Financial Ratios and Stock Returns: An Analysis of Manufacturing Firms in BIST 100 Index

Final Project Report

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Table of Contents

I. Introduction

Predicting stock returns is one of the most discussed subjects in finance, as it can yield a lot of success and money, which is attracting investors' attention. These returns depend on several factors, such as firm performance, political events, inflation, and others. In this report, I will be focusing on the financial ratios which are calculated using the financial statements of companies. Those ratios are indicators of firm performance and can be used to forecast stock returns. Studies by Fama and French (1992) and Lewellen (2004) highlighted the importance of ratios like return on equity (ROE) and book-to-market in predicting stock returns in the long term. Still, in today's economy, the market is very dynamic, especially in developing countries, and it can be affected by news very quickly, which makes it harder to forecast stock returns, especially in the short term. Despite this dynamic nature of financial markets, there is a desire to identify short-term signals like ratios to predict stock returns due to the amount that can be gained. However, there is a heavy influence of noise from one quarter to the next, including macroeconomic or firm-related events that overshadow the influence of ratios. For example, Goyal and Welch (2007) showed how the ratios discussed by previous researchers fail to predict stock returns. They also mentioned that some ratios may provide correct predictions for the long term, but in the short term, those ratios fail.

Considering these ideas, this report aims to investigate the effect of changes in ratios on changes in stock returns in the short term. The report analyses the profitability (return on equity (ROE), return on assets (ROA), net income margin, earnings before tax and amortization (EBITDA)), liquidity (current, quick, and cash ratios), and leverage (debt-to-equity ratio) metrics of firms and whether they have a significant relationship with the share prices. The focus will be on the quarter-by-quarter changes in 27 manufacturing firms within Türkiye's BIST 100 index in eight years. The reason for an eight-year focus is that there is limited data and as I increase the time interval, the number of manufacturing firms decreases in the analysis. Therefore, I choose to investigate those firms between 2016Q1 (first quarter) and 2023Q4 (fourth quarter). The results of this report will answer the following research question of this report: "Are financial ratios useful when forecasting the performance of manufacturing firms in BIST 100 in a short-term period?"

This report will consist of two analyses. Firstly, I will focus on descriptive statistics, multiple regression modeling, and robust statistical techniques. Secondly, some machine learning approaches like random forest will be applied. The findings will suggest whether fundamental ratios could provide any prediction for the next quarter's stock price.

II. Literature Review and Hypothesis

Several researchers discussed the potential and usefulness of ratios in predicting stock returns. Fama and French (1992) mentioned the role of basic financial ratios like book-to-market and earnings to explain the performance of stocks. Their findings showed that those ratios uncover shifts in the firm's profitability and risk profile. Studies by Lewellen (2004) added that changes in ratios like net income margin were linked to price performance. Şanlı (2024) studied the role of financial ratios in BIST 30 between 2016Q2 and 2023Q4, and he found that while the current ratio was significantly and negatively correlated with stock returns, there was a positive relationship between ROE and stock returns.

However, when those ratios are examined in a short-term period, results can lead to uncertain outcomes as the market is more sensitive to unexpected events in the short term. Unexpected macroeconomic or political events can change the actions of investors and they may not even consider the quarterly earnings reports of firms. As Goyal and Welch (2007) underlined, those ratios could be useful in a longer interval, but they are insignificant in a shorter interval. Ndruru (2023) pointed out that there was no significant relationship between ratios like the current ratio and stock returns in manufacturing companies in the Indonesian stock market in the 2018-2020 period. Moreover, Musallam (2018) used 26 Qatari-listed firms to explore any link between stock returns and financial ratios where while they found significant relationship between financial ratios such as earnings per share and stock returns, they found that ratios like ROE or ROA were insignificant to predict stock returns. These discrepancies could happen because ratios can show the general performance of firms, but they cannot show how the investors will react when sudden events occur.

