyin Tolulope Oyewole et al., 2024), (Bhandari et al., 2024). The current body of quantitative research often confuses statistical goodness-of-fit with practical trading alpha, frequently overlooking the generalization challenges posed by models trained on noisy, high-dimensional data (Goluža et al., 2024). Although advanced neural networks such as transformers and recurrent models show strong in-sample predictive performance, they often face difficulties in capturing complex interaction patterns and are sensitive to noise. Moreover, these deep learning methods tend to suffer from look-ahead bias and overfitting if they do not account for shifts between regimes, resulting in poorer performance in actual trading scenarios (Pagliaro, 2026).

To address these structural limitations, researchers have increasingly adopted reinforcement learning and ensemble systems that focus on sequential decision-making and regime detection, aiming to avoid the typical performance decline observed with static supervised learners. Additionally, although some recent research seeks to improve these frameworks by incorporating large language models for formulaic alpha discovery, the ongoing challenge remains finding models that balance predictive power with interpretability in practice (Yu et al., 2026). To reduce these risks, recent developments focus on strict information set discipline and walk-forward validation to maintain robust signal generation amid regime-dependent market volatility. Additionally, the move toward explainable artificial intelligence highlights the increasing awareness that high-dimensional "black-box" models often lack the transparency needed for regulatory compliance and reliable financial decisions (Sathyanarayana et al., 2025).

2. RESEARCH METHOD

The adaptive rolling polynomial regression framework uses a sliding window method to produce smooth, non-linear trend surfaces, which effectively separate actual market momentum from high-frequency noise (Ng, 2026). To maintain temporal accuracy, terminal endpoint locking fixes the polynomial at the current timestamp, preventing future information from influencing the model and eliminating look-ahead bias that can cause performance issues in rolling indicators. Additionally, a dual-layer validation process with gating mechanisms filters out windows that do not meet pre-set goodness-of-fit criteria, acting as an internal performance check rather than a formal statistical validation set. By excluding observations where the polynomial fit significantly diverges from the observed prices, the system avoids periods of market instability or regime changes (Souza, 2026).

2.1 Data and Sampling

The dataset encompasses historical daily price movements for all constituent stocks in the LQ45 index, spanning 2015 to 2024, to capture diverse macroeconomic cycles and liquidity conditions. To handle the non-stationarity inherent in these financial series, the preprocessing pipeline uses a log-return transformation to normalize variance across regimes while maintaining directional movement.

2.2 Dynamic Window Identification and Validation

At each bar, the algorithm evaluates a range of candidate lookback windows [W_min, W_max]. For each window size, a local ordinary least squares (OLS) polynomial regression model of degree d is fitted to the closing prices as a function of the localized time index. $\tau y_{t-w+\tau} = \sum_{k=0}^{d} \beta_k \tau^k + \epsilon_\tau, \quad \tau \in \{1,2,\dots,w\}$. Where the polynomial coefficients $\boldsymbol{\beta} = [\beta_0, \beta_1, \dots, \beta_d]^T$ are computed using the standard OLS matrix-algebraic formulation. The goodness of fit is immediately evaluated using the sample coefficient of determination (R^2):

$$R_w^2 = 1 - \frac{\sum_{\tau=1}^{w} (y_{t-w+\tau} - \hat{y}_{t-w+\tau})^2}{\sum_{\tau=1}^{w} (y_{t-w+\tau} - \bar{y}_w)^2}$$

The algorithm iteratively searches for the optimal window size w^* that satisfies the following constrained maximization problem:

$$w^* = \arg\max_{w} \{R_w^2 \mid R_w^2 \geq 0.65,\ w \in [W_{\min}, W_{\max}]\}$$

If multiple windows satisfy this condition, the model selects the window that maximizes this measure, ensuring that the selected polynomial trajectory meets a R^2 threshold of at least 0.65.

The implementation of R_w^2 acts as a strict filter to differentiate structured trending phases from highly noisy, non-directional market regimes. According to Hair et al. (2019), an R^2 between 0.50 and 0.74 indicates moderate-to-substantial predictive accuracy for empirical data. In highly stochastic environments such as financial markets, a threshold of 0.65 effectively balances statistical confidence and signal responsiveness. Based on Gao's critique, standard OLS tends to overestimate true predictive power because it squares residuals; a threshold of 0.65 roughly corresponds to explaining about 40% of the true variation in prices. Using a stricter threshold (e.g., $R^2 \geq 0.80$) would lead to many missed trends (Type II errors) and delay detection, as the system would need to wait too long within the rolling window, missing early trend signals.

