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Assessing Financial Performance of Tech Enterprises Blending Machine Learning Techniques

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ABSTRACT
In this study, the objective is developing a holistic research model for evaluating Tech business performance by blending machine learning techniques with well-known financial instruments such as Dupont Analysis. Systematic literature review of high-quality journals has helped formed the backbone of this research work. The dependent variable are Return on Equity and Return on Assets. The technique used will be a Machine Learning model using financial data from esteemed databases such as Eikon Refinitiv. The objective is to develop a predictive model utilizing machine learning approach that can analyse and visualize financial performance of tech companies from similar domains using Cluster Analysis. The design of our research model would be such that it is more practical in scope. The proposed model would be put forth as a decision support system for investors wishing to understand the companies better before investing.

Keywords: Firm performance, Cluster Analysis, Dupont Analysis

1. Introduction

Following the post-pandemic tech boom in 2021, there has been a significant market recalibration. The tech stock downturn in 2022 amidst rising inflation and interest rates, led to a shift of investor sentiment towards traditional investments (Hammond,2024). Even industry giants faced unprecedented challenges with their investment choices. This has emphasized the need for more robust assessment of financial and market performance of technology companies, integrating additional variables and leveraging advanced methods.This study proposes the development of a more holistic research model for evaluating tech business, incorporating advancements with machine learning techniques. Behl (2020) and Sezer et al. (2020) highlight such methodologies represent a growing trend in research. Potential investors seek detailed insights into identifying high-tech companies are suitable for investment and understanding which organizations are poised to profit on emerging marketing trends. Hence, this study aims to provide entrepreneurs and investors with an analytic framework to evaluate technology businesses and make sound investment decisions. Venture capital (VC) funds make investments in businesses with the intention of achieving substantial returns on their investments and long-term expansion. A Startup, being human institutions designed to create new product or services, attract lot of VC attention (Ries ,2011). However, the risks are high: 9 out of 10 startups fail, and over 75% of VC firms lose money (Picken, 2017). A business performance prediction model could help VC firms perform better. A study by Harris et al. (2014) found that venture capital funds performed poorly in the S&P 500 index in the 2000s, even though they typically provide a favourable return on investment. Finding organizations that might be bound to succeed is a critical test. We can see that the institutional setting matters in a transition economy from fossil derivatives to knowledge and tech-based economies. The study utilizes modern techniques to develop quantitative models of business performance. The focus will be on tech businesses, which enables national economies to flourish along with prosperity and technology competitiveness.5-year (from years 2018-23) financial information is analysed utilizing Refintiv Eikon Codebook. Refinitiv Eikon previously known as Thomson Reuters Financial & Risk is a cloud-based development environment based on Python Jupyter open-sourced technology. Hence, the researcher can build financial models with large datasets.

Dupont analysis is the method used here to evaluate financial data and is still considered an effective instrument especially for comparing companies in similar industry domains (Soliman, 2008). This method was consistently seen been used to evaluate companies across the years. Many studies on comparative company analysis, such as Panigrahi & Vachhani (2021) and Chang et al. (2014), have used this Dupont approach for automotive and health care, respectively. Machine learning method Clustering Technique will be used to categorize these companies and visualize the analysis.

2. Literature Review:

The literature review provides a current research overview on the topic, highlighting the gaps in the literature that the current study aims to address and this study builds upon such reviews to outline its specific contributions.

2.1 Revisiting the Modigliani and Miller (M&M) Theory

The Modigliani and Miller (M&M) Theory provides two fundamental principles regarding a firm's valuation

1. Capital Structure Irrelevance: According to M&M, the value of a firm is unaffected by the mix of debt and equity it employs. This principle assumes there are no taxes, bankruptcy costs, agency costs, and that information is freely available to all investors. Essentially, the theory suggests that it is the underlying business and its ability to generate revenue that determines a firm's value, not how that business is financed.

2. Dividend Policy Irrelevance: Similarly, M&M argue that a firm's value is not influenced by its dividend policy. This implies that whether a firm decides to distribute profits as dividends or reinvest them into the business should have no impact on its overall valuation. (Modigliani & Miller, 1958)

2.2 DuPont Analysis

The DuPont Analysis, developed by the DuPont Corporation, splits Return on Equity (ROE) into three key components:

- **Profit Margin (NPM)**: Measures the profit generated from sales.
- **Asset Turnover (ATR)**: Assesses the efficiency of asset utilization to generate revenue.
- **Equity Multiplier (EM)**: Evaluates the impact of financial leverage on ROE. *(Alotaibi, 2016; Amir & Kama, 2005)*

