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Explaining Closing Stock Prices Using Daily Market Indicators: Evidence from the Global Restaurant Industry

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Abstract: This study examines the extent to which daily market trading variables explain closing stock prices in a dataset of listed restaurant-related firms. The empirical model uses the closing stock price as the dependent variable and the opening price, high price, low price, and trading volume as explanatory variables, with the adjusted closing price as a comparison variable. Python is employed for data preparation, descriptive statistics, visualization, correlation analysis, and linear regression modeling. The literature review draws on thirty-one studies and shows that accounting information, financial ratios, and market indicators are commonly linked to share prices, although their explanatory strength varies across markets, industries, and methods. The empirical results show that same-day price variables are strongly associated with closing price, whereas trading volume has a weaker direct relationship with price levels. The model therefore provides evidence of same-day price explanation rather than a complete future-forecasting system. The study provides a structured framework for integrating accounting-performance concepts with Python-based market analysis and identifies the accounting data required for a more comprehensive journal-level model.

Keywords: **Accounting Performance; Stock Price Explanation; Restaurant-Related Firms; Market Indicators; Regression; Value Relevance.**

1. Introduction

Restaurant and fast-food companies operate in a competitive environment where brand strength, store expansion, cost control, franchise structure, and consumer demand are reflected in both accounting results and market valuation. Listed restaurant-related companies are monitored by investors because their share prices summarize expectations about profitability, growth, risk, and future cash flows. Accounting performance provides an internal view of firm strength, while stock-price behavior provides an external view of how the capital market values that strength.

The research problem addressed in this study is the relationship between numerical business information and stock-price behavior. Prior studies show that earnings, book value, dividends, profitability ratios, leverage, liquidity, and market indicators can help explain share prices, although the strength of the relationship changes across countries, sectors, periods, and statistical methods [1]-[31]. For that reason, stock-price analysis should not be treated only as a technical exercise. It also belongs to accounting and finance research because financial-statement information and market information both influence investor valuation.

This study uses daily stock-market variables available in the supplied Python notebook. The stated cutoff date is 31 December 2022; records after that date should be excluded before statistical testing and interpretation. The empirical part uses Open, High, Low, Close, Adjusted Close, and Volume to measure statistical relationships and estimate an explanatory linear regression model for closing stock price. Because

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the available output does not include tested annual financial statement ratios, the accounting component is presented as a framework and extension rather than as a completed accounting ratio test.

The study's contribution is threefold. First, it organizes the research around a clear accounting and market-performance framework for restaurant-related listed firms. Second, it applies Python to show how tables, charts, correlation analysis, and regression can be used to test relationships between numerical variables. Third, it reviews 31 studies from 2011 to 2021 and uses them to justify the variables, model interpretation, and proposed accounting extension. The paper is organized into a literature review, research questions and hypotheses, method, results, discussion, limitations, conclusion, and references.

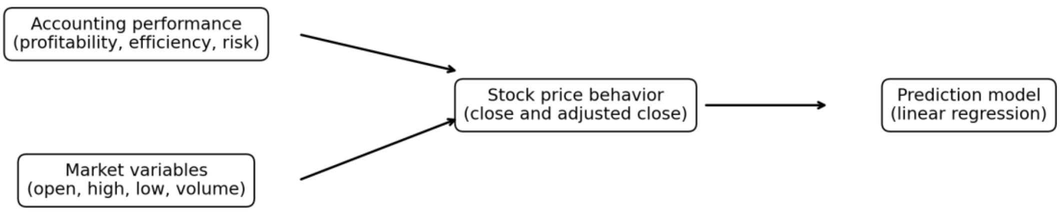

Figure 1. Conceptual framework

The framework connects accounting-performance concepts and market variables with stock-price behavior. The empirical model tests how strongly selected same-day market variables explain closing price before and up to the 2022 cutoff. The accounting-performance variables are retained as a planned extension because the current empirical output does not estimate them directly.

