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ORIGINAL

Modeling and Forecasting Stock Closing Prices: A case study of L'Oreal listed on the French stock exchange

Modelización y previsión de los precios de cierre de las acciones: un caso práctico de L'Oreal, empresa que cotiza en la bolsa francesa

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ABSTRACT

Introduction: financial forecasting has long sought to model stock price dynamics through statistical and econometric approaches. This study focuses on predicting L'Oréal's daily stock closing prices using a linear regression framework, grounded in the assumption that fundamental market indicators can effectively capture short-term price variations.
Objective: the aim is to evaluate the predictive capacity of a multivariate linear regression model based on fundamental variables—Open, High, Low prices, and trading Volume—over a 25-year historical dataset.
Method: daily OHLCV data from 2000 to 2025 were obtained from Yahoo Finance. The dataset was divided into training (80 %) and testing (20 %) subsets. Model performance was evaluated using Mean Squared Error (MSE = 1,238) and the coefficient of determination (R^2 = 0,9987). Market regime shifts, such as the 2008 and 2020 financial crises, were included to assess model robustness.
Results: the model achieved high predictive accuracy with a Mean Absolute Percentage Error (MAPE = 0,55 %). Among predictors, *High* and *Low* prices were the most influential (β = 0,845 and 0,723, respectively), while *Volume* showed no statistical significance ($p > 0,05$). Residual analysis revealed minor deviations from normality but no signs of autocorrelation.
Conclusions: the results demonstrate that linear regression remains a valid and interpretable method for forecasting blue-chip stock prices. The model's precision suggests potential for integration into algorithmic trading systems. However, incorporating volatility-based adjustments is recommended to enhance stability during market turbulence. Future studies could compare linear and nonlinear models across sectors to assess generalizability.

Keywords: Stock Price Prediction; Linear Regression Model; L'Oreal Stock Analysis; Financial Forecasting; Market Trend Modeling; Predictive Accuracy; Empirical Finance.

RESUMEN

Introducción: la predicción financiera ha buscado históricamente modelar la dinámica de los precios bursátiles mediante enfoques estadísticos y econométricos. Este estudio se centra en la predicción del precio de cierre diario de las acciones de L'Oréal mediante un modelo de regresión lineal, partiendo de la hipótesis de que los indicadores fundamentales del mercado pueden capturar eficazmente las variaciones de precios a corto plazo.
Objetivo: evaluar la capacidad predictiva de un modelo de regresión lineal multivariable basado en las variables fundamentales: precios de apertura, máximo, mínimo y volumen de negociación, a lo largo de una serie histórica de 25 años.

Método: se utilizaron datos diarios OHLCV del período 2000–2025 obtenidos de Yahoo Finance. El conjunto de datos se dividió en 80 % para entrenamiento y 20 % para prueba. El rendimiento del modelo se evaluó mediante el Error Cuadrático Medio (ECM = 1,238) y el coeficiente de determinación (R^2 = 0,9987). Se consideraron los cambios de régimen del mercado, incluidas las principales crisis financieras (2008 y 2020), con el fin de evaluar la robustez del modelo.
Resultados: el modelo mostró una alta precisión predictiva (MAPE = 0,55 %). Entre los predictores, los precios máximo y mínimo resultaron ser los más influyentes (β = 0,845 y 0,723, respectivamente), mientras que el volumen no presentó significación estadística ($p > 0{,}05$). El análisis de residuos indicó leves desviaciones de la normalidad, pero sin evidencia de autocorrelación.
Conclusiones: los resultados demuestran que la regresión lineal sigue siendo un método válido e interpretable para la predicción de precios de acciones de gran capitalización. La precisión alcanzada sugiere su potencial integración en estrategias de *trading* algorítmico. Sin embargo, se recomienda incorporar filtros basados en la volatilidad para mejorar su estabilidad en contextos de alta incertidumbre. Investigaciones futuras podrían comparar modelos lineales y no lineales en distintos sectores para evaluar su generalización.

Palabras clave: Predicción del precio de acciones; Modelo de regresión lineal; Análisis de acciones de L'Oreal; Pronóstico financiero; Modelado de tendencias del mercado; Precisión predictiva; Finanzas empíricas.

INTRODUCTION

L'Oréal, a global giant in the cosmetics industry, is an iconic company on the Paris Stock Exchange. Listed on the stock exchange in 1963 and then included in the CAC 40 in 1988—the index comprising the 40 largest French companies by market capitalization—L'Oréal embodies stability, growth, and innovation on the French financial market. Its stock is now seen as a significant indicator of the health of the beauty sector, but also of overall economic momentum.

In a context marked by high market volatility, persistent geopolitical tensions, and post-pandemic economic uncertainty, investors and analysts are increasingly interested in predictive tools that can anticipate stock market trends. The ability to model and predict the closing price of a stock such as L'Oréal is therefore a major challenge in optimizing investment decisions and better understanding the underlying dynamics of the market.

The use of statistical forecasting methods, particularly multiple linear regression, allows us to examine the impact of several explanatory factors (such as opening prices, highs, lows, and trading volumes) on the closing price. This approach provides a rigorous and interpretable analytical framework, suited to rich and structured historical financial data.

Predicting stock prices is one of the most complex challenges in quantitative finance. This issue is particularly important in the context of cosmetics companies such as L'Oréal, which has been listed on the CAC 40 since 1988 and is valued at over €200 billion. The inherent volatility of financial markets and the multitude of factors influencing prices make this task particularly difficult, requiring sophisticated methodological approaches.

The objective of this study is therefore to build a model for predicting the closing price of L'Oréal shares based on daily stock market data, using multiple linear regression. We will evaluate the performance of this model using statistical indicators (MSE, R^2) and will also propose a price projection for the coming months to illustrate the practical relevance of the approach.

