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Can We Optimize Stock Price?—A Mathematical Driven Stock Price Optimization Model in Finance Based on Desirability Function

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Abstract

The research employs response surface analysis utilizing the desirability function approach for stock price optimization. It builds upon prior work introducing a data-driven analytical model to forecast the weekly closing price of MSFT stock, a key entity in the Information Technology Sector of the S&P 500. Central to this study are crucial financial and economic indicators, and their interactions identified through our analytical model, which constitute the foundational elements of our refined predictive framework. By establishing target values for these indicators, our optimization method aims to maximize the weekly closing price of the stock with heightened predictive precision and confidence intervals. Our findings underscore the significance of vigilant monitoring and managing statistically significant financial indicators via predictive modeling to achieve desired stock prices, thereby enhancing investment returns. This research yields valuable insights for investors and firms, aiding in strategic planning by elucidating the nuanced impact of financial and economic indicators on optimizing stock returns. The stock price optimization model based on desirability function can effectively be applied to other individual stocks or sets of stocks to construct an optimal portfolio tailored to achieve desired returns, considering specified risk factors.

Keywords

Contour Plot, Desirability Function, Financial and Economic Indicators, Optimization, Portfolio Management, Response Surface Analysis, Stock Price

1. Introduction

In 1950, Harry Markowitz introduced the renowned Modern Portfolio Optimization Theory. This theory operates under the assumption that, at any given time, an investor seeks to maximize the expected return of a portfolio while considering a certain level of risk, typically quantified by the standard deviation of the portfolio's rate of return (Fabozzi, Markowitz, & Gupta, 2011). Since its inception, portfolio optimization has become a widely adopted concept in finance, extensively utilized by investors and companies alike to enhance the profitability of their investment portfolios.

Every day, a vast number of individuals participate in trading equities and commodities on global exchanges, driven by the enticing profit prospects offered by the stock market. Investors often diversify their portfolios across various stocks in pursuit of attractive returns to bolster their wealth.

Nearly all publicly traded companies aspire to maximize their share prices, thereby enhancing their firm's value and market dominance. In this context, both individuals and companies recognize the importance of comprehending the key financial and economic factors influencing their stock prices. Analyzing the behavior and interactions of these indicators aids in assessing investment risks and forecasting potential stock values with precision.

This study aims to optimize the stock price of a single stock, focusing on the relevant financial and economic indicators that impact the weekly closing price of MSFT stock. Herein, we propose an optimized predictive model leveraging response surface analysis based on the desirability function approach, a widely employed method in industry for optimizing single or multiple response processes. Response Surface Methodology (RSM) is a statistical technique that is typically used in experimental design to optimize processes and understand the relationship between several variables and an outcome of interest. While it's not directly a mainstream tool in finance, some aspects of RSM can be applied to financial problems, especially those involving optimization and risk management.

The Response Surface Methodology (RSM) helps analyze the relationship between financial and economic indicators and a response variable to produce optimal response outcome. RSM aims to minimize or maximize the response variable(s) by achieving a desired target value of the indicators that optimize response variable.

Response Surface Methods (RSMs) are models and methodologies tailored for handling continuous treatments to either optimize or characterize the response variable (Oehlert, 2010). Initially, the primary aim of RSM is to identify the optimal response. When dealing with multiple responses, it becomes crucial to determine a compromise solution that doesn't solely optimize one response. Additionally, when working with design data constrained by limitations, the experimental design must adhere to specific constraints.

Another objective of RSM is to understand how the response changes relative to adjustments in the design variables. Typically, the analysis of the response surface can be represented graphically, allowing for visual interpretation. Through these graphs, the shape of the response surface, including hills, valleys, and ridge lines, can be observed. Consequently, the function $f(X_1, X_2)$ can be graphed against the levels of X1 and X2 to gain insights into their effects on the response (Montgomery, 2017).

The desirability function, initially outlined by Harrington (1965) and further elaborated by Derringer and Suich (1980), stands as a significant tool for factor optimization. The Desirability Function Approach (DFA) constitutes a strategy for response optimization, where the response is optimized based on controllable input factors. By integrating both Response Surface Methodology (RSM) and the desirability approach, a more robust method emerges for achieving optimal dynamics among responses, including stock return responses (multicriteria optimization). This fusion of RSM and the desirability function gives rise to the "Desirability Optimization Methodology".

RSM is frequently used in engineering and manufacturing industries to optimize manufacturing processes, improve product quality, and reduce production costs. Modelling and optimization of copper adsorption in solution using the response surface method through the Box-Behnken model has been studied recently in Senegal (Ba et al., 2023). This method is commonly applied in industrial, microbiology, biochemistry, and chemical analysis, however to the best of our knowledge, such a method has never been applied to the plant biotechnological studies and, more specifically, to the study of the *in vitro* response of a plant secondary metabolism to the environmental factors (Costa, Lourenço, & Pereira, 2011). In greenhouse gas emissions mainly produced by industrial power plants, In this contribution, firstly, a simulation of the process for capturing carbon dioxide from flue gas with the 1-n-hexyl-3-methylimidazolium bis(trifluoromethyl sulfonyl)amide ([hmim] [Tf2N]) ionic liquid is carried out, leading to an optimization of the system, minimizing costs and maximizing the amount of captured carbon dioxide through the response surface methodology (Leonzio & Zondervan, 2020). This profile is then applied in the field of stock return optimization.

In our previous article titled "Predictive Modeling: Impact of Financial and Economic Indicators on Stock" (Pokharel, Tetteh-Bator, & Tsokos, 2022b), we present a real data-driven analytical model to predict the "Weekly Closing Price" (WCP) of the MSFT stock using five financial, four economic indicators and their two-way interactions and, the proposed predictive model has excellent predictive accuracy. The attributable entities that are included in the proposed optimized model have a significant relevance in the literature of finance and economics. We now proceed to identify the target values of the statistically significant indicators and their interactions used in the predictive model that maximizes the WCP of the stock using response surface analysis based on desirability function approach.

The study discusses the importance of the target values of the controllable indicators and their interactions with stock price optimization problems and presents some useful information for related stakeholders.

2. Methodology

The procedures and the methodology of our proposed predictive model-building process are presented in Subsections 2.1, 2.2 and 2.3.