Although developed in 1919, DuPont Analysis remains one of the simplest and most effective methods for studying financial ratios and their changes over time. Since it incorporates data from both the balance sheet and income statement, it provides a comprehensive view but may be considered complex. ROE, the primary variable in DuPont Analysis, is a strong predictor of financial health and wealth. Professionals widely use this methodology for financial ratio analysis. *(Panigrahi & Vachhani, 2021; Herciu & Ogrean, 2017)*

Regression models based on DuPont components will be developed for this study as follows:
Return on Asset, $ROA\_it = β0\_it+ β1NPM\_it + β2ATR\_it + μit$ (1)
Return on equity $ROE\_it = β0\_it+ β1NPM\_it + β2ATR\_it + β3\ EM\_it + μit$ (2

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Each component contributes uniquely to financial performance

- **Net Profit Margin (NPM)** indicates a firm's profitability and its ability to manage costs effectively. *(Moro-Visconti, 2022)*
- **Asset Turnover Ratio (ATR)** shows efficiency of asset utilization to generate revenue. *(Welc, 2022)*
- **Equity Multiplier (EM)** reflects the degree of financial leverage, impacting ROE. *(Welc, 2020)*

The DuPont model is widely recognized for evaluating management efficiency across profit generation, asset utilization, and financial leverage. A company achieves high ROE through:

- Strong profit margins,
- Effective asset utilization, and
- Optimal use of financial leverage. *(Welc, 2022)*

However, financial leverage also introduces risks, especially under rising interest rates or declining returns, which must be carefully managed. *(Arhinful & Mehrshad Radmehr, 2023)*

2.3 Juxtaposing DuPont Analysis with M&M Theory

While the M&M Theory offers a theoretical framework for understanding the irrelevance of capital structure and dividend policy in firm valuation, the DuPont Analysis provides a practical approach to evaluating financial outcomes. By breaking down ROE into operational components, DuPont Analysis bridges the gap between theory and real-world financial decisions. This study leverages DuPont Analysis to provide empirical insights into the practical implications of financial leverage and operational efficiency, contrasting and complementing the theoretical principles of M&M.

2.4 Choosing EV/FCF as a Market Multiple

Enterprise Value to Free Cash Flow (EV/FCF) is selected as the preferred market multiple for this study. Compared to traditional multiples like P/E or EV/EBITDA, EV/FCF offers distinct advantages, especially for capital-intensive sectors like technology:

1. It accounts for required capital expenditures, offering a realistic view of cash generation.
2. FCF reflects a company's cash-generating capacity under various economic conditions.
3. EV/FCF facilitates comparisons across differently leveraged companies, aligning with DuPont's focus on leverage impacts. *(Fazzini, 2018)*

2.5 K-Means Clustering is an unsupervised machine learning technique, is used to classify tech companies into distinct clusters based on selected metrics. This method is effective for grouping stocks and companies by similarity. *(Dzuba & Krylov, 2021; Ketchen Jr. & Shook, 1996)*
The below table shows the current application of K-means clustering in financial markets

Table 1: Application of cluster analysis for financial markets as seen from Literature Review

Author(s) /Year	Research findings	Method
Affonso et al., 2020	KMeans and other machine learning technique are beneficial for financial analysis	KMeans Clustering, RNN (recurrent neural networks), LSTM (Long Short-Term Memory)
Bini &	KMeans Clustering was effective	KMeans Clustering ,EM

Mathew, 2016	as seen in recent studies for classification of stocks compare to other classifiers such	(Expectation Maximization), Hierarchical technique, and DBSCAN (Density-Based Spatial Clustering of Applications with Noise)
Dzuba & Krylov, 2021	Elbow method for determining number of clusters	K-Means Clustering
Han & Li, 2019	K-Means an effective method for optimized data testing	Fast Global K-means optimization algorithm based on neighborhood screening. Use of Mahalanobis distance for global data consideration.
Ketchen Jr. & Shook, 1996	Elbow method for determining number of clusters	K-Means Clustering
Nanda et al., 2010	K means outperforms other clustering	KMmeans, SOM (Self-Organization Map), Fuzzy C-means
Zuhroh et al., 2021	K clustering revealed stock prices correlation with monetary policy and macroeconomic conditions.	K-Means Clustering

3.Methodology:

. This research study analyses the financial performance of 50 technology companies over a five-year period (2018–2023) using financial information retrieved from the **Refinitiv Eikon Codebook**. The below research model employs the **K-Means clustering method** to categorize companies based on market metrics. Following this, **DuPont financial analysis** is applied, and regression is conducted to investigate the relation between financial performance and market metrics.

