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Comparing the Predictive Power of Price-to-Earnings Ratio and Customer Satisfaction Index on Firm Performance

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Abstract

This paper demonstrates that, based on the Root Mean Square Error (RMSE) criteria, the Price-to-Earnings (P/E) ratio serves as a better predictor of both financial and market performance of firms compared to the Customer Satisfaction index (CS). This conclusion was drawn by analyzing a set of five financial and seven market indicators, which we used as proxies for evaluating financial and market performance. The sample for this study comprised eighty-six companies, and the indicators considered included: Book Value, Dividend Yield, Gross Profit Margin, Price-to-Cash Flows, Price-to-Earnings, Price-to-Sales, Annual Return, Return on Assets (ROA), Return on Equity (ROE), Return on Investment (ROI), Volatility, and Tobin's Q. The comparison between P/E ratio and Customer Satisfaction index was conducted with the goal of identifying which metric more accurately reflects a company's financial health and market standing. The superior performance of the P/E ratio, as measured by the RMSE, suggests that traditional financial metrics may offer more reliable insight into firm performance than non-financial measures like customer satisfaction. However, further research may be needed to explore the contexts in which customer satisfaction metrics could play a more significant role in predicting long-term performance. However, the Customer Satisfaction index (CS) clearly outperforms our five benchmarks (Tobin's Q, Price-to-Cash Flows, Price-to-Earnings, Volatility, or the indicator itself) when it comes to forecasting Tobin's Q, Volatility, Return on Equity (ROE), and Return on Investment (ROI). Notably, in periods of heightened market volatility, such as during the financial crisis of 2008, CS proved to be a more stable and reliable predictor of Volatility and ROE than using those indicators directly (i.e., using Volatility to predict Volatility, or ROE to predict ROE). This suggests that, while financial ratios like the P/E ratio may generally be strong predictors of financial performance, non-financial metrics such as customer satisfaction offer valuable insights, particularly in turbulent market conditions. CS appears to capture underlying factors that traditional financial indicators may overlook, making it a more consistent measure during times of uncertainty, when financial and market performance metrics tend to be more erratic. This highlights the importance of incorporating both financial and non-financial indicators to achieve a more comprehensive view of firm performance, especially in volatile markets.

Keywords: Price-to-Earnings Ratio, Customer Satisfaction, Firm Performance, Market Volatility

JEL Codes: G32, M31, C53

1. INTRODUCTION

Over the past fifty years, both academics and practitioners have extensively studied and written about Customer Satisfaction (CS). An in-depth review was provided by Evrard (1993), highlighting the centrality of CS in the field of consumer behavior. CS has long been recognized as a cornerstone concept within this discipline. It is generally regarded as an indicator of a company's ability to generate future cash flows, making it highly relevant for a broad range of stakeholders, including investors, shareholders, and consumers (Fornell, 1992; Vandermerwe, 2000). The importance of CS lies in its ability to reflect the quality of the customer experience, which in turn can signal the company's future performance in terms of revenue, loyalty, and market positioning. As a forward-looking metric, it offers insights beyond immediate financial performance, suggesting its value as a predictor of long-term success. For investors and shareholders, CS can serve as a proxy for potential growth, while for consumers, it is a marker of a company's commitment to meeting their needs and expectations. This makes CS not only a core concept in consumer behavior research but also a critical tool for business decision-making and performance evaluation. Several studies have indicated that investors and shareholders are increasingly interested in non-financial measures, such as Customer Satisfaction (CS), as they seek to understand broader indicators of company performance beyond traditional financial metrics (Ernest & Young, 1997). With this in mind, the core concern of this study revolves around two primary questions: whether a non-financial measure like CS can forecast financial and market performance, and whether conventional financial indicators such as Tobin's Q,

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Price-to-Cash Flows, Price-to-Earnings, and Volatility are more effective predictors of performance than CS. The assumptions guiding this study are based on the belief that financial and market indicators, such as Book Value, Dividend Yield, Gross Profit Margin, Price-to-Cash Flows, Price-to-Earnings, Price-to-Sales, Annual Return, ROA, ROE, ROI, Volatility, and Tobin's Q, serve as reliable proxies for measuring financial and market performance. Additionally, it is assumed that CS possesses predictive power for financial and market indicators in subsequent years, allowing it to forecast performance over periods such as one year or two years ahead. Moreover, traditional financial and market indicators, including Tobin's Q, Price-to-Cash Flows, Price-to-Earnings, and Volatility, are also believed to have predictive power for financial and market outcomes in future periods. To examine these assumptions, the study applies Ordinary Least Squares (OLS) regression analysis over the period from 2004 to 2009. This method will assess the relative strength of CS and financial indicators in predicting future financial and market performance, providing insight into whether non-financial metrics like CS can complement or even surpass traditional financial measures in understanding company success.

