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The Utilization of Autoregressive Forecasting Models in Strategic Management

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Abstract:
This study explores the utilization of autoregressive forecasting models in strategic management. Business forecasting denotes one of the recent developments in the business environment. The approach complements strategic management to foster the optimal performance of businesses. Business strategists use forecasting models to develop foresight on the future performance of their respective firms; however, there is limited literature on the effectiveness of these models. For this reason, this exploratory inquiry delved into generating autoregressive models and further examining their predictive effectiveness. The methods entailed the collection of secondary data (Tesla Motors Inc. revenue data) and subjecting it to univariate regression analysis to generate the linear forecasting equation. The findings revealed that autoregressive models are generated from the current and past data and can be used to forecasting future business performance. However, the accuracy of these equations relies on the quality of data and the stability of the industry. Therefore, the results of this inquiry contribute to the existing literature on forecasting models. Policy planners can use the information to improve the accuracy of their prediction models.

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1.0 Introduction

In the modern corporate world, companies are pushed to their limits in understanding their environments, adopting the best management approaches, and mobilizing adequate resources to ensure business continuity. Administrative decisions no longer focus on the intermediate needs, but the long-term strategies that would sustain a competitive edge. Studies by Makadok, Burton, and Barney (2018), Trigeorgis and Reuer (2017), and Durand, Grant, and Madsen (2017) show the essence of preliminarily adopting strategic management among corporate entities. For instance, one of the commonly agreed ideologies is that a business that uses its performance and market data to evaluate its growth is more likely to succeed in the long-term than a competitor who does not respond to performance and market dynamics. In this regard, the concept of performance forecasting has become an integral component of business strategists. According to Darin and Stellwagen (2020), business forecasting serves as a virtual lens for looking into the future of a firm; however, the choice of the most appropriate prediction model proves daunting to many managers. If a company intends to use its current and past accounts to simulate its future performance, then autoregressive prediction models become an efficient method. This performance forecasting technique generates company-specific models for estimating various performance parameters at any given time in the future (Ramyar & Kianfar, 2019; Claveria, Monte, and Torra, 2019). In other words, firms with an accurate record of their past revenue data can use autoregressive models to examine their future performance if the prevailing market conditions remain relatively constant. In this regard, the current discussion presents an exploratory inquiry into understanding the utilization of autoregressive models in strategic management. The paper consists of a literature review section that explores existing concepts, a data and methodology section that explains the data source, a results and discussion section that facilitates a scholarly presentation of the findings and relevant theory, and finally, a conclusion section that sums up the main arguments of the research.

1.1 Objectives of the Exploratory Study

The general objective of this discussion is to explore the utilization of autoregressive forecasting models in strategic management

1.2 Specific Objectives

The specific objectives of this exploratory inquiry are:

i. To explore autoregressive forecasting models as tools for predicting the future performance of businesses.
ii. To demonstrate the generation of autoregressive forecasting models using Tesla Motors Inc. annual and quarterly revenue data.
iii. To equip strategic managers with knowledge of business forecasting techniques.

2.0 Literature Review

According to Spring, Hughes, Mason, and McCaffrey (2017), the need to maintain a competitive edge is a recurrent one. Companies pursue their dream of being an indisputable leader in the market niches within which they operate. To achieve this goal, firms have been adopting strategic management techniques to bolster internal efficiency and dominance in the already highly-competitive markets. While contemporary scholarly databases are awash with publications on strategic management, less has been done to explore the utilization of and efficiency of autoregressive forecasting models among business strategists. Although a significant number of studies such as Cubadda & Guardabascio (2019), Xie (2019), and Huber and Feldkircher (2019) attempt to discuss various aspects of these models, it is still unclear how the technique ensures accuracy while minimizing bias and error. Apparently, organizations use forecasting models without the technical knowledge of how they are likely to accurately predict future performance. One of the core concerns is the ever-changing business environment (Ahmad, Masri, & Lee, 2019). Market dynamics occur at different magnitudes as determined by technological innovations and entry or exit of new and existing competitors respectively.