Another reason for the discrepancies can be noise in quarterly data. The difference between these fundamental ratios can vary highly from one quarter to another. This could be because of seasonal effects or high one-time expenses which increase the number of outliers within data. Li et al. (2018) argued that these outliers always exist as short-term good or bad news always occurs in the market. Maronna et al. (2006) proposed robust statistics methods to handle that issue which will be applied in this paper as well.

Based on this background, I propose that short-term (quarterly) changes in key fundamentals—such as return on assets (ROA), return on equity (ROE), net income margin, EBITDA margin, and key liquidity and leverage ratios—will not provide reliable signals for predicting the following quarter's stock returns. If any relationship exists, it is likely to be minor compared to the more chaotic elements shaping short-term price changes. Thus, this leads to the central hypothesis of this report:

Hypothesis

Changes in fundamental ratios from one quarter to the next do not meaningfully predict the next quarter's stock returns. In other words, it is unlikely that quarterly shifts in profitability (ROA, ROE, or margins), liquidity (current, quick, or cash ratios), or leverage (debt-to-equity) will give a stable advantage over a simple guess based on average market performance.

This hypothesis reflects the common finding in prior studies that while fundamentals matter over the years, the unpredictable nature of short-term market reactions, combined with sudden news and firm-specific surprises, outweighs the limited information carried by small quarterly ratio adjustments. The sections of this report will investigate whether the data for 27 manufacturing firms in Türkiye's BIST 100 index confirms this view.

III. Data and Methods

The dataset is obtained from the İş Yatırım where I collected financial statements, which include balance sheets, income statements, and statements of cash flows, of 27 manufacturing stocks from BIST 100 using Python. I got the names of those manufacturing stocks from Mynet, where there were initially 43 stocks. However, after increasing the time interval to 8 years, I had the data of 27 stocks due to data limitations and I decided not to expand the time interval further to keep as many stocks as possible. As a result, my final data is between the first quarter of 2016 (2016Q1) and the fourth quarter of 2023 (2023Q4). After clearing and organizing the data using Python, the collected financial statements allowed me to calculate the profitability, liquidity, and leverage ratios discussed above. Below are the formulas for calculating each ratio, which is also discussed in depth in the book of Fraser and Ormiston (2013):

Profitability ratios (multiplied by 100 to show in percentages):

1. Return on Assets (ROA)

$$ROA = \frac{Net\ Income}{Total\ Assets} \times 100$$

This ratio shows how effectively a firm uses its assets to generate profits.

2. Return on Equity (ROE)

$$ROE = \frac{Net\ Income}{Shareholder's\ equity} \times 100$$

Captures the efficiency with which a company uses shareholders' equity to produce earnings.

3. Net Income Margin

$$Net\ Income\ Margin = \frac{Net\ Income}{Net\ Sales} \times 100$$

Also called "net profit margin", this measures what fraction of sales becomes net income.

4. EBITDA Margin

$$EBITDA\ Margin = \frac{EBITDA}{Net\ Sales} \times 100$$

Operation profitability indicator

Liquidity ratios that show the liquidity of firms:

1. Current Ratio

$$Current\ Ratio = \frac{Current\ Assets}{Current\ Liabilities}$$

2. Quick Ratio

$$Quick\ Ratio = \frac{Current\ Assets - Inventory}{Current\ Liabilities}$$

3. Cash Ratio

$$Cash\ Ratio = \frac{Cash\ and\ Cash\ Equivalents}{Current\ Liabilities}$$

Leverage ratio:

1. Debt-to-Equity Ratio

$$Debt - to - Equity\ ratio = \frac{Total\ Liabilities}{Shareholders'Equity}$$

It captures the extent to which a firm finances its operations with debt relative to equity. In addition, I collected historical stock prices for the end of each quarter from İş Yatırım and then I calculated Quarterly Return, which is the dependent variable, to get shifts in stock prices from one quarter to another. Here is the formula:

$$Quarterly\ Return = \frac{Price_t - Price_{t-1}}{Price_{t-1}}$$

where $Price_t$ is the stock price at the end of quarter t.

After clearing due to the missing values mostly, the final data had 27 firms over 32 quarterly intervals with 864 observations. In the end, it enables me to compare the changes in ratios with the changes in stock prices to find an answer to the research question in this report.