2. Literature Review

The literature on accounting information and stock prices is mainly based on value relevance. Value relevance means that accounting numbers are useful to investors when they explain share prices or stock returns. Khanagha [1] and Alfaraih and Alanezi [2] show that earnings and book value are relevant in emerging Gulf markets. Ramezanian, Shaverdi, and Faridi [3] connect financial indicators with neural-network prediction, while Jiang and Lee [4] show that decomposed ratios can help predict returns and fundamentals. Al-Hares, AbuGhazaleh, and El-Galfy [5] add dividends to the valuation model, and Srinivasan [6] confirms that accounting and market variables can explain share prices in India.

Research from 2012 to 2014 gives support for combining accounting variables and market data. Adebiyi, Ayo, Adebiyi, and Otokiti [7] use neural networks for stock-price prediction. Glezakos, Mylonakis, and Kafouros [8] report that accounting information affects stock prices in Athens. Kargin [9] finds that IFRS adoption increased the value relevance of accounting information in Turkey. Lam, Sami, and Zhou [10] show that the value relevance of Chinese accounting information changed over time. Tandon and Malhotra [11], Bepari, Rahman, and Mollik [12], Menike and Prabath [13], Almumani [14], and Jabbari and Fathi [15] support the view that earnings, book value, dividends, ratios, and financial indicators are related to share-price or return behavior.

Later studies extend the discussion by adding reporting quality, sector differences, and more advanced prediction methods. Mironiuc, Carp, and Chersan [16] connect financial reporting with the performance of Romanian listed firms. Zahedi and Rounaghi [17] use neural networks and principal component analysis for stock-price prediction. Arkan [18] shows that financial ratios are useful in predicting price trends in emerging markets. Xu [19] finds that earnings, book value, revenue, and research and development can differ in value relevance. Adetunji [20] confirms that accounting numbers are linked with market values in Nigerian banks.

Studies from 2017 to 2021 show that accounting and prediction research became more data driven. Puspitaningtyas [21] asks whether financial performance is reflected in stock prices. Pražák and Stavárek [22] test the effect of financial ratios on stock-price development. Zhong and Enke [23], Fischer and Krauss [24], Henrique, Sobreiro, and Kimura [26], Shah, Isah, and Zulkernine [27], Basak, Kar, Saha, Khaidem, and Dey [28], and Nti, Adekoya, and Weyori [29] show the growing role of machine learning, dimensionality reduction, tree classifiers, and systematic reviews in financial-market prediction. Hung, Ha, and Binh [25], Rahman and Liu [30], and Zandi, Shahzad, and Lokanathan [31] keep the accounting link clear by showing that accounting information and financial ratios still matter for stock prices and stock performance. The research gap in the present study is the need for a clear, reproducible bridge between accounting-performance concepts and Python-based market-variable modeling in restaurant-related listed firms.

2.1 Comparison Between the 31 Studies

Table 1. Comparison between studies used in the literature review

Ref.	Study	Context	Main variables	Method	Main finding
[1]	Khanagha (2011)	United Arab Emirates	Earnings, book value, stock price	Value relevance / regression	Accounting information was value relevant in the UAE market.
[2]	Alfaraih & Alanezi (2011)	Kuwait Stock Exchange	Earnings and book value	Price and return models	Earnings and book value were useful for equity valuation.
[3]	Ramezanian et al. (2011)	Stock price prediction	EPS, DPS, P/E, E/P, financial indices	Neural network	Financial indicators improved stock-price prediction.
[4]	Jiang & Lee (2012)	Financial ratios and returns	Decomposed financial ratios	Return predictability model	Decomposed ratios helped predict returns and fundamentals.
[5]	Al-Hares et al. (2012)	Kuwait	Book value, earnings, dividends	Ohlson valuation model	Book value and earnings were value relevant; dividends were weaker.
[6]	Srinivasan (2012)	India	EPS, DPS, P/E, size, book value	Panel data regression	Several firm variables explained equity share prices.
[7]	Adebiyi et al. (2012)	Stock market prediction	Hybridized market indicators	Artificial neural network	Neural networks were useful for stock-price prediction.
[8]	Glezakos et al. (2012)	Athens Stock Exchange	Accounting information and stock prices	Ohlson-based regression	Accounting information had a significant effect on stock prices.
[9]	Kargin (2013)	Turkey	Earnings and book value under IFRS	Pre/post IFRS regression	IFRS adoption increased value relevance.
[10]	Lam et al. (2013)	China	Assets, liabilities, earnings, returns	Long-period value relevance models	Value relevance changed across accounting items over time.
[11]	Tandon & Malhotra (2013)	NSE 100 companies	BVPS, EPS, DPS, P/E, size	Multiple regression	Firm-level variables significantly influenced stock prices.
[12]	Bepari et al. (2013)	Global financial crisis period	Earnings and cash flows	Value relevance regression	Earnings and cash flows remained useful during crisis conditions.
[13]	Menike & Prabath (2014)	Sri Lanka	EPS, DPS, BVPS, stock price	Regression analysis	Accounting variables affected stock prices.
[14]	Almumani (2014)	Jordanian banks	EPS, BVPS, P/E, DPS, size	Correlation and multiple regression	Bank share prices were affected by quantitative accounting variables.
[15]	Jabbari & Fathi (2014)	Stock returns	Financial ratios under historical and adjusted cost	Least squares and neural network	Adjusted financial ratios and neural networks improved prediction.
[16]	Mironiuc et al. (2015)	Romania	Financial reporting information	IFRS adoption context	Financial reporting was linked with quoted-firm performance.
[17]	Zahedi & Rounaghi (2015)	Tehran Stock Exchange	Stock-price indicators	ANN and PCA	ANN with PCA showed strong prediction performance.