2.1 An Overview of Strategic Management

The concept of strategic management is widely used in modern-day business administration; nonetheless, its philosophical origins remain submersed in the growing body of literature on contemporary business management. Jelenc (2019) provides an account of the historical background of the idea of strategic business administration. The scholarly paper traces this concept back to the 20th century when the idea was in its embryonic form. Through a thorough search of the relevant literature, Jelenc (2019) develops a list of publications that featured strategic management as presented in the following table:

Table 01: Studies published in the 20th century that discussed strategic management

Author	**Year**	**Main publications**
Christensen, Berg, Salter, Stevenson	1951	*Policy Formulation and Administration*
Barnard	1956	*The Functions of the Executive*
Selznick	1957	*Leadership in Administration*
Moore	1959	*Managerial Strategies*
Chandler	1962	*Strategy and Structure*
Bilmour and Brandenburg	1962	*Anatomy of Corporate Planning*
Barnard	1962	*Organization and Management*
Tilles	1963	*How to Evaluate Corporate Strategy*
Ansoff	1965	*Corporate Strategy*
Learned, Christensen, Andrews, Guth	1965/1966	*Business Policy: Text and Cases*
Steiner	1969	*Top Management Planning*
Ackoff	1970	*A Concept of Corporate Planning*
Newman, Logan	1971	*Strategy, Policy, and Central Management*
Andrews	1971	*The Concept of Corporate Strategy*
Chandler	1977	*The Visible Hand*
Steiner	1979	*Strategic Planning, What Every Manager must Know*

With sixteen (16) research articles published, strategic management gained momentum as an important concept in business administration. Evidently, scholars in the 20th century developed the strategic management concept as a role for the top business administrators, a component of corporate planning, and a tool for determining the future of businesses (Bindra, Parameswar, and Dhir, 2019). This literature is in line with studies by Boone, Lokshin, Guenter, and Belderbos (2019), Demir, Wennberg, and McKelvie (2017), Bergh, Sharp, Aguinis, and Li (2017), and Zhao, Fisher, Lounsbury, and Miller (2017) that place the executive management at the center of strategic planning. The results of these research articles highlight top managers as integral components for foreseeing the future of businesses and charting the strategies for achieving long-term competitiveness. Therefore, strategic management encompasses the role of the executive management in setting company goals, mobilizing necessary resources, developing policies and plans for future growth, adopting the best leadership approach to achieve the set goals (George, Walker, & Monster, 2019).

Figure 01: The concept of strategic management

2.2 Business Forecasting

Business forecasting has been under development for centuries. In accordance with a study by Makridakis, Spiliotis, and Assimakopoulos (2018), "forecasting dates back to 1964 but did not achieve much follow-up until the technique of backpropagation was introduced almost 20 years later" (p.3). This finding presents the art of prediction as a multi-decadal effort to understand the future amid numerous uncertainties. At the core of business continuity are forecasting techniques that assist managers in predicting the future status of their firms. Business forecasting denotes the use of quantitative and qualitative mechanisms to envisage future company performance from past and current data. Various studies have been published with discussions about the various business forecasting methods. Boratyńska and Grzegorzewska (2018) present a study on the quantitative and qualitative business prediction models. The findings reveal that the regression analysis method is an equally important strategy for creating future insights into business performance. Through this approach, businesses develop a tentative idea of the strategies required to maintain competitiveness across a selected timeframe.

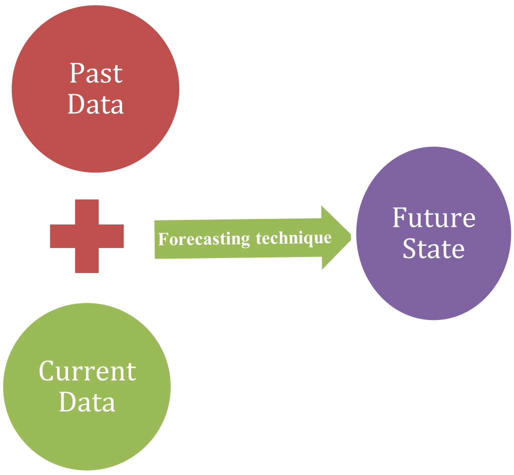

Figure 02: A conceptualized universal model of business forecasting techniques

The outcomes of a forecasting effort can be placed in three broad categories: sustainable, unsustainable, and indeterminate. A sustainable company future is characterized by the accurate use of validated data to predict growth; otherwise, it is unsustainable if the outcome of the prediction suggests a future decline in value or market share (Kumar, Shankar, and Aljohani, 2020; Lee, 2021). Also, the future may be indeterminate if the input data is invalid. The outcome of such predictions reflects the errors in the forecasting process or the input data per se (Taylor & Letham, 2018). These results authenticate the need for proper data screening and the choice of appropriate forecasting technique. As a remedy, data screening allows business analysts to input correct values that reflect accurate prediction results (Petropoulos, Kourentzes, Nikolopoulos, and Siemsen, 2018). Similarly, the choice of the most appropriate forecasting model optimizes the chances of generating the desired output.