2.1. Selection of Appropriate Stock

Microsoft Corp. holds the second position among 75 companies listed in the Information Technology Sector Index of the S&P 500, trailing only Apple Inc. (AAPL) in terms of market capitalization and revenue. Throughout our study period from 2017 to 2019, Microsoft Corp. demonstrated superior performance compared to Apple Inc. across key investor metrics such as revenue growth, net profit growth, and dividend yield (Fiorillo, 2021). Known for its consistent growth and strong financial performance over its extensive history, Microsoft Corp. maintains average volatility relative to other technology sector stocks, making it a highly sought-after investment choice for numerous reasons. This study focuses specifically on MSFT stock within the Information Technology Sector Index of the S&P 500, leveraging real data to develop an optimized predictive model. Titled "Analytical Predictive Modeling: Impact of Financial and Economic Indicators on Stock", our previous research introduced a data-driven analytical model aimed at predicting the Weekly Closing Price (WCP) of MSFT stock (Pokharel, Tetteh-Bator, & Tsokos, 2022b). In this current study, our objective is to optimize the stock price using response surface analysis based on desirability function method. This method aims to identify the target values for financial and economic indicators that maximize the WCP of the stock, thereby enhancing returns and perceived value of the firms.

2.2. Data and Description of the Indicator

In our previous study, we selected MSFT as the leading company and used the required information about the indicators using various sources such as Yahoo Finance, FRED Economic Data, Zacks Investment Research, Alpha Query, Morningstar.com, etc. These databases offer publicly accessible, authentic data sourced from authoritative institutions, ensuring they are not synthetic. They transparently disclose the origins of their data, instilling trust among users in academia, government, and financial sectors that rely on them extensively for economic analysis, research and informed decision-making. The dataset includes the information of the MSFT stock's WCP from January 2017 to December 2019. The main objective of our research is to develop a mathematical-driven optimization model using desirability function to optimize the weekly closing price of the stock on a short-term basis, week to week. Stock market analysis benefits from real-time data that reflects current market conditions, with 3-year data capturing recent trends and market dynamics, while 5-year or long-range data offers a broader historical perspective. Models using 3-year data are simpler and generalize well to new data, whereas those using long-range data may capture complex patterns but risk overfitting to historical conditions. Longer data spans require sophisticated preprocessing, whereas handling 3-year data is simpler. Therefore, in order to achieve our goal of developing a week-to-week real-time stock price prediction and optimization model, we opted to use a three-year dataset instead of extensive historical data.

Figure 1 shows the Weekly Closing Price of the MSFT stock from January 2017 to December 2019. The weekly data information is used to structure the required database. In our earlier study, we selected six financial indicators and four economic indicators to predict the weekly closing price of the stock. Now, we leverage these statistically significant indicators from the predictive model to develop an optimized stock price optimization model. Readers are referred to Pokharel, Tetteh-Bator, and Tsokos (2022a, 2022b) for detailed literature review of the significant indicators used in the analytical predictive model.

Figure 1. *WCP* of MSFT stock from 2017 to 2019 (Source: https://bigcharts.marketwatch.com/quickchart/quickchart.asp?symb=msft).

In addition, for the convenience of the readers, we define below the financial indicators from numbers 1 - 6, and economic indicators from numbers 7 - 10 that are significant entities of our analytical model that significantly attribute to WCP.

1) **Beta**(X_1): The beta value is a statistical measure that compares the volatility of return of a specific stock in relation to those stocks of the market as a whole. In general, stocks with higher beta value are considered to be more riskier, thus, investors will expect higher returns. That is:

$$\text{Beta} = \frac{Cov\left(R_i, R_m\right)}{Var\left(R_m\right)},$$

where R_i is the return on individual stock and R_m is the return on overall market. $Cov(.,.)$ is the covariance between R_i and R_m that measures the changes in stock's returns with respect to the changes in market's returns, $Var(.)$ is the variance of the excess market returns over the risk-free rate of returns.

2) **FCF/Share**(X_2): Free Cash Flow per Share (FCF/Share) is a measure of a company's financial flexibility (Akono, 2016). It calculated by dividing Free Cash Flow of the company by the total number of shares outstanding. That is:

$$\text{FCF/Share} = \frac{\text{Free Cash Flow}}{\text{Number of Share Outstanding}}.$$

3) **P/B Ratio**(X_3): Price-to-Book (P/B) ratio compares a company's current market value to its book value (Indrayono, 2019). And the book value is defined as the value of all assets minus liabilities owned by a company. That is:

$$\text{P/B Ratio} = \frac{\text{Market Value Per Share}}{\text{Book Value Per Share}}.$$

4) **P/E Ratio**(X_4): Price-to-Earnings (P/E) ratio is the ratio that measures the current price of a stock concerning its earnings per share (Shen, 2000) and is given by:

$$\text{P/E Ratio} = \frac{\text{Current Price Per Share}}{\text{Earnings Per Share}}.$$

5) **PEG Ratio**(X_5): Price-Earnings-to-Growth (PEG) ratio is the stock's Price-to-Earnings (P/E) Ratio divided by the growth rate of its earnings for a specified period (Meher & Sharma, 2015) and is given by:

$$\text{PEG Ratio} = \frac{\text{P/E Ratio}}{\text{Annual EPS Growth}}.$$

6) **Dividend Yield**(X_6): Dividend Yield (*Div_Yield*) is the percentage measure of the company's share price that it pays out in dividends each year and is given by:

$$\text{Dividend Yield} = \frac{\text{Annual Dividend Per Share}}{\text{Current Share Price}}.$$

7) **Interest Rate**(X_7): The US Federal Fund Rate is used. It is the target interest rate set by the Federal Open Market Committee (Chen, 2024). This target is the rate at which the Fed suggests commercial banks borrow and lend their excess reserves to each other overnight.

8) **US ICS**(X_8): The Michigan Survey Research Center has developed the Index of Consumer Sentiment (ICS) to measure the confidence or optimisim (passimism) of consumers in their future well-being and coming economic condition (Charoenrook, 2005). The ICS measures short and long-term expectations of business conditions and the individual's perceived economic well-being.

9) **US PSR**(X_9): The US Bureau of Economic Analysis (BEA) publishes the US Personal Saving Rate. The US Personal Saving Rate is the personal saving rate as a percentage of personal income. It is a percentage measure of individuals' income left after they pay taxes and expenditures (Marquis, 2002).