2. LITERATURE REVIEW

In reviewing the existing literature on Customer Satisfaction (CS), we explore its critical role for firms in monitoring demand and implementing strategic initiatives. The relationship between CS and financial and market performance is examined, with a focus on identifying the optimal model to capture this connection. CS serves as a key metric for firms to gauge demand and to inform strategic decisions. Cronin and Taylor (1992) define CS in the context of financial and market performance, describing it as the behavior of repurchasing a product and forming an attachment to it. This connection between satisfaction and consumer loyalty underscores the importance of measuring CS to help companies optimize their investments and make informed organizational decisions. By measuring CS, companies can effectively market products that align with customer demand, build customer loyalty while attracting new clients, and ultimately increase sales. This makes CS measurement fundamental to guiding strategies that prioritize quality. Traditionally, CS measurement (as described by Shin and Elliot, 2001) involves identifying the key attributes of a product or service, evaluating CS relative to each attribute, and assigning a weight to these factors. This approach provides a detailed understanding of which aspects of a product drive customer satisfaction.

However, this traditional approach has been challenged by authors like Veloutsou et al. (2005), who advocate for an international measure of CS. They argue that similar features of satisfaction can be observed across different cultures, suggesting that a more globalized approach may be effective in measuring CS consistently across markets. This perspective opens up the possibility for a standardized method that accounts for cross-cultural variations in customer expectations while capturing universal elements of satisfaction. Overall, the literature emphasizes the vital role CS plays in informing strategy and enhancing financial and market performance through better alignment with customer needs and preferences. Sweden was the first country to introduce a Customer Satisfaction (CS) index in 1989 with the Swedish Customer Satisfaction Barometer (SCSB). This was followed by Germany in 1992, and the United States in 1994 with the American Customer Satisfaction Index (ACSI) (Fornell, 1996). Europe introduced its own index, the European Customer Satisfaction Index (ECSI), in 1998. These global indices face challenges in their construction, particularly in terms of designing comprehensive questionnaires (often closed due to the large sample sizes), creating reliable measurement scales, and developing a valid process to aggregate responses. This aggregation often involves assigning appropriate weights to various questions, ensuring that the data accurately reflects overall satisfaction levels. These indices are built upon data collected from thousands of respondents, targeting products or services from a panel of both private and public companies.

In our study, we utilize the ACSI index as a proxy for CS. The ACSI, developed by Fornell (1994), serves as the U.S. Customer Satisfaction Index for clients of publicly listed companies and government institutions. Published quarterly in the Wall Street Journal, the ACSI is managed in partnership with the University of Michigan. It targets over 200 companies, representing 40 industrial sectors across seven major economic sectors. Each survey focuses on a representative set of customers from a specific market segment that is considered homogeneous, ensuring consistency in the results. The relationship between CS and financial and market performance has been explored by various organizations, such as the European Foundation for Quality Management (EFQM), and authors like Bughin (2005). There is a general consensus that CS plays a critical upstream role in driving the overall performance of a company. Kaplan and Norton (1998) identified four key financial indicators that are closely related to CS, including return, total sales, Return on Assets (ROA), and Return on Equity (ROE). In addition, Neely and Adams (2001) proposed a multidimensional model called the "performance prism", which integrates the needs of all stakeholders—including shareholders, human resources, suppliers, and customers—into a cohesive framework for measuring company performance. This model underscores the importance of understanding and addressing the needs of each stakeholder group in order to achieve sustainable business success, with CS playing a pivotal role in driving financial outcomes.

