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The Influence of Asset Structure, Firm Size, Profitability and Business Risk on Capital Structure in Companies Listed on the IDX

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Abstract

This study aims to determine the effect of asset structure, firm size, profitability and business risk on capital structure in companies listed on the Indonesian Stock Exchange (IDX). The object of research is property, real estate and building construction employee. The type of research used is asosiatif research with secondary data. The population was 91 companies; the research sample used purposive sampling method that collected 20 samples of the companies with 2016-2020 of the study period. The technical analyses used were multiple linear regression analysis. The result showed that the variables of asset structure did not have a significant influence on capital structure, while the firm size, profitability and business risk variable gave a significant influence on capital structure.

Keywords: Capital Structure, Asset Structure, Firm Size, Profitability, Business Risk

JEL Code: G32, M21, N15, N20

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1. Introduction

A good company will be required to be able to manage finances well, meaning that policies in good financial management can be seen from the capital structure. Managers must consider appropriately the decision to use the source of funds in the company's spending because each source of funds has a variety of financial consequences that are not the same. The company

must determine how much capital is needed for its business financing because the capital needed by the company will increase when the company decides to expand. When the company is able to meet the need for its operational costs using capital from the internal, of course, this will minimize dependence on parties outside the company. However, when the need for capital is increasing due to competition in the business industry and the use of internal funds the company can no longer afford to meet then there is no other option to choose from outside the company obtained through debt and stock issuance.

Capital structure is also defined as a balance or comparison of long-term debt and the company's own capital (Andika et al., 2019: 5084). To be able to optimize the capital structure and maximize the profits obtained by the company, it is important to know and understand the variables that have an influence on the capital structure so that the company can plan the best optimization for the company. There are many factors that must be considered because they can influence the decisions of each manager in determining the capital structure. According to (Sugiarto, 2009: 120) there are several factors that can affect the capital structure, namely: the size of the company, the opportunity to grow in the future, profitability, business risk, asset structure, the age of the company, liquidity and the type of industry. Sartono (2019: 248) stated that important factors to consider in determining capital structure are sales rate, asset structure, company growth rate, profitability, tax protection, corporate scale as well as the internal conditions of the company and macroeconomics.

Irman & Hayati (2019: 263) structure of assets as a determinant of how much the allocation of funds for each component of the asset, both for current assets and for non-current assets. Asset structure affects the capital structure because companies with large fixed assets tend to obtain loans that can be used as collateral to increase the company's operational activities. According to Wairooy (2019: 80) firm size is a picture of the financial capabilities of the company at one particular period. Measured through indicators: total sales seen from the balance sheet in the financial statements, the more sales it will increase the amount of capital embedded, the greater the sales, resulting in more increased money turnover, higher market capitalization and the company will be increasingly known in society.

Profitability is the ratio used in measuring a company's ability to make a profit (Mowen, Hansen & Heitger, 2017: 953). The ratio used in profitability aims to make it easier for investors, creditors and managers to evaluate how much investment funds are used efficiently. Sawitri & Lestari (2015: 1241) business risk is the risk of company assets when the company uses debt. Increasing the amount of debt due to the company's funding efforts will have an impact on increasing business risks. Risk arises along with the burden of costs on company loans. The greater the cost burden borne will increase the risk that the company has to face.

Property, Real Estate and Building Construction is one of the industrial sectors whose development is quite good even though the growth trend is slowing, in line with national economic growth. The growth of this sector can also be seen from the increase in company assets that are quite good in every year of research in addition to that according to the Minister of Finance Sri Mulyani property industry, real estate and building construction is an industry that contributes to the national economic growth and job creation this is because the sector intersects a lot with other sectors (Kencana, liputan6.com, 2019). Based on the Indonesian Capital Market Directory 2016 to 2020, the following is an average for variables Asset structure, Firm size, Profitability, and Business risk in property, real estate and

construction building on the IDX:

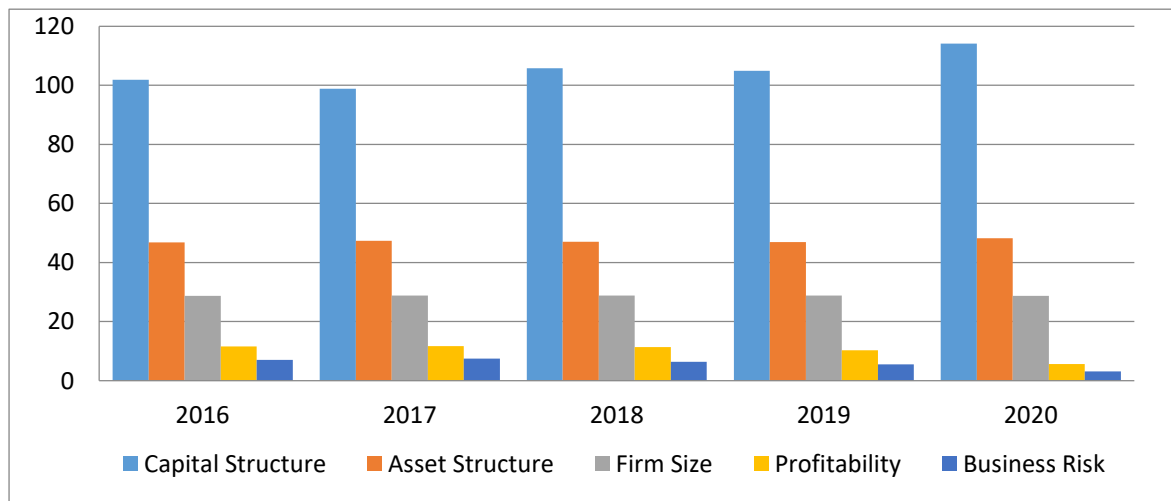


Figure 1: The average of Asset structure, Firm size, Profitability, Business risk and Capital Structure

Based on the chart image above, we can see that the asset structure shows a fluctuating trend. The lowest value of 46.4 in 2019 and the highest value in 2020 of 48.2 this shows that the asset of 48.2% is on average fixed assets, and the remaining 51.8% are current assets, however, the average level of capital structure on average is above 100% this shows that the capital structure is still dominated by capital from external, namely through short-term loans and long-term although the fixed assets held are not as many as current assets.

The average rate for firm size measured using natural logarithms of total sales showed the lowest value in 2019 at 28.6, this shows that total sales in 2019 decreased which may be due to macro and micro factors and the highest value for the average size of the company indicated in 2018 and 2020 which is 28.72 means through an increase in the size of the company. This number of sales, indicates that the company is increasingly established and strongly domiciled among other companies and this allows the company to compile more external capital than internal capital.

Profitability measured using ROE shows a trend that tends to decline every year. The lowest ROE value is 5.6% in 2020 and the highest value in 2016 at 12.7% this shows that in 2016 the company was able to generate maximum return on equity for shareholders, while in 2020 the company's ability to decline in making profits this may be possible due to several factors including The decrease in the rate of return on assets, the decreased availability of cash to pay debt bills and other costs related to the sale of the company in addition to the decline in profitability in 2020 can also be attributed to the impact caused by the Covid-19 pandemic that occurred globally and the low value of profitability will encourage the company to increase capital derived from external companies. Furthermore, based on Figure 1, there can be seen fluctuations in the magnitude of business risks and tend to decrease from year to year, this is also because the ability to generate company profits has also decreased. It can be seen

that the lowest risk value occurred in 2020, which was 3.8%, this low business risk value will encourage companies to increase the proportion of their debt in the capital structure while the highest average value of business risk is 7.5% occurred in 2017, this will make the company even more conservative in the use of its debt.

Several previous studies have linked the capital structure with the asset structure, research conducted by Tijow, Sabijono & Tirayoh (2018) and Andika et al. (2019) shows the result that the asset structure has an influence on the capital structure. In contrast, research conducted by Kanita (2014) and Melodie & Ruslim (2019) showed different results that asset structure has no influence on capital structure. Another variable that can affect the capital structure is the firm size. Research on firm size conducted by Denziana & Yunggo (2017), Wairooy (2019) and research by Shahzad, Azeem & Nazir (2021) showed that firm size affects capital structure while research conducted by Sawitri & Lestari (2015) and Irman, Hayati & Winany (2019) showed that firm size has no effect on capital structure.

Another factor that can also affect the capital structure in addition to the asset structure and size of the company is profitability. Research on profitability has previously been conducted by Putri (2018) and Gharaibeh & AL-Tahat (2020) showing that profitability has an effect on capital structure, while according to research by Andika et al. (2019) and research by Saputri, Nurlaela & Titisari (2020) shows profitability has no effect on capital structure. The last variable that also connects capital structure with business risk is the research of Wairooy, (2019) and Aris, Pratiwi & Hasan (2019) which shows the results that business risk affects the capital structure, while research conducted by Sawitri & Lestari (2015) and research by Rahmi & Swandari (2021) shows the opposite result, namely business risk does not affect the capital structure.

2. Literature Review

2.1 Capital Structure

Capital structure is the use of the dominant source of funds carried out by the company whether through debt or equity so that it will determine the composition of funding on the balance sheet (IAI, 2019: 152). The capital structure reflects the existing wisdom in the company in determining the securities to be issued, because the problem of capital structure is closely related to capitalization, which is composed of the types of funds that make up capitalization is the capital structure. The decision of the capital structure relates to the chosen source of funds both from inside and outside the company. Funds obtained through external sources are funds from creditors which are debts for the company and funds derived from the owners are own capital. In general, the measurement of capital structure is proxied by DER (Debt to Equity Ratio) which is calculated using the formula:

$$DER = \frac{\text{Total Debt}}{\text{Total Equity}} \times 100\%$$

2.2 Asset Structure

The balance between fixed assets and total assets is an asset structure, where these assets can

be collateral when the company will borrow funds from creditors. (Semi, Theorupun & Referli, 2020: 3). Managers can use these assets as collateral to easily obtain loans to creditors. In determining loan alternatives, the flexibility of the company will be influenced by the asset structure. The asset structure is proxied with FAR (Fixed Assets Ratio). This calculation aims to determine the amount of the portion of fixed assets that can be used by the company as collateral for the loan provided and is measured by units of % with the formula:

$$FAR = \frac{\text{Total Fixed Assets}}{\text{Total Assets}} \times 100\%$$

2.3 Firm Size

Firm Size is described by the size of the size or smallness of an enterprise. This will be a reference to the company's possible failure in its debt repayment (Andika et al., 2019: 5807). Large companies have greater capacity, they are more diversified, can meet the commitments of creditors and are less vulnerable to bankruptcy. Large companies tend to have a high asset value, offering the best debt guarantees. Large corporations attract institutional investors because creditors have confidence that large companies have a low risk of bankruptcy. Firm size is measured by the natural logarithm of the total sales owned by the company. the formula used to measure the firm size is as follows:

$$\text{Firm Size} = \ln (\text{Total Sales})$$

2.4 Profitability

Utari, Purwanti & Darsono (2014: 63) management's ability to make a profit is profitability. The profit consists of gross profit, operating profit, and net profit. If management wants an above-average profit, then it must reduce all expenses to maximize the increase in revenue. There are several ways to measure the size of a company's profitability where each measurement is linked to sales volume, total assets and own capital. One of the commonly used analyzes is ROE (Return on Equity) with the following formula:

$$ROE = \frac{\text{Net Profit}}{\text{Total Equity}}$$

2.5 Business Risk

Business risk is the uncertainty that will be inherent in the projected rate of return on assets in the future (Arifin, 2018: 71). Risk has the meaning of insufficient probability of paying interest expenses, so there is a possibility that the company will go bankrupt. There are several ways to be able to estimate risks in one project, using the BRISK (Business Risk) proxy the level of business risk, with the formula:

$$BRISK = \frac{EBIT}{\text{Total Assets}} \times 100\%$$

3. Research Method

The object of research in this study is the Capital Structure (Y) which is measured by the Debt to Equity Ratio (DER) as a dependent variable. While the independent variable is the Asset Structure (X_1), Firm Size (X_2), Profitability (X_3) and Business risk (X_4). This research was conducted on Property, Real Estate and Building Construction Companies listed on the Indonesia Stock Exchange. In this study, the data used was secondary data with a total population of 91 companies and the sample in this study was taken based on several criteria so that there were only 20 companies that met these criteria. The sample criteria set are companies registered in 2016-2020, providing information that has been published in the financial statements as of December 31 of the research year, having a positive profit and presenting financial statements in rupiah currency units. The data analysis technique in this study. However, previously, a classic assumption test will be carried out first on the data. The analysis model used is multiple linear regression analysis; this analysis model is used because of the variables that affect more than one, the model of multiple linear regression equations as follows:

$$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + \varepsilon$$

4. Findings and Discussions

After processing the data, continued by analyzing the data. The steps taken are to use the following data analysis techniques:

4.1 Descriptive Statistics

The results of the descriptive statistical analysis of the variables of this are:

Table 1. Statistik Deskriptif

	N	Minimum	Maximum	Mean	Std. Deviation
Asset Structure	100	10.49	89.65	47.2614	20.83883
Firm Size	100	25.60	31.07	28.6830	1.22413
Profitability	100	.43	32.29	10.4829	6.03220
Business Risk	100	.02	20.16	6.1303	4.32053
Capital Structure	100	4.33	583.32	120.1000	104.22165
Valid N (listwise)	100				

Source: Secondary data processing, 2022

4.2. Classical Assumptions Model Test

4.2.1. Normality Test

The normality test used in this study is a normal test pp plot graph where the assumption of

normality is met if the points on the graph are close to its diagonal axis. the results using the normal test pp plot:

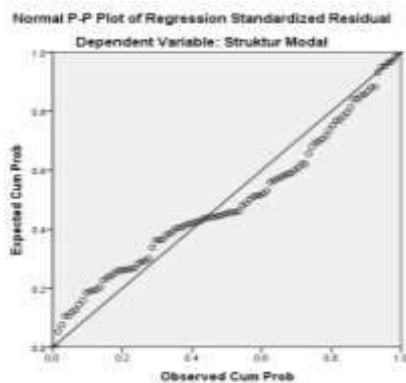


Figure 2. Normality Test Results

Source: Secondary data processing, 2022.

Based on the results of the figure above, it can be seen that the plotting points contained in the figure always follow and approach its diagonal line, therefore in accordance with the decision-making guidelines in the normality test of the probability plot technique, it can be concluded that the residual value is normally distributed.

4.2.2. Multicollinearity Test

The multicollinearity test aims to test whether the regression model found that there is a correlation between independent variables of a good regression model, there should be no correlation between independent variables. the results of the multicollinearity test in this study can be seen in the following Table 2:

Table 2. Multicollinearity test result

Model	Unstandardized Coefficients		Standardized Coefficients	Collinearity Statistics	
	B	Std. Error	Beta	Tolerance	VIF
1 (Constant)	42.192	12.384			
Asset Structure	-.258	.168	-.096	.753	1.327
Firm Size	10.585	2.286	.274	.846	1.182
Profitability	2.982	.471	.641	.288	3.474
Business Risk	-5.182	.550	-1.048	.239	4.188

Source: Secondary data processing, 2022.

Based on the Coefficients output Table 2 above, we can see the tolerance value of the four variables > from 0.10 while, the VIF value < 10.00, it can be concluded that there are no symptoms of Multicollineritas in the regression model.

4.2.3. Heteroskedasticity Test

Heteroskedasticity testing in this study can be seen in the following figure:

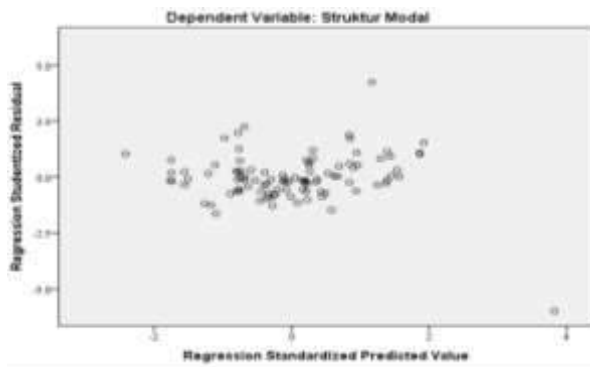


Figure 3. Heteroskedasticity test result

Source: Secondary data processing, 2022.

Based on the figure, we can see that the data points of the spread are above and below or around the number 0 and the points do not collect only above or below. It can be concluded that heteroskedasticity does not occur in regression, so this model can be used to predict capital structure based on inputs from asset structure, firm size, profitability and business risk.

4.2.3. Autocorrelation Test

A good regression model is a regression that is free of autocorrelation symptoms. The results of the test using the Durbin Watson test are as follows:

Table 3. Autocorrelation Test Result

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.848 ^a	.720	.708	2.40063	1.026

a. Predictors: (Constant), asset structure, firm size, profitability and business risk

b. Dependent Variable: capital structure

Source: Secondary data processing, 2022.

From the output Table above, it is known that DW is 1,026 provided that if Durbin Watson (DW) ranges from -2 to +2 indicating that no autocorrelation occurs. The results of the researcher's test showed that the processed data did not occur autokorlation, this is because the

DW value > -2 which is 1.026, this shows that there is no autocorrelation in the regression model.

4.3 Multiple Linear Regression Analysis

This analysis was performed to measure the magnitude of the influence between two/more independent variables on one dependent variable. The multiple linear regression equation models can be described as follows:

$$Y = 42.192 - 0.258X_1 + 10.585X_2 + 2.982X_3 - 5.182X_4$$

The equation model can be explained as follows:

- Constant (α) = 42.192
That is, if the asset structure, firm size, profitability and business risk are equal to zero, then the value of the capital structure is 42,192
- Regression coefficient (b_1) = -0.258
This means that any increase in the asset structure by 1, it will be followed by a decrease in the capital structure by -0.258 assuming other variables are constant or fixed.
- Regression coefficient (b_2) = 10.585
This means that every increase in the firm size by 1, it will be followed by an increase in the capital structure by 10,585 assuming other variables are constant or fixed.
- Regression coefficient (b_3) = 2.982
This means that every increase in profitability by 1, it will be followed by an increase in the capital structure by 2,982 assuming other variables are constant or fixed.
- Regression coefficient (b_4) = -5.182
This means that any increase in business risk by 1, it will be followed by a decrease in the capital structure by -5,182 assuming other variables are constant or fixed.

4.4 Hypothesis Partially Test (t-Test)

Table 4. Partially Test Result

	B	Std. Error	Beta		
(Constant)	42.192	12.384		3.407	.001
1 Asset Structure	-.258	.168	-.096	-1.538	.127
Firm Size	10.585	2.286	.274	4.631	.000
Profitability	2.982	.471	.641	6.328	.000
Business Risk	-5.182	.550	-1.048	-9.425	.000

Source: Secondary data processing, 2022.

In this test, the partial effect can be explained using the t-test with the result:

- The hypothesis test results show a calculated t value for the asset structure was -1,538 and the table t value for the real level (α) 5% was 1,984, in other words $1,538 < 1,984$ so it means that there is no influence of the asset structure on the capital structure of the IDX Listed Company.

- b. The hypothesis test results show a calculated t value for the firm size of 4,631 and a table t value for a real level (α) of 5% of 1,984, in other words $4,631 > 1,984$ so it means that there is an influence of the firm size on the capital of the IDX Listed Company.
- c. The hypothesis test results show a calculated t value for profitability of 6,328 and a table t value for a real level (α) of 5% of 1,984, in other words $6,328 > 1,984$ so it means there is an effect of profitability on the capital structure of the IDX Listed Company.
- d. The results of the hypothesis test show a calculated t value for business risk of -9,425 and a table t value for a real level (α) of 5% of 1,984, in other words $9,425 > 1,984$ so it means that there is an influence of business risk on the capital structure of the IDX Listed Company.

4.4 Discussion

a. The effect of Asset Structure on Capital Structure

The results of the tests carried out on the asset structure showed the value of $t_{count} < t_{table}$ so that it can be concluded that H_{01} received H_{a1} was rejected, which means that the asset structure has no effect on the capital structure. The signification value of $t > \text{sig } \alpha$, this illustrates that there is no signification in the influence of the asset structure (X) on the capital structure (Y). So the first hypothesis in this study was rejected.

Based on the theory of asset structure is one of the factors that can affect the capital structure, the indicator of fixed assets, namely the company will make the fixed assets it owns as collateral to creditors when the company needs additional funds from outside parties so that the company can still increase debt as long as it still has fixed assets that can be used as collateral. However, from the results of testing asset structure data in this study, it was proven that it had no effect on the capital structure because fixed assets and total assets in the company studied could not influence creditors to provide loans to the company. In addition, the facts in the field based on the movement of the average value of the asset structure and capital structure there are things that can cause the results of the study to have no significant effect on the chart below:

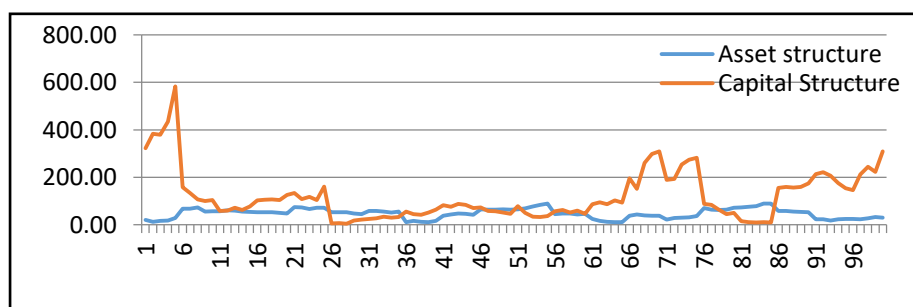


Figure 4. Movement of Capital Structure Value and Asset Structure

Source: Secondary data processing, 2022.

Based on the figure above, it can be seen that the average level of the asset structure and capital structure is very volatile, but the value of the rise and fall of this variable is relatively opposite. When the value of the asset structure increases, the amount of capital structure decreases relatively and vice versa, it is only natural that the asset structure does not have a

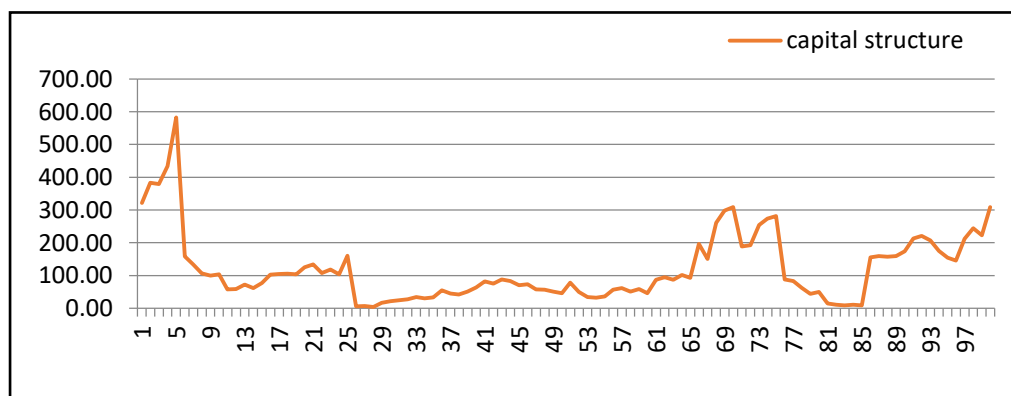
significant effect on the capital structure of property companies, real estate and building construction.

The results of this study are in line with research conducted by Kanita (2014) and Melodie & Ruslim (2019) which showed the results that asset structure has no influence on capital structure. Thus between previous studies and current studies proves a similar result, that is, the structure of assets has no significant effect on the capital structure. On the contrary, the results of research by Tijow et al. (2018) with the results of their research prove that asset structure affects the capital structure. The results that are different from the study can occur because the research sample uses 22 companies while this study uses 20 companies and a different research period of 3 years while this research is carried out in a 5-year research period, the influence caused by the asset structure depends on the capital needs used in the company's operational activities. So that if the company only needs funds that are not large, the asset structure needed does not have a significant effect on the company.

b. The Effect of the Firm Size on the Capital Structure

The results of the tests carried out on the size of the company show the value of t count $>$ t table so that it can be concluded that the H_{o2} rejected H_{a2} is accepted which means that there is an influence of the size of the company on the capital structure in the Property, Real Estate and Building Construction Company. The value of the signification of $t < \text{sig } \alpha$, this illustrates that there is a signification in the influence of the size of the company (X) on the capital structure (Y). So that the second hypothesis in this study is accepted.

From the results of the study, it is proven that the size of the company has a signification effect on the capital structure that the size of the company with the Ln indicator of sales, namely the size of the company, is assessed from the company's ability to make sales of the goods or services it has. This supports the theory put forward by Sartono (2019: 249) Compared to small companies, large companies that have been well-esthablised will have the convenience of obtaining capital in the capital market. In addition, when viewed from the movement of the average value of the capital structure and the size of the company, it shows that the size of the company affects the capital structure, as shown in the figure below:



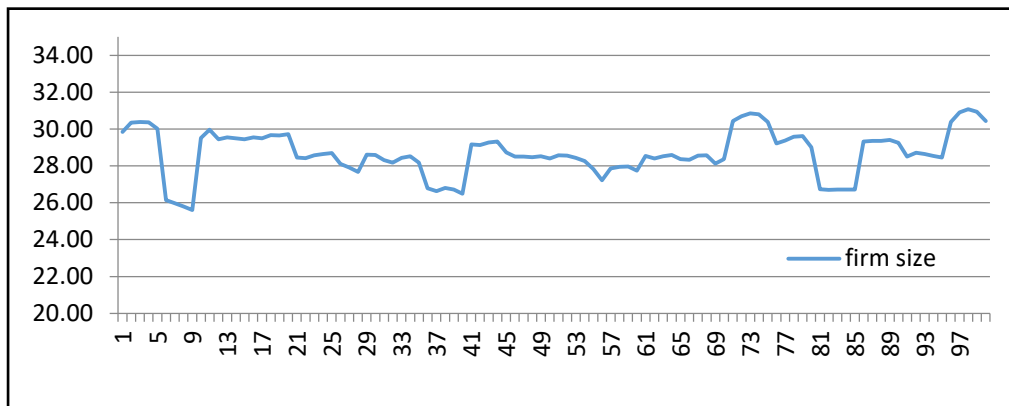


Figure 5. Movement of Capital Structure Value and Firm Size
Source: Secondary data processing, 2022.

Based on the figure above, it can be seen that the average level of the firm size as well as the capital structure fluctuates greatly, the value of the rise and fall of the capital structure and the size of this company are relatively the same. When the value of the firm size increases, the size of the capital structure also increases relatively and vice versa although there are some conditions of value of the two opposite. Thus it can be concluded that the size of the company has been able to answer the existing phenomenon.