Ref.	Study	Context	Main variables	Method	Main finding
[18]	Arkan (2016)	Emerging markets	12 financial ratios	Sector-based statistical tests	Financial ratios helped predict stock-price trends.
[19]	Xu (2016)	High-technology firms	Earnings, book value, revenue, R&D	Value relevance tests	Revenue and R&D were important in valuation for some firms.
[20]	Adetunji (2016)	Nigerian banks	Accounting numbers and market values	Return-earnings relation	Accounting numbers were associated with market values.
[21]	Puspitaningtyas (2017)	Indonesia	Financial performance and stock price	Fundamental analysis approach	Financial performance was reflected in stock prices to different degrees.
[22]	Pražák & Stavárek (2017)	Selected listed firms	Financial ratios and stock price	Regression analysis	Microeconomic financial ratios affected stock-price development.
[23]	Zhong & Enke (2017)	S&P 500-related prediction	Market indicators and reduced features	Dimensionality reduction and learning models	Reduced feature sets improved daily return forecasting.
[24]	Fischer & Krauss (2018)	S&P 500 constituents	Historical financial market data	LSTM deep learning	LSTM models performed well in financial market prediction.
[25]	Hung et al. (2018)	Vietnam energy firms	ROA, leverage, size, current ratio, turnover	OLS and quantile regression	Accounting information affected listed-company stock prices.
[26]	Henrique et al. (2019)	Financial market prediction literature	Machine learning inputs and methods	Literature review	Machine learning was widely used in market prediction.
[27]	Shah et al. (2019)	Stock market analysis literature	Technical, fundamental, sentiment data	Review and taxonomy	Prediction methods differ by data type and research design.
[28]	Basak et al. (2019)	Stock direction prediction	Market and technical features	Tree-based classifiers	Tree-based models predicted stock-price direction effectively.
[29]	Nti et al. (2020)	Stock prediction literature	Fundamental and technical analysis	Systematic review	Stock prediction benefits from both fundamental and technical inputs.
[30]	Rahman & Liu (2021)	China	Accounting information and price reaction	Value relevance and stock reaction tests	Accounting information was relevant to stock-price reactions.
[31]	Zandi et al. (2021)	Shanghai Stock Exchange	Financial ratios and stock performance	SPSS statistical analysis	Financial ratios were related to company stock performance.

The table compares the 31 studies by context, variables, method, and findings. The studies support the use of accounting numbers, market variables, financial ratios, and prediction models, but they also show that a paper should distinguish between accounting-ratio tests and market-price explanation.

3. Hypotheses and Research Questions

The research questions and hypotheses follow the literature review and the variables available in the Python notebook. The hypotheses examine the association between same-day market numbers and the closing price. Accounting ratios are proposed as an extension because the current empirical output does not include annual financial statement variables.