In Sweden, Anderson et al. (1994) examined the positive relationship between Customer Satisfaction (CS), as measured by the Swedish Customer Satisfaction Barometer (CSB) index, and Return on Investment (ROI). In their study, CS data were collected at the beginning of the semester, while ROI data were gathered at the end. They found that the benefits of improved CS are not realized immediately, which is why they measured the efficiency of CS with a time lag. The time delay highlights that the financial impact of enhanced CS can take time to materialize, particularly in the form of long-term profitability. Yeung et al. (2002) also demonstrated the complex and significant relationship between CS and factors such as customer loyalty, buzz marketing, and various financial and market indicators. Furthermore, Anderson et al. (1994) noted that CS plays a critical role in improving a company's financial performance by fostering stronger customer loyalty. This reduced price elasticity allows companies to charge more without losing customers, decreases marketing costs through positive buzz marketing, and lowers transactional costs associated with customer retention. Although the direct impact of CS on accounting ratios may not always be evident, there is a positive comovement between CS and a company’s stock price. Fornell and Lehman highlighted the time consistency of CS in influencing a company's performance, stressing that improvements in customer satisfaction can have long-lasting effects.

Ittner and Larker (1999) analyzed the effect of CS on stock returns, noting that the public announcement of CS scores has an immediate impact on stock returns, which typically adjust over a 10-day period. This highlights the importance of CS in influencing market perceptions and investor behavior. In terms of annual returns, Jacobson and Mizik (2009) found that while there are some exceptions, excess stock portfolio returns for firms with strong customer satisfaction are generally small and statistically insignificant. Any outperformance that does exist tends to be concentrated in a small number of companies, particularly those in the computer and Internet industries. This finding suggests that while CS may contribute to a firm’s long-term market success, its direct effect on annual returns may not be as widespread across all industries. Tuli and Bharadwaj (2009) analyzed the impact of CS on volatility, finding empirical support for the hypothesis that increases in CS result in reductions in overall systematic and idiosyncratic risk, including downside risk. This implies that firms with higher customer satisfaction may experience more stable financial performance and reduced risk exposure. Finally, several authors have highlighted the close link between the Price-to-Earnings (P/E) ratio, growth, and performance. For example, Easton (2004) and Thomas and Zhang (2006) demonstrated that P/E ratios serve as reliable indicators of a firm’s growth potential and financial performance. Our paper aims to build on this literature by emphasizing the forecasting power of the P/E ratio for both the financial and market performance of firms. This metric, in conjunction with CS, may provide a comprehensive framework for predicting a company’s success in both financial and customer-centric terms. Yeung et al. (2002) advocate for the use of the Ordinary Least Squares (OLS) model to forecast performance indicators based on Customer Satisfaction (CS). They initially assumed that the relationship between CS and performance indicators would be non-linear, possibly following an exponential pattern. However, their findings were surprising: not only did they refute their initial assumption of non-linearity, but they also demonstrated that the hypothesis of linearity between CS and performance indicators was acceptable. This outcome suggests that, contrary to the view of many, a simple linear model can adequately capture the relationship between CS and firm performance. Critics argue that a simple model like OLS cannot fully capture the complex, multi-dimensional impact of CS on firm performance. They contend that the relationship between CS and various performance metrics is too intricate, with many intertwined channels that make it difficult to represent with a straightforward linear model. These opponents suggest that a more sophisticated, non-linear model would better reflect the nuances of how CS affects profitability, customer loyalty, and other performance metrics.

Zahorik (2001) tackled this issue by developing a more complex model that integrates CS with individual customer loyalty, aggregated retention, market share, and profits. His model provides a framework for managers to optimally allocate resources to improve CS. It demonstrates how changes in CS can be quantified in terms of dollar value, showing how much to invest to enhance specific attributes of CS. However, Zahorik’s model is challenging to implement for the average manager, as it requires meticulous data collection and a complex calibration of the effort function, which estimates the costs associated with improving CS. As a result, while the model is a valuable academic contribution, it remains largely impractical for day-to-day market practice. In contrast, the OLS model is simple, straightforward, and fits into the "KISS" (Keep It Simple, Stupid) principle. It is a standard, robust, and universally recognized tool that can be easily implemented by any manager. Its reproducibility is one of its key strengths—managers can apply it with ease across various contexts without needing complex assumptions. On the other hand, non-linear models often require numerous hypotheses and assumptions. These models are not standard, and they lack the ease of replication. They can behave like a black box, producing an exponential relationship between CS and one variable, a quadratic relationship with another, and possibly higher-order polynomial relationships with other variables. The vast array of possibilities in non-linear models makes them more difficult to implement and less predictable, further complicating their application in a business environment. Thus, while more complex models may offer theoretically superior accuracy in some contexts, the simplicity and practicality of the OLS model make it an attractive and effective tool for managers seeking to leverage CS to forecast and improve firm performance.