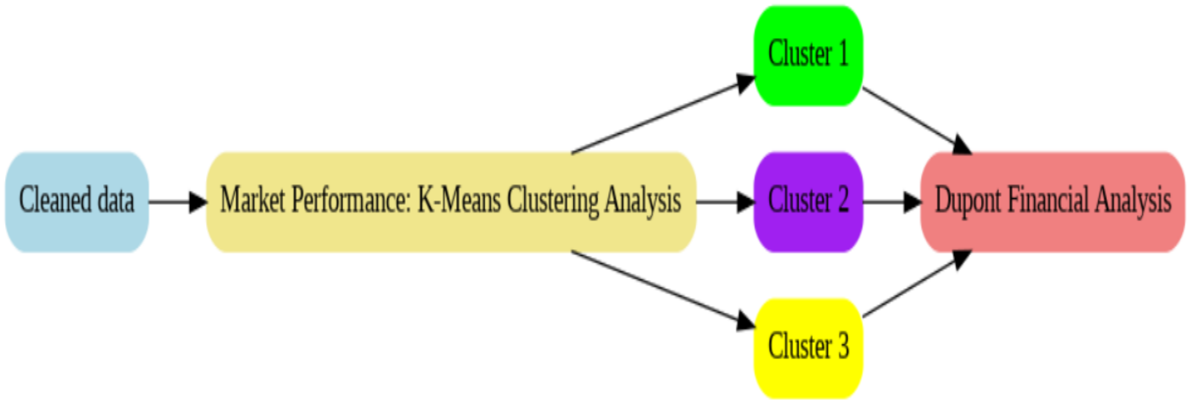


Fig1 :Research Model

Source: The researcher's data analysis

The study analyses financial data from 2018 to 2024 using the Refinitiv Eikon Codebook, a cloud-based development platform built on Python and Jupyter open-source technology. The DuPont analysis has proven effective in industries like automotive (Panigrahi & Vachhani, 2021) and healthcare (Chang et al., 2014). In this study, clustering techniques from machine learning complement the DuPont framework, helping to cluster companies and uncover patterns traditional methods might fail to capture, providing a more nuanced view of company performance across sectors.

3.3 Dataset

Data was taken from 84 selected technology companies from U.S. and European, from diverse sub-sectors such as automotive, hardware, internet, and energy domains.

Data Preparation

The financial data was cleaned and normalized, with outliers, identified using the MARVAL metric (EV/FCF to stock price deviation from the DCF model) have been excluded if they exceed 1.5 × IQR from the first or third quartile.

Table 2: Descriptive Statistics of DuPont Components

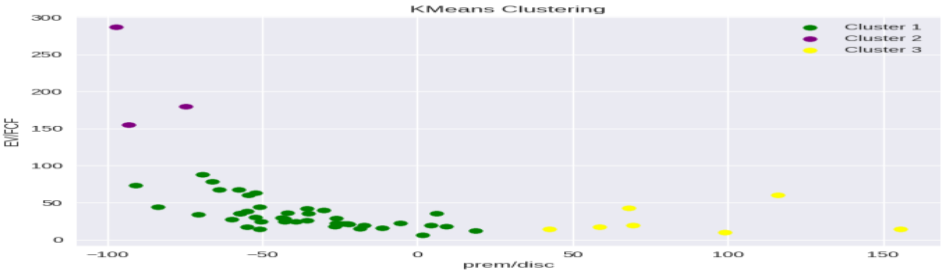
Variable	Count	Mean	Min	Max	Std. Deviation
NPM	251	9.71	-65.25	44.75	15.20
ATR	251	0.894	0.198	2.745	0.485
EM	251	3.73	1.10	58.35	4.64
ROA	251	7.28	-33.84	35.14	9.80
ROE	251	16.62	-373.29	261.58	46.36

Table 3: Pearson Correlation Analysis

Variable	NPM	ATR	EM	ROA	ROE
NPM	1.000	-0.191 (p=0.0024)	-0.240 (p=0.001)	0.889 (p=0.01)	0.604 (p=0.01)
ATR	-0.191 (p=0.0024)	1.000	-0.050 (p=0.4315)	-0.014 (p=0.8312)	0.063 (p=0.3216)
EM	-0.240 (p=0.001)	-0.050 (p=0.4315)	1.000	-0.233 (p=0.02)	-0.452 (p=0.001)
ROA	0.889 (p=0.01)	-0.014 (p=0.8312)	-0.233 (p=0.02)	1.000	0.698 (p=0.01)
ROE	0.604 (p=0.01)	0.063 (p=0.3216)	-0.452 (p=0.001)	0.698 (p=0.001)	1.000