2.3 Business Forecasting in Strategic Management

Business forecasting serves a pivotal role in providing insights into the future of a corporate entity. As Chase (2017) argues, predicting the future of a company bridges the gap between the current and future resource demands. One core purpose of strategic management is to assess the requirements for success. This duty commits business strategists to determine financial, physical, human, and technological resource needs to form the basis for developing business strategies (Teece, 2017). Universally, future business strategies are formulated based on the analysis of patterns in historical and current data. As a result, Shujahat, Hussain, Javed, Malik, Thurasamy, and Ali (2017) describe business forecasting tools as indispensable in strategic management practice. Since the latter focuses on understanding the future performance of a company, then forecasting helps in creating models for determining the performance status at any given time.

2.3.1 Autoregressive Forecasting Model

The use of statistics in business analytics has a long history. In modern corporate environments. Business strategists are not only interested in the past and present data but also in the future performance of their companies. One of the commonly used techniques is the autoregressive prediction model. By definition, autoregressive forecasting entails the development of a linear model using past and current data (Liu, Tseng, & Tseng, 2018; Arora & Taylor, 2018). The resultant equation is used to predict the future performance state by determining the input values corresponding to a given instantaneous time. The universal equation of an autoregressive model is shown below:

$Y=bX+k$ ……………………………………………………………………………....Equation 1

Where Y is the dependent variable, X is the explanatory variable, b is a coefficient obtained after optimizing the model, and c is the intercept.

For businesses to apply the autoregressive model, quantitative data should be available to serve as the input. Most of the firms that use this prediction technique adopt the time-series version. In other words, the business strategists compare changes in a given variable, such as the revenue from product deliveries, with time (Fattah, Ezzine, Aman, El Moussami, & Lachhab, 2018). This process creates an impression of the company’s performance from the past to the current. Consequently, the patterns deduced from the time-series analysis are extrapolated into the future to depict the expected trends if no disruptive events change the firm or industry.

2.3.1.1 Effectiveness of Autoregressive Models in Business Forecasting

The use of autoregressive forecasting models balances between its strengths and weaknesses. These models are important tools for informing decision-makers about the tentative need for resource acquisition and mobilization (Verma & Sharma, 2017). To illustrate this, a study by Wang, Shen, and Jiang, (2019) used to compare the real and predicted values. The research inquiry examined the effectiveness of an autoregressive model in predicting future cases of hemorrhagic fever with renal syndrome in China.

The results showed the power of autoregressive models in predicting the future; however, a significant margin of error exists since the forecasted value does not numerically match the actual figure. For instance, even though the model predicted that 843 cases will be recorded in the month of January, the actual figure was 1180. A relative error of 28.56% separates the actual and forecasted values. Despite being applied in the healthcare domain, the outcome of the autoregressive model can also be replicated in the business world. Managers rely upon the near-perfect accuracy of these forecasting models to determine the future needs and status of their businesses (Taylor & Letham, 2018). In contrast, the linearity of autoregressive models makes them insensitive to changes in the business environment. The statistical difference between the actual and forecasted values reveals the level of accuracy of the prediction model. Evidently, the disparities between the two values may be attributable to the inability of linear autoregressive models to incorporate unforeseeable changes in the business world. For instance, internal variations such as changes in the financial, human, and technological resources may affect the future performance of a company (Popovič, Hackney, Tassabehji, & Castelli, 2018; Prakash, Jha, Prasad, & Singh, 2017; Haseeb, Hussain, Kot, Androniceanu, & Jermsittiparsert, 2019). Equally, external changes such as reforms in the legal aspects of business governance and entry or exit of competitors can influence business performance (Demingo & Herder, 2020; Downing, 2018). The inability of these models to foresee and incorporate industry dynamics compromises their efficiency in predicting the future state of affairs for companies. Therefore, one of the weaknesses of the linear autoregressive models is the lack of flexibility to intervening changes in the business environment.

3.0 Data and Methodology

The research aimed at exploring the utilization of autoregressive forecasting models in strategic management. Owing to their widespread use in the corporate world, a need arises to examine their accuracy in predicting the future scenarios of companies. To achieve this goal, this study obtained the annual and quarterly revenue data for Tesla Motors as presented on the Macrotrends website. The data set for Tesla Motors' annual and quarterly revenue was recorded between 2008 and 2020 and 2010 and 2020 respectively. Further, data validation was done by comparing the values with a report of the National Association of Securities Dealers Automated Quotations (NASDAQ). The comparative endeavor confirmed the consistency of data on both platforms.