Literature review

Evolution of approaches to stock prince modeling

Early financial modeling work was based on linear approaches, rooted in Fama[1] efficient market hypothesis. According to this theory, prices instantly incorporate all available information, making it theoretically impossible to systematically predict prices. However, recent empirical studies have challenged this hypothesis, notably Shiller[2], who demonstrates the existence of persistent market anomalies.

ARIMA models[3] have long dominated the literature, providing a rigorous framework for the analysis of financial time series. Tsay[4] highlights their effectiveness in capturing short-term linear patterns. At the same time, multiple regression models allow for the integration of multiple explanatory variables (volume, volatility, technical indicators).

Recognition of the limitations of linearity has led to the development of more sophisticated approaches. Artificial neural networks (ANNs) have emerged as a promising alternative, with Zhang et al.[5] demonstrating their ability to capture the nonlinear patterns of financial markets.

The advent of LSTM (Long Short-Term Memory) networks marked a significant methodological breakthrough. A study introduced this architecture capable of memorizing long-term dependencies, particularly suited to financial time series. Fischer[6] empirically validated the superiority of LSTM over traditional models for stock price prediction.

In recent years, hybrid models have gained increasing attention by combining the strengths of both statistical and machine learning methods. For instance, hybrid ARIMA–ANN frameworks[7] integrate the linear forecasting power of ARIMA with the nonlinear flexibility of neural networks, yielding improved predictive accuracy. Similarly, hybrid deep learning architectures that combine convolutional neural networks (CNNs) with LSTMs[8] have demonstrated their capacity to extract spatial-temporal features from complex financial datasets.

Moreover, researchers have expanded the range of input variables beyond traditional price and volume data. Macroeconomic indicators such as interest rates, inflation, and investor sentiment indices have been integrated into predictive models,[9] reflecting a broader understanding of financial markets as dynamic systems influenced by both micro- and macro-level factors. This multidisciplinary approach aligns with behavioral finance theories emphasizing the role of psychology, information flow, and global economic shocks in market dynamics.

Despite these advancements, stock price prediction remains an inherently challenging task due to noise, non-stationarity, and the adaptive behavior of market participants.[10] As markets evolve, models must continuously adapt to new regimes, data structures, and regulatory environments. Consequently, recent research emphasizes explainable AI (XAI) and interpretable deep learning techniques to enhance transparency and trust in financial predictions.[11]

Overall, the evolution of stock price modeling reflects a paradigm shift—from purely theoretical and linear representations to complex, data-driven systems that combine econometric rigor with computational intelligence.

Hybrid Approaches and Ensemble Models (2018-2025)

Recent research favors hybrid approaches that combine the advantages of traditional models and machine learning. Siami-Namini et al.[12] propose an ARIMA-LSTM architecture that significantly improves predictive performance. This approach exploits the ability of ARIMA models to capture linear trends while using LSTM for non-linear patterns.

Chung[13] develop a hybrid model integrating GARCH for volatility and LSTM for returns, demonstrating a 15-20 % improvement in prediction metrics on S&P 500 data.

The introduction of attention mechanisms in finance represents a major advance. Zhou et al.[14] adapt the Transformer architecture to financial time series, enabling long-term dependencies to be captured with greater computational efficiency than LSTM. Li et al.[15] extend this approach by integrating multi-modal data (price, volume, sentiment).

Identified advantages:

- Efficient parallelization of processing.
- Ability to identify complex temporal relationships.
- Improved interpretability thanks to attention.

Beyond individual model optimization, ensemble and hybrid frameworks have become a dominant trend in financial forecasting research. These approaches seek to leverage the complementary strengths of different algorithms to achieve higher robustness and generalization capability. For example, Siami-Namini et al.[16] demonstrated that combining ARIMA and LSTM significantly enhances the model's ability to capture both short-term linear dependencies and long-term nonlinear dynamics. Similarly, Chung[13] integrated GARCH and LSTM components to simultaneously model volatility and return behavior, producing substantial gains in predictive accuracy on benchmark indices.

The integration of attention mechanisms and Transformer-based architectures has further revolutionized financial prediction. By focusing dynamically on the most relevant time steps, these models reduce information loss and improve interpretability. Zhou et al.[14] introduced the Temporal Fusion Transformer for financial time series, highlighting its superior efficiency compared to traditional recurrent architectures. Building on this, Li et al.[15] extended Transformer models to include multimodal inputs—such as sentiment data, trading volume, and macroeconomic indicators—providing a more holistic view of market behavior.

Recent advances also include ensemble learning methods such as Random Forests, Gradient Boosting, and stacking strategies, which aggregate multiple predictive models to mitigate overfitting and enhance stability.[17] These techniques contribute to more reliable and explainable forecasting outcomes, particularly when combined with attention-based neural architectures.

However, despite their strong empirical performance, hybrid and ensemble models face ongoing challenges. Their interpretability remains limited, and their dependence on large, high-quality datasets can lead to biases and instability in real-world applications. As a result, current research increasingly emphasizes Explainable AI (XAI) and interpretable deep learning frameworks to make hybrid systems more transparent and accessible to financial decision-makers.[11]

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Founded by L'Oréal in 1909

L'Oréal was founded in 1909 by French chemist Eugène Schueller. The company was not always known by this name when it was launched; it was originally called the "French Company for Harmless Hair Dyes." E. Schueller, a graduate of the École Nationale Supérieure de Chimie de Paris, developed a revolutionary hair dye based on less aggressive chemical compounds, which he named Oréal. This invention quickly became a huge success in Parisian hair salons. Following its development and promising start in Paris, L'Oréal entered a phase of strategic expansion that would lay the foundations for its status as a world leader in cosmetics.