In this study, I use several approaches to see if changes in financial ratios can explain or predict the next quarter's returns using R. Each method is applied to the same dataset of 27 manufacturing stocks from Türkiye's BIST 100 index over 32 quarters (2016Q1–2023Q4). I applied descriptive statistics and outlier analysis to the data to check if there were any issues like outliers in the data. Then, I run the correlation analysis to see the relationship between variables. Below is a clearer summary of other methods, along with references where they are discussed in more detail.

Ordinary Least Squares (OLS) Regression

OLS is one of the most common ways to see if changes in fundamental ratios have a straightforward, linear connection to future returns. It is applied by a lot of researchers as a way to start their analysis. It estimates a linear equation of the form:

$$Quarterly\ Return_t = \alpha+\beta 1\ \Delta ROA_{t-1}+\beta 2\ \Delta ROE_{t-1}+\cdots+\varepsilon t$$

where ΔROA_{t-1} (for example) is the change in ROA from one quarter to the next before time t. If any of these estimated coefficients (β_i) are notably large or significant, it suggests that the corresponding ratio change helps predict future returns. However, OLS can be very sensitive to outliers—extreme observations can distort the estimates (Li et al., 2018; Maronna et al., 2006).

Robust Regression

Because financial data can include very large or small ratio changes (for instance, if a firm's net income was almost zero one quarter and then jumped the next), standard OLS might misrepresent how most firms behave. Robust regression reduces the influence of outliers by assigning them lower weights in the fitting process (Maronna et al., 2006). In this report, an MM-estimator is used, which is a method used in robust regression and keeps the same basic form as OLS but handles unusual data points more carefully. If outliers are driving any apparent relationship between ratios and returns, robust methods can reveal whether there is still a consistent effect once those extreme values are downweighed.

Lasso model (Regularization)

Some of the fundamental changes can overlap or be highly correlated as multiple profitability or liquidity ratios exist in the data, which leads to multicollinearity. As proposed by Tibshirani (1996), Lasso adds a penalty term to the regression that pushes less-important coefficients toward zero. This helps highlight which ratio changes truly stand out as predictors. If Lasso ends up shrinking most variables to zero and keeps only one or two, it suggests that only those few ratio changes are relevant for the next quarter's returns. On the other hand, if even Lasso finds little improvement, it indicates a weak relationship overall.

Machine Learning Model

In this report, I wanted to use machine-learning tools in case of insignificant results. I am aiming to get more accurate outcomes by applying those tools. Some other researchers made use of machine learning models. The model used in this paper is a random forest. As proposed by Breiman (2001), this model creates many decision trees and then averages their predictions. Each tree splits the data along ratio changes that it finds informative. If the random forest consistently splits on certain fundamental changes, it indicates a potential predictive role for those variables. However, if the overall error is still high, the ratio changes do not help much in forecasting short-term returns. In the study of Tsai et al. (2023), this model was also applied to forecast stock behavior and performance. In their research, they highlighted the significance of this model in forecasting returns and analyzing financial ratios.

To assess how well these methods perform, the dataset is divided randomly into a training portion (for model building where 80%) and a test portion (for final evaluation where 20%). Each model predicts the returns in the test set and measures errors using the mean squared error (MSE) or mean absolute error (MAE). I also look at the coefficient of determination (R^2). If a model's R^2 is negative, it means that simply guessing the average return in the test set would have been more accurate than the model's predictions. Hence, negative R^2 strongly indicates that changes in fundamental ratios do not reliably forecast short-term returns.

In summary, I use multiple methods—some linear, some robust to outliers, some regularized for correlated variables, and non-linear—to see if any approach can discover a dependable relationship between quarter-to-quarter ratio changes and next-quarter stock returns. If all of these yield similar conclusions (for instance, no noteworthy improvement over a naive guess), then it would confirm that, at least in this dataset of BIST 100 manufacturing firms, fundamental changes are not reliable short-term predictors.