10) **US GDP**(X_{10}): Gross Domestic Product (GDP) of the United States (in billion) is used. GDP is defined as the measure of monetary value of all finished goods and services made within a country during a specific period (Callen, 2008). The components of GDP include personal consumption expenditures (C), business

investments (I), government spending (G), exports (X), and imports (M). That is:

$$\text{GDP} = C + I + G + (X - M).$$

3. Overview of Response Surface Analysis-Desirability Function Approach

The response surface analysis based on the desirability function is a method used in industry for the optimization of multiple response processes. The desirability function, initially formulated by Harrington (1965) and further developed by Derringer and Suich (1980), is a method employed for optimizing factors. The Desirability Function Approach (DFA) serves as a strategy for optimizing responses by transforming them into a dimensionless desirability value. This approach enables the optimization of responses in relation to controllable input factors. The values of the desirability functions lie between 0 and 1. The value 0 is attributed when the factors give an undesirable response, while the value 1 corresponds to the optimal performance for the important factors (Derringer & Suich, 1980). Let $y(x)$ and $d(y)$ be the response and the desirability function, respectively. For each response $y_i(x)$, a desirability function $d_i(y)$ assigns numbers between 0 and 1 to the possible values of Y_i, with $d_i(y_i) = 0$ representing a completely undesirable value of y_i and $d_i(y_i) = 1$, representing a completely desirable or ideal response value. The individual desirabilities are then combined using the geometric mean, which gives the overall desirability D, that is:

$$D = \left(d_1(y_1)d_2(y_2)\cdots d_k(y_k)\right)^{1/p} = \left[\prod_{i=1}^{k} d_i(y_i)\right]^{1/p}, \tag{1}$$

where p denotes the number of responses. In this study, we want to optimize the single response AWCP where we choose $p = 1$.

Depending on the optimization objectives, whether a particular response y_i is to be maximized, minimized, or assigned to a target value, Derringer and Suich (1980) proposed a useful class of desirability functions. Let L_i, U_i and T_i be the lower bound, upper bound, and target values of the desired response $\hat{y}_i$, with $L_i \le T_i \le U_i$. If the objective is to maximize the response (i.e. the larger the better), the desirability function is defined as:

$$d_i(\hat{y}_i) = \begin{cases} 0, & \text{for } \hat{y}_i(x) < L_i \\ \left(\dfrac{\hat{y}_i - L_i}{T_i - L_i}\right)^{\alpha}, & \text{for } L_i \le \hat{y}_i(x) \le T_i \\ 1, & \text{for } \hat{y}_i(x) > T_i \end{cases} \tag{2}$$

where α is the shape parameter of the individual desirability function $d_i(\hat{y}_i)$ and T_i is interpreted as the large enough value for the response. Similarly, if the objective is to obtain the specific "target" value of the response, the two-sided desirability function is defined as:

$$d_i\left(\hat{y}_i\right)=\begin{cases}0, & \text{for } \hat{y}_i\left(x\right)<L_i \\ \left(\dfrac{\hat{y}_i-L_i}{T_i-L_i}\right)^{\alpha}, & \text{for } L_i\le\hat{y}_i\left(x\right)\le T_i \\ \left(\dfrac{\hat{y}_i-U_i}{T_i-U_i}\right)^{\beta}, & \text{for } T_i\le\hat{y}_i\left(x\right)\le U_i \\ 1, & \text{for } \hat{y}_i\left(x\right)>U_i\end{cases} \tag{3}$$

And if the objective is to minimize the response, the desirability function is defined as:

$$d_i\left(\hat{y}_i\right)=\begin{cases}1, & \text{for } \hat{y}_i\left(x\right)<T_i \\ \left(\dfrac{\hat{y}_i-L_i}{T_i-L_i}\right)^{\alpha}, & \text{for } T_i\le\hat{y}_i\left(x\right)\le U_i \\ 0, & \text{for } \hat{y}_i\left(x\right)>U_i\end{cases} \tag{4}$$

where α and β represent the weighted parameters that define the shape of the individual desirability function $d_i\left(\hat{y}_i\right)$. For $\alpha=\beta=1$, the shape of $d_i\left(\hat{y}_i\right)$ is linearly increasing in the direction of T_i, if $\alpha<1$ and $\beta<1$, the shape of $d_i\left(\hat{y}_i\right)$ is concave, and if $\alpha>1$ and $\beta>1$, the shape of $d_i\left(\hat{y}_i\right)$ is convex (Jeong & Kim, 2009).

We employed the Central Composite Design (CCD), a widely used approach in response surface methodology featuring a two-level full factorial design supplemented with central and axial points. Axial points are positioned at the midpoints of factor levels relative to other factors, while central points are added at the center of the design space. The CCD utilized in this study encompasses 10 continuous factors and identifies 11 significant interactions. A robust prediction model is characterized by its ability to maintain consistent and stable variance across the entire range of independent predictor variables. The contour and surface plots generated by the CCD illustrate a robust prediction model that exhibits uniform and stable variance throughout the range of independent variables.

3.1. Statistical Analysis for Stock Price Optimization

The optimization problem for our study involves a single response, which is called the objective function, and our goal is to maximize the average Weekly Closing Price (WCP) of the MSFT Stock which we abbreviated as "*y*" for convenience. We utilized the desirability function defined by Equation (4) to maximize the objective function-WCP, that is, "*y*" of the stock. The optimization process we adopted involves the following steps:

- Build the regression model that significantly predicts the continuous response/target variable(s) with high degree of accuracy.
- Define the constraints or limits of the response(s) and that of the input/risk factors.
- Identify the desirability function appropriate to optimize the response based on the response optimization objective.

- Execute the function and obtain the optimum value of the response(s), values of the input variables, and the value of the desirability function.
- Validating the optimization process.

The results of the outlined optimization process for the average weekly closing price of the MSFT stock is as follows:

Step 1: The statistical model that accurately predicts the average weekly closing price of the MSFT stock (Pokharel, Tetteh-Bator, & Tsokos, 2022b) is given by:

$$\widehat{WCP} = 61.3432 + \frac{99.9172}{1 + \exp\left(\frac{0.4293 - \widehat{WCP^T}}{0.6113}\right)}, \tag{5}$$

where $\gamma = 0.4293$, $\delta = 0.6113$, $\xi = 61.3432$ and $\lambda = 99.9172$.