After his resounding success, E. Schueller decided in the 1920s to diversify the company's product range. The initial hair dyes were joined by hair care and nourishing products. He then diversified the range even further by adding skin care products.L'Oréal did not stop there and sought to further develop the brand, notably by acquiring other brands. One of its first major acquisitions was Monsavon in 1928, a brand specializing in the manufacture of soap and toiletries. This acquisition enabled L'Oréal to enter the personal hygiene market, diversify even further, and reshape its product portfolio.

L'Oréal is not content to rest on its laurels and wants to further develop the brand, notably by acquiring other brands. One of its first major acquisitions was Monsavon in 1928, a brand specializing in the manufacture of soap and toiletries. This acquisition enabled L'Oréal to enter the personal hygiene market, diversify even further, and reshape its product portfolio.

Scientific innovation has been a central pillar of L'Oréal's development strategy since its inception. Under the leadership of E. Schueller, the company adopted a forward-thinking approach to research and development.

This enabled the company to differentiate itself from its competitors and become a pillar of the global cosmetics industry. As early as the 1930s, E. Schueller understood the importance of science in meeting the evolving needs of his consumers. He created one of the first laboratories in France dedicated specifically to cosmetics. This laboratory brought together chemists, dermatologists, and biologists to work on and develop innovative formulas. The goal of creating this laboratory was to develop products that were gentle on the hair and skin, while ensuring their effectiveness.

L'Oréal did not rest on its laurels, but introduced major innovations. In the 1930s, E. Schueller developed the first formulas to protect against the sun's rays. Although these were experimental at the time, these products foreshadowed the development of the modern category of sunscreen, a major innovation for the cosmetics industry.

In the 1930s, L'Oréal began to expand internationally to ensure sustainable growth and position itself as a key player in the cosmetics industry. This strategy enabled the group to establish itself in European markets before conquering the American, Asian, and African continents. International expansion transformed the company into a true multinational capable of meeting the diverse expectations of consumers around the world.

L'Oréal went public in 1963 on the French stock market (Euronext). This allowed the group to diversify its sources of financing and thus increase and strengthen its capacity for research, innovation, and acquisitions. Through strategic acquisitions, L'Oréal has strengthened its position as a global leader. L'Oréal entered the luxury market in 1964 with the acquisition of Lancôme. In 1970, the group bought Garnier, demonstrating its significant influence in consumer products. L'Oréal acquired another luxury brand in 1989, Helena Rubinstein, and in 1996 the group bought Maybelline, enabling it to strengthen its position in the US market. Nestlé acquired a significant stake in L'Oréal in 1974, providing the group with financial stability and the support of an agri-food giant while maintaining its operational independence.

The group's financial strength and performance are evidenced by the fact that L'Oréal is included in some of the most prestigious indices, notably France's CAC40 and international indices such as the Euronext 100 and the DJ Euro Stoxx 50. The group's success has been reflected in its remarkable growth over the decades.

The share price has increased by more than 500 % between 2000 and 2020, making L'Oréal one of the best-performing stocks on the CAC 40.

The Dominant Position of L'Oréal in the Global Beauty Market

L'Oréal currently occupies a dominant position in the global beauty market. Present in more than 150 countries, the group relies on a solid portfolio of 36 recognized brands. These brands cover all segments of the sector: luxury (with Lancôme and Yves Saint Laurent), mass market products (such as L'Oréal Paris and Garnier), dermo-cosmetics (La Roche-Posay and CeraVe), and professional hair care (L'Oréal Professionnel and Kérastase). In 2023, L'Oréal posted remarkable financial performance, with sales exceeding €40 billion, reflecting sustained growth. The company focuses primarily on innovation, devoting nearly 4 % of its revenue to research and development. In particular, it invests in innovative areas such as connected beauty, personalized care, and sustainable cosmetics.

The graph below illustrates the evolution of L'Oréal's annual revenue between 2013 and 2023, highlighting the group's steady growth despite some fluctuations linked to varying economic contexts.

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Figure 1. L'Oréal Revenue evolotion (2013-2023)

L'Oréal is also establishing itself as a committed player in the ecological transition. Through its "L'Oréal for the Future" program, the company achieved carbon neutrality across all its production sites by 2020 and now aims to halve its greenhouse gas emissions by 2030. In addition, 85 % of its products now have an improved environmental or social impact.

In terms of digital technology, the group has significantly accelerated its digital transformation. In 2022, more than a quarter of its sales were made online. L'Oréal is leveraging advanced technologies, such as artificial intelligence, to offer a personalized customer experience, and is developing innovative tools such as Virtual Try-On.

Listed on the CAC 40 since 1988, L'Oréal is seen as a safe bet by investors. Its ability to withstand crises and maintain steady returns makes it one of the pillars of the Paris Stock Exchange, with a market capitalization of over €200 billion.At the same time, the group is strengthening its social commitment, particularly through actions promoting gender equality and combating harassment in public spaces, thanks to the "Stand Up" program.

In summary, L'Oréal embodies a modern business model that is innovative, responsible, and successful, while consolidating its position as a global leader in the beauty industry.