3. METHODOLOGY

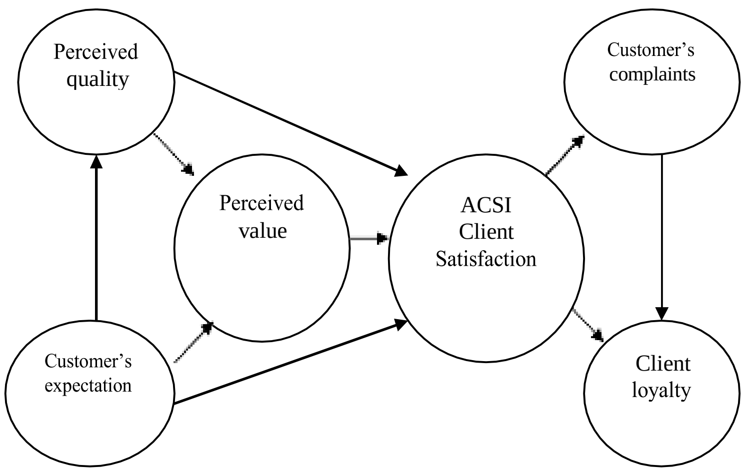
Our paper evaluates the capacity of Customer Satisfaction (CS) to forecast firms' financial and market performance. To do this, we benchmark CS against five key indicators: Tobin’s Q, Price-to-Cash Flows, Price-to-Earnings, Volatility, and the forecasted indicator itself. These financial and market indicators serve as proxies for assessing the overall performance of the firm. By comparing the predictive power of CS with these established financial metrics, we aim to determine the extent to which non-financial measures like CS can effectively forecast a company’s future success.

In addition to the ACSI index, our database includes financial and market indicators from eighty-six public companies covering the period from 2004 to 2009. These indicators include Book Value, Dividend Yield, Gross Profit Margin, Price-to-Cash Flows, Price-to-Earnings, Price-to-Sales, Annual Return, Return on Assets (ROA), Return on Equity (ROE), Return on Investment (ROI), Volatility, and Tobin’s Q. We sourced these indicators from the financial statements and historical prices available through Reuters and Yahoo Finance.

The selection of these twelve indicators was informed by a comprehensive literature review, which identified them as some of the most frequently tested or most representative proxies for market and financial performance. This ensures that the chosen metrics offer a robust basis for evaluating the financial health and market standing of firms within the study.

The sample consists predominantly of eighty-five American companies, with one European firm (Daimler-Chrysler) included. Despite being European, Daimler-Chrysler remains part of our sample due to its significant presence and operations in the U.S. market during the study period, making it relevant to the scope of our analysis.

Figure 1: Methodological framework for building the ACSI CS index



4. RESULTS

The table provides Root Mean Square Error (RMSE) and correlation values for 1-year forecasted volatility across four years: 2006, 2007, 2008, and 2009, with averages for each metric. The forecasts are based on two predictors: "Volatility" and "CS." Starting with the Predictor is Volatility, the RMSE values across the years are relatively high, particularly in 2009, where it reaches 153.52. The average RMSE across the four years is 56.5. RMSE measures the differences between the forecasted and actual values, so higher RMSE values indicate less accurate forecasts. Despite the high RMSE, the correlation between the forecasted and actual volatility is relatively strong, with values ranging from 0.56 in 2008 to 0.78 in 2009, and an overall average of 0.67. This suggests that while the volatility predictor may not always produce precise forecasts, it still captures the general direction of changes in volatility reasonably well. For the Predictor is CS, the RMSE values are slightly lower on average, with an overall RMSE of 34.05. However, the RMSE values fluctuate significantly, with a notably high value in 2008 (61.43) compared to the lower values in 2006 (8.16) and 2009 (52.55). The correlation values for CS as a predictor are considerably lower, with an average of just 0.23. This low correlation indicates that CS is not a strong predictor of volatility, as it does not align well with the actual changes in volatility. In summary, the "Volatility" predictor, despite its higher RMSE, shows a stronger correlation with actual volatility, suggesting it is more reliable in capturing the trend of volatility changes. On the other hand, the "CS" predictor, although having a lower average RMSE, has a much weaker correlation with actual volatility, indicating it is less effective in forecasting volatility trends over the years.