4.0 Results and Discussion

4.1 Results

The results present the outcomes of the autoregression process during which the linear forecast models were generated.

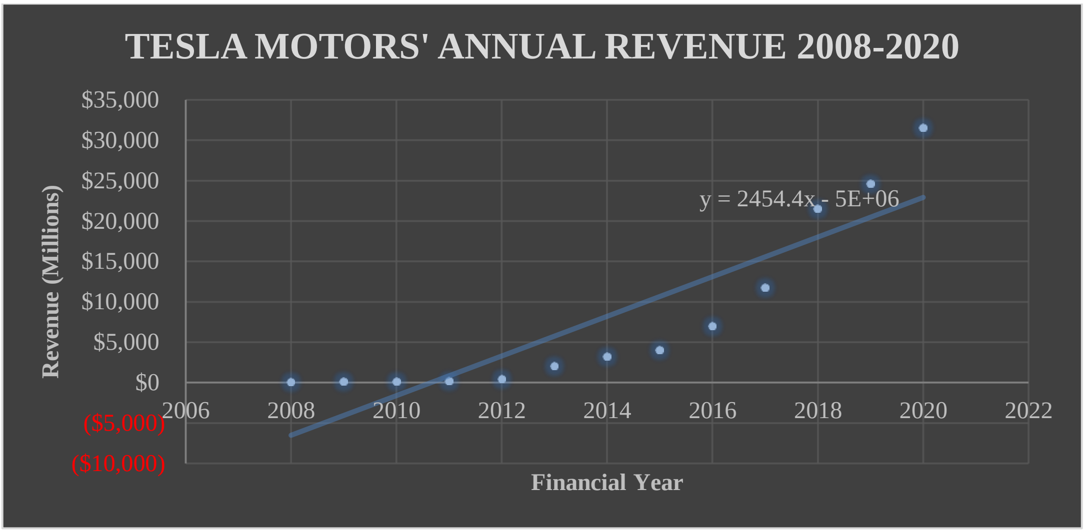

Figure 03: A presentation of Tesla Motors' Annual Revenue and linear forecast model between financial years 2008 and 2020

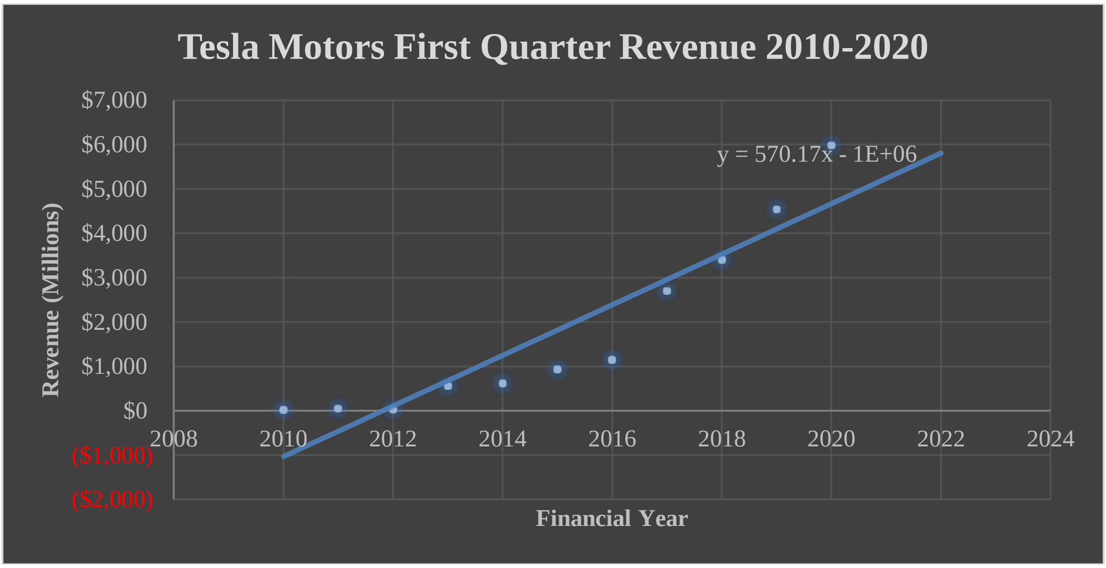

Figure 04: A presentation of Tesla Motors' interannual first-quarter revenue and linear forecast model between financial years 2010 and 2020