Table 2. Research questions and hypotheses

Item	Statement	Expected direction
RQ1	How strongly are same-day price variables associated with closing stock price?	Strong positive association
RQ2	Does trading volume explain closing stock price as strongly as price variables?	Weaker direct association
H1	The opening price is positively associated with the closing price.	Positive
H2	High price and low price have positive associations with the closing price.	Positive

Item	Statement	Expected direction
H3	Trading volume has a weaker direct association with closing price than Open, High, and Low.	Weak or mixed
H4	A same-day linear regression model using market variables can explain the closing stock price, but it should not be treated as a complete future-forecasting model.	Positive explanatory fit

The table states the testable ideas used in the study. The strongest expected links are between the closing price and the other same-day price variables.

4. Proposed Method

The study uses daily stock-price data for listed restaurant-related companies available in the supplied notebook output. The dataset contains Date, Open, High, Low, Close, Adjusted Close, Volume, and Company. The stated cutoff is 31 December 2022; observations after that date should be excluded before analysis. Because the descriptive output indicates the presence of a very large non-restaurant outlier, the final journal submission should screen the company list and either remove non-restaurant observations or clearly define them as benchmark observations before re-estimating the statistics.

The dependent variable is Closing Price. The explanatory variables are Opening Price, High Price, Low Price, and Volume. Adjusted Close is retained as a comparison variable because it reflects dividends, splits, and other corporate actions; it should not be interpreted as an independent measure of accounting performance. The proposed accounting extension adds ROA, ROE, profit margin, asset turnover, earnings per share, book value per share, leverage, and revenue growth when annual financial-statement data are available.

Table 3. Variables used in the study

Variable	Type	Meaning in the study
Close	Dependent variable	Final stock price at the end of the trading day; dependent variable in the explanatory model.
Open	Same-day explanatory variable	First price recorded at the start of the trading day.
High	Same-day explanatory variable	Highest price reached during the trading day; known only after the trading day is complete.
Low	Same-day explanatory variable	Lowest price reached during the trading day; known only after the trading day is complete.
Volume	Same-day explanatory variable	Number of shares traded during the day; represents market activity rather than accounting performance.
Adj Close	Comparison variable	Closing price adjusted for dividends and stock splits; used for comparison, not as an independent accounting measure.
ROA, ROE, Profit Margin, Asset Turnover	Accounting extension	Financial-statement ratios required for a fuller accounting-performance model; not estimated in the current empirical output.

The table separates the market variables used in the current Python model from the accounting ratios proposed for the next stage of the study. This distinction prevents the paper from overstating accounting-performance evidence that has not yet been estimated.

Table 4. Statistical programs and Python tools

Tool	Use
Python	Main program for data cleaning, descriptive statistics, tables, charts, and regression.
pandas and numpy	Filtering by date, handling numerical columns, and preparing tabular outputs.
matplotlib and seaborn	Drawing line charts, diagrams, and the correlation heatmap.
scikit-learn	Estimating the linear regression model and measuring model fit.
Linear regression	Same-day explanatory model for closing price; future forecasting requires lagged inputs and out-of-sample validation.

The table shows the tools used to prepare the data and estimate the explanatory model. A final journal submission should also report regression coefficients, standard errors, p-values, confidence intervals, and residual diagnostics.