The results of this study are in line with research conducted by Denziana & Yunggo (2017), Wairooy (2019) and research by Shahzad et al. (2021) showing that company size affects the capital structure. Thus between previous research and current research proves a similar result, namely the size of the company has a significant effect on the capital structure. Different results in research conducted by Sawitri & Lestari (2015) showed that the size of the company had no effect on the capital structure. Different results from the study can occur because the research sample used 12 companies while this study used 20 companies, and a different research period of 4 years while this study was 5 years, the influence caused by the size of the company depended on the large need for funds.

c. The effect of profitability on the capital structure

The results of the tests carried out on profitability show the calculated t value > t of the table so that it can be concluded that the H_{03} is rejected H_{a3} is accepted which means that there is an influence of profitability on the capital structure. The signification value of $t < \text{sig } \alpha$, this illustrates that there is a signification in the effect of profitability (X) on the capital structure (Y). So that the third hypothesis in this study is accepted.

From the results of the study, it is proven that profitability has a signification effect on the capital structure with indicators of net profit and total equity, namely if the company has obtained a large net profit, then this will affect the high low capital structure. In addition, when viewed from the movement of the average value of the capital structure and profitability, it shows that profitability affects the capital structure, as shown in the figure below:

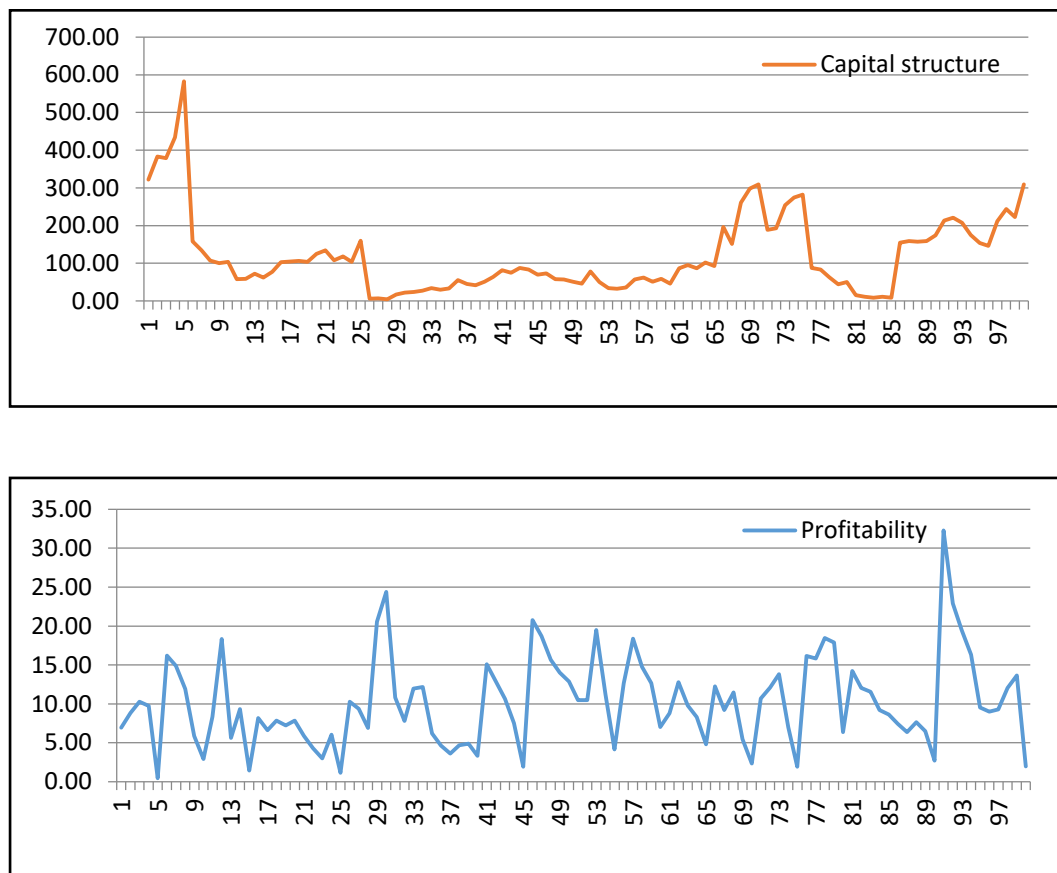


Figure 6. Movement of Capital Structure Value and Profitability

Source: Secondary data processing, 2022.

Based on the figure above, it can be seen that the average level of profitability and capital structure fluctuates greatly, the value of the rise and fall of profitability and capital structure is relatively the same. When the value of profitability increases, the size of the capital structure also increases relatively and vice versa although there are some conditions of value of the two opposites. Thus it can be concluded that profitability has been able to answer the existing phenomenon.

The results of this study are in line with research conducted by Putri (2018) and Gharaibeh & AL-Tahat (2020) showing that profitability affects the capital structure, thus between previous research and current research proves similar results, namely profitability has a significant effect on capital structure. Results differed on the study of Saputri et al. (2020) with the results of his research shows that profitability has no effect on capital structure. The results that are different from the study can occur because the research sample uses 18 companies while this study uses 20 companies, and the different research period is 4 years while this study is 5 years, so the discrepancy of the results with the theory is likely to occur due to a low level of profitability, so the company uses more debt to finance most of its funding needs.

d. The effect of business risk on the capital structure

The results of the tests carried out on business risk show the value of t count $>$ t table so that it can be concluded that the H_{04} rejected H_{04} received which means that there is an influence of business risk on the capital structure. The signification value of $t < \text{sig } \alpha$, this illustrates that there is a signification in the influence of the independent variable (X) on the dependent variable (Y). So that the fourth hypothesis in this study is accepted.

From the results of the study, it was proven that business risk with a comparative indicator, namely EBIT with total assets, has a signification effect on the capital structure. With business risks, of course, it will make the company consider a good capital structure policy for the company so that this will affect the composition of the capital structure in the company. In addition, when viewed from the movement of the average value of the capital structure and profitability, it shows that profitability affects the capital structure, as shown in the figure below:

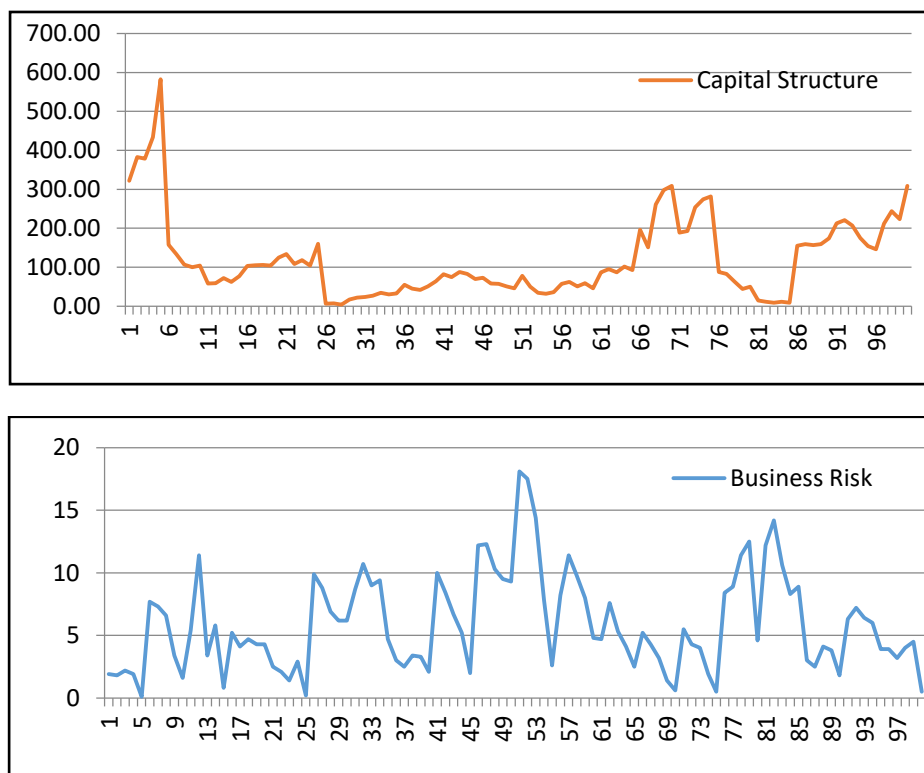


Figure 6. Movement of Capital Structure Value and Business Risk
Source: Secondary data processing, 2022.

Based on the figure above, it can be seen that the average level of business risk and capital structure fluctuates greatly, the value of the rise and fall of business risk and capital structure is relatively the same. When the value of business risk increases, the size of the capital

structure also increases relatively and vice versa even though there are some conditions for the value of the two variables to be opposite. Thus it can be concluded that business risks have been able to answer the existing phenomenon.

The results of this study are in line with research conducted by research by Wairooy (2019) and Aris et al. (2019) which showed the results that business risk affects the capital structure, thus between previous research and current research proves similar results, namely business risk has a significant effect on capital structure. Different results in the study conducted by Rahmi & Swandari (2021) showed the opposite result, namely business risk did not affect the capital structure. Different results from the study can occur because the research sample used 74 companies while this study used 20 companies, and a different research period of 3 years while this study was 5 years, The cause of business risk in the study did not have an influence because every addition or decision to use debt had no impact on the company.

5. Conclusions

Based on the results of research and discussion, it can be concluded that:

- a. The asset structure has no effect and is not significant to the capital structure of companies listed on the Indonesia Stock Exchange. This shows that the ups and downs of the asset structure do not have an influence on the capital structure. Thus, this study under-proves the existing theory.
- b. The size of the company has a significant effect on the capital structure of companies listed on the Indonesia Stock Exchange. This research is empirically proven, this shows that the high and low size of the company has an influence on the capital structure. Thus, this study proves the existing theory and the research conducted earlier.
- c. Profitability has a significant effect on the capital structure of the Company listed on the Indonesia Stock Exchange. This research is empirically proven, this shows that high low profitability has an influence on the capital structure. Thus, this study proves the existing theory and the research conducted earlier.
- d. Business risks have a significant effect on the capital structure of companies listed on the Indonesia Stock Exchange. This research is empirically proven, this shows that the low level of business risk has an influence on the capital structure. Thus, this study proves the existing theory and the research conducted earlier.

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The Effect of Profitability, Company Size and Capital Structure on Stock Prices in the Consumer Goods Industry Sector Listed on the Indonesia Stock Exchange

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Abstract

This study aims to determine the effect of Profitability, Company Size, and Capital Structure on Stock Prices in Consumer Goods Industrial Sector Companies Listed on the Indonesia Stock Exchange (IDX). The type of research used is descriptive research and verification research. The data used in this study is secondary data obtained from the IDX official website (www.idx.co.id). Methods of data collection using the form of documentation. The data analysis used is quantitative analysis. The analysis technique is multiple linear regression. The results of the joint study of profitability, firm size, and capital structure variables have a significant positive effect on stock prices in consumer goods industrial sector companies listed on the Indonesia Stock Exchange. Profitability and firm size have a significant positive effect on stock prices, while the capital structure significantly negatively impacts stock prices.

Keywords: Profitability, Company Size, Capital Structure, Stock Price

JEL Code: G32, M21, N15, N20

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1. Introduction

The company was founded to benefit from its business, whether engaged in services, goods, electronics, textiles, etc. The proceeds will be used to continue the company's operations and fund all company needs. Before and after the company was founded, the company will continue to need capital. This capital can come from own capital or foreign capital. The public and investors have a significant influence in advancing the company, especially concerning the paid-

up capital. From the investor's point of view, an underlying reason for an investor to invest is to take advantage of the excess funds they have and strengthen business relationships or earn profits.

Investments in the capital market have related information regarding the dynamics of stock prices and company value. From this information, the shareholder or investor can make decisions about the shares of companies that are eligible to be selected. Stocks are commodities classified as having high risk; this is due to the nature of stocks that are sensitive to changes. It can be from changes whose sources come from outside or within the country, for example, changes in the economic, political, monetary, and regulatory fields and changes in the industrial sector as well as in the company that issues shares (issuer) itself.

Azis, Mintarti & Nadir (2015: 80), the stock price is defined as the price in the real market and is the price that is most easily determined because it is the price of a stock in the ongoing demand, or if the market is closed, then the market price is the closing price. Brigham and Houston (2010: 7) state that share price determines shareholder wealth. Maximizing shareholder wealth translates into maximizing the company's share price. The stock price at any given time will depend on the cash flows expected to be received in the future by the average investor if the investor buys the stock. This study's factors that affect stock prices include profitability, company size, and capital structure.

Sumiart dan Indrawati (2019: 91) profit-generating companies are financially sound. Profitability is the result of several policies and decisions made by the company. Profitability means the company's ability to generate profits. The ratios used to Calculate profitability show the combined effects of liquidity, asset management, debt, and the company's operating results.

Dewi & Sudiartha (2017: 22) company size is a company picture that shows the company's success which can be reflected in the total assets owned by the company. The larger the company's size, the higher the level of debt used, which aims to develop the company's prospects. Sumiati dan Indrawati (2019: 177) capital structure is related to permanent company funding, which includes long-term debt and equity. The theory of capital structure (Capital Structure) explains whether long-term spending policies can affect firm value (Firm Value), the company's cost of capital, and the company's stock market price.

The consumer goods industry sector companies listed on the Indonesia Stock Exchange (IDX) are a group of companies that are very influential and needed by everyone and are one of the businesses that cannot possibly die because of the need for food and basic human need. The consumer goods industry sector is not too large, but this sector can provide additional income for the state through transactions carried out in this sector. The following is an overview of the average share price, profitability, company size, and capital structure of companies in the consumer goods industry sector in 2015-2020:

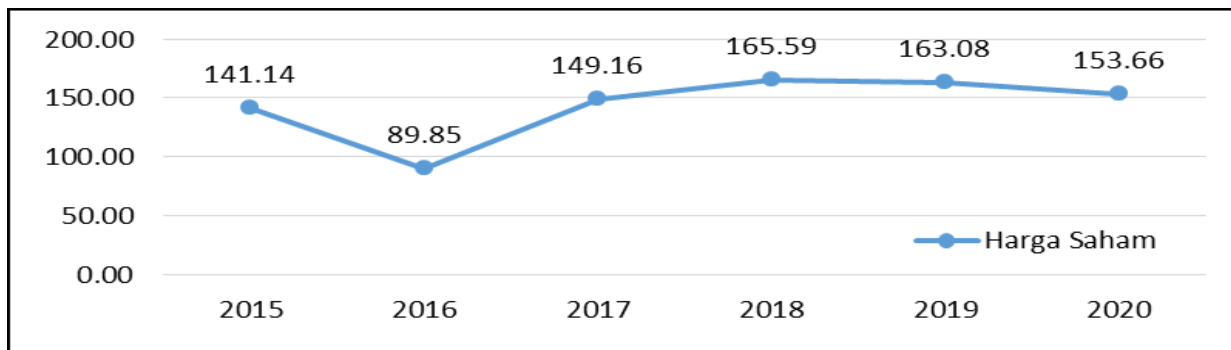


Figure 1. Average share price of companies in the consumer goods industry

Figure 1 above shows that stock prices in consumer goods industrial sector companies on the Indonesia Stock Exchange in 2015-2020 fluctuated or experienced changes in stock prices, both increasing and decreasing according to economic conditions that occurred in Indonesia.

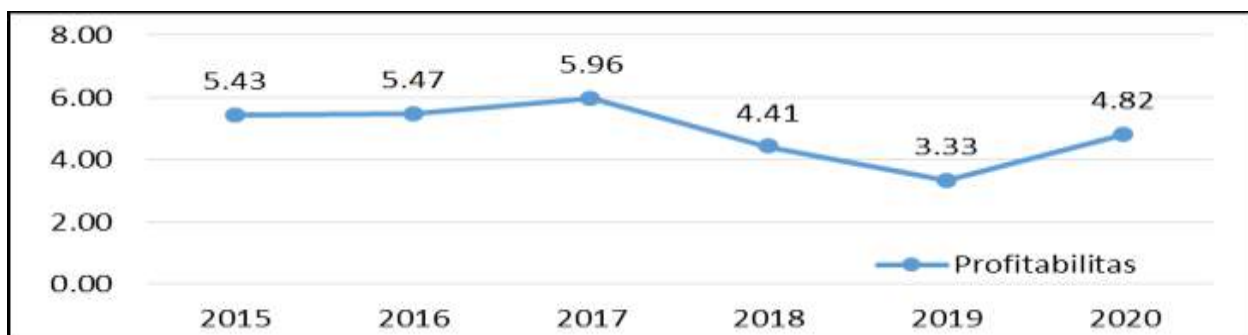


Figure 2. Average profitability of companies in the consumer goods industry.

Based on the picture above, it can be seen that the amount of profitability calculated by the Return On Assets (ROA) of companies in the consumer goods industry sector listed on the Indonesia Stock Exchange has fluctuated from year to year. The highest average occurred in 2017, 5.96%, while the lowest average company profitability occurred in 2019, 3.33%. It shows that in 2017 the capital invested in assets in the company was able to generate maximum profit for the company, while in 2019, these companies experienced a decline in generating profits. Research on the effect of profitability on stock prices has been carried out by Rianisari, Husnah dan Bidin (2018), with the results of profitability research having an impact on stock prices, while Putra & Dana (2015) with the results of his research that profitability does not affect stock prices.

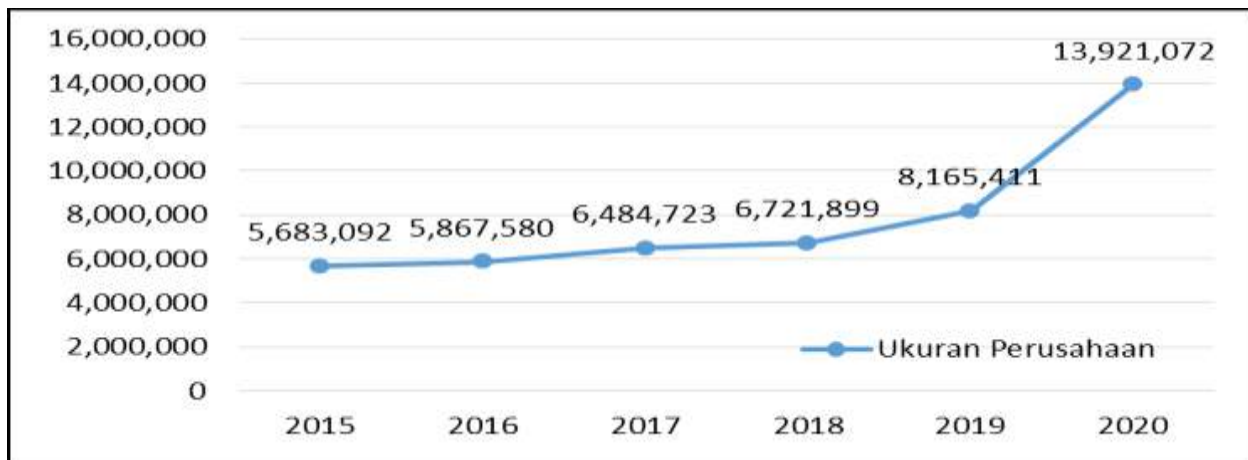


Figure 3. Average company size in the consumer goods industry

Based on the picture above, it can be seen that the company's size calculated by looking at the company's total assets in the consumer goods industry sector listed on the Indonesia Stock Exchange fluctuates from year to year. The highest average occurred in 2020, 13,921,072, while the smallest average company size occurred in 2015, with total assets of 5,683,092. The graph shows that the total assets in 2015-2018 were still stable from year to year, but in 2020 the total assets of companies in the consumer goods industry sector experienced a reasonably high increase. It happens because of macro factors that are happening globally. It means that sales made by the company can increase the total assets owned by the company and assist the company in financing its operational activities from the profits obtained through sales. Research on the effect of company size on stock prices has been carried out by Rosita, Isharijadi & Murwani (2018) with the results of the study that company size affects stock prices, while Wijanti & Sedana (2013) with research results on company size does not affect stock prices.

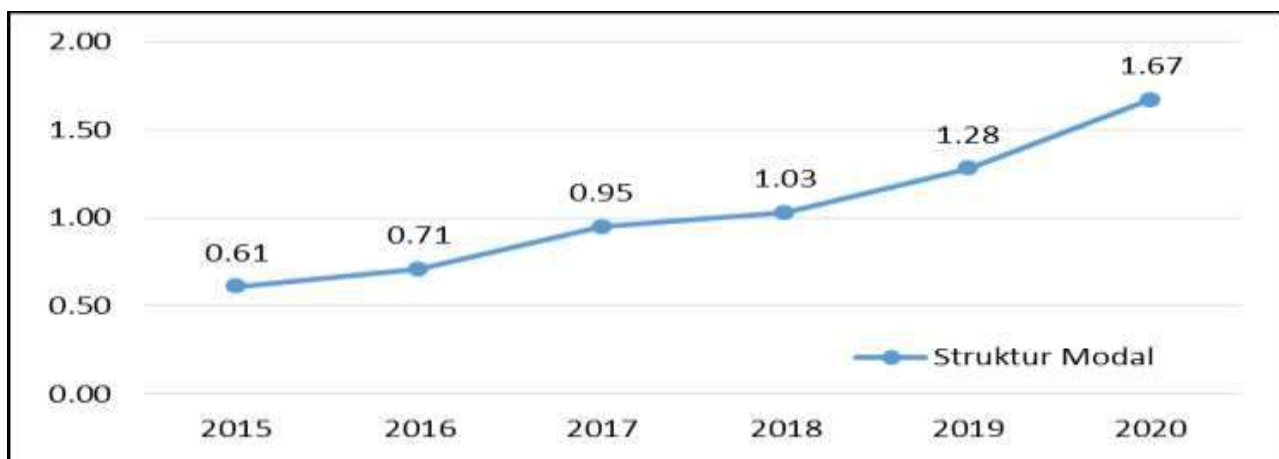


Figure 3. The average capital structure of companies in the consumer goods industry

Based on the figure above, it can be seen that the capital structure is measured using the Debt to Equity Ratio (DER) in the consumer goods industry sector listed on the Indonesia Stock Exchange fluctuates every year. The highest average occurred in 2020, 1.67%, while the lowest average Debt to Equity Ratio (DER) appeared in 2015, which was 0.61%. This means that the company's ability to meet all of its debts or obligations by using all of the company's equity has not been maximized. Research on the effect of capital structure on stock prices has been carried out by Wehantouw (2017). with the results of research that capital structure affects stock prices, while the research of Irham (2014) with the results of his research that capital structure does not affect stock prices.

Based on the background of the problem, the researcher is interested in conducting research with the title "The Effect of Profitability, Company Size and Capital Structure on Stock Prices in Consumer Goods Industrial Sector Companies Listed on the Indonesia Stock Exchange."

2. Literature Review

2.1 Stock Price

According to Husnan and Pudjiastuti (2015: 23), the stock price is the present value of the income that investors will receive in the future. As seen from the Closing Price (Annual).

2.2 Profitability

Sumiati and Indrawati, (2019: 91) companies that generate profits are financially sound. Profitability is the result of some policies and decisions made by the company. To measure profitability, the following formula will be used:

$$ROA = \frac{\text{Laba Bersih}}{\text{Total Aset}}$$

2.3 Company Size

Company size is a measure that classifies the size of the company through assets owned, sales, or market capitalization (Arifin & Agustami, 2016: 29). The larger the size of the company, the higher the level of debt used which aims to develop the company's prospects. Company size is measured by the total assets (TA) owned by the company, which can be used for company operations.

2.4 Capital Structure

Irham Fahmi (2014: 106) states that the company's capital structure or capital is permanent financing represented by long-term debt, preferred stock, and shareholder equity. Ratios to measure capital structure are Debt to Equity Ratio (DER) and Debt to Asset Ratio (DAR). The debt to equity ratio reveals how the company's funding is used from the capital structure owned

by the company, which comes from long-term debt and capital from equity with the following formula:

$$DER = \frac{\text{Total Hutang}}{\text{Total Ekuitas}}$$

3. Research Method

The data used in this study is secondary data based on financial reports obtained through the official website of the Indonesia Stock Exchange. The population in this study is the consumer goods industry sector companies listed on the Indonesia Stock Exchange, as many as 58 companies with a research period of 6 years from 2015-2020. The sample was conducted using a non-probability sampling method, namely by using a purposive sampling technique. The criteria used are consumer goods industrial sector companies registered during the research year, publish complete financial reports, and do not move from sector to company. Based on these criteria, 36 sample companies met the criteria; the following are the names of the sample companies in this study:

Table 1. Sample

No.	Kode	Nama Perusahaan	No.	Kode	Nama Perusahaan
1.	ADES	Akasha Wira International, Tbk	19.	HMSP	Hanjaya Mandala Sampoerna Tbk.
2.	ALTO	Tri Banyan Tirta, Tbk	20.	DVLA	Darya Varia Laboratoria Tbk.
3.	BTEK	Bumi Teknokultura Unggul, Tbk	21.	INAF	Indofarma, Tbk
4.	BUDI	Budi Starch Sweetener Tbk, PT.	22.	KAEF	Kimia Farma Tbk.
5.	CEKA	Cahaya Kalbar Tbk, PT.	23.	KLBF	Kalbe Farma Tbk.
6.	DLTA	Delta Djakarta Tbk, PT.	24.	MERK	Merck Indonesia Tbk.
7.	ICBP	Indofood CBP Sukses Makmur Tbk, PT.	25.	PYFA	Pyridam Farma, Tbk
8.	IIKP	Inti Agri Resources, Tbk	26.	SIDO	Industri Jamu Dan Farmasi Sido Tbk.
9.	INDF	Indofood Sukses Makmur Tbk, PT.	27.	TSPC	Tempo Scan Pacific Tbk.
10.	MGNA	Magna Investama Mandiri, Tbk	28.	ADES	Akasha Wira International, Tbk
11.	MLBI	Multi Bintang Indonesia Tbk, PT.	29.	KINO	Kino Indonesia Tbk.
12.	MYOR	Mayora Indah Tbk, PT.	30.	MBTO	Martina Berto, Tbk
13.	PSDN	Prasidha Aneka Niaga, Tbk	31.	MRAT	Mustika Ratu, Tbk
14.	ROTI	Nippon Indosari Corporindo Tbk, PT.	32.	TCID	Mandom Indonesia Tbk.
15.	SKLT	Sekar Laut Tbk, PT.	33.	UNVR	Unilever Indonesia Tbk.
16.	STTP	Siantar Top, Tbk	34.	CINT	Chitose Internasional Tbk.
17.	ULTJ	Ultrajaya Milk Industry And Trading Company Tbk, PT.	35.	KICI	Kedaung Indah Can, Tbk
18.	GGRM	Gudang Garam Tbk.	36.	LMPI	Langgeng Makmur Industri, Tbk

Sumber : Data processed by the author, 2021.