Table 1: RMSE and Correlation for 1-year forecasted volatility

t+1 year forecast	Forecastedvolatility	2006	2007	2008	2009	Average
Predictor is Volatility	RMSE	7.02	13.64	51.82	153.52	56.5
	Correlation	0.64	0.69	0.56	0.78	0.67
Predictor is CS	RMSE	8.16	14.08	61.43	52.55	34.05
	Correlation	0.1	0.24	0.25	0.24	0.23

Table 2: RMSE and Correlation for 1-year forecasted Tobin's Q

t+1 year forecast	ForecastedTobin's Q	2006	20072008	2009	Average
Predictor is Tobin's Q	RMSE	1.39	6.7311.57	14.66	8.59
	Correlation	0.75	0.60.99	-0.98	0.34
Predictor is CS	RMSE	2.08	7.745.54	10.85	6.56
	Correlation	0.17	-0.03-0.01	0.032	0.04

The table provides Root Mean Square Error (RMSE) and correlation values for 1-year forecasted Tobin's Q over the years 2006, 2007, 2008, and 2009, with average values for each metric. The forecasts are based on two predictors: "Tobin's Q" itself and "CS." Starting with the Predictor is Tobin's Q, the RMSE values show an increasing trend over the years, starting at 1.39 in 2006 and reaching 14.66 in 2009. The average RMSE across the four years is 8.59, indicating the degree to which the forecasted Tobin's Q values deviate from the actual values. Despite the increasing RMSE, the correlation values present an interesting pattern. There is a strong positive correlation in 2006 (0.75) and 2008 (0.99), indicating a high level of accuracy in predicting the direction of Tobin's Q in those years. However, in 2009, the correlation is strongly negative (-0.98), suggesting that the predictor was highly inaccurate that year, potentially predicting trends in the opposite direction of what actually occurred. The average correlation over the four years is 0.34, which reflects the mixed performance of the Tobin's Q predictor across different years. For the Predictor is CS, the RMSE values vary over the years, with an average RMSE of 6.56, which is lower than that of the Tobin's Q predictor. This suggests that the CS predictor, on average, produces forecasts closer to the actual Tobin's Q values. However, the correlation values for the CS predictor are consistently low, ranging from 0.17 in 2006 to slightly negative values in 2007 (-0.03) and 2008 (-0.01), and a small positive value in 2009 (0.032). The average correlation across the years is just 0.04, indicating that the CS predictor has little to no relationship with the actual Tobin's Q values, making it a poor predictor of the direction of changes in Tobin's Q. In summary, while the Tobin's Q predictor exhibits higher RMSE values, indicating greater deviations from the actual values, it still captures some of the directional trends in Tobin's Q, as evidenced by the stronger correlations in some years. However, the predictor's accuracy is inconsistent, particularly with the negative correlation observed in 2009. On the other hand, the CS predictor, while having a lower average RMSE, consistently shows low or no correlation with the actual Tobin's Q, suggesting it is not effective in predicting the trend of Tobin's Q over the years.

Table 3: RMSE and Correlation for 1-year forecasted *ROE*

t+1 year forecast	Forecasted *ROE*	2006	2007	2008	2009	Average
Predictor is *ROE*	RMSE	0.43	1.05	4.93	18.54	6.24
	Correlation	0.69	-0.09	0.61	0.06	0.32
Predictor is CS	RMSE	0.46	0.83	5.01	1.24	1.88
	Correlation	0.29	-0.08	-0.09	0.29	0.10

The table presents the Root Mean Square Error (RMSE) and correlation values for 1-year forecasted Return on Equity (ROE) over the years 2006, 2007, 2008, and 2009, with average values for each metric. The forecasts are based on two predictors: "ROE" itself and "CS." Starting with the Predictor is ROE, the RMSE values show an increasing trend over the years, starting from 0.43 in 2006 and rising significantly to 18.54 in 2009. The average RMSE over the four years is 6.24, indicating that the accuracy of the ROE predictor deteriorates over time, particularly in 2009. Despite the variability in RMSE, the correlation values provide mixed results. In 2006, the correlation is relatively strong at 0.69, suggesting that the ROE predictor was fairly accurate in predicting the direction of ROE that year. However, the correlation drops to -0.09 in 2007, indicating an inaccurate prediction for that year. The correlation improves in 2008 (0.61) but again becomes weak in 2009 (0.06). The average correlation across the four years is 0.32, reflecting the inconsistent performance of the