($-\infty < \gamma < \infty$, γ—Johnson shape parameter;

$\delta > 0$, δ—Johnson shape parameter;

$\lambda > 0$, λ—Johnson scale parameter;

$-\infty < \xi < \infty$, ξ—Johnson location parameter), and

$$\begin{aligned}\widehat{WCP^T} = {} & 0.0931 - 0.1304X_1 + 0.1557X_4 + 0.0501X_5 - 0.0498X_9 + 0.7118X_{10} \\ & + 0.2064X_1X_3 - 0.0933X_2X_5 + 0.2756X_3X_4 + 0.3831X_3X_6 \\ & - 0.1408X_3X_7 - 0.2938X_4X_7 - 0.1186X_5X_6 - 0.2744X_6X_7 \\ & - 0.1223X_7X_8 + 0.0598X_8X_9 + 0.1276X_8X_{10},\end{aligned} \tag{6}$$

where,

$\widehat{WCP^T}$ = Johnson Transformed Estimated Average Weekly Closing Price;

X_1 = Beta, X_2 = FCF/Share, X_3 = P/B Ratio, X_4 = P/E Ratio, X_5 = PEG Ratio;

X_6 = Div_Yield, X_7 = Int_Rate, X_8 = ICS, X_9 = PSR, X_{10} = GDP.

Step 2: The constraints or limits of the WCP and the statistically significant economic and financial indicators are given in **Table 1**.

Table 1. The constraints of the response and indicators/risk factors.

WCP ($)	Input/Indicators
	$0.988 \le X_1 \le 1.278$
	$1.29 \le X_2 \le 4.93$
	$6.930 \le X_3 \le 11.430$
	$20.888 \le X_4 \le 31.856$
	$1.884 \le X_5 \le 2.882$
$62.70 \le y \le 158.96$	$1.227 \le X_6 \le 2.488$
	$0.650 \le X_7 \le 2.420$
	$89.80 \le X_8 \le 101.40$
	$6.60 \le X_9 \le 9.00$
	$19153.912 \le X_{10} \le 21694.458$

Step 3: The optimization objective is to maximize the WCP of MSFT stock. Therefore, we utilized the desirable function defined in Equation (2).

Step 4: After optimization process has been executed, the optimum estimated response and the corresponding values of the input/indicators, and the value of the desirability function is given in Table 2.

Table 2. Optimal values and the desirability function.

$\widehat{WCP}$	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	$d\left(\widehat{WCP}\right)$
206.92	1.28	1.29	11.43	31.86	1.88	2.49	0.65	101.4	9	21694.5	0.999

We can see that the weekly closing price of the MSFT stock can be maximized to \$206.92 by monitoring financial and economic indicators within the range defined in Table 1. The maximum limiting value of Beta, PB Ratio, PE Ratio, Dividend Yield, ICS, PSR and GDP, and minimum limiting value of Free Cash Flow per Share, PEG Ratio and Interest Rate would maximize the weekly closing price of the stock to \$206.92 with desirability of 0.999.

Step 5: The model is validated and assessed the optimization process-ability to achieve the maximum AWCP of MSFT stock based on the value of the desirability function $d\left(\widehat{WCP}\right)$, the R^2, Adj.R^2, R^2 (pred), 95% confidence interval and prediction interval are listed in Table 3. That is, we are at least 95% confident that WCP of the MSFtT stock will be between \$170.30 and \$243.50.

Table 3. Optimization process validation.

Estimated Maximized WCP	\$206.92
Desirability	0.999
R^2	98.34%
Adj.R^2	98.29%
R^2 (pred)	98.2%
95% CI	(170.30, 243.50)
95% PI	(170.0, 243.80)

The statistical model based on the response surface analysis using desirability function can maximize the WCP of the stock with high degree of accuracy. The model has the R^2 of 98.34% and $adj.R^2$ of 98.29%. It implies that by controlling the input indicators in the given level as shown in Table 1, the optimized model can explain more than 98% variation on the weekly closing price of the stock. The maximized value of the average weekly closing price of the stock is \$206.92 with desirability of 0.999.

3.2. Graphical Visualization of the Response Surface

In most Response Surface Methodology (RSM) applications, the specific relationship between the response variable and the independent variables is typically unknown. Therefore, the initial step in RSM involves determining a suitable approximation for the true functional relationship between the response variable and the set of independent variables. The mathematical model used in RSM is often a second-degree polynomial equation, which offers the advantage of being straightforward to estimate and apply for approximating the response. Typically, a low-order polynomial is employed within a specific range of the independent variables. If the response can be adequately represented by a linear function of the independent variables, then a first-order model is utilized. However, if there is curvature or non-linearity in the system, a higher-degree polynomial such as a second-order model is necessary to capture these complexities.

The response surface plots, both in 2D (contour) and 3D (surface), are instrumental in understanding how two input variables affect the response variable while holding the remaining variables constant at a specific level. Contour plots display the response surface as a two-dimensional plane, connecting points of similar response values with contour lines. This visualization helps to analyze how the response changes with variations in one input variable, keeping others fixed. Surface plots, on the other hand, offer a three-dimensional perspective, illustrating the combined influence of two variables on the response variable. They provide insights into the behavior and interaction of the response under different conditions. The analytical predictive model under consideration incorporates six financial and four economic indicators. While economic indicators are challenging to control due to their dependence on various external factors, improving a firm's performance can notably enhance financial indicators. Understanding the relationship between response and risk factors enables firms to optimize their value. The response surface not only offers crucial insights to maximize the response variable to its optimal level but also guides in achieving target response values by managing the associated risk factors effectively.

Contour and surface plots elucidate the dynamics of controllable financial indicators and their impact. This visual representation aids in comprehending how the Weekly Closing Price (WCP) responds to these indicators and identifies optimal combinations that can potentially maximize the WCP to desired levels. The figures depict how the estimated WCP changes when individual or pairs of indicators vary, while holding the remaining indicators constant at predefined levels.

The beta-risk factor and the P/B ratio are the key financial indicators that significantly contribute to the Weekly Closing Price (WCP) in the proposed model. According to the contour plot in Figure 2, WCP reaches its maximum in the dark region located at the bottom left corner of the plot. However, the Beta values horizontally and the P/B ratio values vertically in the bottom left corner are the smallest among all regions. This suggests that we can optimize the WCP value above $100 by keeping Beta around 1 and the P/B ratio around 7 - 8, while holding other indicators constant. The combination of a lower Beta value and P/B ratio would lead to a better stock price, assuming everything else remains unchanged.