2.3 Statistical Residual Channel Construction

Once the optimal window w^* is locked, the local regression residual vector $\mathbf{e}$ is extracted:

$$e_\tau = y_{t-w^*+\tau} - \hat{y}_{t-w^*+\tau}, \quad \forall \tau \in \{1,2,\dots,w^*\}$$

The standard deviation of these residuals (σ_e) is calculated dynamically to capture the asset's current micro-volatility, adjusted for the polynomial degrees of freedom:

$$\sigma_e = \sqrt{\frac{1}{w^* - d - 1}\sum_{\tau=1}^{w^*} e_\tau^2}$$

The Upper Line (UL_t) and Lower Line (LL_t) are then constructed by projecting a specified Zscore threshold (z) onto the current terminal regression endpoint ($\hat{y}_t$), corresponding to $\tau = w^*$:

$$UL_t = \hat{y}_t + (z \times \sigma_e)$$
$$LL_t = \hat{y}_t - (z \times \sigma_e)$$

2.4 Algorithmic Implementation of the APR Framework

```
Algorithm 1: Adaptive Polynomial Regression (APR) Logic
Input: Historical close price series Y, Window range [W_min, W_max],
       Polynomial degree d, Z-score threshold z
Output: Trading Signal Series (BUY, SELL, HOLD, CLOSE)
    For each time step t >= W_max do:
        Set max_R2 = -infinity
        Set optimal_w = NULL

        For each w from W_min to W_max do:
            Slice local price window: Y_local = Y[t-w+1 : t]
            Fit polynomial of degree d: ŷ = OLS(Y_local, degree=d)
            Calculate R2 for current window

            If R2 >= 0.65 AND R2 > max_R2 then:
                max_R2 = R2
                optimal_w = w
            End If
        End For

        If optimal_w is NOT NULL then:
            Recalculate residuals: e = Y_local - ŷ
            Compute degrees-of-freedom adjusted volatility: σ_e = std(e, ddof=d+1)
            Extract terminal baseline endpoint: ŷ_t = ŷ[-1]

            Construct Channels:
                UL_t = ŷ_t + (z * σ_e)
                LL_t = ŷ_t - (z * σ_e)

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        Evaluate Execution Signal:
            If Current_Position == NONE then:
                If Close[t] <= LL_t then Trigger BUY Signal
                Else If Close[t] >= UL_t then Trigger SELL Signal
            Else If Current_Position == LONG AND Close[t] >= ŷ_t then:
                Trigger CLOSE LONG Signal
            Else If Current_Position == SHORT AND Close[t] <= ŷ_t then:
                Trigger CLOSE SHORT Signal
            End If
    Else:
        Status = HOLD (No actionable trend detected; filter out market noise)
    End If
End For
```

3. RESULTS AND DISCUSSION

The proposed adaptive polynomial regression framework was evaluated using representative stocks from the LQ45 Index, which consists of highly liquid and large-cap companies listed on the Indonesia Stock Exchange (IDX). To assess the robustness of the proposed approach across different industry sectors and price dynamics, five representative stocks were selected as experimental samples: ANTM (mining), ASII (automotive and conglomerate), BBCA (banking), PTBA (energy and mining), and TLKM (telecommunications). These companies were chosen because they exhibit heterogeneous market characteristics, including differences in volatility, liquidity, trend persistence, and trading behavior. Such diversity provides a suitable benchmark for evaluating whether the proposed adaptive optimization framework can generalize across various types of financial time series rather than being tailored to a single stock.