4. Results and Discussion:

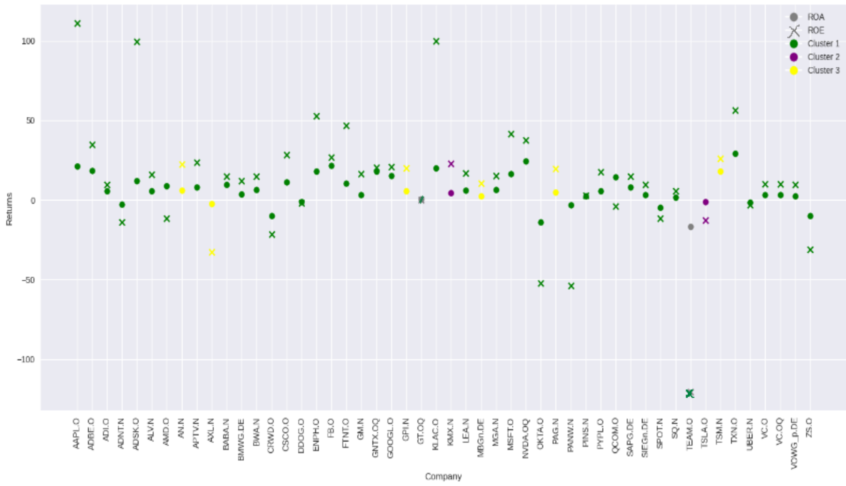
The developed hybrid model categorises selected tech companies into 3 groups based on the ratio of EV/FCF to premium-discount ratio, with Cluster 1(highlighted as Green) includes companies like Microsoft, Alphabet and Cisco, which exhibit stable growth for moderate to high ROA and ROE. Others in the same cluster, such as Netflix, Spotify, and Uber, show higher growth with increased risk. Cluster 2 (purple) has companies such as Tesla, characterised by high financial leverage and elevated EV/FCF ratios. Tesla exemplifies this characteristic being a high growth company that carries considerable financial risk as well. Cluster 3 (Yellow) has Daimler AG and Palo Alto networks which have lower EV/FCF ratios , suggesting possibility of undervaluation if ROA/ROE are in acceptable range.



Plot 1 K-Means Clustering for selected Tech Companies

Source: The researcher's data analysis

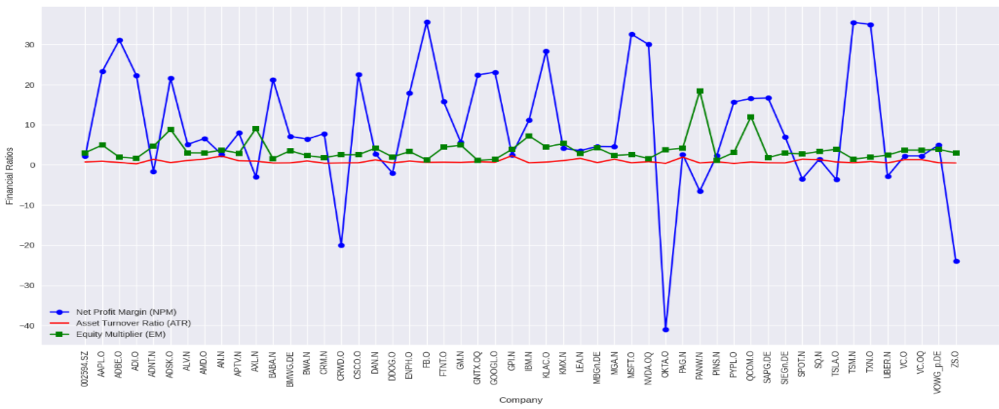
The figure, Plot 2, shown below provides a more detailed glimpse into the financial performance of these 3 clusters, with Cluster 1, Cluster 2 and Cluster 3 reflecting stable metrics, growth-oriented risk profiles and undervalued opportunities, respectively.



Plot 2 ROA and ROE Analysis for Companies with Distinguished Markers

Source: The researcher's data analysis

Plot 3 provides even further insight by focusing on three key financial ratios: Net Profit Margin (NPM), Asset Turnover Ratio (ATR), and Equity Multipler (EM). Companies with high NPM, due to their profitability, attract investor confidence. Spikes in EM reflect debt financing in high levels, which may point to higher financial risk. Steady ATR indicates consistent efficiency on part of senior management of the firms in utilizing assets for revenue generation.



Plot 3. Financial Ratios Analysis for Companies

Source: The researcher's data analysis

5 Conclusion:

Technology companies drive economic growth and innovation of nations and hence, are of increasingly interest to investors, policymakers and public alike. The research study done here combines practical financial tools such as Dupont Analysis with machine learning techniques such as K-Means Clustering for financial performance evaluation of technology companies .The study highlights the potential for further technology company categorization to analyse cross-market patterns, which result from macroeconomic events and national fiscal policy as discussed by Fazzini (2018).This model, hence, provides insights for researchers and investors, alike to navigate and understand performance and future prospects for dynamic complex domains such as technology businesses .

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