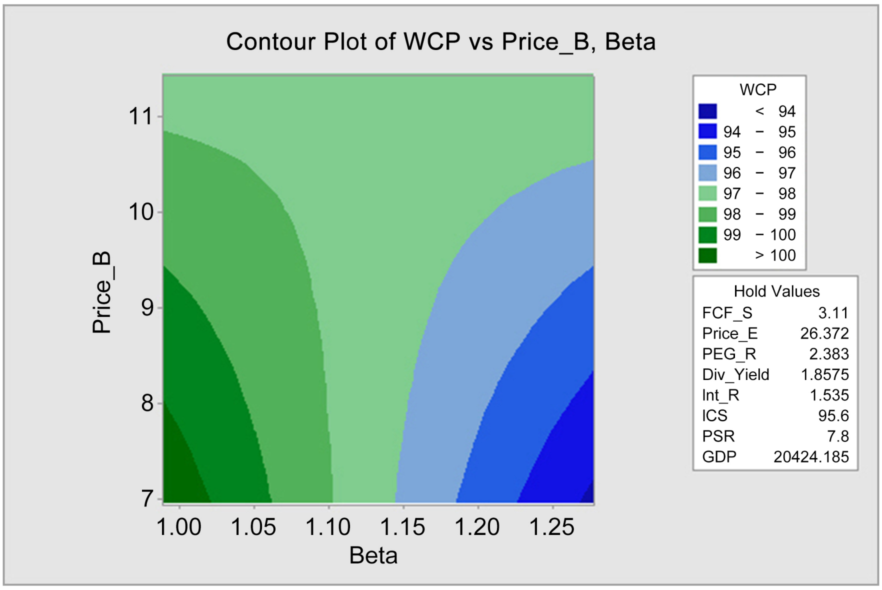

Figure 2. Contour plot: effect of beta & P/B ratio on WCP.

This can be further confirmed by examining the surface plot (Figure 3), which shows that when the beta value is near 1 and the P/B ratio ranges between 7 to 8, the Weekly Closing Price (WCP) exceeds 100, assuming all other indicators remain constant at their specified levels. Therefore, comprehending how beta and the P/B ratio interact to influence WCP yields valuable insights crucial for decision-making processes.

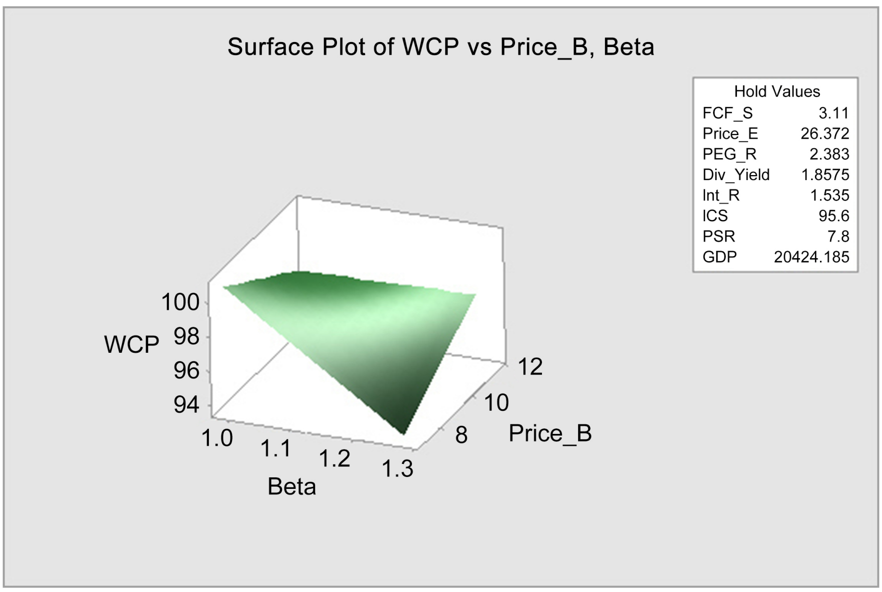

Figure 3. Surface plot: effect of beta & P/B ratio on WCP.

In **Figure 4**, the contour plot illustrates how the interaction between Free Cash Flow per Share and PEG Ratio affects the Weekly Closing Price (WCP) of MSFT stock.

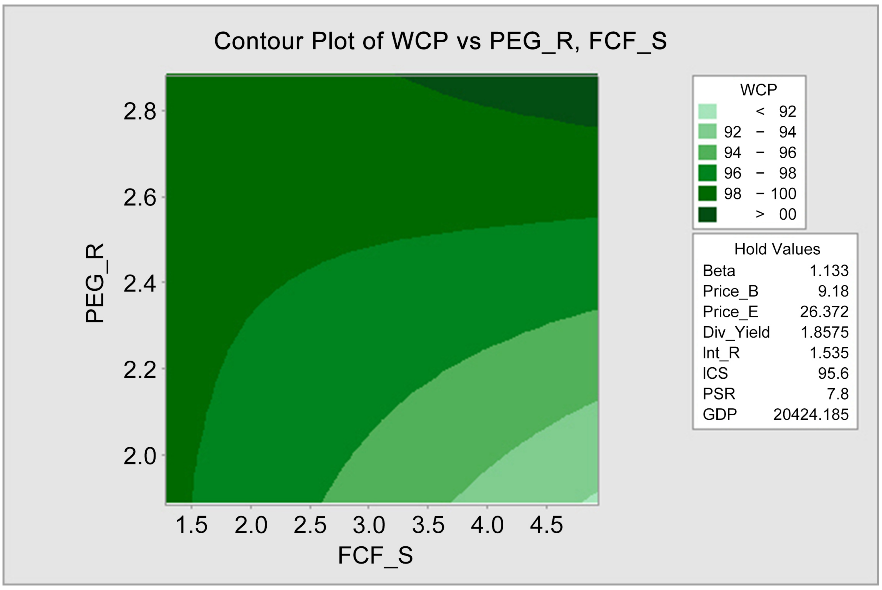

Figure 4. Contour plot: effect of *FCFS* & PEG ratio on WCP.