4. Results and Discussion

4.1 Classical Assumption Test Results

The normality test results, as seen from the picture pp. The plot shows that the data is normally distributed because the data spread around the diagonal line and follows the direction of the diagonal line. The autocorrelation test results show no autocorrelation in the regression model because the Durbin-Watson value is 2.229, which is between -2 to +2. The results of the heteroscedasticity test seen from the scatterplot image show that the data points spread above and below or around the number 0 and do not form a certain pattern, so it can be concluded that there is no heteroscedasticity in the previous study. The results of the multicollinearity test have a tolerance value of more than 0.1, and the VIF is smaller. Of 10, it can be concluded that the variable does not occur multicollinearity.

4.2 Multiple Linear Regression Analysis

Table 2. Multiple Linear Regression Results

Model	Unstandardized Coefficients		Standardized Coefficients
	B	Std. Error	Beta
(Constant)	.864	.205	
1 Profitability	.475	.077	.326
Company Size	.675	.080	.820
Capital Structure	-2.817	.631	-.425

a. Dependent Variable: Harga Saham

The multiple linear regression equation is as follows:

$$Y = 0.864 + 0.475 X_1 + 0.675 X_2 - 2.817 X_3$$

4.3 Hypothesis Test Results

4.3.1 Test results together (Test F)

Table 3. Results of F . Test Analysis ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	14.965	3	4.988	63.210	.000 ^b
Residual	16.730	212	.079		
Total	31.696	215			

a. Dependent Variable: Harga Saham

b. Predictors: (Constant), Struktur Modal, Profitabilitas, Ukuran Perusahaan

Data processing, 2021.

Based on the table above, the results of the F hypothesis test with a calculated F value of 63.210 > F table 0.378 or significant F $0.000 \leq 0.05$ then means H_0 is rejected and H_a is accepted, it can be concluded that there is a positive influence on profitability, firm size, and capital structure jointly to share prices in consumer goods industrial sector companies listed on the Indonesia Stock Exchange.

4.3.2 Partial test results (t-test)

Table 4. Results of t-test analysis

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	.864	.205		4.210	.000
1 Profitability	.475	.077	.326	6.204	.000
Company Size	.675	.080	.820	8.398	.000
Capital Sturcture	-2.817	.631	-.425	-4.465	.000

a. Dependent Variable: Harga Saham

Based on the table above, it can be seen that the calculated t value for profitability is 6.204 > t table 1.97111, and the significant value is $0.000 < 0.05$. This shows a significant positive effect of partial profitability on stock prices. For the size of the company with a t value of 8.398 > t table 1.97111 and a significant value of $0.000 < 0.05$. This shows a significant positive effect of partial firm size on stock prices. And for the capital structure with a t value of -4.465 > t table 1.97111 and a significant value of $0.000 < 0.05$. This shows that there is a significant negative effect of a capital structure partially on stock prices.

4.3 Discussion

4.3.1 Effect of Profitability, Company Size, and Capital Structure Together on Stock Prices

Based on the research that has been processed, the results are that profitability, company size, and capital structure affect stock prices in consumer goods industrial sector companies listed on the Indonesia Stock Exchange. This result is reinforced by the calculated F value 13,403 > F table 2.65 or significant F $0.000 \leq 0.05$. It can be interpreted that profitability, company size,

and moving capital structure together significantly positively affect stock prices in consumer goods industrial sector companies listed on the Indonesia Stock Exchange.

These results align with research by Jelie D. Wehantouw et al. (2017). The result of this research is that the variables of capital structure, firm size, and profitability have a significant positive effect on stock prices. Suppose the management of profitability, company size, and capital structure are carried out better and more effectively by the financial management section of the consumer goods industry sector companies listed on the Indonesia Stock Exchange. In that case, it is possible that the share price obtained in the consumer goods industry sector companies listed on the Indonesian Stock Exchange The Indonesia Stock Exchange will experience an increase in the years to come and can increase the company's profit.

4.3.2 Effect of Profitability on Stock Prices

The results showed a significant positive effect of partial profitability on stock prices; this was strengthened by the t arithmetic value of $6.204 > t$ table 1.97111 and the significant value of profitability $0.000 < 0.05$. Profitability is the company's ability to manage its assets to generate profits. Companies with a high return rate on the assets they manage illustrate the company's ability to generate high profits. This shows that the company's total assets will affect the increase in net profit expected by the company and investors. So, profitability will significantly affect stock prices in the company.

This study's results align with research conducted by Ramandia (2013), Hayati (2013), and Manopo et al. (2017) and Rianisari, Husna & Bidin. (2018) state that returns on assets (ROA) has a significant positive effect on stock prices. However, this study's results differ from Fazria's (2017) research, which states that return on assets (ROA) does not affect stock prices. This means that the high or low profitability or profit earned by the company in a certain period will not affect the current stock price and will not affect potential investors to invest in the company. So potential investors do not consider whether the shares purchased will later receive dividends that will increase or decrease.

4.3.3 Effect of Firm Size on Stock Price

The results showed that the company's size partially has a significant positive effect on stock prices. The value of t arithmetic 8.398 reinforces this $> t$ table 1.97111 and significant company size $0.000 < 0.05$. Then the increase or decrease in the company's size will affect the company's stock price in that year. The results of this study are in line with several studies conducted by Ramandia (2013), Nasir, Diana, & Mawardi (2018), Pratiwi and Badjra (2020) that the firm size variable has a positive influence. Significant to stock prices. Because a company's total assets indicate the company's size at the end of the period, large categories of companies usually report financial statements faster than smaller companies. Large companies tend to have good internal control, and the management of large companies tends to receive incentives to shorten the audit time because it is monitored closely by the capital supervisor from the government. Large

company sizes tend to have more staff in the financial sector, so they are faster in completing their financial statements.

However, this study's results differ from the research of Wehantouw (2017), which states that the firm size variable does not have a significant effect on stock prices. So the size of the total assets owned by the company will not affect the movement of stock prices. While the results of research from Wijanti & Sedana (2018) also have differences, his research states that company size significantly negatively affects stock prices. This means that the size of the total assets owned and acquired by the company hurts stock prices and will affect the movement of stock prices. High total assets will cause stock prices to fall, and small total assets will increase stock prices. This will also impact investors' decisions; they tend to choose low total assets but high stock prices. Because investors want high profits from these shares.

4.3.4 Effect of Capital Structure on Stock Prices

The results showed that the company's size partially has a significant adverse effect on the capital structure on stock prices. This result is strengthened by the calculation if $t_{count} -4.465 > t_{table} 1.97111$ and significant capital structure $0.000 < 0.05$. This is because companies with higher total assets or whose total assets have been able to meet their operational needs through their internal sources, so they do not need external funds in the form of debt. This study's results align with several studies by Rahmandia (2013) and Ircham (2014), which state that capital structure significantly negatively affects stock prices. This means that if the value of the debt to equity ratio (DER) decreases, it will be followed by an increase in stock prices. Long-term creditors prefer a small DER ratio because it indicates that the more significant the number of assets funded by the owners of capital. So that the smaller the creditor's risk, which will indirectly affect the increase in share prices for capital owners. A more significant DER indicates that the business capital structure uses more funds provided by creditors to generate profits. Meanwhile, Pratiwi's (2019) research shows that capital structure does not affect stock prices. This means that the movement down or up from the value of the debt to equity ratio (DER) keeps the stock price at 6.204. This result will be a consideration for investors to invest because the profit earned from the share price will remain the same at 6.204 even though the company's debt to equity ratio (DER) is high. Suppose the company's debt to equity ratio (DER) value is high. In that case, the company's operational funding using debt increases, but the profit earned from the stock price remains at 6.204 and vice versa.

5. Conclusion

The results of jointly testing the hypothesis that the variables of profitability, firm size, and capital structure have a significant positive effect on stock prices in consumer goods industrial sector companies listed on the Indonesia Stock Exchange. The results of the partial hypothesis testing of profitability, company size, and capital structure variables on stock prices in consumer goods industrial sector companies listed on the Indonesia Stock Exchange are: There is a significant positive effect of partial profitability on stock prices, There is a significant partial

effect of company size on stock prices. There is a significant negative effect of a capital structure partially on stock prices.

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Analysis of Output and Employment of Trade in India: A Case of rising Capital Intensity and Its Implications

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Abstract:

Trade is by far labour-intensive sector. The sector is dominated by unorganized activities. Though, post-1990s, the share of organized sector has been rising but at slow pace. Till 2003-04, the sector has grown well as a consequence, output has risen and concomitant increase in the share of employment has been noticed. From 2003-04 onwards a significant increase in capital intensity has been noticed which increased the productivity of the sector. Therefore, contribution of the sector in employment generation has decimated, despite the fact that there was no decline in output. Rise in capital intensity is attributed to formalisation of the sector and resultant increase in investment.

Keywords: Trade, Output, Employment, Structural Change, Growth, Development

JEL Code: E24, O47, B17, L8

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1. Introduction

The acceleration in growth India has experienced in the post-1980 period, the movement from the 'hindu' rate of growth to a higher growth trajectory, has been attributed to the service sector's exceptional growth (Bhattacharya and Mitra, 1990, Rodrik & Subramanian, 2005). The eighties' reforms drive was a half-hearted- tinkering with policy and a complete overhaul was initiated only in the nineties- on structural change and macroeconomic stabilization under the auspices of IMF and is considered as a sea-change in Indian economy.

India's growth performance after 1980, however, defies the classical growth pattern. Not only has it not been preceded by significant industrialization, the enormous rise of the service sector's share in output since 1980 has not led to a concomitant rise in the sector's employment share. This is a unique path of growth because that violates the classical three-sector growth trajectory. However, Kaldor and Kuznets argued for the more influential view that economic growth can only be materialized owing to 'industrialization'.

This peculiarity has to be understood of course with reference to the unique features of the tertiary sector in general – where the sector is blend of variegated services, both traditional as well as modern, and yet with common characteristics that allow them to be collectively

distinguished from the goods producing sectors. Like the other sectors, in India services too have organized and unorganized components.

To advance the understanding of the somewhat unique growth process in India, this article takes up the careful study the trade. It has been attempted to study the output trends of trade, from 1980-81 onwards and also corresponding employment trends. The objective is to understand the factors driving a rapid growth of trade services before 2003-04, and how the employment prospect of the sector get reduced? Also, it is attempted to explain the role of capital in raising the productivity of the sector after 2003-04.

2. Literature Review

Trade is one of the oldest services, and was always dominated by the unorganized sector. Use of technology in the sector has traditionally been limited and it is naturally predisposed to be mostly a labor-intensive sector with limited scope for productivity improvement. However, in the 21st century, the sector has undergone through rising capital intensity with big business houses are showing interest with huge investment.

The initial underplaying of the role of services in the growth process could be traced back to distinction between manufacturing and service made by Adam Smith (1776) who emphasized that services '*perish as soon as they are produced*'. The practices of ignoring or underplaying services continues, and it is termed as 'residual' or 'tertiary' or 'post-industrial' even in the present times, though the services sector is playing sizable role in every sector of the economy.

Trade is one of the oldest services, and also the largest in terms of contribution in GDP. Trade facilitates the distribution of goods. The role of trade, wholesale and retail, in economic development is so pervasive and integral that it becomes inalienable and invisible. The genesis of trade may be traced into uneven distribution of goods and natural resources, and comparative advantage of production. Ordinarily, these services were provided by merchants, in a very unorganized manner. With the big-bang phenomenon of industrialization, the scope of trade grows even faster, and gradually, organised trade activities have gain currency. Organized trade, characterized by high productivity, skilled labour (professional embodied with human capital), high wage, legally stipulated hours of work, skill/capital-intensive technology etc. becomes prominent relative to the relatively low productivity unorganized trade of the past. In recent times, a number of new avenues were created to further facilitate the trade activities world over. For example, supermarket in this regard is an important labor-saving innovation, which has dramatically changed the nature of trade services, especially retail trade. Under one roof consumers are replete with a score of goods. Supermarket is a large-scale method of distributive services. Artificial intelligence is a new potent tool in this field, which can replace selling agents in large scale. In the era of cost-cutting, robots with artificial intelligence can be a game changer for trade. E-commerce is growing by leap and bounds, and giving a credible threat to brick-and-mortar shops. Further, with growing urbanisation, the role of retail trade is likely to rise (Joseph , Soundararajan , Gupta , & Sahu, 2008).

CSO defines trade, "comprising wholesale and retail trade, in following manner- it deals in all commodities. It comprises domestic, imported or exported. It covers wide range of activities of agents, brokers and auctioneers, who engaged in selling or purchasing of goods. Wholesale trade and retail trade veritable activities- resell without transformation, new and

used goods generally to retailers and industries, commercial units, institutional and professional users or to other wholesalers.”

As per NIC 2004 classification, this sector consists of following five categories:

- “Maintenance and repair of motor vehicles
- Sale of motor vehicles
- Whole sale trade except of motor vehicles and auctioning activities
- Repair of personal household goods and
- Retail trade (except motor vehicles)”.

GVA estimates of trade account the ‘activities’ of agents engaged in the sale or purchase of goods (new or used). The term ‘activities’ is ambiguous. It may refer to services provided by the agents, but the agents provide a plethora of services and some of the services may neither be associated with retail trade nor be with wholesale trade. The ‘activities’ related to buying and selling of goods, new and old has been increased in the past for both retail and wholesale trade sector. But question remains that how the contribution of agents’ services is included in the GVA estimates of the trade sector.

3. Research Method

It’s based on simple comparative empirical analysis of data of output and employment of trade in India. Quantitative analysis of output is based on data collected from National Accounts Statistics (NAS). In the analysis used data of base year 2004-05 and back series. On 2004-05 back series, data is available till the year 2011-12. Therefore, to explain long periods, 1950 to 2012, we used 2004-05 data. However, for latest analysis of output along with employment, we prefer to use 2011-12 series GDP data of KLEMS India (published by RBI). Employment data is collected primarily from two sources- NSS and KLEMS India. Principal status and subsidiary status (PS+SS) is used for analysis.

4. Result and Discussion

4.1. Output Trends of Trade

Trade is one of the oldest services and has always had a significant share in GDP. At current prices, trade’s share was 5.95 percent in 1950-51 while at 2004-05 prices it stood at 7.81 per cent. Over the period, the share of trade in GDP has increased steadily (Figure 1), and this has been true both before and after of 1980. The only difference is that for several years before 1980, the trade share in GDP at current prices lay below that at 2004-05 constant prices, but this gap was eliminated in the 1970s.



Figure 1: Percentage Share of Trade in Indian GDP (at constant and current prices)

Source: Calculation based on NAS, CSO.

Within the services sector GDP, trade accounted for 26.4 percent in 1950-51 at constant price and a slightly higher to 26.5 percent in 2011-12. In 1978-79, it achieved the highest share. What is remarkable to note here is that any increase in the trade share within services was limited to the share at current prices and happened in the period before 1980, and a slight recovery from a previous dip in the 2010s decade. Almost no change took place in the share during 1990s, despite economic reform. In fact, the constant price share has remained consistently below the average levels prevailing between the mid-1960s and the end of the 1980s.

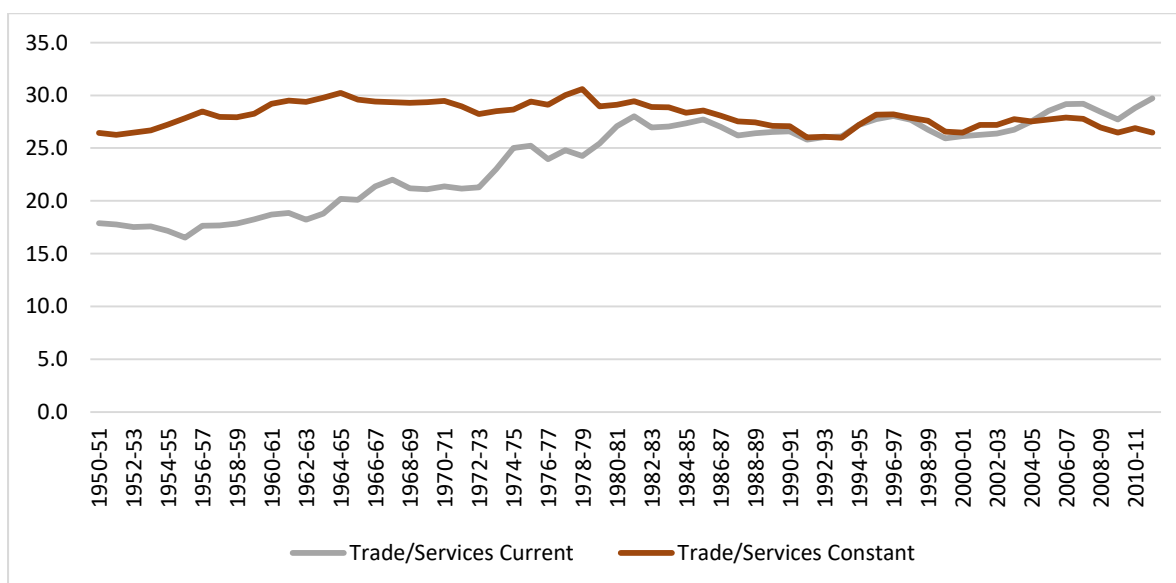


Figure 2: Share of Trade in Service GDP in India

Source: based on CSO data.

Like almost all sectors of the Indian economy, trade is divisible into organized and unorganized components. Data for this division is not available in the back-series with 2004-05 series. Therefore, the 1999-00 base year series data on factor incomes for the period 1980-81 to 2010-11 has been used here to look at the relative shares of organized and unorganized components in trade over time.

As Figure 3 shows, trade has always been dominated by the unorganized sector. However, reversing a slow trend of decline in the 1980s, after liberalization there was a steady trend of increase in the organized sector's share in Trade NDP that continued for a decade and a half. This carried the organized sector's share from less than 5 percent at the beginning of the 1990s to nearly 33 percent by 2006-07, subsequent to which there was a dip in this. However, 2005-06 and 2006-07 were somewhat exceptional years when this share was much higher than the years immediately before or after. If we take them out of the frame, a steady process of trade becoming more organized is perceptible through the 1990s and till the beginning of the high growth phase from 2003-04, after which the distribution that had emerged, of about four-fifths of the NDP coming from the unorganized sector and one-fifth from the organized, stabilized.

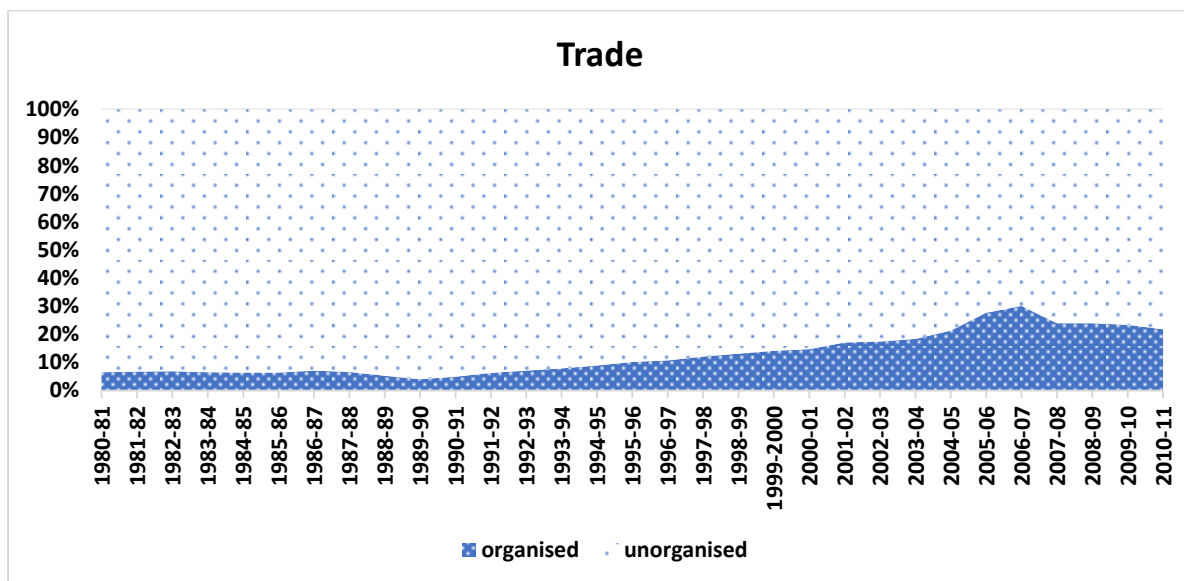


Figure 3: Distribution of NDP of Trade between Organized and Unorganized Sectors, 1980-81 to 2010-11

Source: Based on NAS data

Retailing in India, even of products produced by the organized sector, has always been dominated by mom & pop stores (kirana shops), roadside grocery shops, paan-beedi shops, hawkers and vendors, most of which belong to the unorganized component. According to the study of ICRIER, the unorganised sector dominates in food and grocery business, and the proportion of organised sector is pittance. In India, unorganised sector may have dominated the trade sector, in contrast to Europe where the share of organized retail is as high as 80 percent in the United Kingdom, Germany and France per cent and in USA where it is 85 per cent. Even among the emerging economies, the share of organised retails is well above India (Hoda, 2008): Brazil (36); China (20); Indonesia (30); Korea (15) and Malaysia (55). The scope for expansion of organised retail was therefore immense.

With liberalization, trade did begin exhibiting an inclination towards formalisation- rise in the share of organised sector in output, with the rise of middle class and corporate-backed retail sectors growing fast. With the opening of the economy, inflow-outflow of goods and services has risen many folds. Trade GVA includes both new and old products. The second-hand goods market has also grown in leap and bounds in the past. Government has also been

encouraging recycling-reuse of products for environmental purposes. Over the period, the sector became more competitive and complex. The need for qualified and specialists became indispensable. The MBA, BBA and sundry professionals were engaged in these activities in supermarket and other organised trading activities. Marketing has become a potent tool for promoting products. Foreign capital investment has risen in this sector, which brings sophisticated technology. Government has relaxed the norms for promoting investment in this sector. Though the role of the government in allowing FDI has gone with snail's pace as fearing it may drive out the unorganised sector, especially the mom-and-pop shops. By 2006, FDI was allowed in single-brand up to 51 per cent. The pace of construction of shopping malls also picked up in the 2000s. In 1999, India had just 3 shopping malls. By end of 2006, the number had gone up to whopping 137, and their number was estimated to be about 479 by end of 2008 (ICICI Property Services-Technopak, 2007). Subsequently, digital technologies also came into the picture. The unprecedented rise of ICT created the possibilities for trade services through online platforms i.e- e-commerce. For instance, in China the way Alibaba progressed in short span of time. India's trade sector could also benefit from similar activities (Mehrotra, 2019), though, the penetration of technology is quite low in India.

All these impetuses were the harbinger of formalisation of the trade sector, in the post-reform period. However, the process of change has been modest and at slow pace. Also, it has not taken place on a sustained basis because of the several challenges faced. Retail trade is heavily depended on logistic support, and the logistic cost was as high as 15% of our GDP in 2005-06. India's rank has declined from 44th in 2016 to 35th in 2018 in the Logistics Performance Index rankings. Foreign investment is also not very increasing, though government has approved as many as 51% foreign investment in multi-brand and 100% in single brand retail. Though, government has started a slew of measures to boost credit facilities, but end result is not very encouraging. Organised retail is only 10% and e-commerce accounts for 3% only (Economic Times, 2018). The organized sector is also more affected by archaic laws and acts and red-tapism – thus it was determined that the retail trade industry has to secure a total of 45 licenses, clearances, registration certificates or notification requirements for each outlet (Report of the High Level Group on services sector, 2008). One of the important State level Acts which regulates retail trade, the 'Shops & Establishment Act', was originally enacted in the 1950s.

4.2. Structural Changes in Trade and Determining Factors

Trade is a sector that deals in tradable products. Its growth should therefore be expected to have a close relationship with the growth in production of tradables and the degree to which these are actually traded. As far as tradability is concerned, goods in general possess this characteristic while many services do not. Within the goods producing sectors, manufacturing is the most significant in any process of structural change. Moreover, the component of the manufacturing sector in India which produced mainly for local use had ceased to be a significant part of that sector even before independence. In post-1980s the sector exhibited a very lacklustre performance on output and employment front. In the case of the other major goods producing sector, namely agriculture, too there had been a process of commercialization during the colonial period. At the time of Independence, the sector was in total ramshackle and the marketed surplus of the sector was palpably low but increased over time after independence even as the use of purchased inputs like chemical fertilizers, pesticides, commercial seeds, diesel, etc. also went up. In relation to the impetus the sector

provided for growth of trade, therefore, these would have partially counteracted the effects of the declining relative significance of agriculture in GDP.

Figure 4 shows that for the period before 1980-81, there clear correlation between the changes in trade and manufacturing shares in GDP. The share was 10.5 and 6 respectively for manufacturing and trade in 1950-51. In 1980-81, it became 16.2 and 10.8 respectively. However, even though the manufacturing sector's share in GDP remained nearly unchanged after that, the share of trade continued to rise. After 2009-10, the share of trade become higher than that of manufacturing.

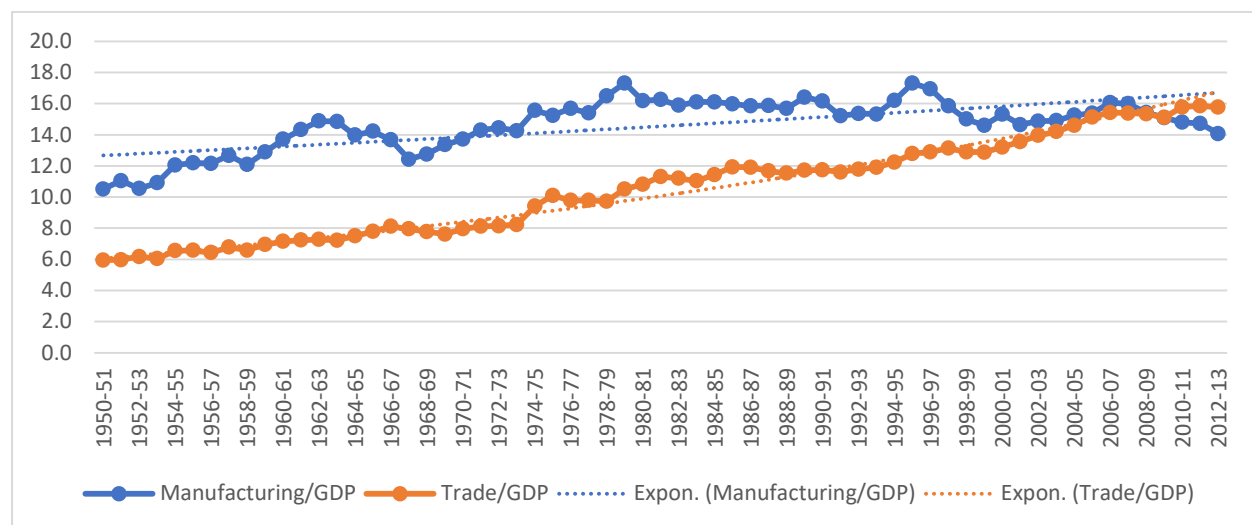


Figure 4: Percentage Share of Manufacturing and Trade in GDP (current price)

Source: NAS, CSO.