IV. Results and Interpretations

Descriptive Statistics and Correlation Analysis

After the data was cleaned, I checked for the missing values in case the issue was not handled in Python. In the final data, there are 27 manufacturing firms and each stock has 32 quarters, which makes a total observation of 864. After making sure that there were no issues with the data, I ran

Table 1: Descriptive Statistics

	mean	sd	min	max	median	IQR
Change.in.ROA..in...	0.4773824	24.5907290	-515.0998345	410.224489	0.2123435	1.5121641
Change.in.ROE..in...	-0.8868553	58.6162370	-1656.9305761	370.042597	0.1857051	1.4209851
Change.in.Net.Income.Margin..in...	0.0988981	16.1012970	-290.7529595	305.300374	-0.0406897	0.6133831
Change.in.EBITDA.Margin..in...	0.1566191	8.6575140	-99.3281154	230.183635	-0.0121181	0.3128821
Change.in.Current.Ratio	0.0081778	0.1779684	-0.5731239	1.984881	-0.0030232	0.1368364
Change.in.Quick.Ratio	0.0108813	0.2076953	-0.5697196	2.361100	-0.0105605	0.1770515
Change.in.Cash.Ratio	2.8189877	61.7841627	-0.9993639	1810.644321	-0.0154423	0.6990071
Change.in.Debt.to.Equity	0.0467479	0.3784144	-1.1602546	5.096233	0.0125098	0.2576243
Quarterly.Return	0.1316447	0.4164753	-0.8863370	3.052004	0.0476491	0.3537223

descriptive statistics in which results as shown in Table 1. In the table, it can be seen that there are