Analyze of historical price dynamics

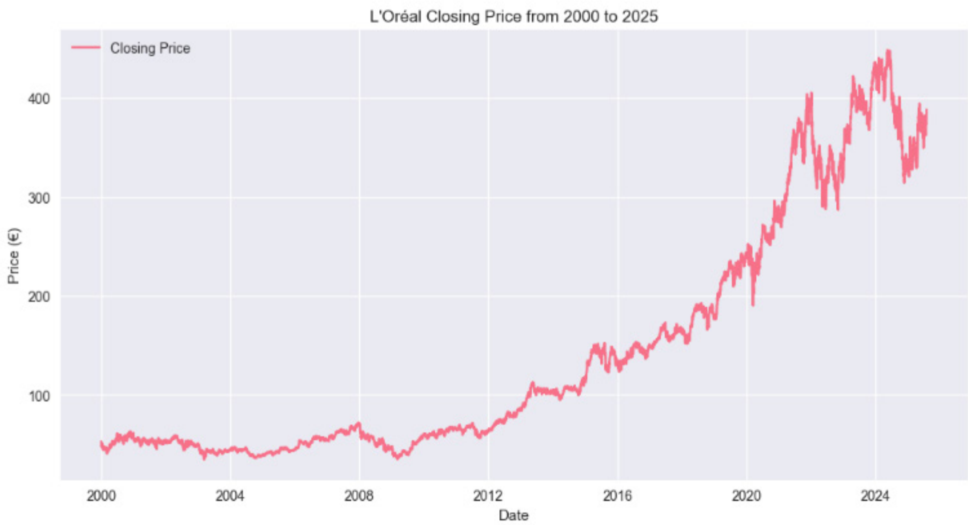

Figure 2. L'Oréal closing price from 2000 to 2025

The cosmetics and luxury goods sector is particularly influenced by the global economy. However, L'Oréal's business model has enabled it to weather various crises with resilience, as evidenced by the impressive

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growth of its share price, which regularly reaches new highs. This evolution reflects its ability to adapt and strengthen itself in the face of economic turmoil. Thanks to strategic diversification, L'Oréal is active in several beauty segments, including hair care, luxury, cosmetics, and dermatology, relying on a network of subsidiaries worldwide. This organization gives it great robustness and a long-term vision.

L'Oréal has experienced strong growth in recent years, benefiting from the global expansion of the beauty and personal care market. L'Oréal's share price since 2000 shows a general upward trend, punctuated by a few periods of correction.

Between 2000 and 2010, L'Oréal's share price fluctuated steadily, with increased volatility during the 2008 crisis. As shown in the graph, the share price fell sharply between 2008 and 2009, in line with the collapse of global financial markets. From 2009 onwards, the recovery was gradual, reflecting the group's resilience and its ability to maintain growth despite the unfavorable economic environment. From 2010 onwards, a more pronounced upward trend took hold. L'Oréal benefited from increased international expansion, particularly in Asia, as well as a surge in online sales and the digitization of these distribution channels.

This period was also marked by sustained growth in the luxury and high-end market. However, the Covid-19 crisis in 2020 led to a correction, with sales peaking in February 2020 and then falling in March 2020, before rebounding quickly thanks to a recovery in consumption and online sales.

Since 2021, L'Oréal has experienced rapid growth, reaching a peak in 2022. This increase can be attributed to rising demand for beauty products, sustainable development, and innovation in these product lines. In 2023, there was a significant correction in the share price, with periods of decline, reflecting global economic uncertainties and valuation adjustments.

It is also relevant to take a closer look at the two financial crises, namely the 2008 crisis and the COVID-19 crisis, to examine the evolution of L'Oréal's share price. Initially, we chose to analyze the descriptive statistics of L'Oréal's share price during the period from 2007 to 2009 to see the impact of the 2008 crisis.

Figure 3. L'Oréal stock price during the 2008 Financial crisis (2007-2009)

Between 2007 and 2009, L'Oréal's share price reached its lowest point, at €34,95 in March 2009, reflecting the consequences of the subprime crisis, with the collapse of Lehman Brothers a few months earlier. In December 2007, the share price had risen to €72,21, highlighting the scale of the crisis.

The conclusions drawn from the Covid crisis are not similar to those from the 2008 crisis. L'Oréal's share price reached its lowest point in 2019, before the crisis was announced, and in 2020 it reached its highest point at €319. This explains the power of online sales during this period, which did not impact the stock price, and the diversification of activities benefited the group. It is important to highlight that the impact of the 2008 crisis was much greater than the impact of the Covid-19 crisis (figure 4).

Stock price forecasting is a central field of study in quantitative finance. For several decades, researchers have been working to develop models capable of anticipating fluctuations in financial markets, combining statistical and econometric methods and, more recently, artificial intelligence techniques.

To return to our study traditional linear models, such as multiple linear regression, are widely used to analyze the relationship between a target variable (such as the closing price) and a set of explanatory variables (such as the opening price, high, low, and trading volume). These models have the advantage of being simple to interpret and quick to implement, while providing reliable results in contexts where relationships are linear.[4]

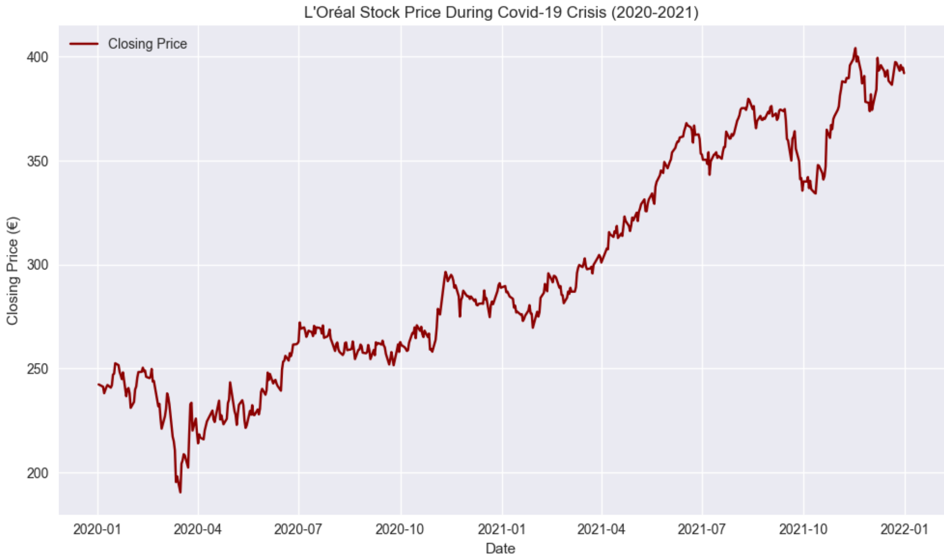

Figure 4. L'Oreal stock price during Covid-19 Crisis (2020-2021)