ROE predictor in forecasting future ROE trends. For the Predictor is CS, the RMSE values are generally lower, with an average RMSE of 1.88, suggesting that the CS predictor produces forecasts closer to the actual ROE values. The RMSE remains relatively stable, except for a spike in 2008 (5.01), indicating some variability in prediction accuracy. However, the correlation values for the CS predictor are consistently low, ranging from 0.29 in 2006 to slightly negative values in 2007 (-0.08) and 2008 (-0.09), and a modest improvement to 0.29 in 2009. The average correlation across the years is only 0.10, indicating that the CS predictor has a weak and mostly insignificant relationship with the actual ROE, making it a less reliable predictor of the trend in ROE. In summary, the ROE predictor shows higher RMSE values, particularly in later years, indicating greater deviations from actual ROE values, but it still captures some directional trends in certain years, as evidenced by the stronger correlations in 2006 and 2008. However, its predictive accuracy is inconsistent. The CS predictor, while having a lower average RMSE and more stable error rates, consistently shows low correlations with actual ROE, suggesting it is less effective in forecasting the direction of ROE changes over the years.

Table 4: RMSE and Correlation for 1-year forecasted *ROI*

t+1 year forecast	Forecasted ROI	2006	2007	2008	2009	Average
Predictor is ROI	RMSE	0.51	1.28	0.12	0.63	0.63
	Correlation	0.83	0.16	0.38	0.13	0.37
Predictor is CS	RMSE	0.71	0.32	0.12	0.63	0.44
	Correlation	0.11	0.21	0.16	0.06	0.13

The table presents the Root Mean Square Error (RMSE) and correlation values for 1-year forecasted Return on Investment (ROI) over the years 2006, 2007, 2008, and 2009, with average values provided for each metric. The forecasts are based on two predictors: "ROI" itself and "CS." Starting with the Predictor is ROI, the RMSE values indicate the accuracy of the forecasts, with an average RMSE of 0.63 across the four years. The RMSE values vary slightly, with the highest error occurring in 2007 (1.28) and the lowest in 2008 (0.12). These results suggest that the ROI predictor generally produces forecasts that are fairly close to the actual ROI values, particularly in 2008. The correlation values, which measure the strength and direction of the relationship between the forecasted and actual ROI, vary as well. In 2006, the correlation is strong (0.83), indicating that the predictor was highly accurate in capturing the trend of ROI that year. However, the correlation drops significantly in subsequent years, with values of 0.16 in 2007, 0.38 in 2008, and 0.13 in 2009. The average correlation across the years is 0.37, suggesting that while the ROI predictor is somewhat effective, its accuracy in predicting the direction of ROI is inconsistent over time.

For the Predictor is CS, the RMSE values are generally lower, with an average RMSE of 0.44, indicating that this predictor tends to produce forecasts that are closer to the actual ROI values compared to the ROI predictor. The RMSE values are relatively stable, except for a higher value in 2006 (0.71) and a lower value in 2007 (0.32). However, the correlation values for the CS predictor are consistently low, with an average correlation of just 0.13 across the four years. The correlations range from a low of 0.06 in 2009 to a modest 0.21 in 2007. These low correlation values suggest that while the CS predictor may generate forecasts with lower RMSEs, it is not particularly effective at predicting the direction of changes in ROI.

In summary, the ROI predictor shows moderate RMSE values and relatively higher correlations in certain years, particularly in 2006, indicating it can capture trends in ROI reasonably well but with some inconsistency. The CS predictor, while producing forecasts with lower RMSE values on average, has consistently low correlations, suggesting it is less effective at predicting the directional changes in ROI. Overall, the ROI predictor appears to be more reliable for capturing trends, while the CS predictor offers closer forecast values but lacks the ability to accurately predict the trend direction.