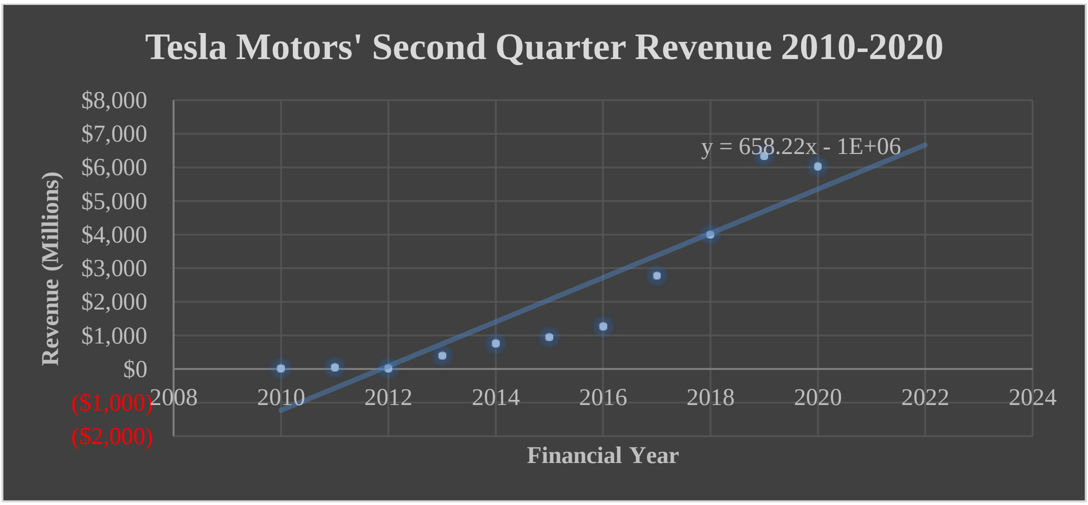

Figure 05: A presentation of Tesla Motors' interannual second-quarter revenue and linear forecast model between financial years 2010 and 2020

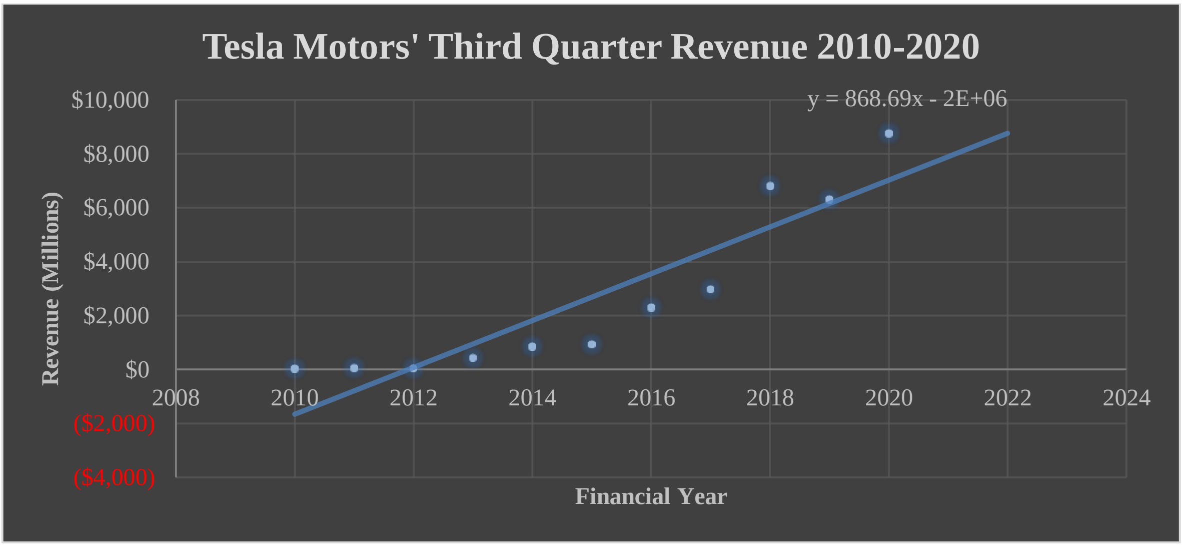

Figure 06: A presentation of Tesla Motors' interannual third-quarter revenue and linear forecast model between financial years 2010 and 2020.