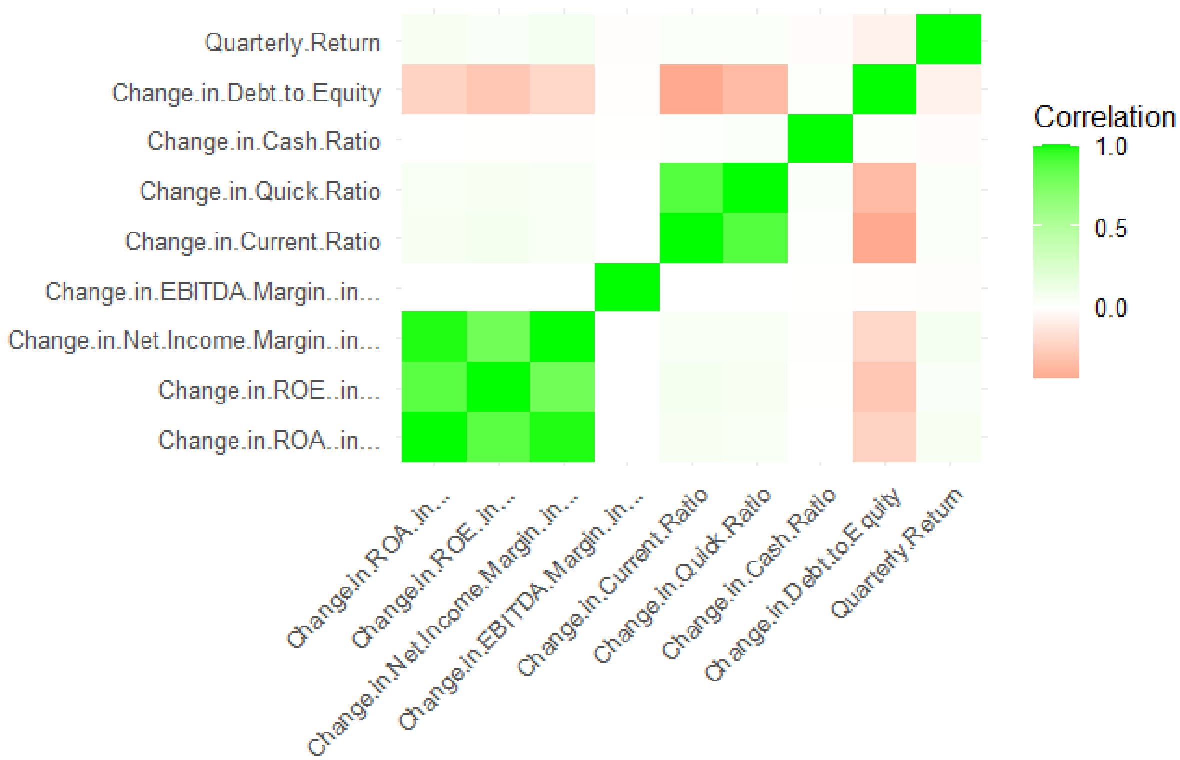
Table 2: Number of Outliers

Variable	Number_of_Outliers
Change.in.ROA..in...	67
Change.in.ROE..in...	75
Change.in.Net.Income.Margin..in...	144
Change.in.EBITDA.Margin..in...	135
Change.in.Current.Ratio	72
Change.in.Quick.Ratio	50
Change.in.Cash.Ratio	77
Change.in.Debt.to.Equity	71
Quarterly.Return	59

extreme values exist for ratios. For example, the mean change in ROA is about 0.48%, but by checking standard deviation (sd) and min and max, there are extreme outliers like -515%. This means that there were high fluctuations in some quarters. In addition, ROE, Net Income margin, and Cash ratio also have large outliers, especially the Cash ratio had a standard deviation of 62 while its mean was about 3, indicating extreme fluctuations. Table 2 further shows the number of outliers for each ratio, indicating large amounts of outliers for each variable.

In the correlation analysis, as shown in Figure 1, most changes in profitability ratios (ROA, ROE, net income margin) had moderate to high correlation among themselves—ROA and net income margin, for example, were correlated at about 0.98. Meanwhile, changes in EBITDA margin did not correlate significantly with them, possibly reflecting that EBITDA excludes certain expenses

Figure 1: Correlation Heatmap



that directly affect net income. On the liquidity side, the current ratio and quick ratio were strongly correlated (about 0.89). Debt-to-equity ratio generally showed a modest negative correlation with the profitability changes, suggesting that higher increases in leverage might coincide with smaller improvements in profitability. Moreover, profitability ratios except EBITDA and liquidity ratios except Cash ratio, had a very slight positive relationship with Quarterly Returns, on the other hand, it can be seen that debt-to-equity ratio has a slight negative relationship with Quarterly returns. These results are normal as profitability and liquidity ratios are expected to have positive effects on Quarterly returns, and leverage ratios should have negative effects.

OLS Regression Results

I first employed a standard Ordinary Least Squares (OLS) model to see if any linear combination of ratio changes could predict next-quarter returns. The combined model (with all ratio changes as predictors) yielded a negative or near-zero R^2. More precisely, the multiple R^2 was about 1.06%, and the adjusted R^2 was roughly 0.14%, implying that the model explained almost none of the short-term return variation. In other words, even though the intercept was statistically significant, none of the ratio changes—apart from a borderline result for debt-to-equity changes—demonstrated strong predictive power. As also illustrated in Table 3, only Debt-to-equity had a

Table 3: OLS Regression

	Term	Estimate	Std_Error	t_value	p_value	Significance
(Intercept)	(Intercept)	0.1344544	0.0145724	9.2266473	0.0000000	***
Change.in.ROA..in...	Change.in.ROA..in...	0.0005031	0.0049767	0.1010935	0.9194999	
Change.in.ROE..in...	Change.in.ROE..in...	-0.0005101	0.0006670	-0.7647403	0.4446372	
Change.in.Net.Income.Margin..in...	Change.in.Net.Income.Margin..in...	0.0021842	0.0061149	0.3571961	0.7210332	
Change.in.EBITDA.Margin..in...	Change.in.EBITDA.Margin..in...	-0.0005712	0.0016366	-0.3489983	0.7271765	
Change.in.Current.Ratio	Change.in.Current.Ratio	-0.0802104	0.1816590	-0.4415439	0.6589309	
Change.in.Quick.Ratio	Change.in.Quick.Ratio	0.0824142	0.1494589	0.5514169	0.5814920	
Change.in.Cash.Ratio	Change.in.Cash.Ratio	-0.0000979	0.0002297	-0.4263528	0.6699581	
Change.in.Debt.to.Equity	Change.in.Debt.to.Equity	-0.0768725	0.0440066	-1.7468413	0.0810239	.