5. CONCLUSION

Our paper demonstrates that, based on the Root Mean Square Error (RMSE) criteria, the Price-to-Earnings (P/E) ratio serves as a better predictor of companies' financial and market performance compared to Customer Satisfaction (CS). This conclusion is drawn from our analysis, which used five financial and seven market indicators as proxies for financial and market performance. The indicators include Book Value, Dividend Yield, Gross Profit Margin, Price-to-Cash Flows, Price-to-Earnings, Price-to-Sales, Annual Return, Return on Assets (ROA), Return on Equity (ROE), Return on Investment (ROI), Volatility, and Tobin's Q. Our sample consists of eighty-six companies, making this evaluation robust across a range of firms and performance metrics. This comparison provides valuable insights into the relative forecasting power of financial ratios versus non-financial measures like CS in predicting firm performance. However, Customer Satisfaction (CS) clearly outperforms our benchmarks, including Tobin's Q, Price-to-Cash Flows, Price-to-Earnings, Volatility, and even the indicator itself, when it comes to forecasting Tobin's Q, Volatility, Return on Equity (ROE), and Return on Investment (ROI). Previous studies have highlighted the strong relationship between CS and both market indicators (such as Volatility and Tobin's Q) and financial indicators (such as ROE and ROI).

During periods of market volatility, such as in 2008, CS proves to be a more stable predictor of metrics like Volatility and ROE than using the indicator's own historical values (e.g., Volatility at t-1 to predict Volatility at t, or ROE at t-1 to predict ROE at t). This suggests that CS provides valuable insights into a firm's resilience and performance stability in uncertain market conditions, outperforming traditional financial metrics in these specific contexts. We found that the optimal forecasting lag for predicting a firm's financial and market performance is 1 year when using Customer Satisfaction (CS), Price-to-Earnings (P/E), and Volatility as individual predictors. In contrast, a 2-year lag is optimal for Tobin's Q, Price-to-Cash Flows, and the indicator itself. The optimal lag for CS at t+1 year is justifiable, as previous authors have noted that the profits generated from improvements in CS are not immediate. Our findings align with the work of Anderson, Fornell, and Lehmann (1994), who also identified a significant impact of CS at t+1 year on Return on Investment (ROI). However, our study goes further by highlighting the impact of CS at t+1 year on additional performance metrics, including Return on Equity (ROE), Volatility, and Tobin's Q. This suggests that CS influences a broader range of financial and market indicators over a 1-year horizon, reinforcing its value as a predictive tool. Moreover, our paper demonstrates that when forecasting a given financial or market indicator, the indicator itself at t-1 often serves as a reliable predictor and can compete effectively with the two leading predictors: the Price-to-Earnings ratio and Customer Satisfaction (CS). This finding underscores the importance of historical data in predicting future performance, as past performance often remains a strong indicator of future trends.

Additionally, we introduced the use of two evaluation criteria, Root Mean Square Error (RMSE) and correlation, to enhance the assessment of forecasting power. While RMSE is a widely used measure of accuracy, it alone may not capture outliers in the data. By combining RMSE with correlation analysis, we were able to better identify and address outliers, which improves the robustness of our forecasting models. Our study, however, has several limitations. The time frame of the sample is relatively short, and the number of companies included is limited. We attempted to replicate the S&P 500 index to create a homogeneous sample, but we overweighted certain sectors—namely Utilities, Consumer Staples, and Consumer Discretionary—because we believed that these sectors have a stronger emotional and loyalty-driven impact on consumers compared to other industries in the S&P 500. This approach introduces a bias in favor of CS, which may be questionable in terms of its generalizability to other sectors. Another limitation is the presence of survivor bias in our sample. Initially, the sample comprised around one hundred companies, but this number was reduced to eighty-six due to survivorship, meaning we excluded companies that did not survive the period under study. This could affect the representativeness of the sample and the robustness of our findings. Looking ahead, future research could extend the study by incorporating additional indicators or exploring alternative forecasting approaches, such as Principal Components Analysis or neural networks, to further enhance predictive accuracy and capture more complex relationships between CS and financial performance. These methods may offer new insights and help overcome the limitations of traditional linear models.

REFERENCES

Ailawadi, K. L., Farris, P. W., & Parry, M. E. (1999). Market share and ROI: Observing the effects of unobserved variables. *International Journal of Research in Marketing, 16*(1), 17-33.

Anderson, E. W., Fornell, C., & Lehmann, D. R. (1994). Customer satisfaction, productivity, and profitability: Differences between goods and services. *Marketing Science, 16*(2), 129-145.

Anderson, E. W., Fornell, C., & Mazvancheryl, S. K. (2004). Customer satisfaction and shareholder value. *Journal of Marketing, 68*, 172-185.