The picture is slightly different when we look at constant price data (Figure 7). Here, the divergence between the trends of movement between the two shares appears to have happened a little later, from the mid-1990s.

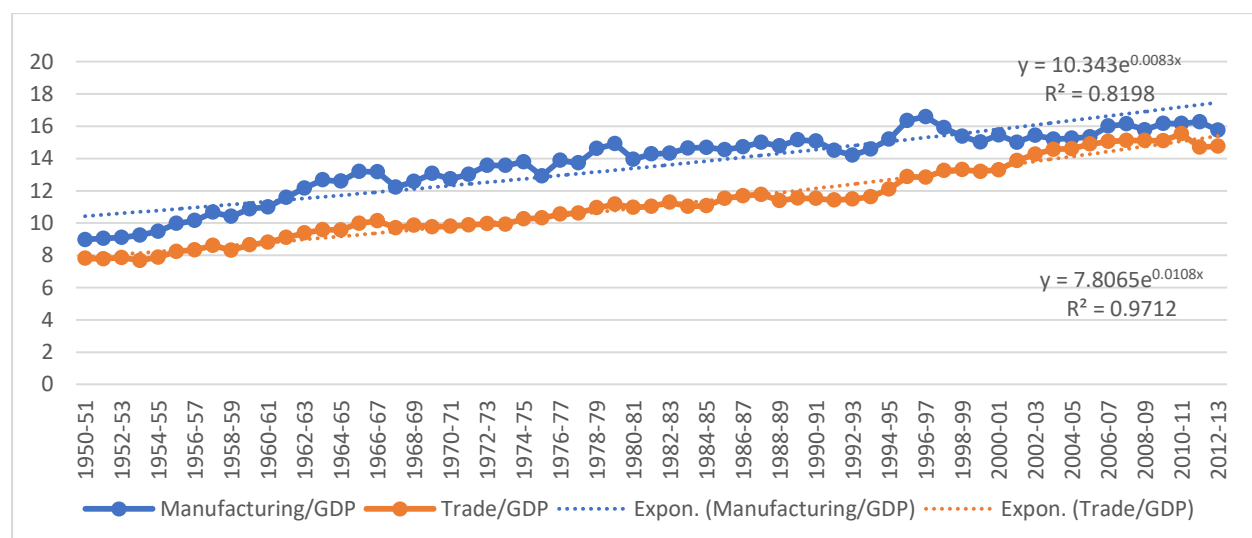


Figure 5: Percentage Share of Manufacturing and Trade in GDP (constant price)

Source: NAS, CSO.

After 2009-10, no significant change is found in manufacturing share. But rise in the share of trade continued. It means trade's growth must have been induced by some other factors. Furthermore, analysis of change in the share of manufacturing and trade entails more than the fact that the performance of manufacturing determines the performance of trade. Rate of rise of trade share is quite high than the manufacturing. Furthermore, the rise is quite high for current price than the constant price.

Table 1 depicts the manufacturing elasticity of trade sector- responsiveness of trade output to change in manufacturing output – in different periods. It shows, firstly, that elasticity tends to increase in any period of relatively slow industrial growth (both 1965-1980 and 1995-2003 are such periods). Additionally, what is notable is the general rise in the elasticity after 1980, most pronounced in the period 1995-2003, suggesting that in this period the trade sector's growth became less dependent on manufacturing growth and came to be influenced by other factors.

Table 1: Manufacturing elasticity of Trade

1950-51 to 1979-80		1980-81 to 2002-03			2003-04 to 2012-13	
1950-51 to 1964-65	1965-66 to 1979-80	1980-81 to 1994-95	1995-96 to 2002-03		2003-04 to 2008-09	2009-10 to 2012-13
0.79	0.97	1.03	1.38		0.99	1.02

Source: calculation based on CSO data.

The broader picture of the growth of trade relative to the goods producing sectors is presented in Figures 8 and 9, which show how the ratio of trade GDP to those of different combinations of goods producing sectors moved over time. Both bears out the fact that trade GDP before 1980 rose faster than that of goods producing sectors as a whole (agriculture, manufacturing and mining) but not relative to industrial GDP. The overall rise therefore could be attributable to the greater penetration of market relationships into an otherwise slow growing agriculture. However, this cannot explain the rising ratio in the period of increased globalization of the Indian economy – by which time the transformation in agriculture was completed and trade grew faster than even industry. Transformation in agriculture has also been witnessed.

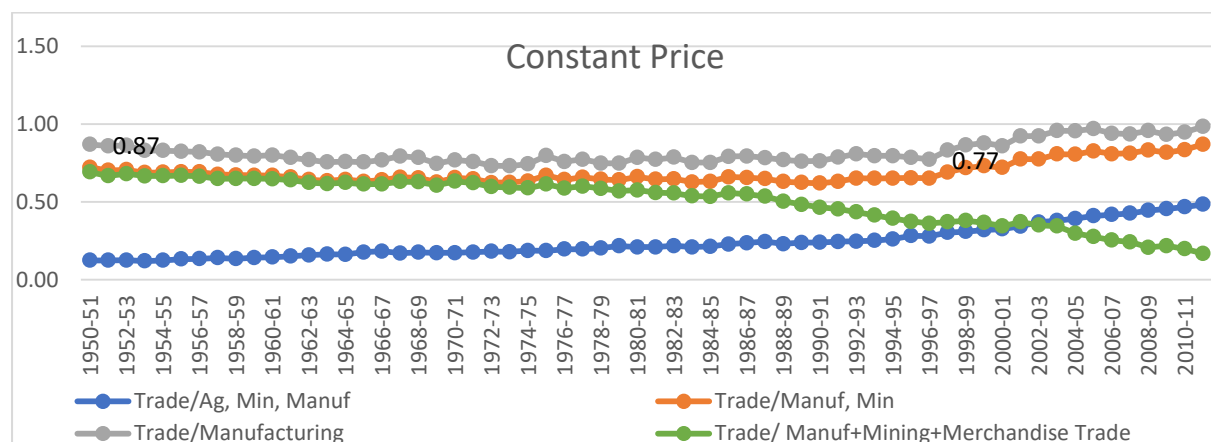


Figure 6: Ratio of Selected Sectors' share in GDP (Constant price).

Source: Calculation based on NAS, CSO.

The interesting factor that reveals itself as an important factor in driving the growth of the trade sector independent of the growth of goods production is foreign trade in goods or merchandise trade. When this is added to the GDP of goods producing sectors and the ratio of trade GDP to this combined total is seen, the post-1980 rising trend seen in the other ratios completely disappears. At constant prices in fact, the trend is downwards.

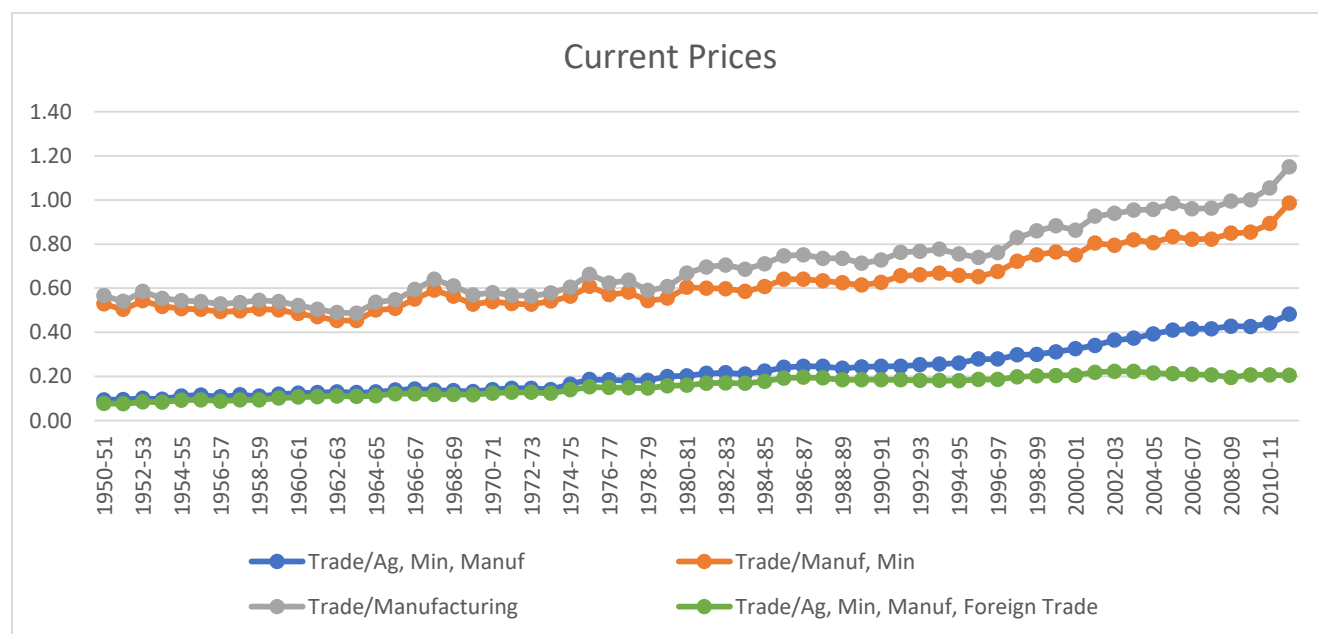


Figure 7: Ratio of Selected sectors' share in GDP (Current prices)

Source: Calculation based on NAS, CSO.

If we simply look at the ratio of trade GDP to the value of foreign merchandise trade, a clear reversal of trend can be seen to have taken place in the period between 1970 and the mid-1980s. From Figure 10 it is quite discernible that in 1970-71, the ratio is highest, and then in 1986-87 a second peak (crest) was seen. Since 1986-87 onward, the declining trend in the ratio is palpable. Therefore, it is found that till 1970-71, the role of domestic factors was dominating in setting the contour of trade share in national income. As the role of domestic factors, especially the performance of manufacturing (key factor) subsided, the influence of foreign factors was decisive in determining the share of trade during the period of liberalization.

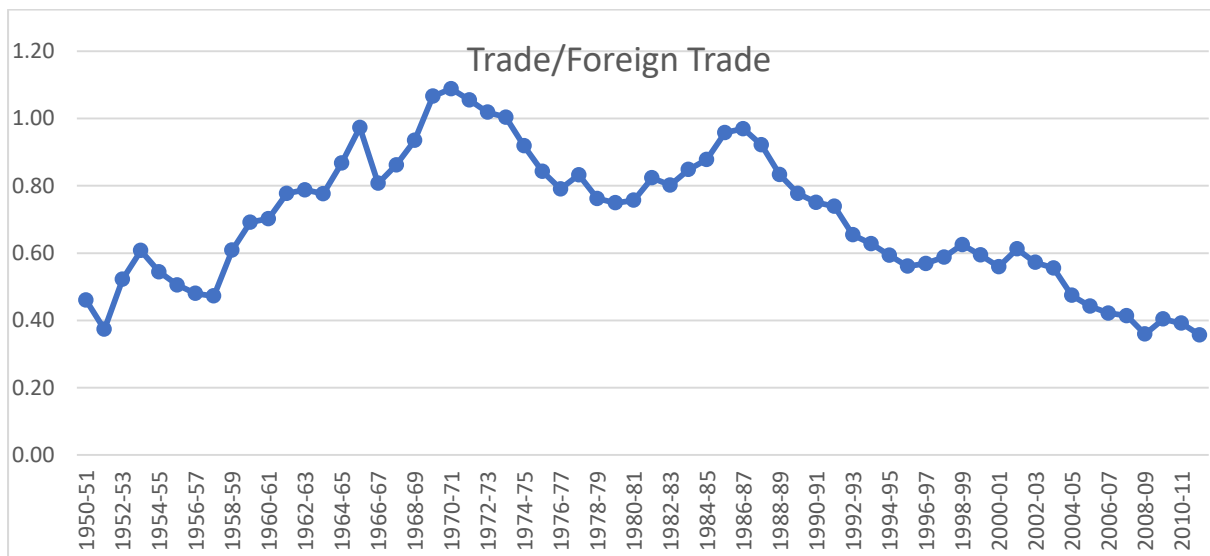


Figure 8: Ratio of share of Trade and Foreign Trade in GDP (Constant price)Source: Calculation based on NAS, CSO.

Figures 9 to 11 show the relation between trade and foreign (international) trade for various period. For 1950 to 1970, the R-square is quite low, but in the subsequent period, the fit of the regression equation much better. These results further fortify the conclusion that the acceleration in growth of the trade sector during liberalization was accompanied by a transition from a scenario where the growth of the sector was mainly influenced by growth of the goods producing sectors in the economy to one where foreign trade became the most dominant factor – and enabled trade to expand faster than the goods producing sectors and contribute to the process of increasing importance of services in Indian growth.

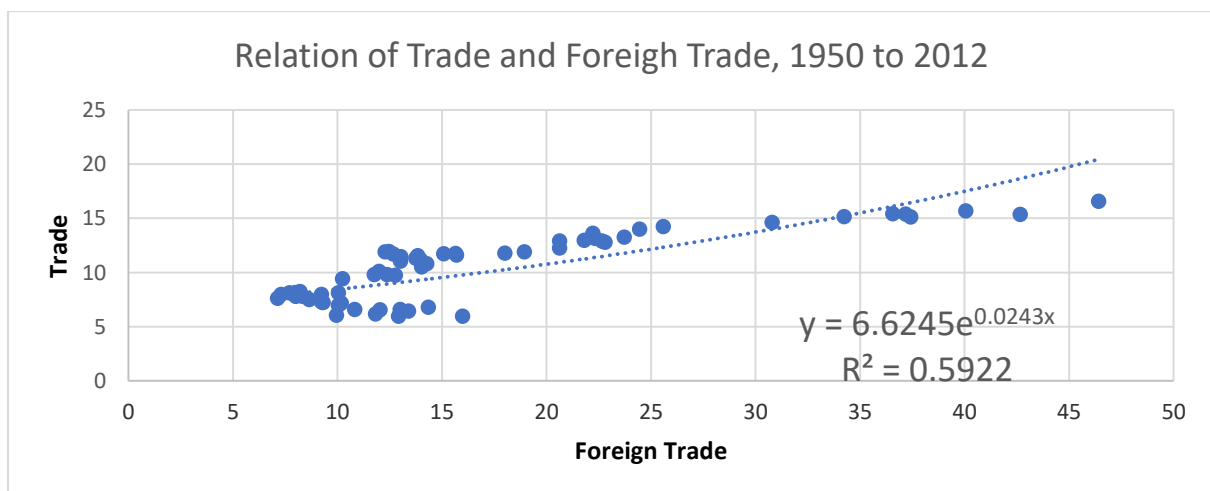


Figure 9: Relation of Percentage share of Trade and Foreign Trade, 1950 to 2012
Source: Calculation based on NAS, CSO.

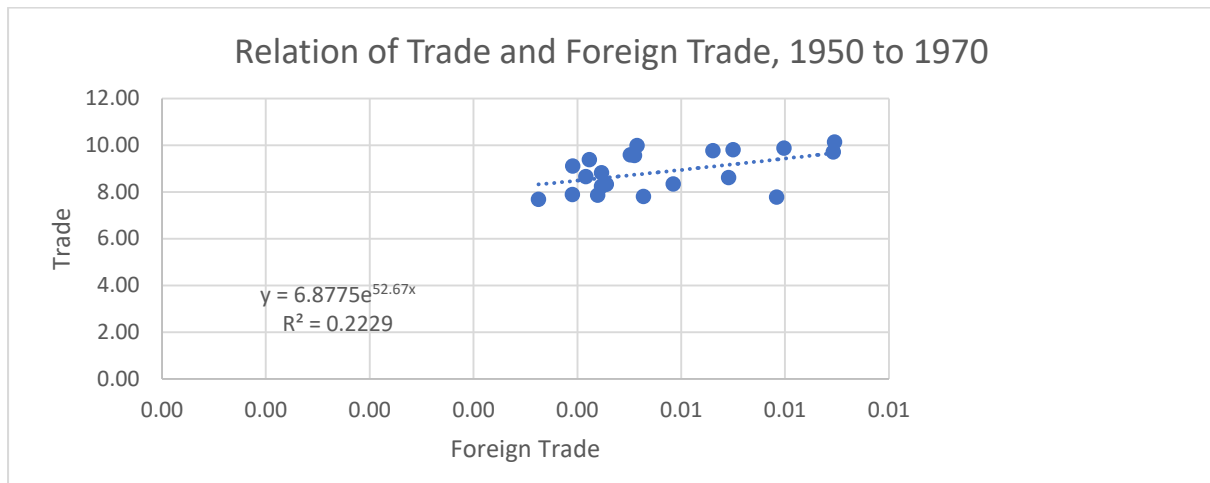


Figure 10: Relation of percentage share Trade and Foreign Trade, 1950 to 1970
Source: Calculation based on NAS, CSO.

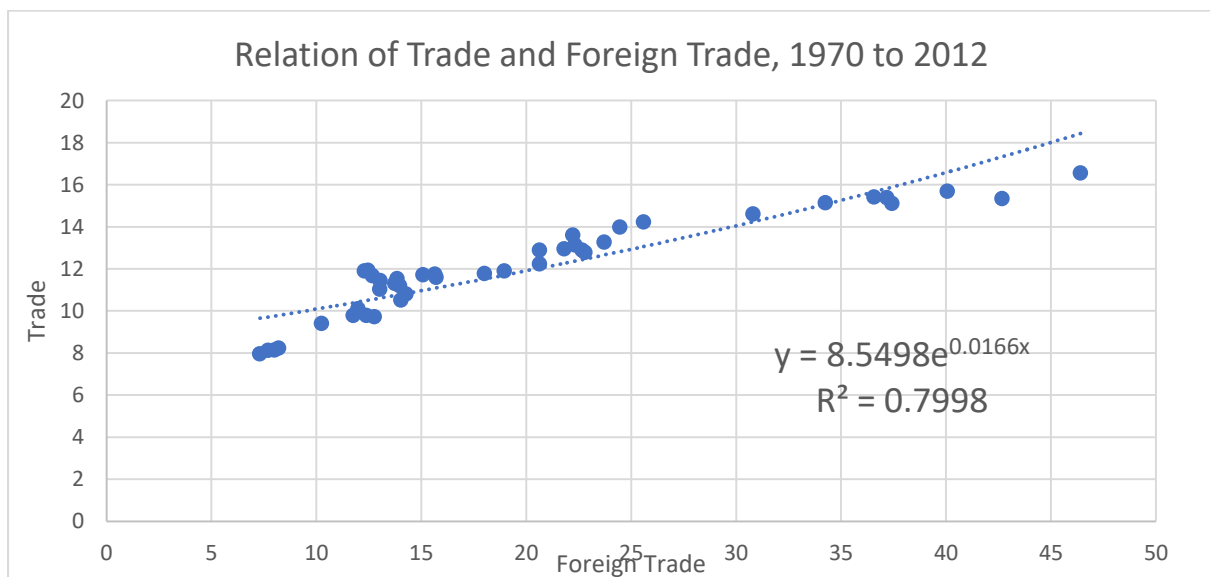


Figure 11: Relation of percentage share Trade and Foreign Trade, 1970 to 2012
Source: Calculation based on NAS, CSO.

4.3. Trade: Output vis-à-vis Employment

Table 2 shows the patterns of change in the broad structure of output and employment since the early 1980s, and where trade is placed in that process. Looking at the three broad sectors, it can be seen that the structural change in output has taken place without a corresponding structural change in employment, though both have the same direction. In 1983, primary sector accounted for 41% of total output and as much as 69% of total employment. The share of employment was and remained disproportionately higher. As time progressed, the share of primary activities in GDP declined rapidly but decline in the share of employment has not taken place in the same proportion. Secondary sector's share in GDP on the other hand increased at a slow pace and so did its share of employment was also roughly in the same

proportion. However, historically manufacturing is considered to be job provider. But the middle is missing in our Indian economy in both fronts, output and employment (Mehrotra, 2019).

The greatest increase in GDP share has happened in the case of the tertiary sector. This sector not only had the highest relative product per worker at the beginning, it has also shown no consistent and significant decline like the ones observed in the primary and secondary sector. However, looking at the trends of various sectors, one can see quite clearly that there is heterogeneity underlying the overall picture for services. Further, as can be seen from Table 2, this difference in their employment shares has also been much higher than in their shares in GDP. In the case of trade, its share in both GDP as well as employment have tended to be close to each other.

Table 2: Percentage Share of GDP of Selected Sectors along with Employment Share in Total Employment in parentheses

	1983	1987-88	1993-94	1999-00	2004-05	2009-10	2011-12	2017-18	2018-19
Primary	40.46 (68.44)	34.62 (65.16)	32.46 (63.97)	27.82 (59.93)	24.77 (56.70)	18.66 (50.62)	19.00 (47.85)	15.62 (42.29)	15.14 (41.23)
Secondary	25.49 (13.82)	26.67 (15.71)	26.66 (15.12)	27.16 (16.06)	27.74 (17.87)	31.35 (21.23)	30.76 (23.01)	29.90 (23.93)	29.64 (23.97)
Tertiary	34.05 (17.74)	38.71 (19.13)	40.89 (20.90)	45.02 (24.01)	47.49 (25.43)	50.00 (28.15)	50.23 (29.14)	54.48 (33.79)	55.22 (34.80)
Trade	6.98 (6.29)	7.45 (7.02)	7.30 (7.63)	8.65 (8.95)	9.70 (9.46)	9.36 (9.96)	10.04 (10.06)	12.19 (10.90)	12.54 (11.32)

Source: Calculation based on India KLEMS database. *data in the parentheses show share of employment.

A slightly longer and more continuous picture is presented in Figure 3 making use of the India KLEMS data with 2011-12 base year. This shows the trends in GDP (both at current as well as constant prices) and employment shares of trade for the period. Thus, in the case of trade, the decade of the 1980s saw its employment share increase faster than its share in GDP but the exact opposite situation marked the last decade of the period till 2018-19.

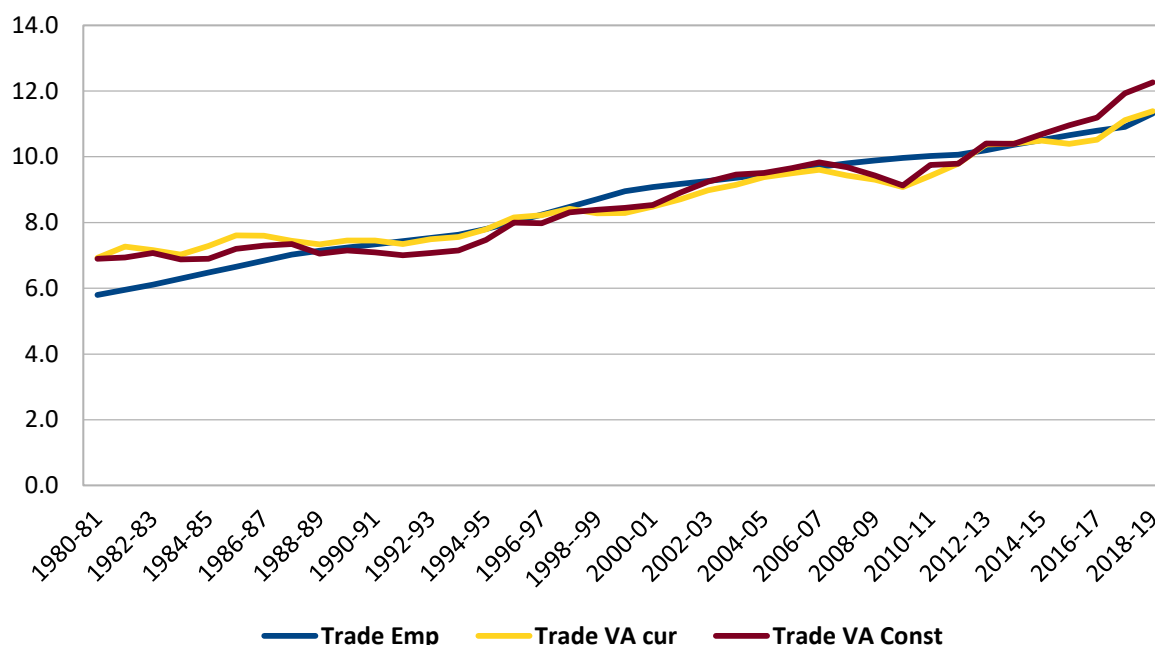


Figure12: Shares of Trade in GDP (Current and 2011-12 prices) and Employment, 1980-81 to 2018-19

Source: India KLEMS.

Table 3 bring out the important turning points. For the entire period from 1980-81 to 2018-19, the share of trade in both output as well as employment has increased. Further, the increase of trade share in employment was greater than in output. However, the larger part of its increase in employment share took place up to 2003-04, though the increase in GDP share after was as much as till then. The further break-up of the periods before and after 2003-04 into two sub-periods each also show how that that process of change gathered strength.

Table 3: Changes in Shares of Trade in Value Added and Employment

Item	1980-81 2018-19	to 1980-81 1987-88	to 1987-88 2003-04	to 2003-04 2011-12	to 2011-12 2018-19	to
Trade VA Current	4.46	0.52	1.70	0.65	1.60	
Trade VA Constant	5.36	0.45	2.11	0.34	2.47	
Trade Employment	5.52	1.22	2.34	0.70	1.26	

Source: India KLEMS.

Structure of Employment by Type

An examination of the structure of employment by type of the trade shows that self-employment has always been the dominant category of employment, followed by regular salaried. Casual employment on the other hand has been a relatively small portion of employment.

Table 4: Structure of Employment by Type (%)

Survey Round	SE	RE	CE	SE	RE	CE
	Trade			Services		
38th round	84.19	11.47	4.34	46.39	44.13	9.48
43rd round	84.62	11.25	4.13	48.01	42.3	9.69
50th round	83.71	12.22	4.07	49.81	40.86	9.34
55th round	75.73	16.55	7.72	48.18	40.97	10.85
61th round	78.16	16.57	5.27	52.04	39.89	8.07
66th round	78.31	16.64	5.05	49.6	42.11	8.29
68th round	75.49	19.06	5.44	49.52	43.57	6.9
PLFS 2017-18	70.64	24.93	4.43	45.84	48.66	5.5
PLFS 2018-19	70.15	25.53	4.32	44.96	49.6	5.44

Source: NSSO. Note- SE- Self-employed, CE- Casual employed, RE- Regular employed.

Over the long term, a trend is seen of shift from self-employment towards regular employment in the case of trade. It is believed that regular employment is largely created in organized sector, on the contrary, unorganized sector generates self-employed and casual employment. Thus, the dominance of self-employment in trade reflects the fact that trade is unorganized sector dominated, while the trend of increase in regular employment is consistent with the rising share of organized trade. On the other hand, when the share of its unorganized component was very high, it correlates well with the high share of self-employment, and the reversal thereafter indicates the ceasing of that process of increasing importance of unorganized, and rise in the share of organized. However, structural changes in employment have been slower than that of output for trade.