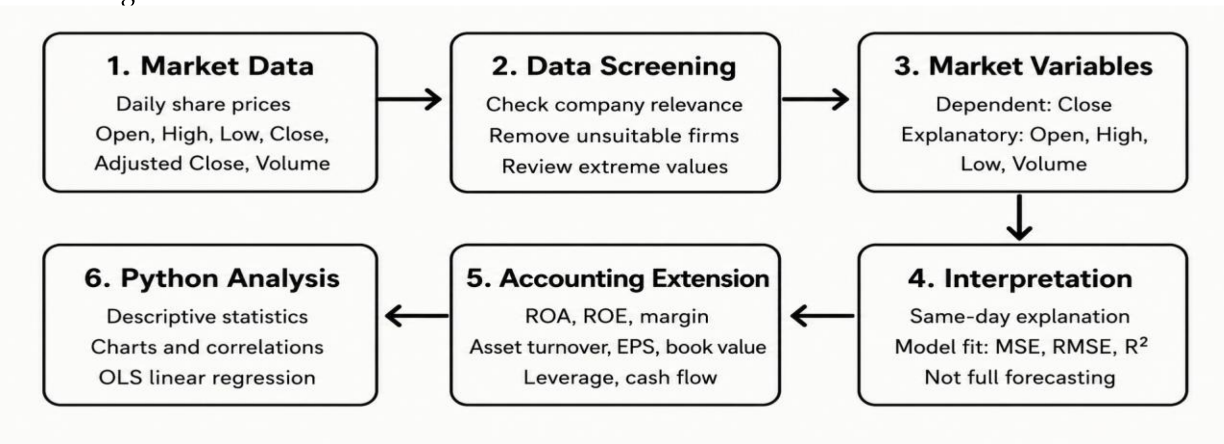

Figure 2. Proposed Method

The Diagram shows the Proposed method of the study, including the data source, variables, same-day explanatory model, and accounting extension required for a fuller journal-level analysis.

The same-day explanatory regression model is written as:

$$\boldsymbol{Close_{it} = beta_0 + beta_1 Open_{it} + beta_2 High_{it} + beta_3 Low_{it} + beta_4 Volume_{it} + epsilon_{it}}$$

In this equation, i represents the firm and t represents the trading day. The model explains the closing price using variables observed during the same trading day, so it should not be described as a complete out-of-sample forecasting model unless lagged predictors and proper train-test validation are added.

Model accuracy is evaluated using Mean Squared Error, Root Mean Squared Error, and R-squared. These metrics show model fit, but they do not replace coefficient-level inference or future-period validation.

5. Results

The results are arranged as descriptive evidence, visual evidence, correlation evidence, and model-fit evidence. The available notebook output supports an explanatory interpretation of same-day price relationships. It does not fully support causal claims or a complete future-prediction claim without additional diagnostics and out-of-sample testing.

Table 5. Sample rows from the stock dataset

Date	Company	Open	High	Low	Close	Adj Close	Volume
1992-06-26	Starbucks	0.3281	0.3477	0.3203	0.3359	0.2591	224,358,400

Date	Company	Open	High	Low	Close	Adj Close	Volume
1992-06-29	Starbucks	0.3398	0.3672	0.3320	0.3594	0.2772	58,732,800
1992-06-30	Starbucks	0.3672	0.3711	0.3438	0.3477	0.2682	34,777,600
1992-07-01	Starbucks	0.3516	0.3594	0.3398	0.3555	0.2742	18,316,800
1992-07-02	Starbucks	0.3594	0.3594	0.3477	0.3555	0.2742	13,996,800

The sample rows illustrate the dataset's structure. Each row is one trading day for one company.

Table 6. Descriptive statistics from the uploaded notebook output

Statistic	Open	High	Low	Close	Adj Close	Volume
count	69,459.00	69,459.00	69,459.00	69,459.00	69,459.00	69,459
mean	19,321.89	19,454.18	19,173.99	19,316.33	19,311.01	3,559,892
min	0.0000	0.1564	0.1523	0.1543	0.0664	0
25%	8.2188	8.5312	8.2515	8.3903	4.7527	112,500
50%	25.0000	25.2552	24.7376	25.0000	17.3908	1,373,600
75%	104.2350	105.3100	103.2050	104.3300	95.7545	4,337,675
max	718,849	741,971	711,466	715,910	715,910	585,508,800
std	72,533.73	73,043.21	71,952.14	72,494.81	72,496.22	7,112,762

The table gives the sample size, average, range, and spread of the stock numbers. The very large maximum price is caused by Berkshire Hathaway Class A shares in the supplied output, which indicates that the company list should be screened before a final industry-specific journal submission. Until that re-estimation is completed, the numerical results should be read as preliminary evidence from the supplied market dataset rather than definitive fast-food-industry averages.