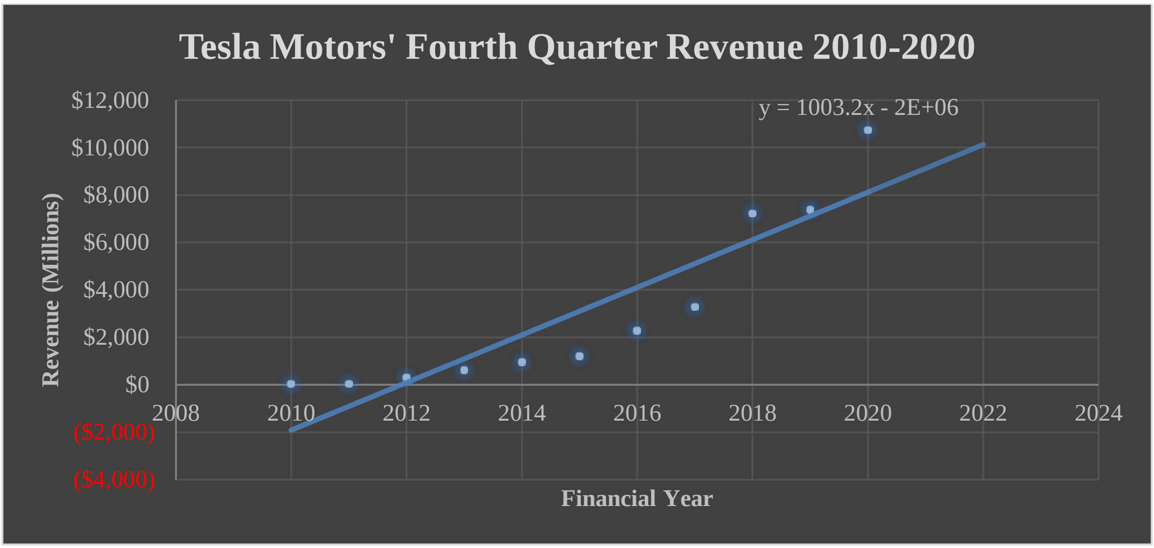

Figure 07: A presentation of Tesla Motors' interannual fourth-quarter revenue and linear forecast model between financial years 2010 and 2020.

4.2 Discussion

Autoregressive forecast models are derived from historical data. In this case, the study relied on Tesla Motors' annual and quarterly data collected between 2009 and 2020. Theoretically, autoregressive models are presented as the equations of the lines of best fit in a regressive scatter plot (Banihabib, Bandari, & Peralta, 2019). This study explored the changes in Tesla Motors' revenue across twelve financial years. The following linear forecast models were derived from the data:

Autoregressive linear forecast model for Tesla Motors' annual revenue

y = 2454.4x - 5E+06……………………………………………………………….Equation 2

Autoregressive linear forecast model for Tesla Motors' interannual first-quarter revenue

y = 570.17x - 1E+06…………………………………………………………………..Equation 3

Autoregressive linear forecast model for Tesla Motors' interannual second-quarter revenue

y = 658.22x - 1E+06…………………………………………………………………..Equation 4

Autoregressive linear forecast model for Tesla Motors' interannual third-quarter revenue

y = 868.69x - 2E+06…………………………………………………………………..Equation 5

Autoregressive linear forecast model for Tesla Motors' interannual fourth-quarter revenue

y = 1003.2x - 2E+06…………………………………………………………………..Equation 6

Based on the above models, Tesla Motors has been achieving a cumulative growth in revenue gained at the quarterly and annual intervals. Furthermore, figures 03, 04, 05, 06, and 07 demonstrate that the company expects a further increase in profits in the following financial years. The linear forecast models can be extrapolated to provide an estimate of the value of revenue at any point in the future (Rabinowicz, & Rosset, 2020; Harshinei, 2020). Business strategists at Tesla Motors can use the available revenue data to estimate their future value. Equation 2 presents the linear autoregressive model for forecasting the company's future annual revenue. In practice, these models provide a tentative estimation depending on the dynamics of the industry. In this regard, the reliability of linear autoregressive models depends on two principal factors- the accuracy of historical data used to create the model and the stability of the industry and the market. According to Büyükşahin and Ertekin (2019), wrong input data creates misleading patterns. As a result, the observed trends cannot be used to accurately predict a company's future performance. Similarly, forecasting models perform best in relatively stable industries. In industrial sectors where the effects of the dynamic global business environment are infinitesimal, a company can solely rely on a single model to predict its long-term performance.