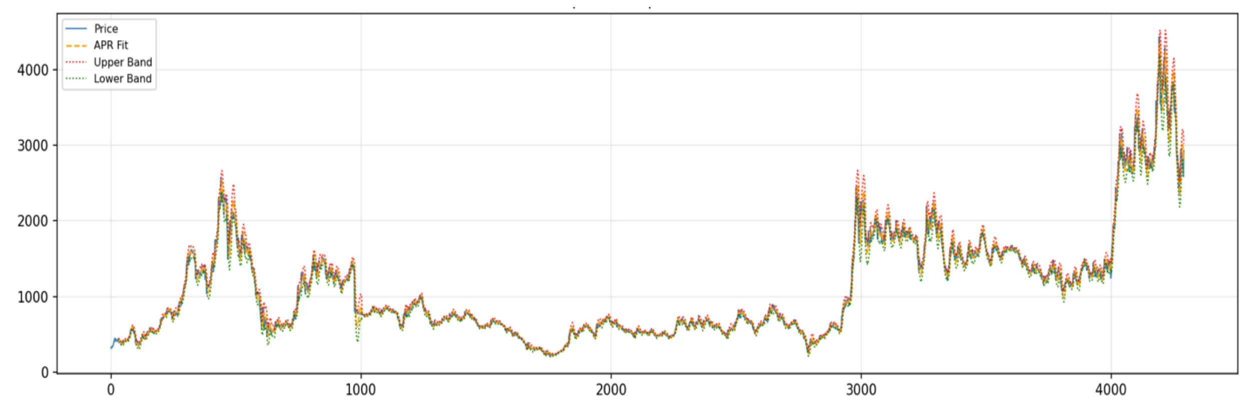

Figure 1. Adaptive Polynomial Regression (APR) Fit and Residual Channels for ANTM

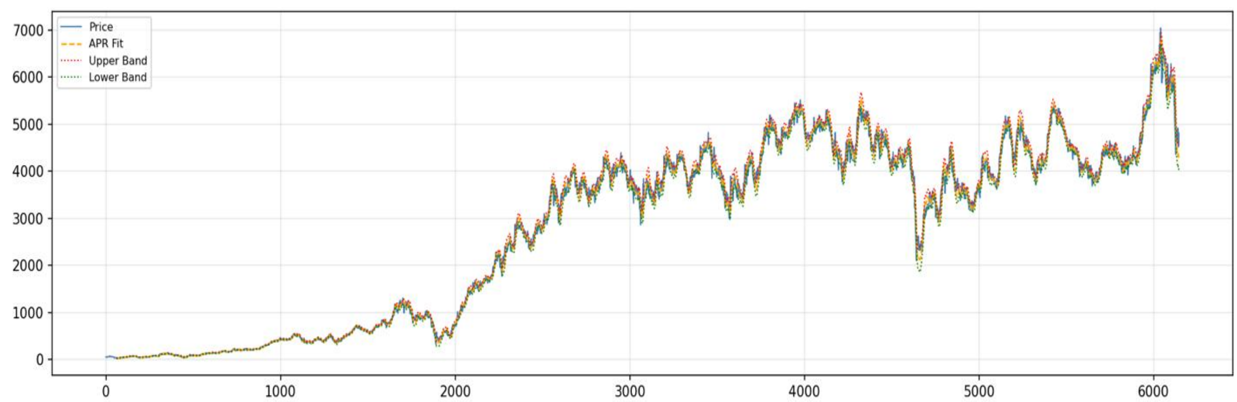

Figure 2. Adaptive Polynomial Regression (APR) Fit and Residual Channels for ASII

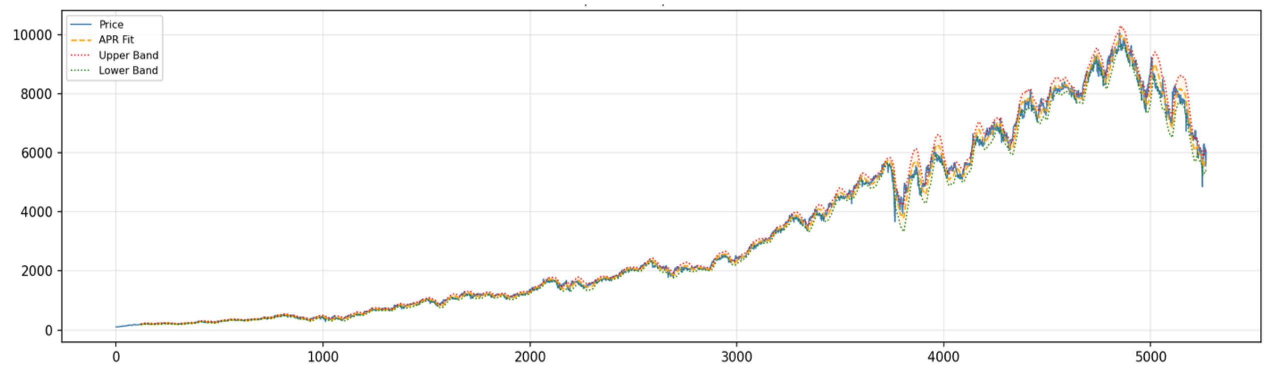

Figure 3. Adaptive Polynomial Regression (APR) Fit and Residual Channels for BBCA