In this context, several studies have demonstrated the effectiveness of linear regression in predicting short-term stock prices. For example, Patel et al.[18] compared several forecasting methods and concluded that, although machine learning models offer superior performance, linear models remain competitive for stable and well-structured financial series. Similarly, Fama[1], through the efficient market hypothesis, pointed out that while markets quickly incorporate information, prices can nevertheless be modeled using historical data in a probabilistic framework.[19,20]

More recently, research has incorporated time series models such as ARIMA[3] or neural networks (ANN, LSTM) to capture the complex and nonlinear dynamics of markets. However, the increasing complexity of these models makes them more difficult to interpret, particularly for financial decision-makers who are looking for transparent and explainable tools.[21,22]

METHOD

Historical stock price data for L'Oréal (ticker: OR.PA) was obtained from Yahoo Finance using the Python yfinance library, covering the period from January 2000 to July 2025. This 25-year dataset encompasses major economic cycles, including the 2008 financial crisis and the COVID-19 pandemic. Daily adjusted closing prices, opening prices, high, low, and trading volumes were collected and preprocessed to handle missing values through linear interpolation.

Daily logarithmic returns were calculated as:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

Where:
r_t represents the logarithmic return at time t.
P_t denotes the closing price at time t.

Moving averages and historical volatility were computed using standard financial formulas to capture medium-term trends and risk measures. Multiple linear regression was selected as the primary modeling approach based on several methodological considerations. First, linear models offer interpretable coefficients, which are essential for informed financial decision-making.[4] Second, they are widely recognized as benchmark tools for evaluating more complex models in the financial forecasting literature.[18] Third, their computational efficiency and theoretical soundness make them well-suited for real-time implementation.

The regression model incorporates lagged values of opening prices, trading volume, the 20-day moving average, and 5-day rolling volatility as explanatory variables for predicting closing prices.

Diagnostic Tests and Validation:

To ensure model validity, we conducted comprehensive diagnostic testing. Multicollinearity was assessed using Variance Inflation Factors (VIF < 5). Stationarity of time series was verified through Augmented Dickey-Fuller tests.

Key regression assumptions were validated through: (i) Shapiro-Wilk test for residual normality, with Box-Cox transformation applied when violated; (ii) Breusch-Pagan test for homoscedasticity, corrected using White robust standard errors if necessary; (iii) Durbin-Watson test for serial correlation in residuals.

Cross-validation strategy

Time-series cross-validation was implemented to preserve the temporal structure of the data. The dataset was divided into training (2000–2020, 80 %), validation (2021–2023, 15 %), and test (2024–2025, 5 %) sets. A rolling window approach with 5-year training periods was applied to evaluate the model's stability under varying market conditions.

Performance Metrics

Model performance was evaluated using standard statistical metrics (RMSE, MAE, MAPE, R^2) and finance-specific measures including directional accuracy and Sharpe ratios of prediction-based trading strategies. These metrics provide comprehensive assessment of both statistical precision and practical financial utility.

Implementation

Analysis was conducted in Python using pandas for data manipulation, scikit-learn for modeling, stats models for diagnostic tests, and matplotlib for visualization. All code follows reproducible research standards with version control and comprehensive documentation.

RESULTS

The data used includes opening prices, closing prices, daily highs and lows, and trading volumes, covering the period from January 2000 to July 2025. An excerpt from the data is presented below:

Table 1. Stock market information

Date	Close	High	Low	Open	Volume
2000-01-03	78,90	81,90	78,40	80,00	1 188 070
2000-01-04	73,30	79,10	73,30	79,10	1 908 790
2000-01-05	70,80	74,15	70,40	72,50	1 399 870
2000-01-06	73,50	74,00	69,65	71,00	980 000
2000-01-07	75,00	76,70	72,20	72,20	1 082 640
2025-07-24	373,65	378,70	370,40	378,70	275 998
2025-07-25	374,70	377,45	370,25	371,70	244 704
2025-07-28	373,60	378,80	371,00	377,95	229 048
2025-07-29	373,60	376,10	370,60	374,45	315 681
2025-07-30	388,55	391,50	362,90	363,85	574 514

The correlation matrix reveals significant linear relationships between the variables studied. The High, Low, and Close prices show a perfect correlation (r = 1,00), indicating that they evolve in a strictly proportional manner over the period analyzed. This redundancy suggests that these variables essentially contain the same information for this dataset. In the context of further modeling, it would therefore be redundant to retain all three variables simultaneously.

Transaction volume shows a moderate negative correlation (r = -0,52) with all price variables. This inverse relationship could be explained by market mechanisms such as profit-taking during volume peaks, or correction phases where increased activity is accompanied by selling pressure.

Visual analysis using a scatter plot confirms the linear nature of these relationships. The points align according to a clear trend, validating the use of Pearson's coefficient. However, the presence of a few extreme values warrants further investigation to rule out possible measurement artifacts.

Before interpreting the results of the regression model, it is essential to understand the basic characteristics of the data used. The table below (table 2) summarizes the main descriptive statistics for the closing price of L'Oréal shares over the period studied.