Significance codes: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1

slightly significant relationship with the dependent variable (Quarterly Return).

To examine each variable individually, I ran simple linear regressions of returns on each ratio change alone. As described in Table 4, the results mostly confirmed the weakness of fundamental ratio changes for short-horizon forecasting, where almost all variables produced negative or very small R^2. Significant relationships were only found in net income margin and debt-to-equity ratios where p values were 0.039 and 0.033 respectively. Nevertheless, its overall effect was tiny considering R^2. Overall, these findings suggest that short-term returns may be driven more by news

Table 4: Individual OLS Regression for each Ratio

	Variable	Estimate	Std_Error	t_value	p_value	R_squared	Adjusted_R_squared	Significance
Estimate	Change.in.ROA..in...	0.0011212	0.0005756	1.9479941	0.0517399	0.0043829	0.0032279	.
Estimate1	Change.in.ROE..in...	0.0003023	0.0002418	1.2503980	0.2114935	0.0018105	0.0006525	
Estimate2	Change.in.Net.Income.Margin..in...	0.0018186	0.0008788	2.0694132	0.0388048	0.0049435	0.0037891	*
Estimate3	Change.in.EBIDTA.Margin..in...	-0.0005276	0.0016384	-0.3220201	0.7475155	0.0001203	-0.0010397	
Estimate4	Change.in.Current.Ratio	0.0793755	0.0796605	0.9964229	0.3193243	0.0011505	-0.0000083	
Estimate5	Change.in.Quick.Ratio	0.0733995	0.0682524	1.0754132	0.2824907	0.0013399	0.0001813	
Estimate6	Change.in.Cash.Ratio	-0.0000997	0.0002296	-0.4341313	0.6643017	0.0002186	-0.0009412	
Estimate7	Change.in.Debt.to.Equity	-0.0799571	0.0373868	-2.1386422	0.0327451	0.0052780	0.0041240	*

Significance codes: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1

events, investor sentiment or other factors than by incremental changes in fundamental ratios.

Robust Regression Results

As suggested by some researchers, outliers in the data can decrease the significance of the model. Therefore, I run a robust regression analysis which downweighs the outliers in the data. As Table 5 and Table 6 shows, the combined robust regression model shows a slightly higher R^2 of around

Table 5: Robust Regression Coefficients

	Term	Estimate	Std_Error	t_value	p_value	Significance
(Intercept)	(Intercept)	0.0633441	0.0113418	5.5850288	0.0000000	***
Change.in.ROA..in...	Change.in.ROA..in...	-0.0124927	0.0104423	-1.1963606	0.2318875	
Change.in.ROE..in...	Change.in.ROE..in...	0.0207969	0.0094018	2.2120081	0.0272298	*
Change.in.Net.Income.Margin..in...	Change.in.Net.Income.Margin..in...	-0.0100100	0.0108567	-0.9220109	0.3567830	
Change.in.EBITDA.Margin..in...	Change.in.EBITDA.Margin..in...	-0.0005232	0.0007358	-0.7110389	0.4772540	
Change.in.Current.Ratio	Change.in.Current.Ratio	-0.1241565	0.1885595	-0.6584477	0.5104278	
Change.in.Quick.Ratio	Change.in.Quick.Ratio	0.0946441	0.1578154	0.5997138	0.5488559	
Change.in.Cash.Ratio	Change.in.Cash.Ratio	-0.0000669	0.0000167	-4.0082675	0.0000665	***
Change.in.Debt.to.Equity	Change.in.Debt.to.Equity	-0.0870598	0.0365081	-2.3846698	0.0173115	*

Significance codes: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1

Table 6: Robust Regression Model Statistics

Metric	Value
Robust Residual Standard Error	0.2586329
Multiple R-squared	0.0182873
Adjusted R-squared	0.0091017

1.83%, which is still very low. In the table, the debt-to-equity ratio is still significant and cash ratio became very significant with a negative coefficient. This could mean that when the firms increase their cash holdings relative to their liabilities, it is negatively affecting the investor behavior, leading to slight negative returns. However, low R^2 shows that these ratios still do not explain the volatility in stock returns.