Employment and Output Growth: Employment Elasticity and Productivity Trends

In this section, we looked at the relative trend of the *share* of trade in output and employment. However, it is worth mentioning that the work-participation rates have been falling in India in the 21st century, beginning precisely when growth rates of GDP accelerated. Therefore, it is important to not only compare shares but also the rates of growth of employment vis-a vis those of output. This we do in this section along with the two related concepts that are also relevant in this regard – namely, labour productivity and employment elasticity of growth.

Employment Elasticity

The employment elasticity is ratio of percentage change in employment to percentage change in income. In other words, employment elasticity is the responsiveness of employment to change in output. Employment intensity of the service sector is determined by primarily, structural characteristics- technological change, policy intervention, productivity growth, international competition, labour market reforms, economic structure (Pattanaik & Nayak, 2010). Significance of employment elasticity is it depicts the ability of the economy or sector to generate employment due to growth of output. Employment elasticity is not free from deficiencies though. Calculation of employment elasticity is done with the assumption that the technology, government policies, wages are given. The relation between output

production and employment generation is not linear or unidirectional (Misra & Suresh, Estimating Employment Elasticity of Growth for the Indian Economy, 2014).

Table 5: Employment Elasticity of the Indian Economy (CAGR Approach)

Year	Employment Growth	GDP Growth	Elasticity
1972-73 to 1977-78	2.6	4.6	0.57
1977-78 to 1983	2.1	3.9	0.54
1983 to 1987-88	1.7	4	0.42
1993-94 to 1999-2000	1	6.8	0.15
1999-2000 to 2004-05	2.8	5.7	0.50
2004-05 to 2009-10	0.1	8.7	0.01
2009-10 to 2011-12	1.4	7.4	0.18
1999-00 to 2011-12	1.5	7.3	0.20
1993-94 to 2011-12	1.1	6	0.18

Source: Excerpts from Misra S. & Suresh A. K.; RBI working paper, 2014.

A general drift downwards of the employment elasticity of Indian growth is noticeable in Table 5. It declined from 0.57 in the period 1972-73 to 1977-78 to as low as 0.15 in 1993-94 to 1999-2000. However, CAGR of GDP is concerned, it was roughly 4 per cent during 1972-73 to 1987-88. During 1993-94 to 1999-2000, the CAGR of GDP was quite handsome, as high as 6.8 per cent. This is why the period is called 'jobless growth'. In the very next period, 1999-2000 to 2004-05, the employment elasticity was very high. The reason was high employment growth. Mehrotra et al (2014) has termed this phenomenon as progressive structural change as large amount of job were, for the first time, created in non-agriculture sector. During 1999-2000 to 2004-05, non-farm employment has grown by 7.5 million per year on an average. However, on average 12 million per annum were joining labor force in the same intervening period.

The decline in elasticity of employment has been followed by a concomitant decline in unemployment rate between 1999-2000 and 2009-10. It may be attributes to secular fall in labor force participation rate (LFPR). The decline in LFPR is quite palpable rural, especially females. Part of this is possibly because en masse persons are opting for education or skill enhancement programme. The argument is supported by recent trends in rising Gross Enrolment Ratio (GER). It has risen from 20.5 per cent (1993-4) to 24.3 per cent (2004-5), and further to 26.6 per cent in 2009- 10 (Thomas, 2012; Chaudhary, 2011; Himanshu, 2011; Misra & Suresh, 2014). The rise was much faster in rural areas, and especially among females (GoI, 2013). As a result, the unemployment rate went down. However, compared to these numbers, the number of available jobs into which such an educated workforce could be absorbed have not grown anywhere close to the requisite degree.

Table 6: Employment Elasticity of Trade

	38th- 43 rd	43rd- 50th	50th- 55th	55th- 61st	61st- 66th	66 th - 68th	50 th - 68th	38 th - 68 th
Trade	0.13	0.31	0.26	-0.02	0.00	-3.78	2.72	1.55
Organized sector	-0.36	0.24	-0.71	0.04	0.01	-4.09	2.38	1.42
Unorganized sector	0.21	0.31	0.40	-0.02	0.00	-3.77	2.76	1.57

Source: Calculated based on NSSO and CSO data.

Table 6 shows that the employment elasticity of trade has not been very encouraging since 1980s. However, before economic reforms employability of the sector was much greater. In the post-90s, it declined consistently. During 2009-10 and 2011-12, it became negative even. Not just the Organized sector, even the Unorganized sector's employment elasticity has been poor in the 21st century. Between 1999-2000 and 2004-05, when a progressive structural change was taking place, and 2004-05 has registered highest ever non-farm employment, trade still exhibited poor or negative employment elasticity.

A remarkable transition is palpable in trade sector. The essence of the transition is captured in subsequent Figures 4 and 5. Figure 4 shows that the capital intensity of trade is constantly rising. The rise in capital intensity is quite significant after 2003-04.

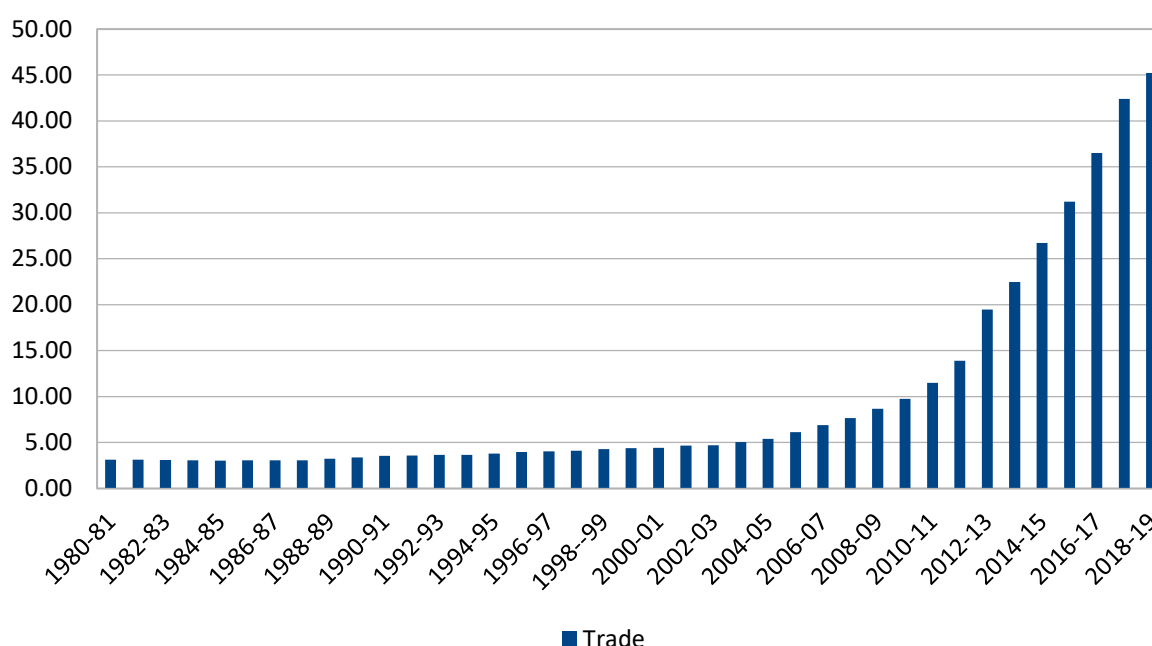


Figure 13: Capital Intensity (Capital Stock at 2011-12 Prices per Employed Person) of Trade, 1980-81 to 2018-19

Source: India KLEMS

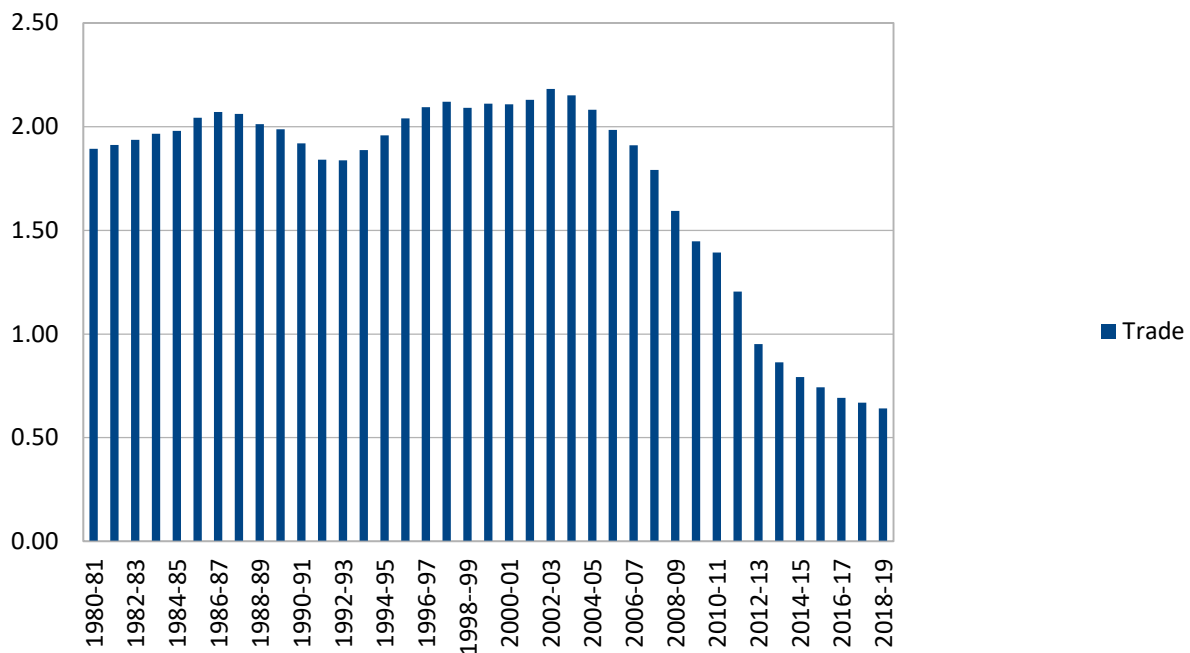


Figure 14: Value Added/Capital Stock (2011-12 Prices) of Trade, 1980-81 to 2018-19
Source: India KLEMS

In fact, as Figure 14 shows, value added per unit of capital in trade has declined. Thus, the return to investment in trading activities became relatively far more attractive, a means of increasing both capital as well as labor productivity. That appears to be the reason why the capital stock in trade, which had tended to grow relatively slower since 1980 saw a huge spurt from 2003-04 onwards.

5. Conclusion

Trade is by far labour-intensive activities. The sector is dominated by unorganized activities. Though, post-1990s, the share of organized sector has been rising but at slow pace without consistency. Till 2003-04, the sector has grown well as a consequence, output has risen and concomitant increase in the share of employment has been noticed. From 2003-04 onwards a significant increase in capital intensity has been noticed which increased the productivity of the sector. Therefore, contribution of the sector in employment generation has decimated. A gap between output and employment share has been noticed. The gap was yawning. The yawning gap has arisen due to poor employment generation, though the output growth was roughly consistent and undeterred. The poor employment, though was a general trend in the economy in post-1990s in the economy, was attributed to rise in capital intensity. Rising capital intensity is attributed to formalisation of the sector and resultant increase in investment by big players.

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Deep Learning on SPY Stock Prices Using Improved Multi-Step LSTM

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Abstract

Stock price prediction has been a widely pursued topic by researchers in recent years due to the great impact that significant research can have on the economy. LSTM is commonly used for stock price prediction as it has strong time series predictive capabilities. However, it is limited by its loss function, which only takes one parameter (predicted stock price) into account. This paper proposes a multivariate multi-step, vector output predictive model using LSTM, with both the stock price and the relative return as inputs of the neural network. Furthermore, a novel loss function that combines both the standard mean squared error, and the relative return mean squared error to hone accuracy is introduced. The model's predictive capabilities are demonstrated on the S&P 500 Index. This improved LSTM model reaches a test MSE of 0.0076, which is a result that is significantly stronger than results demonstrated by standard LSTM stock prediction networks, and which outperforms most of the LSTM models mentioned in the literature.

Keywords: SPY, Stock, Multistep, LSTM, Deep Learning, S&P 500, Multivariate

JEL Code: C45, C53, E17, G17

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1. Introduction

The inherent volatility of the stock market makes prediction a very difficult process. As such, the individual trader cannot profitably depend on their own intuition to predict stock. Therefore, a precise method of prediction is in high demand. This paper will showcase an improvement to the standard LSTM model for stock prediction by predicting Standard and Poor's 500 (SPY) stock index. The S&P500 is a stock market index that tracks the largest 500 companies in America. It is widely acknowledged by investors to be the single strongest indicator of American stock market

performance. Therefore, the ability to accurately predict the S&P 500's stock value is of paramount importance to the government, investors, and investment companies.

Technical indicators, including Bollinger Bands and Relative Strength Index (RSI), have been very popular for traders to predict stock price. We can see from Figure 1 that stock prices of SPY 500 has been on a steady incline in the past decade, with a surge in late 2021. It should be noted that the S&P 500 is less likely to be affected by outstanding events which may drastically influence one company, as it is a conglomeration of the largest companies and is only affected by nationwide trends. This makes the data relatively less volatile than most stocks.

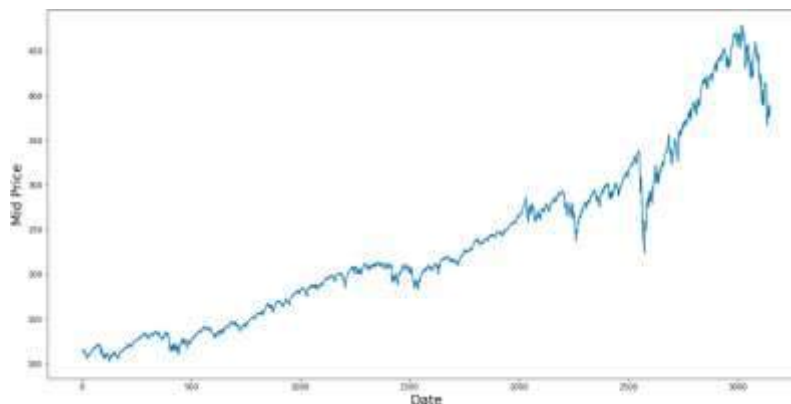


Figure 1: SPY stock price from 2010-01-01 to 2022-07-08

Bollinger band is an efficient indicator for traders to predict the short-term trend of a stock. Bollinger bands are placed at one standard deviation above and below the simple moving average (SMA) of the price. This makes it a strong trend-following indicator. We can see that up to now, there has been a strong decline to the present. The RSI also indicate that there will be a short-term incline starting in July 2022.



Figure 2: Bollinger Bands of SPY stock from 2021-Jan to 2022-July.

Another important technical indicator is the Relative Strength Index, often abbreviated as RSI, which is used as a momentum indicator, see Figure 3. Essentially, it measures how overbought or oversold a stock is. With a range of 0 to 100, it is usually considered overbought when above 70, and oversold when below 30. RSI from the past year indicates that the momentum has been fairly stable, fluctuating between 70 and 30. But by July 2022, the stock has an up-momentum in buying strength, because the stock price is low and affordable, which attracts more investors.



Figure 3: Relative Strength Index of SPY stock from 2021-Jan to 2022-July

The contribution of this research is that a Multivariate Multi-Step, vector output predictive model using LSTM, with both the stock price and the relative return as the input of the neural network is built. A novel improvement is that a new loss function which is based on the idea of the

physically-informed neural network is introduced. More precisely the formula of the relative return as a loss function is used. The improved loss function combines the standard mean squared error loss function with a relative re- turn mean squared error. The improved LSTM model is shown to be able to reach standards of accuracy beyond the prediction capability of standard LSTM stock prediction models. Furthermore, this can be applied to LSTM variants, such as previously discussed wavelet transformation LSTM neural networks. This improvement can also be applied on a large variety of stock, but is demonstrated convincingly on the SPY index.

2. Literature review

The success of Neural Networks (NN) in other applications such as speech and image recognition, and weather forecasting have prompted research to be done on stock market prediction. Studies such as Atsalakis and Valavanis (2009) now say that the use of neural networks is one of the most common methods for future financial stock prediction. Compared to stock predictions using more traditional models, such as Mustapa and Ismail (2019), who used an ARIMA-Garch model to predict the monthly stock price of S&P 500 (SPY) stock, stock predictions that implement LSTM have been shown to significantly outperform the predictions produced by ARIMA, Muncharaz (2020). Similarly, Borovkova and Tsiamas (2019), whom used ensembles of LSTM models to predict the direction of large cap US stocks with a large variety of technical indicators including open, close, bollinger bands, and relative strength index as network inputs, found that LSTM models significantly outperformed benchmark lasso and ridge regression models. Research has also been done on the comparison between LSTM and alternative methods of prediction, like Patel et al. (2015). They tackled the problem of predicting movement of Indian stock using Artificial Neural Network (ANN), Support Vector Machine (SVM), random forests (RF) and naive-Bayes by using two different inputs for all models; the first approach involving computation of ten technical parameters using stock trading data (open, high, low close prices), and the second approach representing technical parameters as trend deterministic data. They found that performance for all models improved when technical parameters were expressed as trend deterministic data. However, it has been shown that LSTM networks outperforms most alternative models of prediction. The authors of [8] used LSTM to predict directional movements of SPY stock. They found that LSTM networks outperformed classification methods that did not use memory, namely a random forest (RAF), a deep neural net (DNN), and a logistic regression classifier (LOG). And furthermore, Lakshminarayanan and McCrae (2019), who did an extensive comparison of stock market prediction on the Dow Jones Index with added parameters of crude oil and gold prices found that predictions with SVM with advanced moving averages compared to LSTM were inferior in all scenarios due to the LSTM's superior ability to efficiently remember and forget information. Research such as Kamalov et al. (2020) affirms that LSTM models generally produce very strong stock price prediction results. However, even compared to the models which yield the strongest results (CNN, MLP, RNN), LSTM is able to often perform better than these models. For example, Kamalov (2020) found that LSTM was more effective than multi-layer perceptron (MLP), Convolutional Neural Network (CNN), Random Forest (RF), and relative strength index methods at predicting significant changes in stock price.

Recently, research has been done on variations of and additions to the LSTM model which may produce better results than the standard LSTM model. In Bao et al. (2017), Bao et al. found that applying a wavelet transformation to a financial data set to de-noise it, then passing the de-noised data to stacked autoencoders to generate meaningful features, and finally feeding it to LSTM networks produced better predictions than simpler models. Then, in Liang et al. (2019), the authors proposed a multi-optimal combination wavelet transform (MOCWT) method to de-noise the financial data. They found that the MOCWT method outperformed the original wavelet method. In Qiu et al. (2020), the authors proposed that a wavelet transform to reduce noise in historical stock data combined with a LSTM model and an attention mechanism would perform better than a standard LSTM model, a standard gated recurrent unit NN model, and a wavelet LSTM model on predicting SPY stock. The proposed wavelet transform LSTM model with attention outperformed all other tested models, with a test mean-squared error of less than 0.05. In a different path, there has also been research done on multi-variate multi-step LSTM. This classification of LSTM essentially defines the class of LSTM that not only predicts some dependent variable y based on multiple independent variables x (multivariate), but also predicts more than one time unit per time step. (multi-step). For example, yang2022multivariate first used LASSO and Random Forest models to filter the features and to produce a dataset of a predetermined size. Then, they compared an ARIMA model, a multivariate multistep LSTM model, and a hybrid multi-step ARIMA- LSTM model to predict tuberculosis outbreaks in the Liaoning Province, China. The result of the study was that the multivariate 2-step LSTM model reduced the error of the LSTM model by 15.94%, and the 3-step ARIMA-LSTM reduced the error of the LSTM model by 33.14%, show that multi-step LSTM produce very strong results when applied to time series prediction. In Unterluggauer et al. (2021), two multi-step LSTM models which produced 4 time step and 96 time step predictions respectively were tested on electric vehicle charging site volume prediction. Gathering real charging data from shopping centers, residential, public, and workplace charging sites, and forecasts of the aggregated charging load being in 15-min resolutions, they found that that both models produced strong predictions, with the 4 time step model (which corresponds to predicting an hour ahead) outperforming the 96 time step model (which corresponds to predict a day ahead). In Wu et al. (2021), they used a long short term memory model combined with Critical Point Search to produce a forecast for train delays. This multi-step model showed significant improvement when compared to standard LSTM models at predicting train delays. However, there has only been very limited research done on multi-step LSTM models done on stock prediction. Aasi et al. (2021) used a multivariate, multistep LSTM model. They combined this model with many data sources, such as Google Search Trends, e-News headlines, and Tweets which effectively gauge public sentiment on Apple (APPL) stock. Using internet search trends, reactions to current events, Twitter data, and historical stock returns as input data, they were able to predict 7 days per time step, and they found that their proposed model outperformed ARIMA and Random forest models trained on the same data set, along with most other LSTM models.

Specifically for predicting SPY stock price, there have been novel methods to enhance accuracy. It is known that neural networks must be trained on a large set of data. Sun et al. (2017) have shown that neural network models which were applied to image classification problems increase logarithmically in effectiveness with the size of data. To solve this problem, Lee and Kang (2020) used only data from individual companies instead of SPY stock price, because SPY is

computed by averaging top companies. This was done as an effort to increase the amount of data available to analyze, which successfully improved accuracy rate compared to other LSTM models.

3. Research Method

In this paper, the Long-short term memory (LSTM) neural network is used to forecast the SPY stock price. The LSTM recurrent neural networks are able to almost seamlessly model problems with multiple input variables. This is especially advantageous in time series forecasting, where classical linear methods can be difficult to adapt to multivariate or multiple input forecasting problems.

We begin with an introduction of the structure of a neural network. An artificial Neural Network usually contains 3 stages of layers: the input layer, the hidden layers, and the output layer. The layers are made of nodes: the input layer has the same amount of nodes as the dimension of the input data, and the nodes of the input layer connect to the nodes of the hidden layers via “synapses”, each synapse having a weight and a bias which are adjusted through training. The nodes in the hidden layer apply an “activation function” to the weighted sum of the inputs. The sigmoid function is used as the activation function, which is defined as

$$S(X) = \frac{1}{1 + e^{-x}}$$

, and is extensively used as an activation function in the input, output, and forget gates of LSTM because it “squishes” data into the range [0,1]. In the first forward pass, random values are assigned to the weights and biases. After the forward propagating process finishes and we obtain values for the output layer, the loss function is calculated and then the back propagating process begins. The backpropagation process goes from the output layer to the input layer, and uses a gradient descent method on the loss function to optimize the weights of each synapse. The forward and backwards propagation processes are then repeated many times. The amount of time this happens is usually measured in “epochs”, which is formally defined as the number of times an entire dataset is passed forward and backwards through the neural network.

Recurrent Neural Networks (RNN) are neural networks that have “memory”. They are able to use previous inputs to help predict the current input and output. While in feedforward neural networks all input is taken in at once, RNN goes through each input in a sequence and does calculations for each input before producing an output called a “hidden state”. This “hidden state” is then combined with the next input to calculate the new hidden state. In this way, RNN’s are able to take information from previous inputs into account. Here, the Multivariate, Multi-step, Vector-output LSTM neural network, which is one of the most complex RNN model, is used.

The data feeding into the LSTM gates are the input at the current time step and the hidden state of the previous time step. They are processed by three fully connected layers with a Sigmoid activation function to compute the values of the input, forget, and output gates. Define x_t as the

input at timestep t , C_t is the cell state, h_t is the hidden state, f_t is the output. The forward process of LSTM to update these values is shown in below equations:

$$\begin{aligned} X'_t &= [x_t, h_{t-1}] \\ S_t &= \tanh(W_s x'_t + b_s) \\ C_t &= i_t \cdot S_t + f_t \cdot C_{t-1} \\ &= o_t \tanh(C_t) \end{aligned}$$

where i_t , o_t , f_t are called the input, output and forget gates given by:

$$\begin{aligned} i_t &= \sigma(W_i x'_t + b_i) \\ o_t &= \sigma(W_o x'_t + b_o) \\ f_t &= \sigma(W_f x'_t + b_f) \end{aligned}$$

We call C_t the *memory cell* at time t , and it is arguably the main component of the LSTM architecture. We can think of the LSTM in the following manner:

$$C_t = i_t \odot S_t + f_t \odot C_{t-1}$$

$$\text{memory}_t = \text{read} \odot \text{input}_t + \text{remember} \odot \text{memory}_{t-1}$$

The training process will try to learn the parameters W_i , W_a , W_f , W_o . We need to unfold the input training sequence into a feed-forward neural network, as shown in Figure 4. Here Γ_f , Γ_i and Γ_o

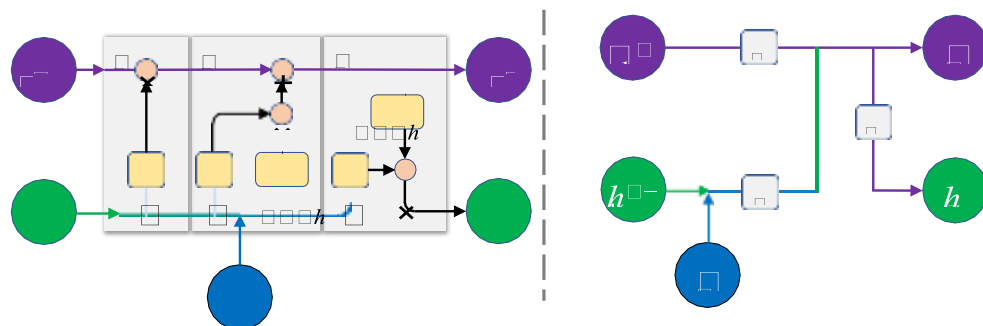


Figure 4: Network structure of LSTM neural network

represents the forget gate, input gate, and the output gate.

LSTM can be used to build deep learning models that have the ability to learn complex patterns in massive data stacks. To improve the accuracy of forecasting the movement of the stock market index, a multivariate time-series forecasting model is created by an improved LSTM, which implements a multivariate time-series analysis method into the model for simultaneous forecasting of parallel time-series using series correlation analysis.

4. Result and discussion

The data used in this paper consists of daily adjusted price extracted from yahoo finance of SPY

stock from 2010-01-01 to 2022-07-08. We denote the stock prices as a time series $S_t, t = 0, \dots, T$. To improve the forecasting of the stock price, we also use another time series: the relative return.