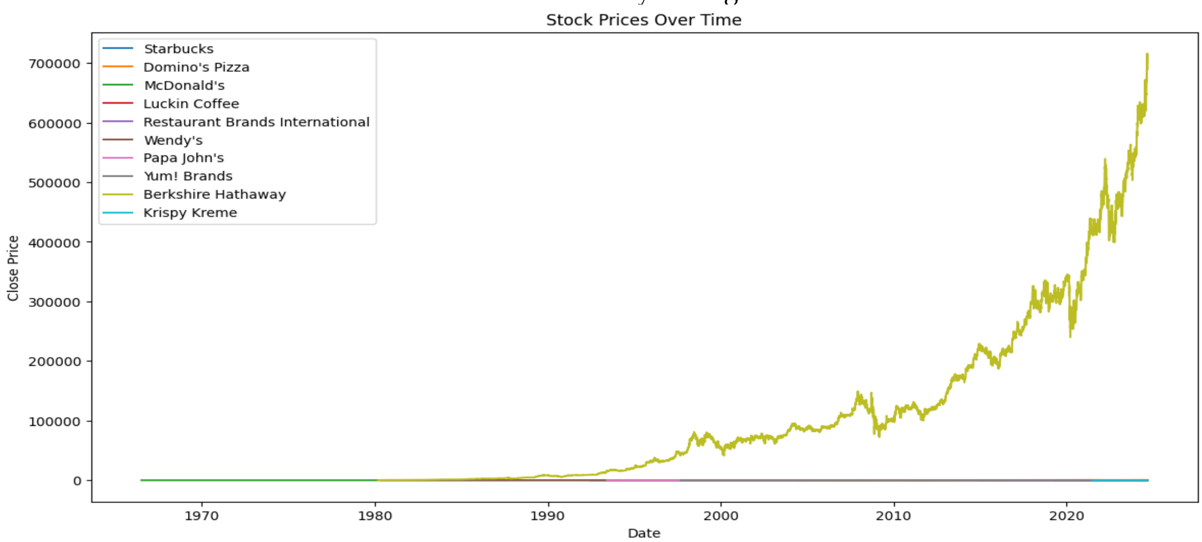

Figure 3. Closing stock prices over time

The chart shows long-term price movement. Berkshire Hathaway Class A has a much higher share price than the other companies and dominates the scale; this supports the need for sample screening or separate benchmark treatment in the final version.

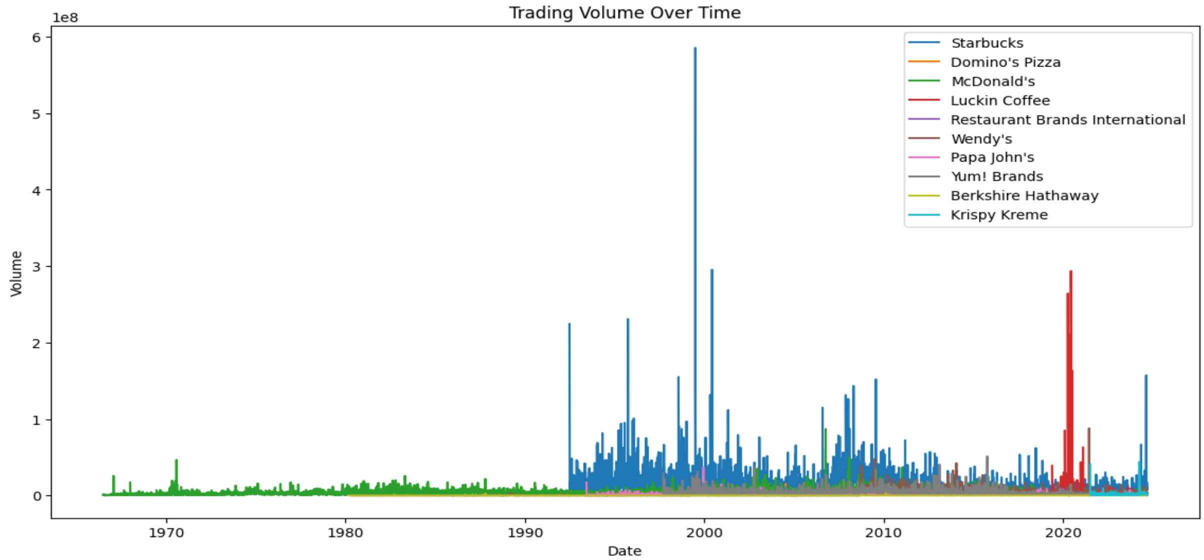

Figure 4. Trading volume over time

The chart shows market activity. Higher volume means more shares were traded, but it does not automatically mean the stock price increased.