4.2.1 Causes of Unreliability of Revenue Forecasting Models

Operational serenity in the corporate environment is almost illusionary since nearly all local and international markets are affected by changes in consumer tastes and preferences (Paddock, 2017), entrance and exit of competitors (Chan, Chen, & Wang, 2019), availability of substitutes (Lee, Fox, & Nayga, 2019), technology (Nasiri, Rantala, Ukko, & Rantanen, 2018), and new legislation (Gaganis, Pasiouras, & Voulgari, 2019). Equally, internal company operations may be affected by changes in the financial power (Hieu & Nwachukwu, 2020), client bases (Theodos, Stacy, & Daniels, 2018), employee turnover rate (Sun & Wang, 2017), individual employee productivity (Gubler, Larkin, & Pierce, 2018), use of technology (Ilcus, 2018), or a change in the company's goal (Sull & Sull, 2018).

4.2.1.1 Changes in Consumer Tastes and Preferences

One of the goals of strategic management is to align business operations with the changes in the industry. Deliu (2019) describes this approach as pivotal in ensuring the resilience and continuity of businesses. Consumer tastes and preferences are the like or dislike that customers develop based on the utility of the purchased goods and services (Meagher, Wong, & Zauner, 2020). Since this parameter depends on individual perceptions of a particular product, it is likely to fluctuate with time. A negative change in the preference for a product, say Tesla Motors' car models, results in a corresponding decline in both quarterly and annual revenues for the company (Osharin & Verbus, 2018). Therefore, the way customers perceive a product determines its preferences over other competing brands. A company may not rely on linear autoregressive forecasting models for its long-term prediction since such changes result in a significant shift in market share and profitability.

4.2.1.2 Entrance and Exit of Competitors

Business forecasting models are developed after the determination of the average influence of factors operating internally or in the market. New entrants into an industry trigger dynamism in consumer bargaining power and product competition (Beladi & Mukherjee, 2017; Sheikh, 2018). Consequently, an influential entrant may encroach the competitor's market share and shift customer loyalty hence leading to low revenue generation. By contrast, the exit of a competitor increases the client base for the surviving firms (Stef & Zenou, 2021; Lieberman, Lee, & Folta, 2017). This new scenario allows strategically effective companies to increase revenue generation by tapping into the new customers. These changes in the market impair the accuracy of a forecasting model to predict future corporate performance for business strategists.

4.2.1.3 Technological Changes

Changes in technology have been identified as one of the principal causes of industrial dynamism (Chen, Zeng, Lin, & Ma, 2017). The reference to the term "industry" means that technological changes can occur either within a company or in the external business environment. Technological advancements bolster a firm's internal production capacity and activity in the market; therefore, the shift in production and market operations cause a corresponding alteration of the long-term historical trends (Nakamura, Kaihatsu, & Yagi, 2019). The outcome is the development of new patterns of production and sale whose salient characteristics may not be forecasted using a pre-existing prediction model.

4.2.1.4 Changes in the Legal Landscape

Business operations are usually governed by specialized laws. Whether applying at the local or international level, changes within the legal environment can influence the performance of a company (Blakyta, Matusova, Lanovska, & Adamenko, 2017). In the case of Tesla Motors, a change in favor of the company's car production and marketing processes would trigger an increase in market dominance and growth. Conversely, punitive laws may hinder operational growth hence undermining revenue generation. For this reason, new legislation disrupts patterns of performance hence rendering historical forecasting models obsolete. Equation 2 and figure 03 demonstrate this aspect clearly. Although prediction models may lose accuracy due to a multiplicity of factors, Tesla Motors' supernormal annual profit for 2020 is attributable to changes in the legal environment in favor of green technologies (Newell, Pizer, & Raimi, 2019). Based on the model, Tesla Motors' predicted annual revenue for the financial year 2020 was $20, 000; however, the actual revenue recorded in the year was $24,578. This disparity proves that the higher actual revenue could be attributable to the favorable green technology law in the United States of America and globally.

4.2.1.5 Changes in the Company's Financial Power

Financial resources form part of the indispensable inputs for company growth. A decline in the financial resource base impairs a firm's ability to sustain or increase its production (Ivanenko, Hrushko, & Frantsuz, 2018). In a similar way, an increase in the financial endowment of a company bolsters its resilience in the prevailing market forces (Mzid, Khachlouf, & Soparnot, 2019). Consequently, changes in the financial power of a firm undermine the predictability of its future performance.