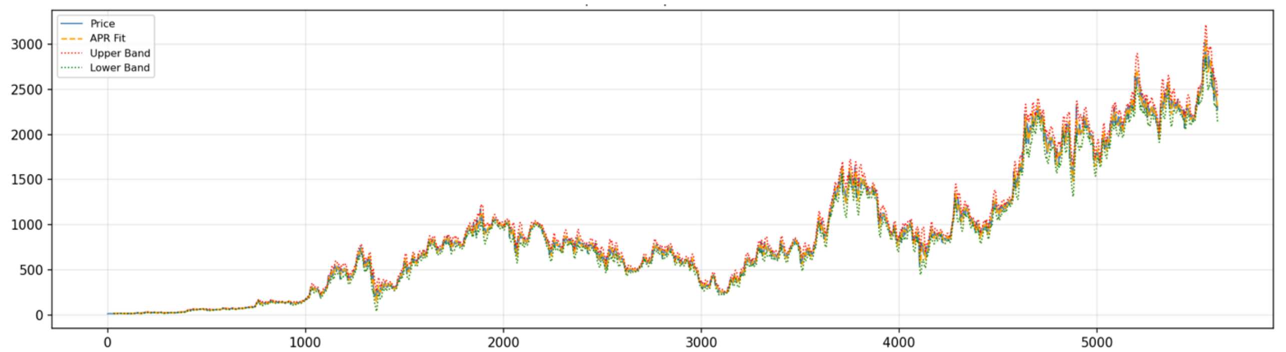

Figure 4. Adaptive Polynomial Regression (APR) Fit and Residual Channels for PTBA

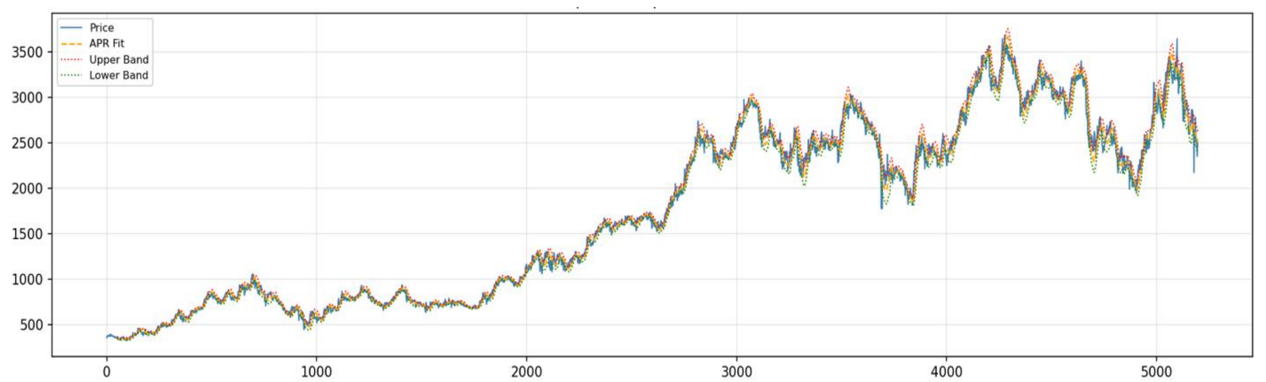

Figure 5. Adaptive Polynomial Regression (APR) Fit and Residual Channels for TLKM

3.1 Experimental Results

The adaptive window optimization also demonstrated variability, with shorter windows (30 observations) preferred for ANTM and PTBA, a medium window (60) for ASII, a longer window (120) for BBCA, and an intermediate window (50) for TLKM. These findings suggest that no single regression configuration is universally optimal, reinforcing the importance of adaptive parameter selection for non-stationary financial time series.

Table 1. Statistical Performance for Selected LQ45 Equities.