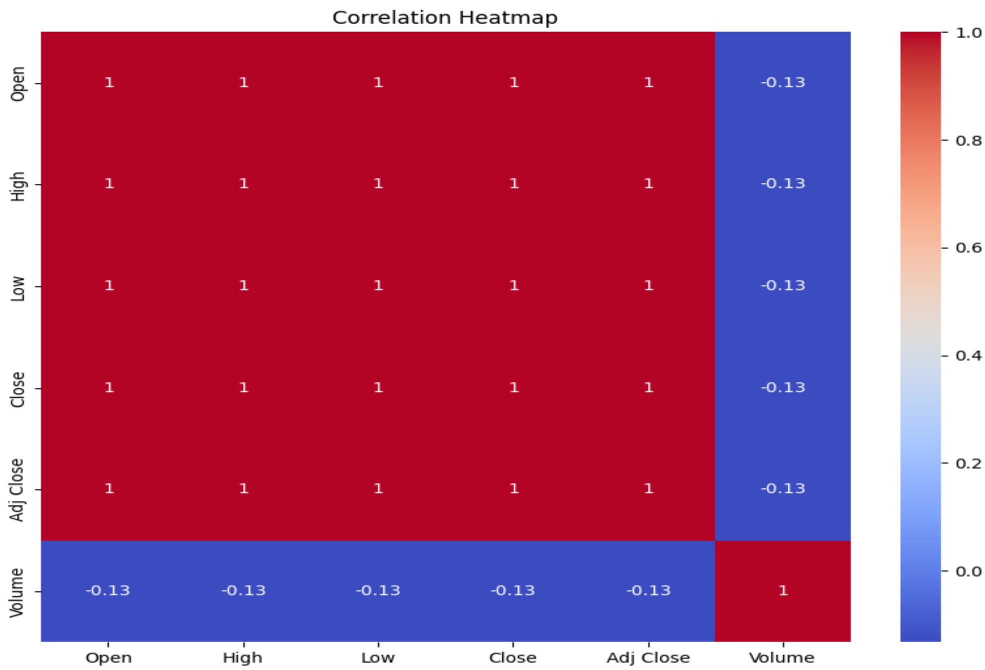

Figure 5. Correlation heatmap

The heatmap shows the strength of the relation between numerical variables. Price variables move very closely together, while volume has a weaker relation with price. Because Open, High, Low, and Close belong to the same trading day, the correlations should be interpreted as evidence of same-day price co-movement rather than independent forecasting power.

Table 7. Main relation expected from the analysis

Variable	Expected relation with Close	Reason
Open	Strong positive association	The opening price starts the trading day and is usually close to the daily price range.
High	Strong positive association	The highest daily price is part of the trading range in which the closing price is formed.
Low	Strong positive association	The lowest daily price sets the lower part of the daily trading range.
Volume	Weak to mixed association	Volume shows market activity, but activity alone does not always raise or lower price.
Adjusted Close	Strong mechanical association	Adjusted close is derived from close after dividend and split adjustments and therefore should be interpreted carefully.

The table explains the direction of the main relations. Price variables have the strongest relation with closing price.

Table 8. Prediction accuracy from the uploaded notebook output

Measure	Value	Meaning
Mean Squared Error (MSE)	171,219.54	Average squared prediction error.
Root Mean Squared Error (RMSE)	413.79	Prediction error in price units.
R-squared (R2)	0.999966	Share of price variation explained by the model.

The model has a very high R-squared because same-day price variables are naturally close to closing price. This is strong explanatory fit, not a guarantee of accurate future forecasting. The result supports the market-variable model in a descriptive sense, but the final submission should add coefficient tests, residual checks, and out-of-sample validation.