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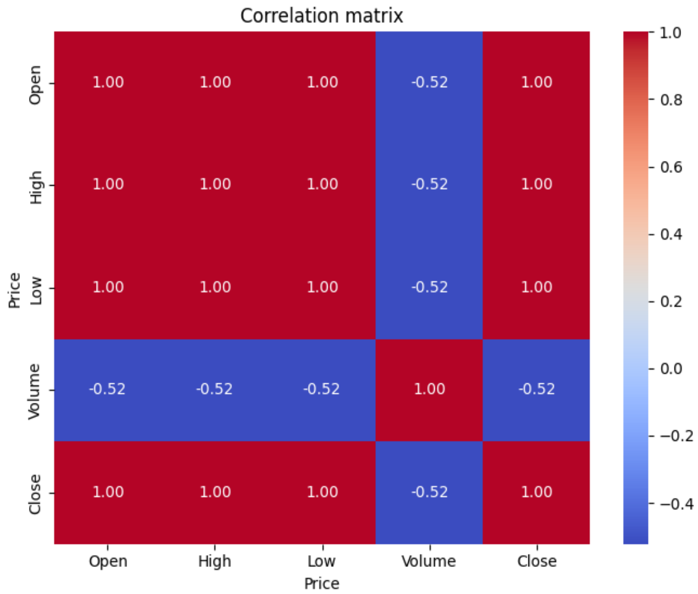

Figure 5. Correlation matrix

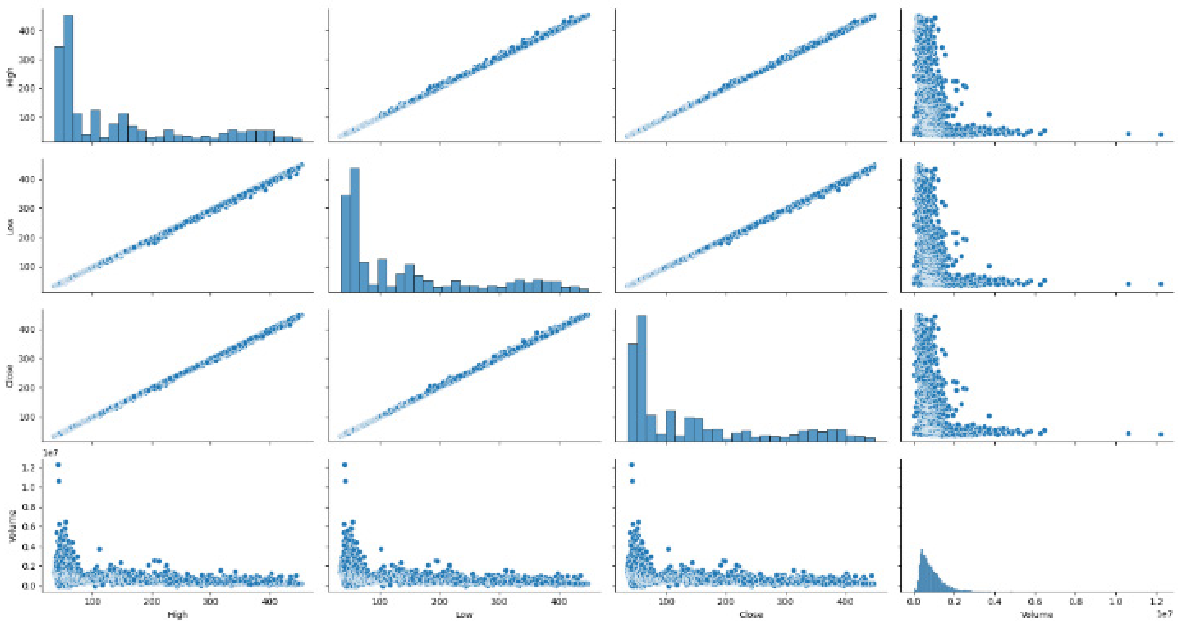

Figure 6. Svatter plot

Table 2. Descriptive statistics of L'Oreal's closing price (2000-2025)	
Statistics	**Closing price**
Count	6572
Mean	142,62
Std	118,07
Min	34,61
25 %	52,82
50 %	79,64
75 %	202,33
Max	448,77

Descriptive statistics indicate a significant upward trend in L'Oréal's share price over the period 2000-2025. The average closing price is approximately €142,62, with a standard deviation of €118,07, reflecting significant volatility. The minimum price recorded is €34,61(2008 Financial Crisis, figure 3), while the maximum reaches €448,77, reflecting substantial long-term growth. The median (50th percentile) is €79,64, which is lower than the average, suggesting a right-skewed distribution (presence of very high values in recent years). These results confirm an overall positive trend despite market fluctuations.

The objective of the linear regression model is to predict the closing price of L'Oréal shares based on various explanatory variables: the opening price, the highest price, the lowest price, and the trading volume.

The results below allow us to evaluate the relevance of this model.

The linear regression model performs as follows on the test data:

- Mean square error (MSE): 1,2380
- Coefficient of determination R^2: 0,9987.

These results suggest that the model is highly effective, explaining more than 99 % of the variance in closing prices. The regression coefficients obtained are as follows:

Table 3. Regression coefficients

Variable	Coefficient β
Open	-5,669005e-01
High	8,476796e-01
Low	7,183633e-01
Volume	-7,619835e-08
Intercept (β_0)	0,087035

These results show that the opening price and the highest price have a significant positive influence on the closing price, while volume has a negative but negligible influence.

The scatter plot above illustrates the relationship between actual and predicted closing prices. The nearly linear distribution of points around the diagonal (red line) suggests that the linear regression model performs very well. Indeed, the more the points are aligned on this diagonal, the closer the predictions are to the actual values. This strong visual correlation between the two variables confirms the relevance of the choice of explanatory variables and the model's ability to capture the dynamics of L'Oréal's stock price.