The relative return is the profit or loss an investor expects from an investment. The expected value of the relative return predicts future returns. This financial concept can be useful when there is a robust pool of historical data on the returns of a particular investment. The formula to calculate relative return is as follows:

$$R_{t+1} = \frac{S_{t+1} - S_t}{S_t}$$

The time series of relative returns ($R_t \geq 1$) will be used in the training to improve the accuracy rate of the forecast. More precisely, we take the 2-dimension time series ($S_t, R_t \geq 1$) as the input of the LSTM neural network. The output vector has two steps. More precisely, given $[(S_t, R_t), t = 1, \dots, s]$, we need to predict $[S_{s+1}, R_{s+1}), (S_{s+2}, R_{s+2})]$. Thus the neural network defines two functions f_S and f_R , such that

$$(\hat{S}_{T+1}, \hat{S}_{T+2}) = f_S(S_{t+1}, S_{t+2}, \dots, S_{t+s}; R_{t+1}, R_{t+2}, \dots, R_{t+s})$$

$$(\hat{R}_{T+1}, \hat{R}_{T+2}) = f_R(S_{t+1}, S_{t+2}, \dots, S_{t+s}; R_{t+1}, R_{t+2}, \dots, R_{t+s})$$

where $s > 0$ is the sample size, which is taken to be $s = 6$ in our simulations. Our deep learning of the SPY stock price is based on the construction of an ensemble model that can predict multiple financial time-series data simultaneously.

80% of the data was used for training, and 20% of the data for testing. Six preceding values were used to predict two values.

A unique feature of this model is that we input both the stock data and the relative return values into the model. Hence, why the output shape for the input layer is (6,2).

Layers	Output Shape	Parameters
Input Layer	(6, 2)	0
LSTM1	(6, 500)	1006000
LSTM2	(200)	560800
dense1	(32)	6432
dense2	(4)	132
Reshape	(2,2)	0

We reshape the model to dimension size (2,2) at the end so that it will output the two predicted stock price values, but also the two corresponding relative return values.

The standard LSTM model uses some integer x preceding values to predict 1 value. The standardMSE loss function, defined as

$$L_{mse}(y_{true}, y_{pred}) = \frac{1}{N} \sum_{i=1}^N (y_{true}(i) - y_{pred}(i))^2$$

is then used. However, as shown in the literature, deep learning neural networks' ability to predict stock prices are limited.

To improve the accuracy, we propose a novel loss function, by implementing the relative return function. We first construct the multivariate, multi-step LSTM, with the 2-dimension output $(S_{t+s+1}, S_{t+s+2}; R_{t+s+1}, R_{t+s+2})$. The new loss function is defined as

$$L_D = \frac{1}{s} \sum_{k=1}^s \left(R_{t+s+2} - \frac{S_{t+s+2} - S_{t+s+1}}{S_{t+s+1}} \right)^2$$

which uses the definition of the relative return R_t .

Our new total loss function is

$$L_{loss} = \lambda L_{mse} + (1 - \lambda) L_D$$

where $\lambda > 0$ is a regulation parameter. In our training process, we take $\lambda = 0.6$ in the pre-trainings, and then $\lambda = 0.4$ in further trainings, in order to improve the accuracy rates.

The motivation to do this is because if relative return is added to the loss function, the improved model will have to learn weights and biases that will be optimal not only for the relative return loss function, but also for standard stock price loss function. Because this effectively cuts down on the set of acceptable weight and bias values, this model should achieve higher accuracy after extensive training.

Training loss continued to decrease incrementally until finally stabilizing at around 10,000 epochs. The improved LSTM model is evaluated using MSE, which is a standard accuracy criterion in machine learning. Our training MSE after 10,000 epoch is $2.6 \cdot 10^{-6}$, and our test MSE is 0.00764.



Figure 5: Prediction of stock prices compared with test set

As we can see, both the training and test MSE are objectively strong. The improved LSTM model outperforms the LSTM model used to predict SPY in [3], which reaches a test mean-squared error of 0.12.

In Liang et al. (2019), for the S&P 500 dataset, data from January 3, 2000 to May 16, 2019 is used. This is the comparison of the test MSE of the LSTM, Wavelet-LSTM, GRU, and Wavelet-LSTM + attention models that are found in Liang et al. (2019) with our improved LSTM model:

	MSE
LSTM	0.1208
WLSTM	0.1067
GRU	0.1000
WLSTM + attention	0.0546
Improved LSTM	0.0076

5. Conclusions

This paper's proposed improvement to the loss function produces an accurate prediction which significantly outperforms the standard LSTM stock prediction model. The results of training, thus, indicates that adding limiting parameters to the loss function by adding a relative return MSE allows for a more accurate prediction.

The proposed architecture of the LSTM (typically used in state-of-art language modeling deep learning tasks) can be considered very promising as it has proven to be able to predict well in comparison with other strategies employed and tested in the literature. However, the relative return limiting parameter may not be optimal. Furthermore, if one includes a set of relevant technical indicators in the training process, it may provide a positive influence to the performance of the model. In the same way, employing all the features available in the financial time series such as High, Low, Open, Close and Volume prices, which are the most relevant variables, enriches the model. More research may be done on different limiting parameters and additional features.

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Homo-Hetero Pairing Regression Model: An Econometric Predictive Model of Homo Paired Data

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Abstract

The study aimed to examine the technical and fundamental hypotheses in NYSE, NASDAQ and S&P 500 stock exchange markets. The main determinants (variables) that were examined were stock trading volumes, closing stock prices and stock information available in the stock exchange market. The 240 days, 197 days and 253 days data of closing stock prices and trading volumes at NYSE, S&P500 and NASDAQ stock exchange markets were systematically collected from June 2021 to June 2022. The data was analysed by using the Homo-Hetero Pairing (HHP) Regression Model. This model was developed to detect the linear and non-linear behaviour of data. The study evidenced that both the technical and fundamental hypotheses in NYSE, S&P500 and NASDAQ stock exchange markets are defined by the inverse and S-curved models in two distinctive pairing classes called the positive-positive pairing (PPP) class and the negative-positive pairing (NPP) class. The study concluded that the optimal prediction of the stock price or return is achieved by the fundamentalists in the stock exchange markets. The study recommends that stock investors should priorities the use of the fundamental hypothesis to make their portfolio investment decision. Moreover, the study recommends the application of the HHP regression model in financial markets, economics, psychology, sociology, and medicine studies. In addition, the HHP regression model is recommended for the prediction of water waves in the investigation of hydrodynamic and erosion-accretion processes.

Keywords: Homo-Hetero Pairing Regression, Stock Price, Trading Volume, Econometric Predictive Model, Homo-Paired Data

JEL Codes: C01, C02, C18, C51, D91

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1. Introduction

The homo paired data are data of the same (homo) items sampled from the same population or level of analysis (Niroumand, Zain and Jamil, 2013). In other words, the homo paired data are

data in the couple or dyads (Teachman, Varver, and Day, 1995). The basic requirement of the homo paired data is it should be collected from two or more members /items of the same groups. In practice, these kinds of data are mostly and frequently used in our daily life activities. For example, the homo paired data may include the household data, family data, inflation rate, and economic growth sampled in a series of times (historical data). On the other hand, unpaired (hetero) data are data that sample from different populations or levels of analysis (Oyeka and Umeh, 2012). For example, the data sampled from individuals and that of the households, or data sampled from the country level (e.g., inflation rate or GDP per capita) and individual level (e.g., monthly income). These kinds of data are sampled from different levels of analysis and different populations, hence are unpaired data.

In the econometrics studies, both the short and long-run economic plans involve the prediction of the homo paired data such as inflation rate, stock prices, economic growth rate, stock trading volume, foreign direct investment (FDI) inflow and outflow in a country. These kinds of econometric data require robust predictive models. The accurate prediction of homo paired data helps the decision-makers to reduce the risk due to uncertainty planning of the economic plans. Moreover, the appropriate predicted plans use an appropriate resource and timely resourcing (managing the supply and demand). In practice, the prediction of data is done from historical data; the historical data may behave either linearly or non-linearly depending on changing factors such as time, technology, market forces, etc. The phenomena of the homo paired data behaving either linearly or non-linearly pose a predictive challenge to decision-makers in selecting which appropriate predictive model will be used (Soni, Tewari, and Krishnan, 2022). Recently, in the econometric studies, the application of artificial intelligence such as neural network analysis and the use of the learning machine techniques such a support vector machine (SVM), random forest, K-neighbour and others are mostly applied and recommended because they have shown the least predictive error (Prasad, Gumparthi, Venkataramana, ..., and Nishanthi, 2022; Srivinary, Manujakshi, Kabadi and Naik, 2022). However, the use of artificial intelligence and learning machine techniques is not supported by some studies. For example, Soni, et al. (2022) claimed that SVM is mostly demonstrating high accuracy on non-linear classification data; the random forest method demonstrates high accuracy in the binary classification data. In other words, some of the artificial and learning machine methods can distort the predictive accuracy if they are used inappropriately. Another drawback is that artificial intelligence method such as neural network analysis, it not interpreted directly and deep neural analysis require more training time and dimensional reduction of the data (Seethalakshmi, 2018; Enke, Grauer and Mehdiyev, 2011; Guraray, Shriya and Ashwini, 2019). Moreover, Prasad, et al. (2022) contended the application of the learning machine and artificial intelligence methods does not grant predictive accuracy, in comparison to the statistical methods.

One of the active econometric challenges is the prediction of the stock price in the stock exchange market (Wang, 2014; Srivinary, et al. 2022; Prasad, et al. 2022; Gharehchopogh, Bonab and Khaze, 2013; Bhuriya, Kaushal, Sharma, and Singh, 2017). The stock prices are one of the homo paired data that are volatile due to the different factors that influence the stock price at the stock exchange market. Traditionally, the prediction of the stock price was done by technical aids (price and trading volume trends) and brokers. This prediction was based on historical prices, volume, and price trends (Sahoo and Charlapally, 2015). Today stock prediction

has become very complex than before as stock prices are not only affected by the company's related information but also socio-economic conditions of the country, political atmosphere and others (Sahoo and Charlapally, 2015). Specifically, the stock prices are influenced by internal factors such as the company's profitability, liquidity, asset tangibility, management or governance effectiveness of the company, and goodwill. On the other hand, the stock prices are influenced by external factors such as the inflation rate, level of economic growth, government policy, global market uncertainty, the interest rate of the financial markets, etc (Bhuriya, et al., 2017). Notably, the returns from the stock market are always uncertain and ambiguous hence traditional techniques will not give accurate predictions (Sahoo and Charlapally, 2015). In most practice, the homo paired data in a short term behave linearly but in the long run, behave non-linearly. In the stock market prices, the data may behave either linearly or non-linearly in the short or long term, this phenomenon increases the complexity of the prediction of the stock price at the stock exchange market. Adversely, the inaccuracy predictive model increases the risk of trading on stocks, hence hurting economic growth. A lot of studies have been made in this area and advanced intelligence techniques ranging from the pure mathematical model and expert system to neural networks have been proposed for stock predictive, however, they have been evidenced to have methodological drawbacks (Sahoo and Charlapally, 2015; Singh, Rehan and Kumar, 2022; Demiray and Gurhanli, 2021).

Some studies such as Karin, Alam and Hossain (2021) use linear regression and decision tree regression to analyse the stock price and conclude that the stock market is a more perplexing and sophisticated way of doing business. Gururay, et al. (2019) showed that linear regression is the basic tool by which linear trend is obtained. However, Gharehchopogh, et al.(2013) evidenced that the market fluctuation affects the stock price and trading volume which became hard to predict, therefore increasing the risk of the investors' returns. That is, a better predictive model is required to assist the investors to trade the stock with greater certainty. That is, the investors do not know when the price will go up (increase) or down (decrease). Gharehchopogh, et al.(2013) suggested that data mining techniques have more successful performance in predicting various fields such as economy, policy and engineering compared to traditional statistical methods by discovering the hidden knowledge of the data. Moreover, the experience has shown that learning machine techniques can be successfully predicting daily stock prices and their trading volume. In that sense, Gharehchopogh, et al.(2013) contradicts Prasad, et al. (2022), Sahoo and Charlapally (2015) and Karim, et al.(2021) who advocate for statistical methods. Bhuriya, et al.(2017) stated that the stock market is a messy spot for anticipating since there are not any critical guidelines (model) to access or foresee the estimation of the offer(price) inside the stock market. They contended that numeral techniques like specialised investigation, principal examination, factual examination and so forth arrange to anticipate the value inside the stock market nevertheless none of these approaches is incontestable as a faithfully worthy expectation instrument. They conclude that stock price data is notoriously difficult or impossible to predict. The linear regression fails when a randomly or stochastic and unpredictable event occurs. That is, not every stock price has a steady linear change or trend. Moreover, Bajzik (2020) concluded that one can not rely on any general conclusions about stock markets; the predictability of the stock returns varies with different markets and stock types. Enke, et al.(2011) suggested that to have a predictive model that predicts stock price level precisely, the model should consider or capture

the non-linearity and discontinuities of the factors which are considered to impact the stock market.

From the literature, we notice that there is no consensus on which predictive model is the best or optimal for stock price prediction. Some studies concluded that the prediction of the stock price in the stock exchange market is impossible (Bhuriya, 2017). Moreover, some studies advocate for artificial intelligence and learning machine techniques (Seethalakshmi, 2018; Smith and Rajan, 2017; Cai and Gao, 2017; Wang, 2014; Srivinary et al., 2022; Soni et al., 2022). On the other hand, some studies advocate for traditional statistical methods (Prasad et al., 2022; Chaudhary, Arora and Singh, 2018; Gupta and Wagalakshmi, 2019; Mali, Karchalkar, Jain,..and Kumar, 2017). Therefore, the researchers reached the opposite diametric conclusion on the best choice of the powerful predictive model of the stock price. The literature exhibits the contradictory evidence gaps that this paper forced to establish a new statistical model that predicts the data in pairs.

On the other hand, the study on the relationship between the stock price and trading volume is still debatable in the literature. Mahajan and Singh (2008) found in the Indian Stock Market that there is a weak causality running from volume to return (price). That is, volume is an informational signal to investors. Mpofu (2012) found a positive relationship between the stock price and contemporary changes in trading volume in the JSE security exchange in South Africa. This study was supported by Pathirawasam(2011) on the Colombia stock exchange. Kaizoji (n.d) studying the Tokyo stock exchange found that the relationship between the stock price and trading volume is defined by power laws. A recent study by Alhussayen (2022) in the Saudi Arabia stock market evidenced that there is a unidirectional relationship running from a return to volume. He concluded that the volume does not carry informational content and cannot predict the stock price. That is, the returns (price) do impact the trading volume but the effect is not steady, which also causes the problem of prediction. This conclusion contradicts Mahajan and Singh (2008). Karpoff (1987) confirmed that volume is positively related to the magnitude of the price change which also supports Mahajan and Singh (2008) and contradicts Alhussayen (2022). The specific studies on NYSE by Huang and Heian(2010) using the conventional method developed by Jegadeesh and Titman (1993) found there is a statistically abnormal return for higher volume. However, the historical studies in NYSE by Granger and Morgenstern (1963) using the same approach found that a high trading volume tends to follow high returns and vice versa. The recent study on NYSE done by Yoni (2013) found that there is a positive contemporaneous relationship between return and trading volume, which contradicts Huang and Heian(2010) and supports Granger and Morgenstern (1963) and Gallant and Rossi (1990). The fundamentalists' studies such as Huana, Capretz and Ho (2021), Malinowska (2010), Wu, Liu, Zou and Weng(2022) and Bajzik (2020) empirically evidence that the stock price adjustment is due to the information released. That is, the price response to public new information is gradual and accompanied by increases in trading activities.

Specifically, the study examined the impact of homo pairing changes in daily stock information relatively to changes in daily closing stock price on homo pairing changes in daily closing stock prices relative to changes in daily stock information (fundamental analysis), and the impact of homo pairing changes in the daily closing stock price relative daily trading volume on homo

pairing changes in daily trading volume relative to daily closing stock (Technical analysis) in New York Stock Exchange Market (NYSE), Standard and Poor's 500 (S&P 500) and the National Association of Securities Dealers Automatic Quotation System (NASDAQ). In other words, the study asks “does daily stock information available on the stock exchange market significantly influence the next (future) price level of the stock?” On the other hand, the study examined if the statistical data (records) of daily stock prices and their trading volume convey a significant message or signal to the investor’s decisions. The next sections of the paper cover the concept and model development, methodology, findings, conclusion and recommendation, and references.

2. Literature Review

2.1. The Concept and Model Development

The homo-paired data may behave linearly or non-linearly; data moves up and down for a range of periods. The data that may acquire both behaviours of linearity and non-linearity, its prediction will not be accurately done by the traditional linear regression (Bhuriya et al., 2017; Gharehchopogh, 2013; Karin et al., 2021; Gururay et al., 2019). It requires a model that can capture the up and down movement of data; that is the non-linearity and discontinuities of the data (Enke, et al., 2011). The study used the homo-hetero pairing (HHP) regression model. The HHP regression model tackled the question of how the homo pairing changes in x relative to change in y can accurately predict the homo pairing changes in y relative to changes in x . The term “pairing changes” means the “*net pairing change effect*” of the two paired variables x and y , that changes from one value to the next value, that is, x_1 to x_2 and y_1 to y_2 . Therefore, the net pairing change effect is $(x_2 - x_1) - (y_2 - y_1)$. This can be expressed as the percentage of change in x , $(x_2 - x_1)$ and become x -homo pairing changes, ∂_x , i.e., $[(x_2 - x_1) - (y_2 - y_1) / (x_2 - x_1)]$. When the net pairing change effect is divided by change in y , $(y_2 - y_1)$ that $[(x_2 - x_1) - (y_2 - y_1) / (x_2 - x_1)]$, the equation becomes “ y -homo pairing changes, ∂_y ”.

For a clear illustration of the concept of the homo-hetero pairing regression model, let's consider the difference between the traditional linear regression modelling approach and the homo-hetero pairing regression modelling. In the traditional linear regression modelling the estimated or predicted value $\hat{y}_n$ is due to the new value of x_n with no memory of the past data, x_{n-1} . That is $x_1 \rightarrow \hat{y}_1 \dots x_n \rightarrow \hat{y}_n$. This means that x_{n-1} is useless in the estimation or prediction of $\hat{y}_n$. On the other hand, in the homo-hetero pairing regression model the estimated or predicted y -homo pairing changes relative to changes in x , (∂_y) or simply relative x -homo pairing changes in y are due to the x -homo pairing changes relative to y , (∂_x) or relative y -homo pairing change in x . That is, x_1 and y_1 are involved in the estimation of y_2 (Table 1).

Table 1: The traditional linear and homo-hetero pairing regression modelling

Traditional Linear Regression Model			Homo-hetero Pairing Regression Model		
X	Y	Description	X	Y	Description
x_1	y_1	$\hat{y}_n$ is due to the new value of x_n with no memory of x_{n-1} . That is $x_1 \rightarrow \hat{y}_1 \dots x_n \rightarrow \hat{y}_n$. That is x_{n-1} is useless in the estimation of $\hat{y}_n$.	∂_{x_1}	∂_{y_1}	$\hat{\partial}_y$ is due to the homo pairing change effect/difference of x_n and x_{n-1} . That is, x_1 and y_1 are involved in the estimation of y_2
x_2	y_2		∂_{x_2}	∂_{y_2}	
x_3	y_3		∂_{x_3}	∂_{y_3}	
.	.		.	.	
.	.		.	.	
.	.		.	.	
x_n	y_n		∂_{x_n}	∂_{y_n}	
Modelling: Regression: $X \rightarrow Y = x_n \rightarrow \hat{y}_n$ Correlation: $X \leftrightarrow Y = x_n \leftrightarrow y_n$				Modelling: Regression: $\partial_x \rightarrow \hat{\partial}_y$ Correlation: $\partial_x \leftrightarrow \partial_y$	

Source: Author (2022).

Where,

$$\partial_x = \frac{(x_n - x_{n-1}) - (y_n - y_{n-1})}{x_n - x_{n-1}}$$

$$\partial_y = \frac{(y_n - y_{n-1}) - (x_n - x_{n-1})}{y_n - y_{n-1}}$$

$$\partial_x \rightarrow \hat{\partial}_y = \left[\frac{(x_n - x_{n-1}) - (y_n - y_{n-1})}{x_n - x_{n-1}} \right] \rightarrow \left[\frac{(y_n - y_{n-1}) - (x_n - x_{n-1})}{y_n - y_{n-1}} \right]$$

The predictions of the y -homo pairing changes relative to the changes in x can be done by establishing the linear regression between the y -homo pairing changes relative to changes in x (dependent) and x -homo pairing changes relative to changes in y (independent); hereafter, y -homo pairing changes and x -homo pairing changes respectively. The common principle of least squares can be applied to establish the “homo-hetero pairing regression model”; the model that predicts the y -homo pairing changes (dependent). That is the regression modelling of the x -homo pairing changes on y -homo pairing changes. Now, let us predict the y -homo pairing changes by a homo-hetero pairing (HHP) regression model, that is,

$$\partial_y = \lambda_0 + \sum_{i=1}^n \lambda_i \partial_{x_i} + \varepsilon_i$$

$$\varepsilon_i = \partial_{y_i} - \hat{\partial}_{y_i}$$

If the HHP regression model is reduced to the HHP simple regression model, then the equation becomes,

$$\partial_y = \lambda_0 + \lambda_1 \partial_{x_i} + \varepsilon_i$$

The term error or residuals of the model, ε is determining the prediction accuracy of the model. It is measured as the difference between the actual value of the y-homo pairing changes (∂_{y_i}) and predicted y-homo pairing changes ($\hat{\partial}_{y_i}$), that is, $\varepsilon_i = \partial_{y_i} - \hat{\partial}_{y_i}$. This value can be illustrated by using the graph (Figure 1).

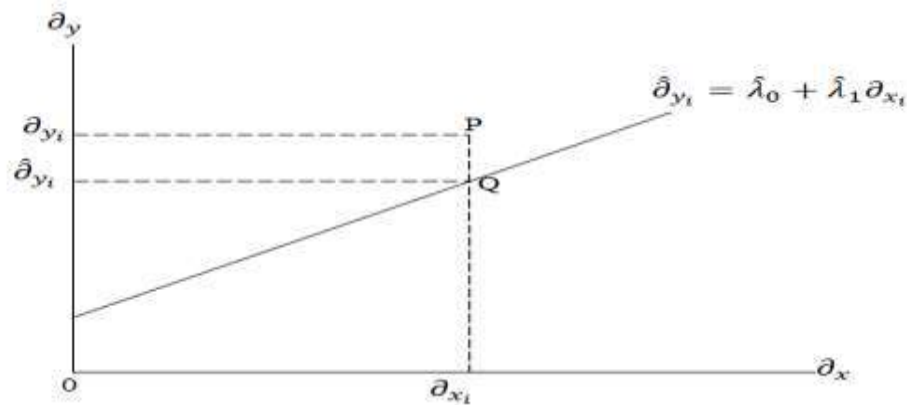


Figure 1: The profiling of residuals of the homo-hetero pairing regression model

The residuals of the model are given $\varepsilon_i = \partial_{y_i} - \hat{\partial}_{y_i}$, that is determined by the differences between the values P and Q, that is, P-Q, which measures the vertical distance of the y-homo pairing changes, (∂_y). The coordinate or data point at Q is ($\partial_{x_i}, \hat{\partial}_{y_i}$) and the data point at point P is ($\partial_{x_i}, \partial_{y_i}$). The difference between the actual value of y-homo pairing changes, (∂_{y_i}) at point P and the predicted value of the y-homo changes, ($\hat{\partial}_{y_i}$) at point Q is called the error or residual. It is the vertical distance of the y-homo pairing changes, (∂_y). It can be obtained by P-Q, that is, ($\partial_{x_i}, \partial_{y_i}$) - ($\partial_{x_i}, \hat{\partial}_{y_i}$) which is equal to ($\partial_{y_i} - \hat{\partial}_{y_i}$) for a single point data, ∂_{x_i} . For data set ∂_x with a subset $\partial_{x_1}, \partial_{x_2} \dots \partial_{x_n}$. The total residuals are given by the summation of ε_i , that is $\sum_{i=1}^n (\partial_{y_i} - \hat{\partial}_{y_i})$. The principle of the HHP equation is based on the minimisation of the sum of squared residuals or errors (SSR or SSE). The SSE is given by,

$$SSE = \sum_{i=1}^n \varepsilon_i^2 = \sum_{i=1}^n (\partial_{y_i} - \hat{\partial}_{y_i})^2$$

$$\text{since } \hat{\partial}_{y_i} = \hat{\lambda}_0 + \hat{\lambda}_1 \partial_{x_i}$$

$$SSE = \sum_{i=1}^n \varepsilon_i^2 = \sum_{i=1}^n \left(\partial_{y_i} - \hat{\lambda}_0 + \sum_{i=1}^n \hat{\lambda}_i \partial_{x_i} \right)^2, \text{ HHP multiple regression Model}$$

$$SSE = \sum_{i=1}^n \varepsilon_i^2 = \sum_{i=1}^n (\partial_{y_i} - \hat{\lambda}_0 - \hat{\lambda}_1 \partial_{x_i})^2, \text{ HHP simple regression model}$$

Since the optimal parameter $\hat{\lambda}_0$ and $\hat{\lambda}_1$ will be obtained at the minimal point of the function curve of SSE. Therefore, we differentiate the function of SSE to determine where its slope is equal to zero. That is the point value that there is no increase of error or residual. This means the point that the estimated value or predicted value is close to the actual values of the paired data. Taking the SSE function of the HHP simple regression model, we find its first derivative with respect to their parameters, $\hat{\lambda}_0$ and $\hat{\lambda}_1$. That is,

$$\frac{d(\sum_i \varepsilon_i^2)}{d\hat{\lambda}_0} = \frac{d \sum_i (\partial_{y_i} - \hat{\lambda}_0 - \hat{\lambda}_1 \partial_{x_i})^2}{d\hat{\lambda}_0} = 2 \cdot (-1) \cdot \sum_i (\partial_{y_i} - \hat{\lambda}_0 - \hat{\lambda}_1 \partial_{x_i})$$

$$\frac{d(\sum_i \varepsilon_i^2)}{d\hat{\lambda}_1} = \frac{d \sum_i (\partial_{y_i} - \hat{\lambda}_0 - \hat{\lambda}_1 \partial_{x_i})^2}{d\hat{\lambda}_1} = 2 \cdot (-\partial_{x_i}) \cdot \sum_i (\partial_{y_i} - \hat{\lambda}_0 - \hat{\lambda}_1 \partial_{x_i})$$