6. Discussion

The evidence supports the expected relationship between daily market numbers and closing stock price. Opening price, high price, and low price are all part of the same trading-day price formation, so their strong relationship with closing price is expected. This result is consistent with the wider literature showing that numerical variables can carry value-relevant information when they are linked to investor pricing decisions [1]-[31].

Trading volume has a different interpretation. It records how many shares were traded. Heavy trading can occur during good news, bad news, panic, strong demand, or market uncertainty. For that reason, volume is useful as a market-activity variable, but it is not as direct as Open, High, and Low when explaining the daily closing price.

The high R-squared should be read carefully. The model explains closing price very well because the independent price variables are drawn from the same day. A stronger forecasting design would use lagged prices, lagged returns, annual accounting ratios, earnings measures, cash-flow variables, macroeconomic data, or company news available before the trading day.

For the accounting side, the study points to a clear next step. Annual revenue, net income, total assets, total equity, cash flow, earnings per share, and book value per share can be used to calculate ROA, ROE, profit margin, asset turnover, leverage, and valuation measures. These ratios can then be joined to annual stock returns or market value to test whether stronger accounting performance is linked with stronger market performance.

Table 9. Accounting data needed for the next stage

Accounting item	Ratio created	Use in future model
Net income and total assets	ROA	Tests how efficiently assets create profit; should be linked to annual returns or market value.
Net income and total equity	ROE	Tests return earned for shareholders; should be included in the accounting extension.
Net income and revenue	Profit margin	Tests how much profit is retained from sales.
Revenue and total assets	Asset turnover	Tests how strongly assets support sales.
Annual stock return	Market performance	Market-performance outcome for testing whether accounting strength is linked to investor returns.

The table shows the accounting data needed to turn the current market-variable analysis into a fuller accounting-performance study. These data requirements are essential for a stronger journal submission.

7. Limitations and Future Research

The main limitation is that the present empirical output explains closing price using same-day price variables. This design is statistically useful for showing price co-movement, but it is not sufficient for a full forecasting claim. A final forecasting model should use lagged variables, a clear training and testing split, and future-period validation.

A second limitation is sample definition. The descriptive output includes Berkshire Hathaway Class A, which is not a fast-food or restaurant operating company and strongly affects the price scale. Before journal submission, the raw dataset should be screened so that the final sample contains only the intended restaurant-related companies, or the paper should explicitly define non-restaurant observations as benchmark controls and report results with and without them.

A third limitation is the absence of tested accounting-ratio variables in the empirical model. The literature review justifies accounting-performance analysis, but the available results do not yet estimate ROA, ROE, profit margin, leverage, book value, earnings per share, or cash-flow variables. Future research should add these financial-statement variables and examine their relation to annual stock returns, market value, or risk-adjusted performance.

8. Conclusion

This study finds a clear relationship between same-day market variables and closing stock price in the supplied dataset. Opening price, high price, and low price explain most of the variation in closing price because they are part of the same daily price-formation process. Adjusted close also moves closely with close because it is based on the closing price after corporate adjustments. Trading volume is useful as a market-activity indicator, but it has a weaker direct relationship with price level.

The main contribution of the study is its structured connection between market-based stock-price analysis and accounting-performance thinking. The available dataset supports a strong same-day market analysis, while the literature review shows that accounting variables such as earnings, book value, profitability, leverage, and efficiency ratios can also help explain stock prices.

However, the results should be interpreted carefully. The high explanatory power of the model does not mean that it can fully predict future stock prices, because the model uses same-day price variables that are naturally related to closing price. A stronger model would need lagged market variables, annual accounting ratios, earnings data, and other information available before the closing price is known.

Therefore, the paper should be considered a strengthened academic draft rather than a fully final journal article. Before submission, the dataset should be screened, inappropriate outliers should be removed, and annual accounting variables should be added. After these improvements, the manuscript will be better positioned for submission to an accounting, finance, business analytics, or applied economics journal.

Author Contributions

The author conducted the conceptualization, methodology, data analysis, investigation, writing, review, editing, and final approval of the manuscript.

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Data Availability

The dataset will be available from the author upon reasonable request.

Conflicts of Interest

The author declares no conflict of interest.

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