Anderson, E. W., Fornell, C., & Rust, R. T. (1994). Customer satisfaction, market share, and profitability: Findings from Sweden. *Journal of Marketing, 58*(3), 53-66.

Anderson, E. W., Sullivan, M. W. (1993). The antecedents and consequences of customer satisfaction for firms. *Marketing Science, 12*(2), 125-143.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*, 99-120.

Bearden, W. O., & Teel, E. J. (1983). Selected determinants of consumer satisfaction and complaint reports. *Journal of Marketing Research, 20*, 21-28.

Bharadwaj, A. S., Bharadwaj, S. G., & Konsynski, B. R. (1999). Information technology effects on firm performance as measured by Tobin's q. *Management Science, 45*, 1008-1024.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*, 307-327.

Bolton, R. N., & Lemon, K. N. (1999). A dynamic model of customers' usage of services: Usage as an antecedent and consequence of satisfaction. *Journal of Marketing Research, 36*, 171-186.

Charreaux, G. (1998). La mesure de performance des entreprises. *Banque & Marchés, 34*, 46-50.

Dumontier, P. (1999). Information comptable et création de valeur: Le cours de bourse ne suffit pas. *Revue Française De Gestion*, 99-105.

Easton, P. (2004). PE ratios, PEG ratios, and estimating the implied expected rate of return on equity capital. *The Accounting Reveiw, 79*(1), 73-95.

Eccles, R. G., & Pyburn, P. G. (1992). Creating a comprehensive system to measure performance. *Management Accounting, 41*, 4.

Fornell, C. (1992). A national customer satisfaction barometer: The Swedish experience. *Journal of Marketing, 56*(1), 6-21.

Fornell, C., Mithas, S., Morgeson III, F. V., & Krishnan, M. S. (2006). Customer satisfaction and stock prices: High returns, low risk. *Journal of Marketing, 70*, 3-14.

Hogan, J. E., Lehmann, D. R., Merino, M., Srivastava, R. K., Thomas, J. S., & Verhoef, P. C. (2002). Linking customer assets to financial performance. *Journal of Service Research, 5*(1), 26-38.

Ittner, C. D., & Larcker, D. F. (1999). Are nonfinancial measures leading indicators of financial performance? An analysis of customer satisfaction. *Journal of Accounting Research, 36*, 1-35.

Jacobson, R. (1990). Unobservable effects and business performance. *Marketing Science, 9*(1), 74-85.

Jones, T. O., & Sasser, W. E. (1995). Why satisfied customers defect? *Harvard Business Review, 73*(6), 88-99.

Kaplan, R. S., & Narayanan, V. G. (2001). Measuring and managing customer profitability. *Journal of Cost Management, September/October*, 5-15.

Kaplan, R. S., & Norton, D. P. (1992). The balanced scorecard: Measures that drive. *Harvard Business Review, 70*(1), 71-79.

Mizik, N., & Jacobson, R. (2009). The financial markets and customer satisfaction: Reexamining possible financial market mispricing of customer satisfaction. *Marketing Science, 28*(5), 810-819.

Rust, R. T., Zahorik, A. J., & Keiningham, T. L. (1993). Customer satisfaction, customer retention, and market share. *Journal of Retailing, 69*(2), 193-215.

Rust, R. T., Zahorik, A. J., & Keiningham, T. L. (2001). Return on quality (ROQ): Making service quality financially accountable. *Journal of Marketing, 59*, 58-70.

Srivastava, R. K., Shervani, T. A., & Fahey, L. (1998). Market-based assets and shareholder value: A framework for analysis. *Journal of Marketing, 62*, 2-18.

Srivastava, R. K., Shervani, T. A., & Fahey, L. (1999). Marketing business processes and shareholder value: An organizationally embedded view of marketing activities and the discipline of marketing. *Journal of Marketing, 63*, 168-179.

Thomas, J., & Zhang, H. (2006). Another look at P/E ratios. *Working paper*, Yale University.

Tuli, K. R., & Bharadwaj, S. G. (2009). Customer satisfaction and stock returns risk. *Journal of Marketing, 73*, 184-197.

Vandermerwe, S. (2000). How increasing value to customers improves business results. *Sloan Management Review, 42*(1), 27-37.

Yeung, M. C. H., & Ennew, C. T. (2001). Measuring the impact of customer satisfaction on profitability: A sectoral analysis. *Journal of Targeting, Measurement and Analysis for Marketing, 10*, 106-116.