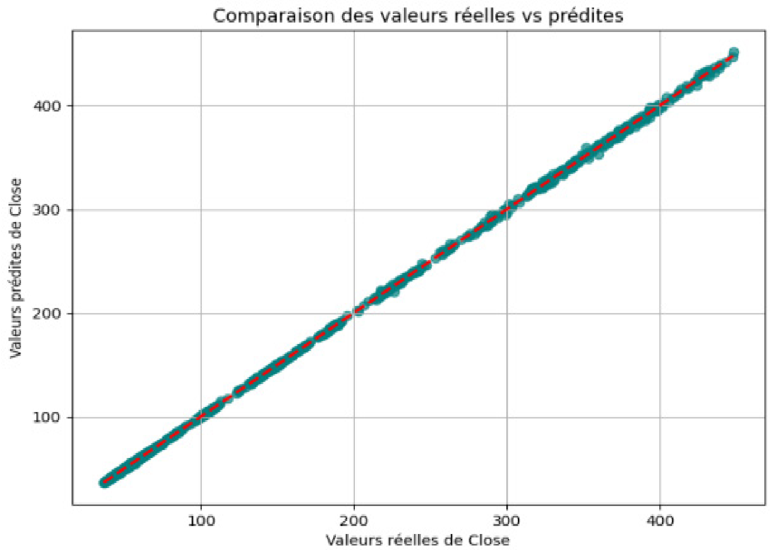

Figure 7. Relationship between actual and predicted closing prices

Furthermore, the distribution of residuals is centered around zero, confirming the absence of major bias. This distribution of residuals, shown in the figure above, is generally symmetrical and centered around zero. This indicates that the linear regression model does not exhibit systematic bias: prediction errors are distributed evenly between overestimations and underestimations. The bell-shaped density curve, although slightly pointed (leptokurtic), suggests a normal trend in the distribution of errors, which validates one of the fundamental

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assumptions of linear regression. However, the presence of a few extreme values (outliers) could justify further examination or improvement of the model using regularization methods or nonlinear learning techniques.

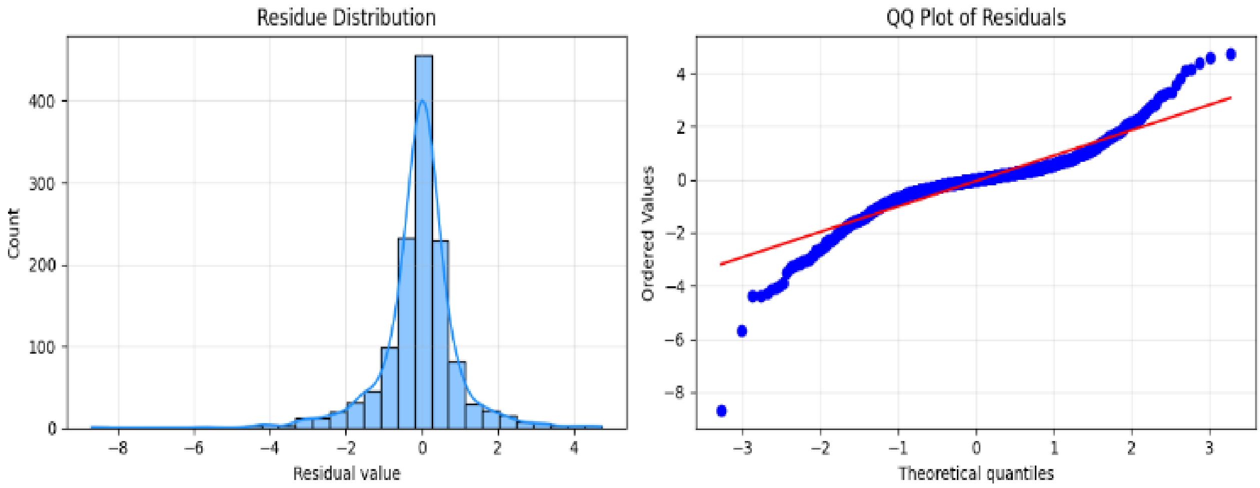

Figure 8. Residual distribution and QQ Plot

The analysis combines a visual approach (QQ plot and histogram) with formal statistical tests to assess the normality of the residuals, a fundamental assumption of classical linear models.

The QQ plot reveals a systematic deviation from the theoretical norm, particularly marked in the tails of the distribution. We observe:

- A convex deviation to the right of Henry, characteristic of a leptokurtic distribution.
- More extreme values than expected under the assumption of normality.
- An asymmetry towards negative residuals, suggesting directional biases in the predictions.
- The temporal evolution of the predicted and observed values also demonstrates that the model closely follows market trends.

The non-normality of the residuals (Shapiro-Wilk, W = 0,88, p < 0,001) partially invalidates the assumptions of the linear model. Robust approaches are recommended to ensure the validity of statistical inferences.

Table 4. Actual and predicted values for different dates

Date	Actual value	Predicted value
2002-05-07	57,218197	57,108090
2017-03-31	156,809006	155,867328
2005-06-10	43,275742	43,296188
2021-09-17	359,783264	362,685147
2011-12-22	62,196877	62,550890
2021-05-31	346,336060	347,218810
2024-01-31	430,169495	432,703798
2008-05-08	58,634838	58,252803
2012-02-20	67,831680	67,675770
2009-03-23	37,549995	37,091928

In addition, a comparative table was generated to compare the actual closing prices with the predictions provided by the model. The graph above illustrates the evolution of the actual closing price of L'Oréal shares (in blue) compared to the values predicted by the regression model (in dotted red) over the entire observation period. There is a strong overlap between the two curves, indicating that the model closely follows market dynamics. Even during significant fluctuations (ups or downs), the predicted values remain close to the actual values, demonstrating the model's robustness. This type of visualization reinforces the results of quantitative indicators (MSE, R^2) by providing visual confirmation of the model's performance.