The dark green region in the top right corner of the Contour plot indicates where WCP is maximized, corresponding to maximum values of both indicators. Specifically, WCP is maximized when Free Cash Flow per Share exceeds 3.5 and PEG Ratio exceeds 2.8. **Figure 5**, the surface plot, further confirms this information. Achieving the right balance of these indicators is crucial in optimization problems.

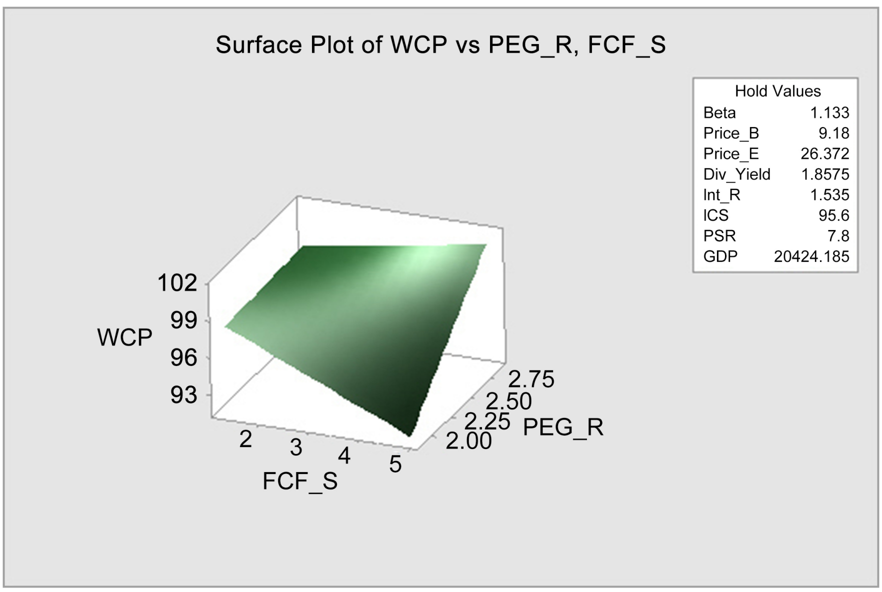

Figure 5. Surface plot: effect of *FCFS* & PEG ratio on WCP.

Therefore, comprehending the interactive relationship between Free Cash Flow per Share and the PEG Ratio, and how it influences the Weekly Closing Price (WCP), offers valuable insights.

Figure 6 illustrates the interaction between the P/B ratio and P/E ratio and their combined effect on WCP. The highest achievable WCP corresponds to maximum values of both ratios. When the P/B ratio is high but the P/E ratio is too small, the WCP falls within the dark blue region, indicating a lower WCP value.

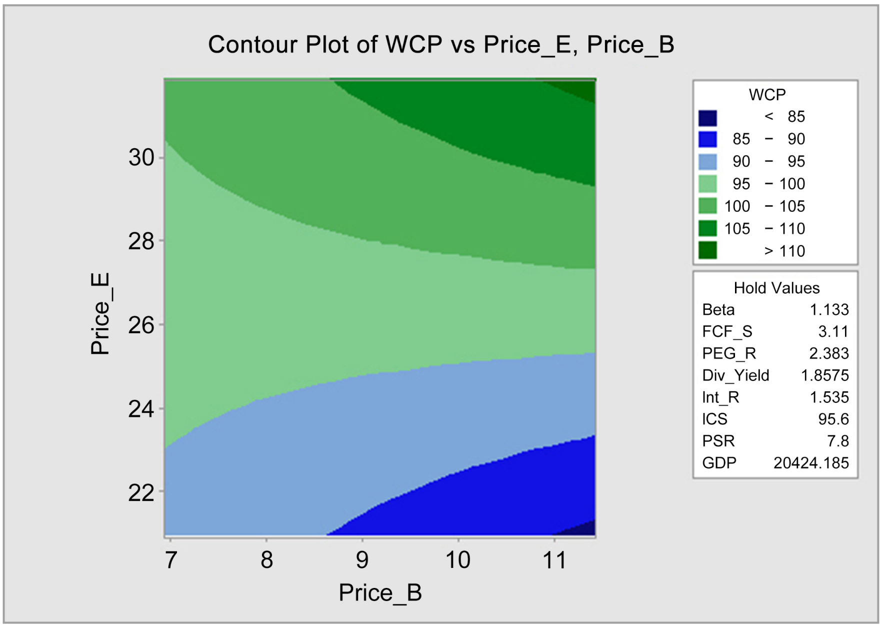

Figure 6. Contour plot: effect of P/B ratio & P/E ratio on WCP.

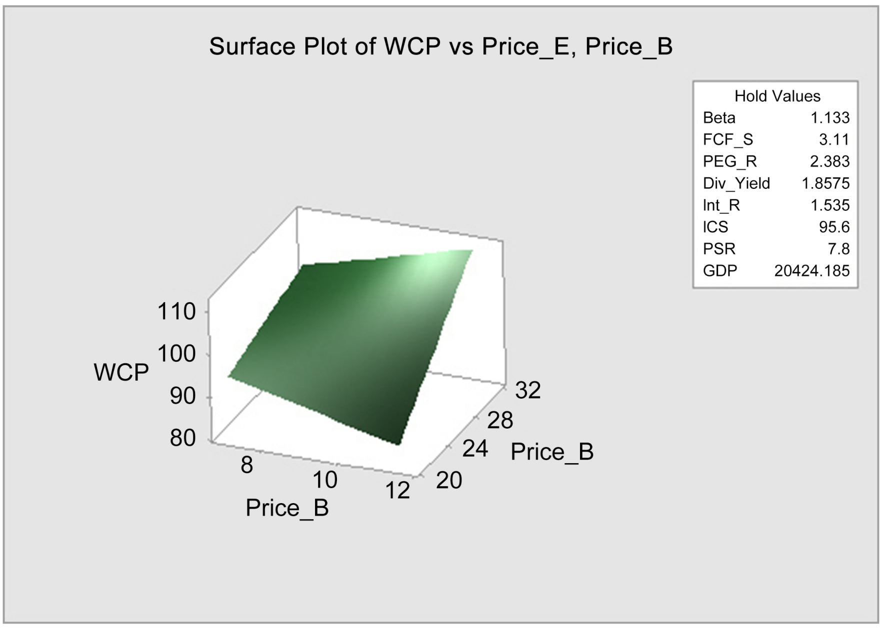

Figure 7. Surface plot: effect of P/B ratio & P/E ratio on WCP.