Symbol	Degree	Window	MSE	RMSE	MAE	R2
ANTM	2	30	6167.9836	78.5365	46.6508	0.9881
ASII	2	60	16774.8985	129.5179	86.4531	0.9952
BBCA	2	120	31628.8379	177845	105.4025	0.9961
PTBA	2	30	1652.1772	40647	26.1247	0.9966
TLKM	1	50	6528.5562	80.7995	55,239	0.9929

From the prediction perspective, all evaluated stocks achieved excellent goodness-of-fit, with coefficient of determination (R^2) values ranging from 0.9881 to 0.9966. BBCA produced the highest prediction accuracy with $R^2 = 0.9961$, while PTBA achieved the overall best fit with $R^2 = 0.9966$ despite using the shortest rolling window. Prediction errors remained relatively small compared with each stock's price scale, where RMSE values ranged from approximately 40.65 to 177.85, and MAE values ranged from 26.12 to 105.40. These results indicate that the adaptive optimization successfully balances model complexity and fitting accuracy without requiring unnecessarily high polynomial degrees. The dominance of low-order polynomial models also suggests that medium-term market trends in LQ45 constituents can be effectively approximated using relatively simple mathematical structures when combined with adaptive rolling-window selection. Overall, the evaluation demonstrates that adaptive polynomial regression provides robust trend estimation across heterogeneous LQ45 stocks while preserving high interpretability. This performance forms the foundation for the subsequent signal generation and backtesting stages, where the practical usefulness of the estimated trends is evaluated in terms of trading performance rather than prediction accuracy alone.

3.2 Trading Performance Evaluation

To assess the practical effectiveness of the proposed adaptive polynomial regression framework, the generated trading signals were evaluated using a historical backtesting procedure on five representative LQ45 stocks. Unlike conventional prediction studies that focus solely on statistical accuracy, this evaluation emphasizes investment performance through return, risk-adjusted return, profitability, and drawdown metrics. The results show that the proposed framework can generate profitable trading strategies for all tested stocks, though performance varies widely. ASII delivered the strongest results, with a total return of 2680.16%, a CAGR of 14.61%, a Sharpe ratio of 0.8921, and a profit factor of 1.4897, indicating good risk-adjusted profitability throughout the period. While BBCA's total return was lower at 457.09%, it still achieved a solid Sharpe ratio of 0.7713 and a profit factor of 1.5603, reflecting a more consistent balance between return and risk. Among the remaining stocks, PTBA exhibited the highest trading efficiency with the largest profit factor (1.8558) while simultaneously recording the lowest maximum drawdown (−15.86%), indicating effective downside risk control despite a more moderate cumulative return (187.39%). TLKM also generated positive returns (174.93%) with acceptable risk characteristics, whereas ANTM delivered the weakest performance, achieving only 39.50% cumulative return while experiencing the deepest drawdown (−65.81%) and the lowest Sharpe ratio (0.2008).

Interestingly, all strategies produced relatively low win rates, ranging from 1.6% to 8.7%. Nevertheless, every stock maintained a profit factor greater than one, implying that profitable trades were sufficiently larger than losing trades to generate positive long-term returns. This characteristic is consistent with trend-following strategies, where a limited number of large winning trades compensate for more frequent small losses. Overall, these results show that the proposed adaptive polynomial regression framework is effective for trend estimation and making profitable trading decisions in non-stationary market conditions. The integration of adaptive trend filtering with dynamic signal creation allows the strategy to identify sustained market movements while managing risk levels across various LQ45 constituents. Although performance varies across stocks due to differing volatility and market structures, the consistently positive profit factors indicate that this framework provides a strong basis for systematic trading in the Indonesian equity market.

Table 2. Backtesting Results and Risk Profiles

Symbol	Return (%)	Cagr (%)	Sharpe	Win rate	Profit Factor	Max Drawdown (%)
ANTM	39.5	1.97	0.2008	0.0471	1.1155	-65.81
ASII	2680.16	14.61	0.8921	0.0867	1.4897	-20.93
BBCA	457.09	8.56	0.7713	0.0566	1.5603	-27.68
PTBA	187.39	4.86	0.5659	0.016	1.8558	-15.86
TLKM	174.93	5.03	0.4442	0.0797	1,206	-25.41

3.3 Discussion

The experimental results show that the proposed adaptive polynomial regression framework successfully balances prediction accuracy, model simplicity, and trading profitability. Unlike traditional forecasting methods that focus on minimizing prediction error, this approach aims to estimate stable market trends that lead to actionable trading decisions. This is important because highly accurate point forecasts do not always result in better investment outcomes. All evaluated LQ45 stocks demonstrated exceptionally high goodness of fit from a predictive perspective, with R^2 values ranging from 0.9881 to 0.9966. These consistently elevated figures show that the adaptive optimization effectively selects rolling windows and polynomial degrees suited for capturing medium-term market dynamics, without the need for complex nonlinear models. Notably, four out of five stocks favored a second-order polynomial, while only TLKM preferred a linear model. This suggests that moderate nonlinear trend structures are generally adequate for modeling Indonesian blue-chip stocks.