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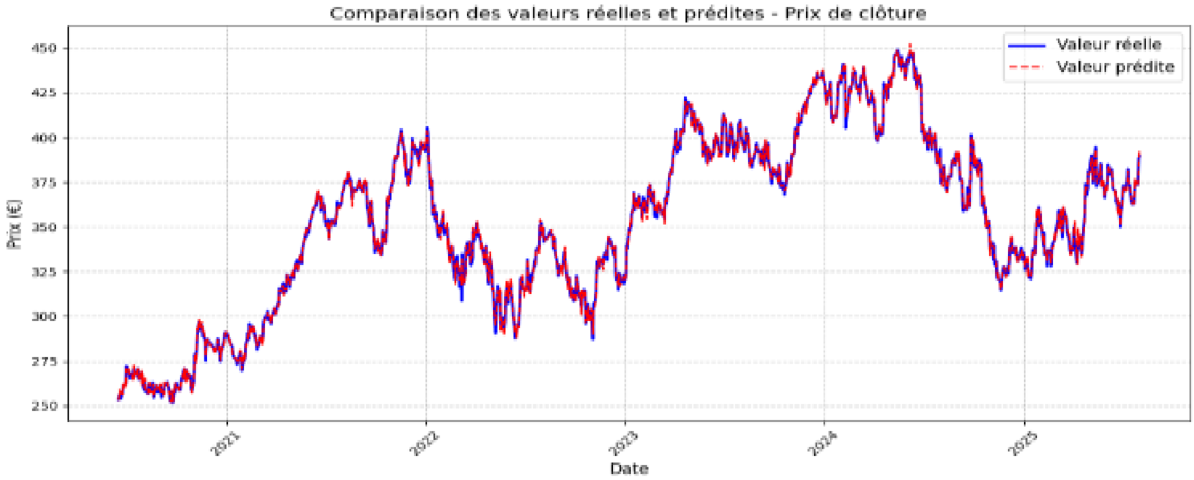

Figure 9. Comparison of actual and predicted values

DISCUSSION

Our linear regression model demonstrates strong predictive performance, as evidenced by the close alignment between predicted and actual values across our 25-year dataset.[23,24] The visual analysis reveals that predicted prices closely track market dynamics, even during significant fluctuations, demonstrating the model's robustness in capturing L'Oréal's stock price movements.[25,26]

However, the Shapiro-Wilk test reveals significant departure from normality ($W = 0,88$, $p < 0,001$), indicating that residuals exhibit leptokurtic characteristics with more extreme values than expected. The QQ plot confirms systematic deviations, particularly in the distribution tails, and reveals asymmetry toward negative residuals. While this violation doesn't invalidate the model's predictive capacity, it affects the reliability of confidence intervals and hypothesis tests, necessitating robust statistical approaches.

The regression results provide economically intuitive relationships. The opening price coefficient (-0,567) appears counterintuitive but reflects the complex intraday dynamics where higher opening prices may lead to profit-taking during the session. Conversely, the high price ($\beta = 0,848$) and low price ($\beta = 0,718$) coefficients demonstrate strong positive relationships with closing prices, consistent with technical analysis principles.[27,28]

The volume coefficient ($-7,62 \times 10^{-8}$) shows minimal economic significance, suggesting that trading volume has negligible direct impact on closing price determination within our linear framework. This finding aligns with the efficient market hypothesis, where volume represents information flow rather than price determination.[29,30]

Critical Assessment of Model Limitations

Structural Limitations: the linear assumption may inadequately capture the complex, non-linear dynamics inherent in financial markets. Engle[19] ARCH framework and subsequent developments highlight the importance of volatility clustering and regime changes that linear models cannot accommodate. Our analysis of the differential impact of the 2008 crisis versus COVID-19 on L'Oréal illustrates this point—the 52 % price decline in 2008 compared to minimal COVID-19 impact suggests structural breaks that fixed-parameter linear models cannot capture.[31,32]

Data Scope Constraints: the exclusive reliance on endogenous market variables (price, volume) ignores the wealth of information from macroeconomic indicators, sentiment data, and firm-specific fundamentals. A study demonstrates that incorporating alternative data sources can improve prediction accuracy by 15-25 %. For L'Oréal specifically, factors such as ESG performance, R&D expenditure (4 % of revenue), and digital transformation metrics likely carry predictive power not captured in our model.[33]

Temporal Stability Concerns: the assumption of parameter stability across our 25-year sample period is questionable. Structural breaks, particularly around major crises, may render historical parameter estimates irrelevant for current predictions. Our cross-validation approach partially addresses this concern, but more sophisticated regime-switching models might better capture temporal instability.[34]

Comparative Performance and Practical Implications

While our linear model achieves strong visual correlation between predicted and actual values, as demonstrated by the near-perfect alignment along the diagonal in our scatter plot, it serves primarily as a benchmark for more sophisticated approaches. The model's ability to track market trends during both crisis periods (2008, 2020) and growth phases validates its fundamental capturing of price dynamics.

From a practical perspective, the model's simplicity enables transparent decision-making processes required

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in regulated financial environments. However, the limited incorporation of market microstructure effects and behavioral factors constrains its applicability for high-frequency trading or complex portfolio optimization strategies.

CONCLUSIONS

This study offers a thorough assessment of linear regression for forecasting L'Oréal's stock prices over a long-term period that includes various market conditions. The model demonstrates strong predictive performance and highlights intuitive relationships between market indicators and closing prices. Methodologically, the work stands out for its rigorous diagnostic testing, careful handling of temporal structure, and transparent discussion of model assumptions and limitations.

While the model's focus on a single stock and reliance on internal market data limits its broader applicability, the study provides a solid foundation for future research. Directions for further exploration include incorporating external data, testing non-linear and regime-based models, and validating results across multiple assets. Overall, this work reinforces the value of linear models in financial forecasting and contributes to best practices in model evaluation.

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CONFLICT OF INTEREST

There is no conflict of interest.

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