These equations (slopes of the SSE function curves) are commonly known as the slopes (normal) equations which can be jointly solved to obtain the algebraic equations of the parameters $\hat{\lambda}_0$ and $\hat{\lambda}_1$. Now, since the first derivative of the SSE function is the slope or rate of error term which changes as the independent variables change, then to have an optimal linear model, the error rate should be equal to zero in the estimate in $\hat{\lambda}_0$ and $\hat{\lambda}_1$, therefore, slope equations are equalized to zero,

$$2 \cdot (-1) \cdot \sum_i (\partial_{y_i} - \hat{\lambda}_0 - \hat{\lambda}_1 \partial_{x_i}) = 0$$

$$\sum_i \partial_{y_i} - n\hat{\lambda}_0 - \hat{\lambda}_1 \sum_i \partial_{x_i} = 0$$

$$\hat{\lambda}_0 = \frac{1}{n} \sum_i \partial_{y_i} - \hat{\lambda}_1 \frac{1}{n} \sum_i \partial_{x_i}$$

$$\hat{\lambda}_0 = \bar{\partial}_{y_i} - \hat{\lambda}_1 \bar{\partial}_{x_i}$$

$$2 \cdot (-\partial_{x_i}) \cdot \sum_i (\partial_{y_i} - \hat{\lambda}_0 - \hat{\lambda}_1 \partial_{x_i}) = 0$$

$$\sum_i \partial_{x_i} \partial_{y_i} - \hat{\lambda}_0 \sum_i \partial_{x_i} - \hat{\lambda}_1 \sum_i \partial_{x_i}^2 = 0$$

$$\text{substitute } \hat{\lambda}_0 = \bar{\partial}_{y_i} - \hat{\lambda}_1 \bar{\partial}_{x_i}$$

$$\sum_i \partial_{x_i} \partial_{y_i} - (\bar{\partial}_{y_i} - \hat{\lambda}_1 \bar{\partial}_{x_i}) \sum_i \partial_{x_i} - \hat{\lambda}_1 \sum_i \partial_{x_i}^2 = 0$$

$$\sum_i \partial_{x_i} \partial_{y_i} - \bar{\partial}_{y_i} \sum_i \partial_{x_i} - \hat{\lambda}_1 \left(\sum_i \partial_{x_i}^2 - \bar{\partial}_{x_i} \sum_i \partial_{x_i} \right) = 0$$

$$\sum_i \partial_{x_i} \partial_{y_i} - \bar{\partial}_{y_i} \sum_i \partial_{x_i} = \hat{\lambda}_1 \left(\sum_i \partial_{x_i}^2 - \bar{\partial}_{x_i} \sum_i \partial_{x_i} \right)$$

$$\hat{\lambda}_1 = \frac{\sum \partial_{x_i} \partial_{y_i} - \bar{\partial}_{y_i} \sum \partial_{x_i}}{(\sum \partial_{x_i}^2 - \bar{\partial}_{x_i} \sum \partial_{x_i})}$$

Therefore, we get the normal equations of the least squared errors or residuals, which are

$$\begin{aligned}\hat{\lambda}_1 &= \frac{\sum \partial_{x_i} \partial_{y_i} - \bar{\partial}_{y_i} \sum \partial_{x_i}}{(\sum \partial_{x_i}^2 - \bar{\partial}_{x_i} \sum \partial_{x_i})} \\ \hat{\lambda}_0 &= \bar{\partial}_{y_i} - \hat{\lambda}_1 \bar{\partial}_{x_i}\end{aligned}$$

Now, we can recall the covariance term of ∂_{x_i} and ∂_{y_i} given by,

$$\sigma_{\partial_{x_i} \partial_{y_i}} = \frac{1}{n} \sum (\partial_{x_i} - \bar{\partial}_x)(\partial_{y_i} - \bar{\partial}_y)$$

And the variance of ∂_{x_i} is given by

$$\partial_{x_i}^2 = \frac{1}{n} \sum (\partial_{x_i} - \bar{\partial}_x)^2$$

Therefore, $\hat{\lambda}_1$ can be simplified to,

$$\hat{\lambda}_1 = \frac{\sigma_{\partial_{x_i} \partial_{y_i}}}{\partial_{x_i}^2}$$

2.2.1. Goodness-of-fit statistics

The goodness-of-fit statistics are statistics that explained the predictive accuracy of the linear model. In other words, goodness-of-fit statistics are statistics that measure the degree of the deviation between the predicted and observed values of the y-homo paired changes. That is explained by the difference between the observed value and the predicted value of the y-homo pairing changes. The common goodness-of-fit statistics of the HHP regression are y-homo paired Ψ^2 , y-homo paired adjusted Ψ^2 , homo-hetero paired P-values, y-homo paired root MSE, and homo-hetero paired t-value, homo-hetero paired confidence interval and y-homo paired F-statistic value.

2.2.1.1. The y-homo paired Ψ^2

The y-homo paired Ψ^2 , or simply Ψ^2 is the homo-hetero pairing coefficient that determines the line of best fit of the HHP regression model. It is the common measure of goodness-of-fit of the HHP regression model. It is given as,

$$\Psi^2 = 1 - \frac{SSE}{SST} \text{ or } \frac{SSR}{SST}$$

Where SSE (sum of squared residuals) = $\sum_{i=1}^n (\partial_{y_i} - \hat{\partial}_{y_i})^2$, SST (total sum of squares) = $\sum_{i=1}^n (\partial_{y_i} - \bar{\partial}_y)^2$ and SSR (regression sum of squares) = $\sum_{i=1}^n (\hat{\partial}_{y_i} - \bar{\partial}_y)^2$. Alternatively, SSR can be obtained by the formula, $SSR = SST - SSE$. Therefore, Ψ -Squared can be obtained by the formula,

$$\Psi^2 = \frac{SSR}{SST} = \frac{\sum_{i=1}^n (\hat{\partial}_{y_i} - \bar{\partial}_y)^2}{\sum_{i=1}^n (\partial_{y_i} - \bar{\partial}_y)^2}$$

The value of Ψ^2 is ranging from 0 to 1, that is $0 \leq \Psi^2 \leq 1$. The value of Ψ^2 near or close to one indicates the data is well paired in the model. That is, the regression sum of squares (SSR) is closely equal to the total sum of squares (SST). On the other hand, the value of Ψ^2 near or close to zero indicates that the model is poorly paired in the model. If Ψ^2 is equal to 1, indicates the perfect pairing of the data in the model, and if Ψ^2 is equal to 0 indicates the model is perfectly poorly paired to the paired data.

2.2.1.2. The y-homo paired adjusted Ψ^2

The y-homo paired adjusted Ψ^2 , simply adjusted Ψ^2 is the modified y-homo-paired Ψ^2 that has been adjusted to the number of predictors, p in the model. It is used to determine how reliable the correlation is and how much it is determined by the addition of the predictor. In other words, the adjusted Ψ^2 is the statistical tool that measures the goodness-of-fit for HHP multiple regressions by indicating the additional effect of each predictor in the model. The addition of a better predictor increases the value of adjusted Ψ^2 and the addition of a poor predictor in the model reduces the value of adjusted Ψ^2 . Technically, adjusted Ψ^2 offers a small penalty for adding more predictors in the model. If the predictor raises the adjusted Ψ^2 for the homo-hetero pairing regression model, that is a better indication that the predictor has improved the model and can raise the unadjusted Ψ^2 . The adjusted Ψ^2 is expressed as

$$\text{Adjusted } \Psi^2 = 1 - \frac{SSR/(n-p-1)}{SST/(n-1)} = 1 - \frac{n-1}{n-p-1} (1 - \Psi^2)$$

For HHP simple regression, the equation reduced to

$$\text{Adjusted } \Psi^2 = 1 - \frac{n-1}{n-2} (1 - \Psi^2)$$

Where n is the sample size or the number of observations, p is the number of predictors in the model, therefore, $n - p - 1$ is the degree of freedom of the model with sample size, n and number of predictors, p .

2.2.1.3 The y-homo paired root mean square deviation or error

The y-homo paired root mean square deviation or error (MSE) or (RMSE) is another goodness-of-fit statistic that indicates the predictive power of the homo-hetero pairing regression model. It presents the aggregated magnitude of the predictive errors, i.e., the difference between the predicted value and actual values of y-homo pairing changes. In general, the y-homo paired root MSE, or simply root MSE measures the overall accuracy of the predictive model. The lower the y-homo paired root MSE the better as indicates that the predicted values are closest to the actual values, hence the minimal error. The y-homo paired root MSE is the square root of mean square error. That is, the y-homo paired RMSE is the square root of SSE divided by the degree of freedom ($n - p$) of the model; where n is the sample size and p is the parameter to be estimated, for HHP simple regression $p = 2$, which are $\hat{\lambda}_0$ and $\hat{\lambda}_1$. That is,

$$\text{Root } MSE_H = \sqrt{\frac{SSE}{n-p}} = \sqrt{\frac{\sum_{i=1}^n (\partial_{y_i} - \hat{\partial}_{y_i})^2}{n-p}} = \sqrt{\frac{\sum_{i=1}^n (\partial_{y_i} - \hat{\partial}_{y_i})^2}{n-2}}$$

2.2.1.4. The homo-hetero paired confidence interval for lambda coefficients

The homo-hetero paired confidence interval or simply confidence interval provides a means of quantifying the uncertainty produced by the sampling error. The rule of thumb is the same; the 95 percent confidence interval (CI) for the *lambda* coefficient is given by

$$CI = \hat{\lambda}_i \pm 2SE$$

If we assume the predictive model yield unbiased estimates of the parameter $\hat{\lambda}_i$, $\hat{\lambda}_i = \lambda_i$, but if there is a 95 percent chance that our estimate $\hat{\lambda}_i$ will lie with the 2 standard error (SE) of its mean values, λ_i . The standard error of $\hat{\lambda}_i$ or $Se(\hat{\lambda}_i)$ is given,

$$Se(\hat{\lambda}_i) = \sqrt{\frac{SE}{\sum (\partial_{x_i} - \bar{\partial}_x)^2}}$$

The larger is $Se(\hat{\lambda}_i)$, the larger will be the range values, i.e., the wider the confidence interval, and the larger SE, the larger will be $Se(\hat{\lambda}_i)$, and so the wider the CI for the true lambda coefficient. The higher degree of variation of ∂_{x_i} is due to a smaller $Se(\hat{\lambda}_i)$ (tighter confidence interval). The more ∂_{x_i} has varied in the sample, the better the chance we have of accurately picking up any relationship that exists between the *x*-homo pairing changes (∂_{x_i}) and *y*-homo pairing change (∂_y).

2.2.1.5 The homo-hetero paired t-test

The homo-hetero paired t-statistic t_ψ is another measure of the significance of the model. In other words, the homo-hetero paired t-test or simply paired t-test is a method used to test whether the mean difference between pairs of measurements is zero or not. It is applied when the data are separated for “before” and “after” measurements for each pair and need to calculate the differences. The paired t-test is used to test when the data values are paired measurements (Moore, et al. 2013). The assumptions of the use of paired t-tests are subject must be independent, each of the paired measurements must be obtained from the same subject and the measured differences are normally distributed (Moore, et al. 2013). Paired t-test assumes that the changes of observed variables *x* and *y* are linearly pairing or matched variables. Therefore, the appropriate statistical significance test is the *homo-hetero paired t-test*, modified from the traditionally paired t-test (Moore, et al. 2013). That is,

$$t_\psi = \frac{\sum (\partial_{x_i} - \partial_{y_i}) \sqrt{n-1}}{\sqrt{n \sum (\partial_{x_i} - \partial_{y_i})^2 - (\sum (\partial_{x_i} - \partial_{y_i}))^2}} \sim t(n-1)df$$

2.2.1.6. The y-Homo paired F-statistics

The y-homo paired F-test, or simply F-test is the statistical significance test for the homo-hetero pairing regression model, whether any of the predictors are significant (not equal to zero). In other words, the y-homo paired F-tests aimed to provide statistical evidence that the lambda coefficient of the homo-hetero pairing regression model is not zeros. It is given as the ratio of the explained variance and unexplained variance of the y-homo pairing changes, that is,

$$F_H - test = \frac{MSR}{MSE}$$

Where MSR is the mean of squares for regression, which is given by the expression $MSR = \frac{SSR}{p-1}$ and MSE , is the mean of square errors, which is given by the expression $MSE = \frac{SSE}{n-p}$, $p - 1$ is the degree of freedom for regression (model) with p number of predictors, and $n - p$ is the degree of freedom for error with sample size n and the number of predictors p . Therefore,

$$\begin{aligned} F_H - test &= \frac{MSR}{MSE} = \left(\frac{SSR}{p-1} \right) \times \left(\frac{n-p}{SSE} \right) \\ &= \left(\frac{SSR}{SSE} \right) \times \left(\frac{n-p}{p-1} \right) \\ &= \left(\frac{SSR}{SSE} \right) \times \left(\frac{n-p}{p-1} \right) \\ &= \frac{\sum_{i=1}^n (\hat{\partial}_{yi} - \bar{\partial}_y)^2}{\sum_{i=1}^n (\partial_{yi} - \hat{\partial}_{yi})^2} \times \left(\frac{n-p}{p-1} \right) \end{aligned}$$

For simple regression, the formula is reduced to, $p = 2$,

$$F_H - test = \frac{\sum_{i=1}^n (\hat{\partial}_{yi} - \bar{\partial}_y)^2}{\sum_{i=1}^n (\partial_{yi} - \hat{\partial}_{yi})^2} (n - 2)$$

2.3. The HHP Multiple regression modelling

Considering the expanded form of a homo-hetero pairing multiple regression model,

$$\partial_{\bar{y}} = \lambda_0 + \lambda_1 \partial_{x_1} + \lambda_2 \partial_{x_2} + \lambda_3 \partial_{x_3} + \cdots + \lambda_{n-1} \partial_{x_{n-1}} + \lambda_n \partial_{x_n} + \varepsilon$$

This can be written in condensed form, that is,

$$\partial_{\bar{y}} = \lambda_0 + \sum_{i=1}^n \lambda_i \partial_{x_i} + \varepsilon_i$$

$$\varepsilon = \partial_{\bar{y}} - \hat{\partial}_{\bar{y}}$$

Where $\partial_{\bar{y}}$ is a pivotal y-homo pairing change and can be written as,

$$\partial_{\bar{y}_i} = \frac{(y_n - y_{n-1}) - (K_n - K_{n-1})}{(y_n - y_{n-1})}$$

Where K is the pairing means of the independent variables, it is given as,

$$K_i = \frac{1}{p} \sum_{i=1}^p IV_i$$

Where p the number of predictors (independent variable) in the HHP multiple regression model and IV_i is the individual values of predictor (independent variable) in the HHP multiple regression models.

2.4. The HHP regression model and Bundala pairing correlation coefficient

We notice that $\hat{\partial}_{y_i} = \hat{\lambda}_0 + \hat{\lambda}_1 \partial_{x_i}$ is obtained from minimising $\sum_i (\partial_{y_i} - \hat{\lambda}_0 + \hat{\lambda}_1 \partial_{x_i})^2$, and

$\hat{\partial}_{x_i} = \hat{\alpha}_0 + \hat{\beta}_1 \partial_{y_i}$ is obtained from the minimisation of $\sum_i (\partial_{x_i} - \hat{\alpha}_0 + \hat{\beta}_1 \partial_{y_i})^2$, combining the linear equation that $\hat{\partial}_{y_i} = \hat{\lambda}_0 + \hat{\lambda}_1 \partial_{x_i}$ and $\hat{\partial}_{x_i} = \hat{\alpha}_0 + \hat{\beta}_1 \partial_{y_i}$, we get $\hat{\partial}_{x_i} = -\frac{\hat{\lambda}_0}{\hat{\lambda}_1} + \frac{1}{\hat{\lambda}_1} \hat{\partial}_{y_i}$ compares to $\hat{\partial}_{x_i} = \hat{\alpha}_0 + \hat{\beta}_1 \partial_{y_i}$ we get the relations that $\hat{\alpha}_0 = -\frac{\hat{\lambda}_0}{\hat{\lambda}_1}$ and $\hat{\beta}_1 = \frac{1}{\hat{\lambda}_1}$, since there is a relationship between two regression coefficients $\hat{\beta}_1$ and $\hat{\lambda}_1$, and we noticed that,

$$\hat{\lambda}_1 = \frac{\sigma_{\partial_{x_i} \partial_{y_i}}}{\sigma_{\partial_{x_i}}^2},$$

$$\text{Then, } \hat{\beta}_1 = \frac{\sigma_{\partial_{x_i} \partial_{y_i}}}{\sigma_{\partial_{y_i}}^2}$$

Therefore, a product of $\hat{\lambda}_1$ and $\hat{\beta}_1$ should be equal to one, if the two coefficients are perfectly paired and correlated, $\Psi^2 = 1$. That is,

$$\hat{\lambda}_1 \cdot \hat{\beta}_1 = \left(\frac{\sigma_{\partial_{x_i} \partial_{y_i}}}{\sigma_{\partial_{x_i}}^2} \right) \cdot \left(\frac{\sigma_{\partial_{x_i} \partial_{y_i}}}{\sigma_{\partial_{y_i}}^2} \right) = \frac{\sigma_{\partial_{x_i} \partial_{y_i}}^2}{\sigma_{\partial_{x_i}}^2 \cdot \sigma_{\partial_{y_i}}^2}$$

$$\hat{\lambda}_1 \cdot \hat{\beta} = \frac{\sigma_{\partial_{x_i} \partial_{y_i}}^2}{\sigma_{\partial_{x_i}}^2 \cdot \sigma_{\partial_{y_i}}^2} = \Psi^2$$

The Ψ^2 is the same as R^2 in the Pearson correlation.

2.5. The HHP regression model as a data classifier

The HHP regression model can be used as the “classifier” of the structured and unstructured. The classifier is the algorithm that maps or assigns the input data to a specific category. The classification is done to categorise the data into a certain or given number of classes that the new data can fall under. Therefore, the classification model predicts the class label or categories for the new data. The HHP regression model can be applied in the classification modelling of the data. The model can detect and separate the minor homo pairing changes of the paired data x and y which cannot be separated in the normal or traditional linear regression. When the data are closely paired they cannot be separated or categorised into attribute classes. To separate the data we introduce the concept of *homo-hetero pairing scattering*. The homo-hetero pairing changes of x and y are scattered together to identify the classes of pairing behaviour (patterns) of the data. Moreover, the classes can be obtained or established with the application of variable pairing ratios (τ) of the interval of the original data. That is,

$$\tau = \frac{D_min_d_x}{D_min_d_y} \leq \tau \leq \frac{D_max_d_x}{D_max_d_y}$$

Where $D_min_d_x$ and $D_min_d_y$ are sampled data of variables x and y which corresponds to minimum values d_x and d_y respectively. Similarly, $D_max_d_x$ and $D_max_d_y$ are the sampled data of the variables x and y which corresponds to maximum values of d_x and d_y respectively. The τ can be used to classify or assign the new input data in the model by allocating the variable or data to its variable/data pairing ratio interval class. From this concept, each class has a specific variable pairing ratio interval. The ratio can be positive or negative but its sign does not distort the meaning, only the magnitude is considered for the evaluation of the classification model.

2.6. The HHP regression model as a non-linear predictive model

From the classification concept, we notice that the homo-hetero pairing changes can be classified into four homo-hetero classes of paired data. These classes of data are the positive-positive pairing (PPP) class, negative-positive pairing (NPP) class, positive-negative pairing (PNP) class, and negative-negative pairing (NNP) class. Assume each class is bounded or described by the non-linear function relationship between variable x and y by the curve (Figure 2).

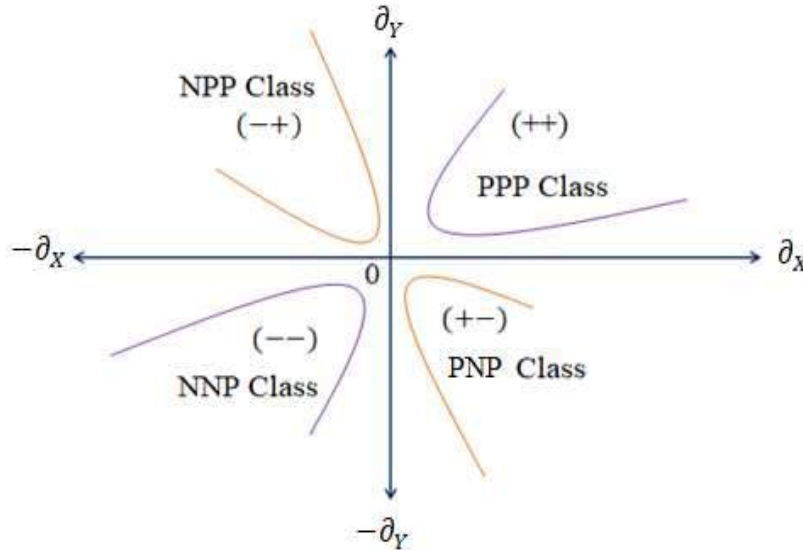


Figure 2: The pairing classes of the homo-hetero non-linear paired data
Source: Author (2022).

Figure 2 shows the four homo-hetero pairing classes of the non-linear paired data. The classes of the non-linear data are termed “quadrant bounded/pairing classes”. Each class is bounded or defined initially by the lowest non-linear function of the paired data – the quadratic curve/function.

$$\partial_Y = \lambda_0 + \lambda_1 \partial_x + \lambda_2 \partial_x^2$$

Multiply the lambda coefficient of the equation by the squares of inverse factors of the independent variable (the lowest non-linear inverse factor, $\frac{1}{\partial_x^2}$) to restrict the pairing relationship in the one quadrant (homo-hetero pairing). That is,

$$\partial_{Y_P} = \lambda_0 + \frac{\lambda_1 \partial_x}{\partial_x^2} + \frac{\lambda_2 \partial_x^2}{\partial_x^2}$$

$$\partial_{Y_P} = \lambda_0 + \lambda_2 + \frac{\lambda_1}{\partial_x}$$

Where, λ_2 is the non-linear accelerating factor or quadrant coefficient or the coefficient (slope) of the second-degree term. This value determines the non-linear pairing attributes of the class. At the perfect pairing classification, $\lambda_2 = 0$, implies that the classes are bounded with quadrant function (inverse functions). That is,

$$\partial_{Y_P} = \lambda_0 + \frac{\lambda_1}{\partial_x}$$

Alternatively, the inverse function can be obtained from the HHP simple regression model, when the data are assumed to be perfectly classified by the liner homo-hetero pairing equation, That is, $\lambda_2 = 0$, and multiplied linear HHP regression model by $\frac{1}{\partial_x^2}$

$$\begin{aligned}\partial_Y &= \lambda_0 + \lambda_1 \partial_x \\ \partial_{Y_P} &= \lambda_0 + \frac{\lambda_1 \partial_x}{\partial_x^2} = \lambda_0 + \frac{\lambda_1}{\partial_x}\end{aligned}$$

$$\text{when, } \ln \partial_{Y_P} \approx \partial_{Y_P}$$

The equation becomes an S-curve function/model that is expressed as

$$\ln \partial_{Y_P} = \lambda_0 + \frac{\lambda_1}{\partial_x}$$

$$\partial_{Y_P} = e^{\lambda_0 + \frac{\lambda_1}{\partial_x}}$$

The mathematical modelling of the quadrant pairing classifier was done for four classes of the homo-hetero pairing classes. The classes PPP, NNP, NPP, and PNP are mathematically defined by the homo-hetero inverse function in its four-quadrant bounded (paired) equations (Figure 3).

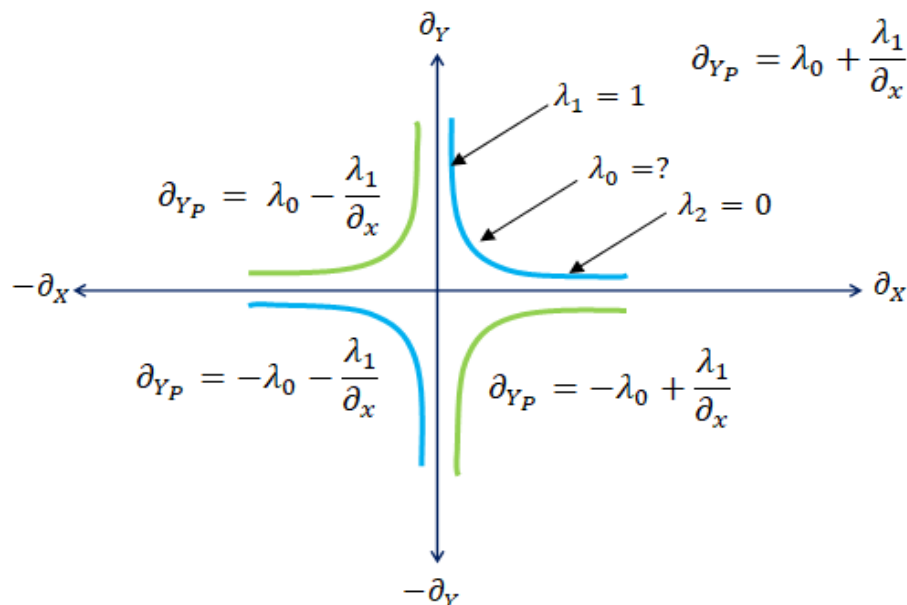


Figure 3: The non-linear equation of the pairing classed of the homo-paired data
Source: Author (2022).

Figure 3 shows the class classifier model of each class. The figure describes the four homo-hetero classes of the paired data. That is,

$$\partial_{Y_P} = \lambda_0 + \frac{\lambda_1}{\partial_x} ; \text{PPP classifier model}$$

$$\partial_{Y_P} = -\lambda_0 - \frac{\lambda_1}{\partial_x} ; \text{NNP classifier model}$$

$$\partial_{Y_P} = \lambda_0 - \frac{\lambda_1}{\partial_x} ; \text{NPP classifier model}$$

$$\partial_{Y_P} = -\lambda_0 + \frac{\lambda_1}{\partial_x} ; \text{PNP classifier model}$$

If the equation is not restricted to the quadrant pairing classes function, the equation can take higher functions or degrees such as quadratic, cubic, etc. That is,

$$\partial_Y = \lambda_0 + \lambda_1 \partial_x + \lambda_2 \partial_x^2 + \dots + \lambda_{n-1} \partial_x^{2n-1} + \lambda_n \partial_x^n$$

If the paired data take a higher degree function (polynomial regression), they describe the multiple informational changes or influences. In other words, the prediction of a stock price is highly influenced by multiple external and internal factors. The HHP polynomial regression has no clear or definitive classes; the data are either paired in more than one or two quadrants (Figure 4).