Similar insights can be gleaned from the surface plot in Figure 7. It's notable that even with a lower P/B ratio, a reasonably good WCP can be achieved if the P/E ratio is sufficiently higher, assuming all other indicators are held constant at their specified levels.

Figure 8 and Figure 9 depict the interaction between the P/B ratio and Dividend Yield on WCP. Both the contour and surface plots indicate that higher values of P/B ratio and lower values of Dividend Yield result in a WCP above 105, assuming other factors remain constant.

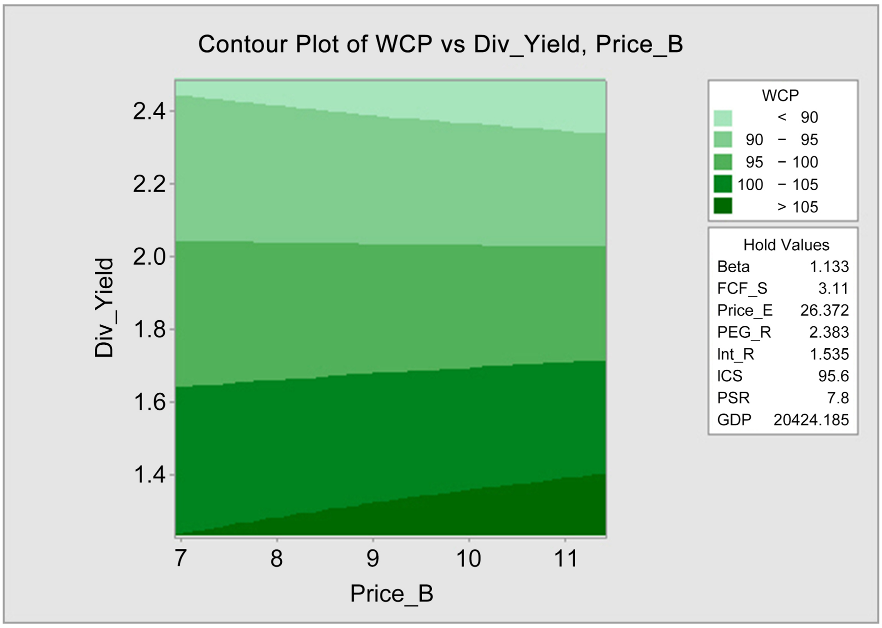

Figure 8. Contour plot: effect of P/B ratio & dividend yield on WCP.

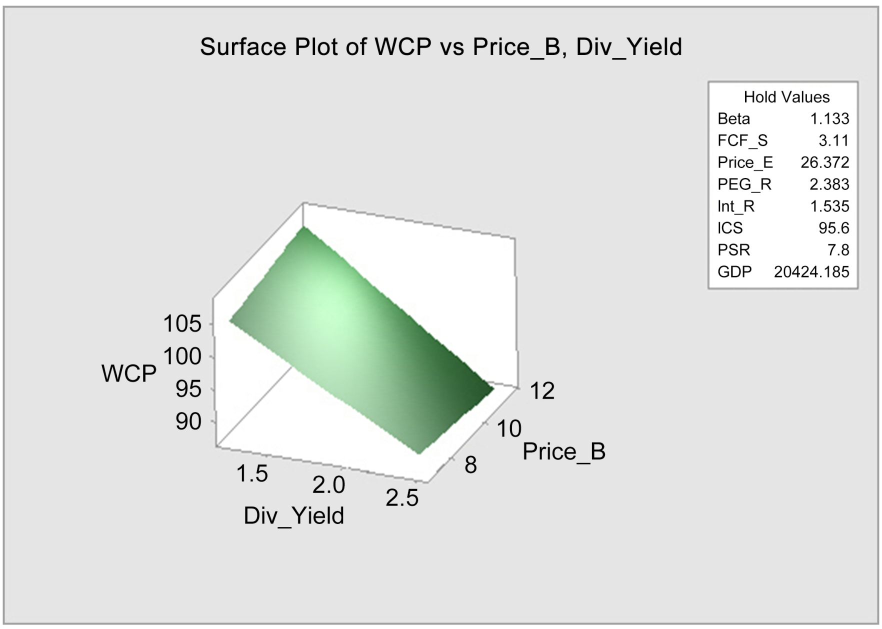

Figure 9. Surface plot: effect of P/B ratio & dividend yield on WCP.

Figure 10 illustrates the impact of PEG Ratio and Dividend Yield on WCP. According to the contour plot, maximizing WCP above 110 occurs with a PEG ratio of approximately 2.75 and a dividend yield of approximately 1%, assuming other indicators are held constant at their respective levels.

The surface plot depicted in Figure 11 provides a clearer view of how Dividend Yield and PEG Ratio influence WCP through a 3-D diagram. Optimal WCP is achieved with a low Dividend Yield and a high PEG Ratio, assuming all other indicators are held constant at specified levels.

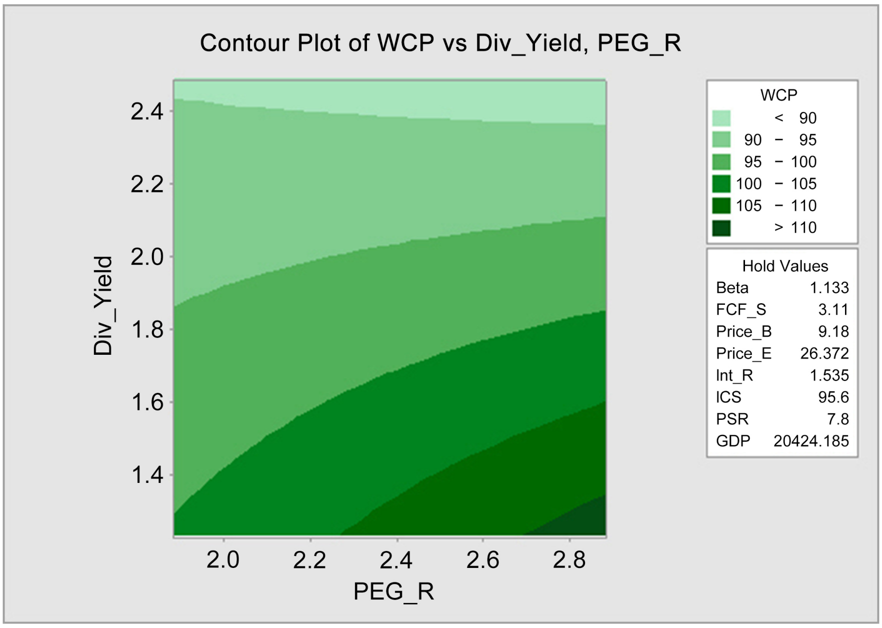

Figure 10. Contour plot: effect of PEG ratio & dividend yield on WCP.