The adaptive window optimization underscores the diverse nature of financial time series. It found that optimal window sizes vary from 30 to 120 trading periods, suggesting that different assets exhibit distinct temporal traits and trend durations. This finding aligns with the idea that fixed-window regression models are insufficient to capture the changing market dynamics, especially in non-stationary settings where volatility regimes often shift.

The backtesting results further confirm the practical effectiveness of the proposed framework. All examined stocks showed a profit factor above one, indicating that profitable trades consistently surpassed losses during the testing period. Specifically, ASII achieved the highest cumulative return and the best risk-adjusted performance, while PTBA demonstrated superior capital protection, with the lowest maximum drawdown and the highest profit factor. These results suggest that the adaptive regression framework can generate financially significant trading signals, not just enhance statistical prediction metrics. A notable feature of the proposed strategy is its relatively low win rate across all assets. Although win rates stayed below 10%, the overall strategies remained profitable in the long run because winning trades were much larger than losing ones. This aligns with trend-following systems, where success relies more on capturing prolonged market trends than on having a high percentage of winning trades. Therefore, the proposed framework shows that reliable trend estimation can be more beneficial than frequent trading signals.

Compared with deep learning models commonly used for financial forecasting, the proposed method offers several practical benefits. Firstly, the regression model is fully interpretable, enabling investors to understand the relationship between past data and the resulting signals. Secondly, adaptive optimization prevents unnecessary complexity and reduces the risk of overfitting associated with high-parameter neural networks. Lastly, the framework demands significantly less computational power, making it ideal for real-time deployment and ongoing portfolio oversight. Overall, the experimental results indicate that adaptive polynomial regression offers a balanced solution that considers prediction accuracy, computational efficiency, interpretability, and real-world trading outcomes for emerging equity markets such as the Indonesian LQ45 index.

While the proposed framework consistently delivered high predictive accuracy and strong trading results across all tested assets, statistical validation is required to confirm that these improvements are not just due to chance. The consistently high R^2 values (0.9881–0.9966), along with relatively low RMSE and MAE, indicate that the adaptive optimization yields stable regression models across diverse market conditions. The minimal variation in prediction accuracy across the five LQ45 stocks also indicates that the proposed optimization method effectively generalizes to different asset classes. From a trading standpoint, all assessed stocks had profit factors above one, signifying positive expected profitability. Additionally, the steady accumulation of positive cumulative returns across all assets provides empirical support for the adaptive regression framework, effectively translating statistical trend predictions into profitable trading strategies.

4. CONCLUSION

This study introduced an Adaptive Polynomial Regression framework for trend filtering and trading signals in the Indonesian LQ45 stock market. Unlike traditional regression models with fixed parameters, this approach simultaneously optimizes the rolling window size and polynomial degree via Bayesian Optimization. This allows the model to adapt to the diverse and non-stationary nature of financial time series. The derived trend estimates are then converted into practical trading signals using a dynamic Z-score channel mechanism. An experimental evaluation of five representative LQ45 stocks showed that the proposed framework consistently achieved high predictive accuracy, with R^2 values ranging from 0.9881 to 0.9966. It also maintained relatively low prediction errors across various market conditions. The optimization process selected different window lengths and polynomial degrees for each stock, indicating that adaptive parameter selection is preferable to fixed configurations for modeling dynamic market conditions. Historical backtesting revealed that the trading strategies generated positive cumulative returns and profit factors exceeding 1 across all evaluated stocks. This shows that the trend-filtering method effectively turned statistical trend estimates into profitable trading decisions. While win rates were somewhat low, the strategy stayed profitable because larger winning trades offset the more frequent small losses, aligning with typical trend-following strategies. Future work will expand the framework by analyzing a broader range of Indonesian stocks, including formal statistical significance tests against benchmark models, and adding more market data such as trading volume, macroeconomic indicators, and alternative data sources. Additionally, the adaptive regression framework could be combined with advanced machine learning or reinforcement learning approaches to create hybrid trading systems that can adapt dynamically to evolving market conditions.

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