4.2.1.6 Employee Turnover Rate and Productivity

Employee turnover denotes the rate at which workers leave an organization within a given timeframe (Lee, 2019; Grotto, Hyland, Caputo, & Semedo, 2017). The voluntary resignation or dismissal of employees causes a change in the production patterns of a company. This trend is accompanied by the exit of skilled and experienced personnel that affects the overall productivity of employees (Kurniawaty, Ramly, & Ramlawati, 2019). In the case of Tesla Motors, a revenue forecasting model may not be effective in the long-term due to the recurrent changes in the company's workforce. These fluctuations trigger a corresponding change in revenue generated within a given timeframe.

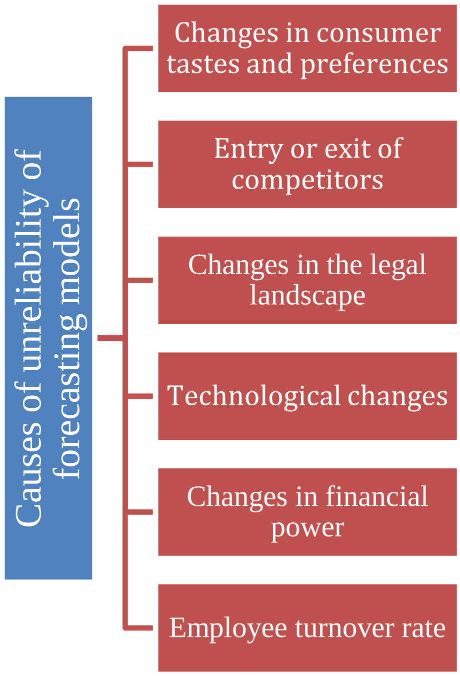

Figure 08: A summary of the factors affecting the long-term reliability of business forecasting models

4.3 An Ideal Forecasting Model for Strategic Management

Upon realizing that the stability of the business environment depends on a multiplicity of factors, the new challenge for business strategists is to create a responsive and inclusive framework. This approach enables forecasts to be made based on all elements that may potentially or actively influence the future operations of a company. Thus, an in-depth internal and external research is necessary to identify these elements. Next, a multiple linear regression is developed to predict future performance by incorporating all relevant factors. As Hesamian & Akbari (2020) note, the multiple regression model is universally presented as:

$Y= b_1x_1 + b_2x_2 + \ldots + b_nx_n + c$ ....Equation 7

Where: Y is the dependent element; x_1, $x_2 \ldots x_n$ are the explanatory elements, b_1, $b_2 \ldots b_n$ are coefficients and c is the intercept.

In the context of Tesla Motors, the universal multi-variate model can be customized to include quantitative parameters that affect its revenue generation. For instance, assuming that Y is the amount of revenue that the company records within a given financial year, some of the explanatory variables would be employee turnover, legal fees, production cost, overhead costs, and service fees. Nevertheless, these variables must be reviewed occasionally to determine their relevance in the equation and the possibility of additional influential factors (Van der Kamp, Lorentzen, & Mattingly, 2017). If the selection of the explanatory variables is conducted diligently, then the predictive efficiency of the multi-variate autoregressive model increases substantially. Despite this, the quality of data remains a prioritized parameter. A multiple regression forecasting model would be accurate if the data collected is consistent and valid; otherwise, data gaps would compromise the determination of the actual historical performance patterns. Although Shahzad, Rehman, and Ahmed (2017) suggest the use of various data filling techniques such as the mean arithmetic method, such approaches have some degree of bias and may ultimately undermine the efficacy of the generated model.

5.0 Conclusion and Policy Implications

Strategic management has been in practice for centuries. Alongside this new administration style is the need for effective methods of informing current and future decisions. Since the 20th century, business scholars have been to improve corporate management through revolutionary techniques one of which is business forecasting. A growing body of literature describes business forecasting as an integral tool for strategizing future business performance. However, historical data is a prerequisite to an effective prediction. Autoregressive forecasting models are part of the large spectrum of techniques for empirically looking into the future of businesses. Being data-driven, these models necessitate the use of relevant quantitative data. The featured case of Tesla Motors demonstrates the varying predictive efficiencies of autoregressive models. While policy planners may have other options for determining the future of their businesses, empirical models are inevitable in such processes. Depending on the availability of data, the policymakers can develop either simple or multivariate autoregressive models. The former relies on a single explanatory variable, strategic managers can use such models to generate short-term forecasts; however, the outcome could be significantly biased due to the failure to include other determinant factors. This problem is solvable if policy planners develop the multi-variate version of predictive models. These forecasting tools incorporate all noticeable explanatory variables. Furthermore, the models are customizable with regard to the specific influential factors in a particular company. Thus, business strategists can choose a multiple autoregressive model for its improved forecasting reliability and flexibility.

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