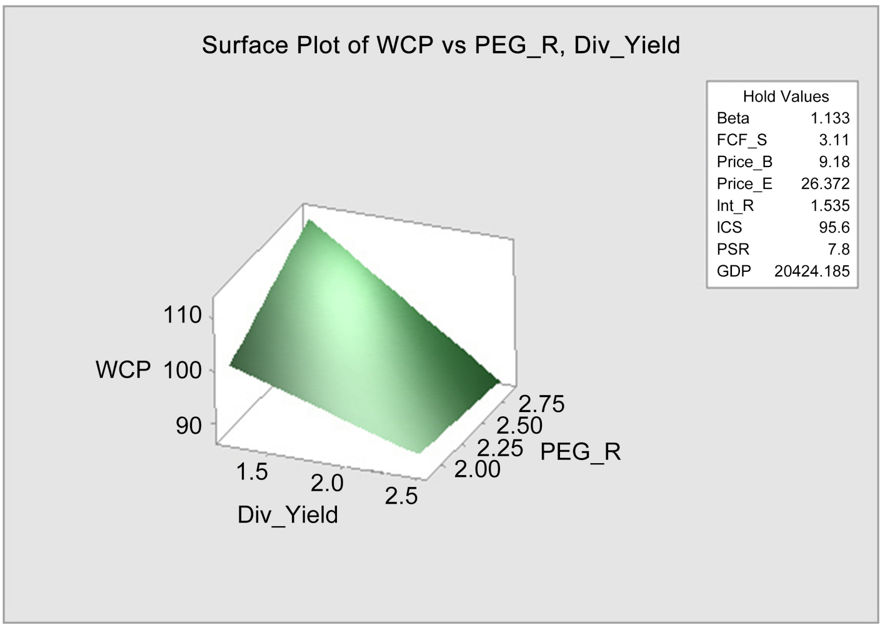

Figure 11. Surface plot: effect of PEG ratio & dividend yield on WCP.

Response surface analysis employing the desirability function approach helps establish the target response value using Equation 3. Given that the economic indicators in our predictive model are non-controllable, we constrain them within specified limits to determine the optimal values of financial indicators. This approach yields various target values for the Weekly Closing Price (WCP) of the stock. Table 4 presents the target WCP values alongside the corresponding input values of the indicators required to achieve each desired response.

Achieving the target Weekly Closing Price (WCP) of 175 is feasible by controlling the economic indicators within their specified range and adjusting the values of financial indicators accordingly, as detailed in Table 4. The 95% confidence interval and predictive interval for the target value of 175 are (164.02, 185.98) and (163.19, 186.81), respectively. The economic indicators such as Interest Rate, ICS, PSR GDP, and their interaction effects, which are not controlled in this study, are omitted from the discussions presented in this article.

Table 4. Optimal values and the desirability function.

$\widehat{WCP}$	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	$d\left(\widehat{WCP}\right)$
175	1.28	1.32	11.41	31.86	2.88	1.25	0.68	101.25	8.98	21290.1	0.999

3.3. Usefulness of the Proposed Optimized Predictive Model

The proposed optimized predictive model can be extremely useful to understand the behavior of the attributable indicators and their effect on the response indicator-"WCP" of the MSFT stock. We state some of the usefulness of the proposed optimized model using response surface analysis based on the desirability function method.

1) It maximizes our objective function-WCP, based on the given value of input financial and economic indicators.

2) It identifies the target values of the financial and economic indicators within certain range that maximizes the WCP of the stock with high degree of accuracy.

3) It also identifies the target values of the significant indicators that will maximize the WCP of the MSFT stock.

4) It produces 2-D Contour Plots and 3-D Surface Plots giving very useful visualization of the two or more indicator effects on the weekly closing price keeping other indicators fixed at a given level which are easy to interpret and understand.

5) The methodology and the procedures can be utilized to build optimized predictive model for any stock.

6) It assists investors and companies in strategic planning by elucidating the appropriate balance of financial indicators and their target values for optimizing stock prices, thereby bolstering firm returns and enhancing the perceived value of the company.

4. Conclusion

The proposed advanced predictive model, utilizing a response surface based on the desirability function approach, is highly pertinent within applied finance and economics. To the best of our knowledge, this methodology has not been previously explored in financial literature for optimizing stock prices or returns. Developed with a strong theoretical basis in statistical concepts and financial expertise, the model has undergone rigorous testing and validation, demonstrating exceptional predictive accuracy of 98.34%.

The key findings emphasized in Subsection 3.3 underscore the model's utility and distinction, serving as evidence of its singular contribution to the field of applied finance and economics. Our analysis revealed that the optimal or maximum value of the Weekly Closing Price (WCP) of the stock is 206.92 in the given time, achieving a desirability function score of 1. This finding suggests that the selected values for financial and economic indicators are highly effective in maximizing stock returns.

Moreover, we established a 95% confidence interval of (170.30, 243.50) and a prediction interval of (170.0, 243.80), which further supports the statistical significance of the optimal response point. With an R^2 of 98.34% and an adj.R^2 of 98.29%, alongside a high prediction accuracy of 98.2%, our analytical model provides robust validation. The response surface optimization process we devised enables the attainment of desired response values, offering flexibility for firms and investors to set their optimal targets and obtain corresponding risk factor values.

Understanding the interactive dynamics of financial and economic indicators is paramount for comprehending stock price fluctuations for risk mitigation and return optimization in investment. Effectively harnessing the proposed optimized predictive model empowers both MSFT stock investors and the company itself to achieve maximum returns by making well-informed investment decisions. The aforementioned procedure and methodology can effectively be applied to other individual stocks or sets of stocks to construct an optimal portfolio tailored to achieve desired returns, considering specified risk factors.

Statements and Declarations

To the best of our knowledge, this manuscript represents our original work and meets the ethical standards set by the Committee on Publication Ethics (COPE).

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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