Checking each ratio change one by one under robust regression confirmed that in most cases, the variable did not meaningfully predict next-quarter returns. As Table 7 describes, Cash Ratio still very significant, and ROE became 99% significant where it was 95% significant previously. Even so, the overall predictive ability as measured by R^2 remained close to zero or negative. Thus, while robust regression avoided the pitfalls of outliers, it did not fundamentally alter the conclusion that short-term returns are not strongly driven by these ratio shifts.

Table 7: Robust Regression Results for each Ratio

	Variable	Estimate	Std_Error	t_value	p_value	R_squared	Adjusted_R_squared	Significance
Estimate	Change.in.ROA..in...	0.0009377	0.0008347	1.1233965	0.2615819	0.0064949	0.0053423	
Estimate1	Change.in.ROE..in...	0.0001719	0.0000489	3.5130463	0.0004660	0.0014902	0.0003319	***
Estimate2	Change.in.Net.Income.Margin..in...	0.0017737	0.0012050	1.4720001	0.1413858	0.0102850	0.0091369	
Estimate3	Change.in.EBITDA.Margin..in...	-0.0004839	0.0007217	-0.6705542	0.5026841	0.0002594	-0.0009004	
Estimate4	Change.in.Current.Ratio	0.0446356	0.0654061	0.6824379	0.4951454	0.0008305	-0.0003286	
Estimate5	Change.in.Quick.Ratio	0.0449349	0.0554303	0.8106557	0.4177872	0.0011436	-0.0000152	
Estimate6	Change.in.Cash.Ratio	-0.0000813	0.0000122	-6.6475238	0.0000000	0.0003889	-0.0007707	***
Estimate7	Change.in.Debt.to.Equity	-0.0509267	0.0265513	-1.9180514	0.0554346	0.0050198	0.0038655	.

Significance codes: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1

Lasso (Regularization) and Random Forest results

Given the strong collinearity among certain ratios such as between ROA and Net Income Margin, I used Lasso to shrink or eliminate unimportant coefficients. When I extracted the coefficients from the Lasso model, the result was that all variables except net income margin and debt-to-equity ratios were shrunk to zero, where net income margin and debt-to-equity ratio coefficients were very close to zero. In other words, most ratio changes did not have enough separate predictive content to remain in the model. Consequently, Lasso pointed toward the same conclusion: fundamental ratio changes did not appear to offer a stable short-term signal.

So far, all the results indicate that ratios are only explaining a very small part of volatility, which is around 1.8% at most, in stock returns. To further test the data, I used random forest analysis with 80/20 train-test split. However, the R^2 was about -0.086 which means that ratios still underperformed a guess of the average return. This negative R^2 strongly indicates that ratio changes, by themselves, do not help in predicting short-term price fluctuations. Although random forest typically excels when strong nonlinearities are present, in this context the data appears too noisy or overshadowed by short-term events.

V. Conclusion

In conclusion, every method consistently reveals that quarterly changes in ROA, ROE, net income margin, EBITDA margin, and liquidity or leverage ratios do not help in predicting the next quarter's stock returns in a reliable manner. Although each method highlight an occasional variable that is Debt-to-Equity with significance, none of these findings translate into a meaningful improvement over a naive guess. This underscores the likely dominance of other short-term forces—news events, investor psychology, or broader market shifts—over minor changes in fundamentals. This conclusion aligns with literature indicating that while fundamentals might guide investor decisions over longer horizons, they tend to lose relevance when faced with short-run market volatility. Consequently, investors seeking reliable quarter-ahead forecasts based solely on these measures are unlikely to find them effective in outmaneuvering news shocks, investor sentiment changes, and other transitory forces that dominate short-term price movement in manufacturing firms in BIST 100.

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