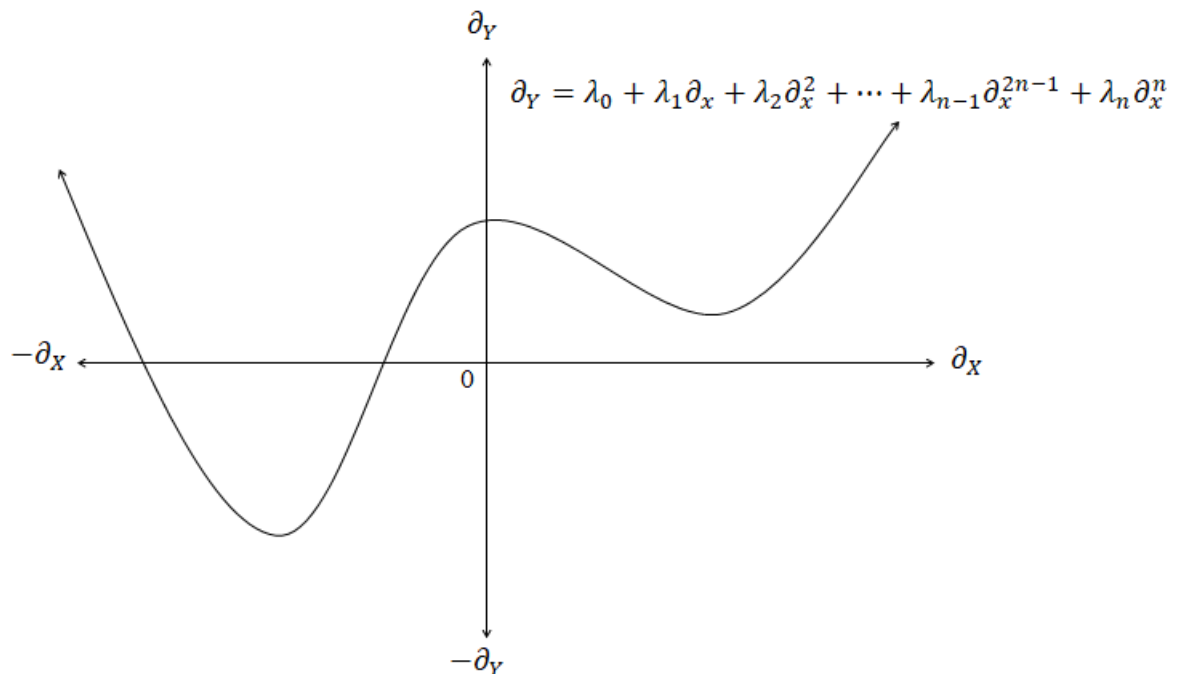


Figure 4: The HHP polynomial regression model

Source: Author (2022).

Figure 4 describes the general non-linear equation of the quadrant unrestricted classes function". This implies that the data can be defined in the quadratic function, cubic function, etc. The HHP polynomial regression is the best predictive model because it captures the general trending behaviour of the paired data (Gururay et al., 2019; Demiray and Gurhanli, 2021; Karim et al., 2021; Sahoo and Charlapally, 2015).

3. Research Method

The study aimed to examine the technical and fundamental hypotheses in the New York Stock Exchange Market (NYSE), Standard and Poor's 500 (S&P 500) and the National Association of Securities Dealers Automatic Quotation System (NASDAQ) stock exchange markets. The Homo-Hetero Pairing Regression Model, simply the HHP regression model was used. This model was introduced to detect the linear and non-linear data, hence being an appropriate econometric predictive model for homo paired data. The data were collected from the three largest stock market exchanges in the world which are the New York Stock Exchange Market (NYSE), Standard and Poor's 500 (S&P 500) and the National Association of Securities Dealers Automatic Quotation System (NASDAQ). The 240 days' daily closing prices and trading volumes data at NYSE were systematically collected from 4, June 2021 to 3, June 2022. Moreover, the closing price and trading volume data for 197 days were collected from 4, June 2021 to 2, June 2022, and the 253 days' closing price and trading volume data of NASDAQ were systematically collected from 4 June 2021 to 3 June 2022.

The independent variable of the first objective (fundamental analysis) is defined as the daily information available at the stock exchange market and measured by homo-pairing changes in days of trading. The dependent variable is defined as the daily closing stock price level and measured by homo-pairing changes of the daily stock closing price level. The variables of the study are measured as follows,

The change of daily information is the independent variable proxies as homo-pairing changes in days of trading, d with a given closing price P is given by,

$$\partial_{DP} = \frac{(d_2 - d_1) - (P_2 - P_1)}{d_2 - d_1}$$

The dependent variable is the change of the daily closing stock price measured in the homo pairing changes in daily closing stock price, P with days of trading, d , it is given as,

$$\partial_{PD} = \frac{(P_2 - P_1) - (d_2 - d_1)}{P_2 - P_1}$$

The second, objective independent variable is measured by the homo-pairing changes in daily stock closing prices P , with a given daily trading volume V ; it is expressed as,

$$\partial_{PV} = \frac{(P_2 - P_1) - (V_2 - V_1)}{P_2 - P_1}$$

The dependent variable is the changes of the daily trading volumes measured by homo-pairing changes in daily trading volumes V , with a given daily closing stock price, P . It is expressed as,

$$\partial_{VP} = \frac{(V_2 - V_1) - (P_2 - P_1)}{V_2 - V_1}$$

The tests of linear assumptions were done. The Breusch-Pagan/Cook-Weisberg test for heteroscedasticity was conducted and found to have an F-value of 0.63 with a p-value of 0.6564 which is greater than the recommended critical value of the significance level of 0.05; this indicates that the data do not have a constant variance; the null hypothesis was rejected at 95 percent of confidence level. On the hand, the normality test was done by using the Jarque-Bera normality test and found to be 5.381 and Chi (2) is 0.0678) which indicates that the data are normally distributed (Thadewald and Herbert, 2004). Furthermore, the multicollinearity test was done by using variance inflation factors (VIF) and found to have a mean value of VIF of 1.38 which is good as it is below 5 (Murray, Nguyen, Lee...and David, 2012). Moreover, the reliability test was done by using Cronbach alpha and found to be 0.6775 which is reasonably better as suggested by Tavakol and Dennick (2011).

4. Results and discussion

4.1 Descriptive statistics

The study specifically aimed to find out the operational behaviour of the three stock exchange markets, S&P 500, NYSE and NASDAQ which are among the largest stock exchange market in the world. The data was analysed by using the newly introduced HHP regression model that can detect both linear and non-linear pairing effects and impacts of the paired data such as stock prices and trading volumes. The descriptive statistics are displayed to show the general characteristics of the three markets (Table 2).

Table 2: The Descriptive statistics for daily closing stock prices and trading volumes

Variable	Obs	Mean	Std. Dev.	Min	Max
Price_S&P 500	197	4421.932	176.8439	3900.79	4796.56
Volume_S&P 500	197	3.41e+09	5.34e+08	2.37e+09	4.75e+09
Price_NASDAQ	219	14331.83	1136.294	11264.45	16057.44
Volume_NASDAQ	219	4.74e+09	7.31e+08	3.38e+09	8.11e+09
Price_NYSE	240	16543.59	498.9996	14902.14	17353.76
Volume_NYSE	240	3.50e+09	7.34e+08	2.19e+09	6.68e+09
$\partial_{PV_S\&P500}$	196	2023092	3.30e+07	-1.46e+08	1.25e+08
$\partial_{VP_S\&P500}$	196	1	3.13e-07	.9999995	1.000001
∂_{PV_NASDAQ}	218	1343238	6080752	-1.46e+07	2.54e+07
∂_{VP_NASDAQ}	218	1	2.62e-06	.99999	1.000013
∂_{PV_NYSE}	239	812524.2	1.31e+07	-6.07e+07	6.28e+07
∂_{VP_NYSE}	239	.9999999	1.88e-06	.9999879	1.000005

Source: Author (2022).

Table 2 shows the descriptive statistics of daily stock prices and trading volumes of the S&P 500, NYSE and NASDAQ stock markets. The average daily stock closing price of S&P 500 stock for 197 days is 4421.932 US\$ million and varies from 3900.79 to 4796.56 US\$ Million. The daily stock trading volume is averaged at 3.41e+09 US\$ million and varies from 2.37e+09 to 4.75e+09 US\$ million. On the other hand, the daily closing stock price of the NASDAQ stock for 219 days is 14331.83US\$Million and has a range of a minimum of 11264.45 to a maximum of 16057.44 US\$ million, its corresponding daily stock trading volume is averaged at 4.74e+09 US\$ million and ranges from 3.38e+09 to 8.11e+09 US\$ million. Furthermore, the daily closing stock price of the NYSE for 240 days is averaged at 16543.59 US\$ million and has a range of minimum value of 14902.14 to a maximum value of 17353.76 US\$ million, and its corresponding daily stock trading volume is average at 3.503e+09 and ranges from minimum 2.19e+09 to maximum value of 6.68e+09 US\$ million.

On the other hand, the mean homo-pairing changes in daily closing stock price relative to its trading volume in S&P 500 stock exchange market is 2023092, which ranges from -1.46e+08 to 1.25e+08. The mean homo-pairing changes in daily trading volume relative to its daily closing stock price in the S&P500 stock exchange market is 1 which ranges from 0.9999995 to 1.000001. The mean homo-pairing changes in the daily closing stock price relative to daily trading volume in NASDAQ stock exchange markets is 1343238 which ranges from -1.46e+07 to 2.54e+07, and its mean homo-pairing changes in daily trading volume relative to daily closing stock price are 1 and range from 0.99999 to 1.000013. Moreover, the mean homo-pairing changes in the daily closing stock price relative to daily trading volume in NYSE is 812524.2 and has a range from -6.07e+07 to 6.28e+07, and its mean homo pairing changes in daily trading volume relative to the daily closing stock price is 0.9999999 and ranges from 0.9999879 to 1.000005. From the descriptive statistics, we learn that there is an extremely “daily variation” of the mean homo-pairing changes in the daily closing stock price relative to daily trading volume. On the other hand, there is a slight variation in the mean homo-pairing changes in daily trading volume relative to the daily closing stock price.

The descriptive statistics for mean homo-pairing changes in daily stock information relative to daily closing stock price and mean homo-pairing changes in daily closing stock price relative to daily stock information were provided (Table 3).

Table 3: The Descriptive statistics for daily stock information and closing stock prices

Variable	Obs	Mean	Std. Dev.	Min	Max
∂_{PD_SP}	196	1.013207	.2070717	-.1111111	2.754386
∂_{DP_SP}	196	.7292347	57.49828	-307.93	229.54
∂_{PD_NASD}	252	1.017135	.562253	-3.347826	8.692308
∂_{DP_NASD}	252	-6.149841	213.8699	-646.17	488.93
∂_{PD_NYSE}	239	.9942284	.0499585	.5260664	1.102459
∂_{DP_NYSE}	239	-2.8141	167.191	-507.69	432.97

Source: Author (2022).

Table 3 shows the descriptive statistics for fundamental hypothesis analysis in S&P 500, NYSE and NASDAQ stock exchange markets. The mean homo-pairing changes in daily stock information relative to daily closing stock price and the mean homo-pairing changes in daily closing stock price relative to the daily stock information. The mean homo-pairing changes in daily closing stock price relative to daily stock information in the S&P500 stock exchange market is 1.013207 with a range value from -0.1111111 to 2.754386. The mean homo-pairing changes in daily stock information relative to the daily closing stock price are 0.7292347 and range from -307.93 to 229.54. The mean homo-pairing changes in daily closing stock price relative to daily stock information in the NASDAQ stock exchange market is 1.0117135 and has the range from -3.347826 to 8.692308, and its mean homo-pairing changes in daily stock information relative to daily closing stock price are -6.149841 and have ranged from -646.17 to 488.93. And, the mean homo- pairing changes in daily closing stock price relative to daily stock information in the NYSE is 0.9942284 and ranges from 0.5260664 to 1.102459, and has to mean homo- pairing changes in daily stock information relative to the daily closing stock price of - 2.8141 and ranges from -507.69 to 432.97.

4.2 Technical analysis in the S&P 500 Stock market

The technical analysis is objectively done by examining the statistical records available, particularly the daily closing stock price and the daily trading volumes in S&P 500 stock exchange market. In other words, the study examined how the statistical information or data can convey or signals the stock price level in the S&P 500 stock exchange market. The linear and non-linear pairing impact of the homo pairing change in daily trading volume relative to a change in daily closing stock price, ∂_{VP} on the homo pairing changes in daily closing stock price relative to change of daily trading volume, ∂_{PV} was examined by using the HHP regression model. The study hypothesis (alternative hypothesis) is that the homo pairing change in daily trading volume relative to the change in daily closing stock price has a non-linear pairing impact on the homo pairing change in daily closing stock price relative to the change in daily trading volume in the S&P500 stock exchange market. The HHP regression model was run using IBM SPSS software and the model summary and parameter estimates were provided (Table 4).

Table 4: Model summary and parameter estimates in the S&P 500 stock exchange market

Dependent Variable: Relative price-homo pairing changes in daily stock trading volume (∂_{VP})							
Model Summary					Parameter Estimates		
Equation	Ψ^2	F	df1	df2	Sig.	Constant (λ_0)	λ_1
Linear	0.007	1.287	1	194	0.258	1.000	7.690E-16
Inverse	1.000	692312462527441.6	1	194	0.000	1.000	1.000
S	1.000	2764868125663971	1	194	0.000	3.016E-14	1.000

The independent variable is Relative volume- homo pairing changes in daily closing stock price (∂_{PV})

Source: Author (2022).

Table 4 shows the HHP regression model summary and its parameter estimates. The table provides the three parameters of the three models; the linear, inverse and S-curved models. The

linear model has a positive lambda coefficient of $7.690\text{E-}16$ and a constant value of 1.000, a p-value of 0.258 which is greater than the recommended critical value of a significant level of 0.05. The model is poorly determined as it has a linear pairing determination coefficient, Ψ^2 of 0.007. Therefore, we reject the null hypothesis and accept the alternative hypothesis at a 95 percent of confidence level since its p-value of 0.258 is greater than the critical value of 0.05. The second model is the inverse model which has a positive lambda coefficient of 1.000, a non-linear pairing determination coefficient of 1.000 (perfect correlation) and a constant value of 1.000, with a p-value of 0.000 which is less than a recommended critical value of the significant level of 0.05. Hence, we reject the null hypothesis and accept the alternative hypothesis at a 95 percent of confidence level since its p-value of 0.000 is less than the recommended critical value of 0.05. The third model is the S-curved model which has a positive lambda coefficient of 1.000, a constant value of $3.016\text{E-}14$, a non-linear pairing determination coefficient of 1.000 (perfect correlation) and the p-values of 0.000, which is less than the recommended critical value of the significant level of 0.05. Hence, we reject the null hypothesis and accept the alternative hypothesis at a 95 percent of confidence level since its p-value of 0.000 is less than the recommended critical value of 0.05.

The two significant models-inverse and S-curve models are described in non-linear pairing classes; the PPP class and NPP class. The classes are explained by the homo-hetero scattering plots established by curve estimation (Figure 5). The curve estimation plots the scattering of the homo-pairing changes of the daily closing stock price and the daily stock trading volume to reveal the classes that are described by the non-linear pairing function; the inverse and S-curve models.

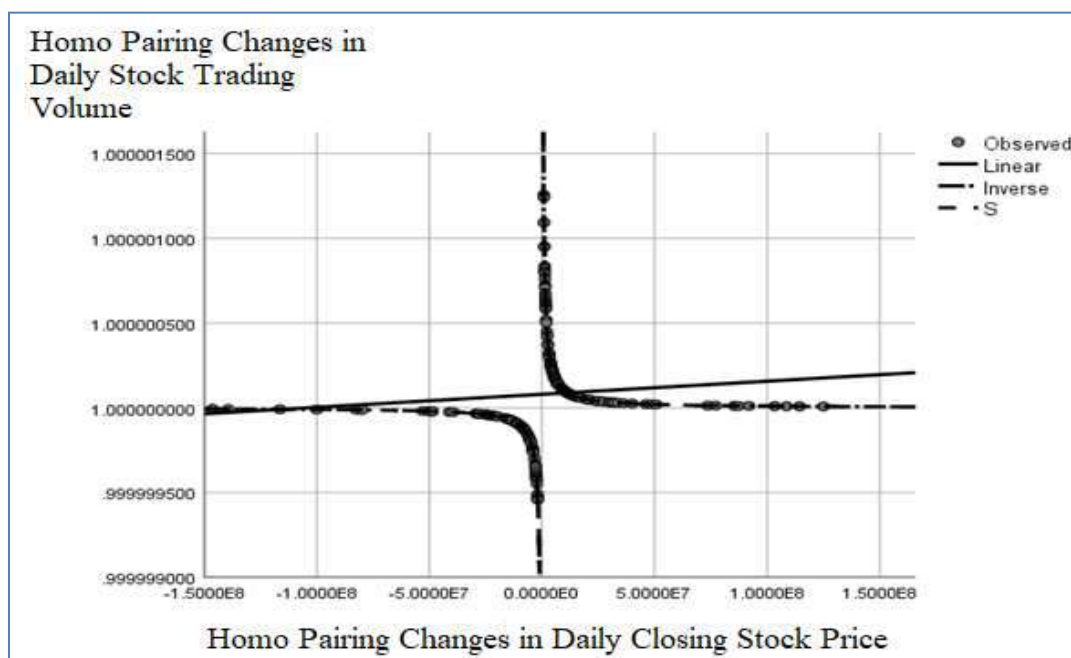


Figure 5: Curve estimation of homo pairing changes of stock price and trading volume
Source: Author (2022).

Figure 5 shows the curve estimation of the homo-pairing changes in the daily trading volume relative to the change in the daily closing stock price in the S&P 500 stock exchange market. The figure exhibits two classes that are described by the non-linear pairing functions; the inverse and S-curved models. Each model is described by two non-pairing classes, the PPP and NPP classes. Therefore, since the inverse model has a lambda coefficient is one, and the constant value is one, the S&P 500 stock exchange market technical model is described as;

$$\partial_{VP} = 1 + \frac{1}{\partial_{PV}} ; \text{ PPP class model}$$

$$\partial_{VP} = 1 - \frac{1}{\partial_{PV}} ; \text{ NPP class model}$$

On the other hand, the S&P 500 stock exchange market technical model can be determined by the S-curved function. Since the S-curved model has a unit lambda coefficient and the constant value of 3.016E-14, therefore, S&P500 stock exchange market technical model is described as;

$$\ln \partial_{VP} = 3.016 \times 10^{-14} + \frac{1}{\partial_{PV}} ; \text{ PPP class model}$$

$$\ln \partial_{VP} = 3.016 \times 10^{-14} - \frac{1}{\partial_{PV}} ; \text{ NPP class model}$$

In conclusion, both empirical models-inverse and S-curved models that represent the S&P500 stock exchange market technical models proved that the homo pairing changes in daily closing stock price relative to the daily trading volume are non-linearly related to the homo pairing changes in daily trading volume relative to the change in the daily closing stock price.

4.3 Fundamental analysis in the S&P 500 Stock exchange market

The fundamental analysis of the S&P 500 stock exchange market was done to examine the impact of the daily stock information available in the market on the stock price. The study assumed that if the change in daily closing price happened due to the change of a day (that next day), therefore the change was done due to the information attained about the specific stock immediately available or collected at the market. That is, the change in trading days relative to the change in closing stock price indicates the “impactful information signal”. The study regressed the homo-pairing changes in daily closing stock price relative to changes in daily stock information, ∂_{PD} to homo pairing change in daily stock information relative to daily closing stock price, ∂_{DP} to determine the linear and non-linear pairing impact of the two paired variables. The study hypothesis (alternative hypothesis) is that the homo pairing change in the daily closing stock price relative to the change in daily stock information available in the stock exchange market has a non-linear pairing impact on the homo pairing changes in the daily stock information available relative to a change in the daily closing stock price in the S&P 500 stock exchange market. The HHP regression model was run using IBM SPSS software and the model summary and parameter estimates were provided (Table 5).

Table 5: Model Summary and Parameter Estimates in S&P 500 stock exchange market

Dependent Variable: Homo Pairing Changes of Closing Stock Price (∂_{PP})							
Equation	Model Summary					Parameter Estimates	
	Ψ^2	F	df1	df2	Sig.	Constant (λ_0)	λ_1
Linear	0.050	9.780	1	186	0.002	1.002	0.000
Inverse	0.969	5776.651	1	186	0.000	1.008	0.909
S	0.992	23142.589	1	186	0.000	0.004	0.947

The independent variable is Homo Pairing Changes of Days of Stock Trading (∂_{DP})

Source: Author (2022).

Table 5 shows the HHP regression summary and parameter estimates for the S&P 500 stock exchange market fundamental model. The table described three fundamental models in the S&P 500 stock exchange market-the linear, inverse and S-curved models. The linear model has a positive lambda coefficient of 0.000, a constant value of 1.002, a linear pairing determination coefficient of 0.050, with a p-value of 0.002, which is less than the recommended critical value of the significant level of 0.05, therefore, we reject the null hypothesis and accept the study hypothesis at a 95 percent of confidence level; although, the linear model is poorly determined at 0.050. The second model is the inverse model that has a positive lambda coefficient of 0.909 and constant value of 1.008, with a non-linear pairing determination coefficient, Ψ^2 of 0.969, and a p-value of 0.000, which is less than the recommended critical value of a significant level of 0.05. Hence, the study rejects the null hypothesis and accepts the alternative hypothesis at a 95 percent of confidence level. The third model is the S-curved model which has a positive lambda coefficient of 0.947, a constant value of 0.004, and a non-linear pairing determination coefficient, Ψ^2 of 0.992, with a p-value of 0.000 which is less than the recommended critical value of the significant level of 0.05, hence, the study rejects the null hypothesis and accepts the alternative hypothesis at a 95 percent of confidence level.

The two significant models- inverse and S-curve models are described in non-linear pairing classes; the PPP class and NPP class. The classes are explained by the homo-hetero scattering plots established by curve estimation (Figure 6). The curve estimation plots the scattering of homo pairing changes in the daily closing stock price relative to the change in daily stock information and the homo pairing changes in daily stock information relative to the change in the daily closing stock price in the S&P500 stock exchange market. The classes are described by the non-linear pairing function-the inverse and S-curve models.

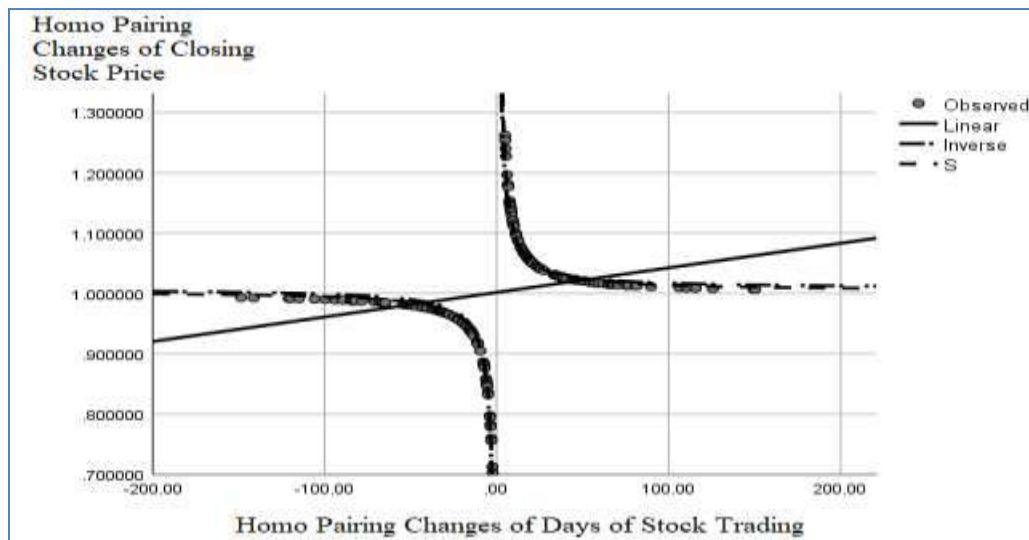


Figure 6: Curve estimation of homo pairing changes in stock price and days of stock trading
Source: Author (2022).

Figure 6 shows the curve estimation of the homo-pairing changes in the daily closing stock price relative to the change in daily stock information and homo pairing change in daily stock information relative to a change in the daily closing stock price in the S&P 500 stock exchange market. The figure exhibits two classes that are described by the non-linear pairing functions; the inverse and S-curved models. Each model is described by two non-pairing classes, the PPP and NPP classes. Therefore, since the inverse model has a lambda coefficient is 0.909, and the constant value is 1.008, the S&P500 stock exchange market fundamental model is described as;

$$\partial_{PD} = 1.008 + \frac{0.909}{\partial_{DP}} ; \text{ PPP class model}$$

$$\partial_{PD} = 1.008 - \frac{0.909}{\partial_{DP}} ; \text{ NPP class model}$$

On the other hand, the S&P stock exchange market technical model can be determined by the S-curved function. Since the S-curved model has a lambda coefficient of 0.947 and the constant value is 0.004, therefore, S&P500 stock exchange market fundamental model is described as;

$$\ln \partial_{PD} = 0.004 + \frac{0.947}{\partial_{DP}} ; \text{ PPP class model}$$

$$\ln \partial_{PD} = 0.004 - \frac{0.947}{\partial_{DP}} ; \text{ NPP class model}$$

In conclusion, both empirical models-inverse and S-curved models that represent the S&P500 stock exchange market fundamental models proved that the homo pairing changes in daily closing stock price relative to changes in daily stock information are non-linearly related to the changes in daily stock information relative to the changes in daily closing stock price.

4.4 Technical analysis in the NASDAQ Stock exchange market

The technical analysis in the NASDAQ stock exchange market was done by regressing the homo-pairing change in the daily closing stock price relative to daily trading volume, ∂_{PV} and the homo-pairing changes in daily trading volume relative to daily closing stock price, ∂_{VP} . The study aimed to examine the linear and non-linear pairing impacting behaviours between the stock prices and trading volume in the NASDAQ stock exchange market. The study hypothesis (alternative hypothesis) is that the homo pairing changes in daily closing stock price relative to the daily stock information have a non-linear pairing impact on the homo pairing change in daily trading volume relative to the change in the daily closing stock price in the NASDAQ stock exchange market. The HHP regression model was run using IBM SPSS software and the model summary and parameter estimates were provided (Table 6).

Table 6: Model Summary and Parameter Estimates in the NASDAQ Stock Exchange Market

Dependent Variable: The relative Price- homo pairing changes in daily stock trading volume, ∂_{VP}							
Model Summary						Parameter Estimates	
Equation	Ψ^2	F	df1	df2	Sig.	Constant (λ_0)	λ_1
Linear	0.002	0.532	1	216	0.467	1.000	2.134E-14
Inverse	1.000	3258307635319.490	1	216	0.000	1.000	1.000
S	1.000	13032401156115.164	1	216	0.000	3.014E-12	1.000

The independent variable is relative volume - homo pairing changes in daily closing stock price, ∂_{PV}

Source: Author (2022).

Table 6 shows the HHP regression model summary and its parameter estimates. The table provides the three parameters of the three models; the linear, inverse and S-curved models. The linear model has a positive lambda coefficient of 2.134E-14 and a constant value of 1.000, a p-value of 0.467 which is greater than the recommended critical value of a significant level of 0.05. The model is poorly determined as it has a linear pairing determination coefficient, Ψ^2 of 0.002. Therefore, we reject the null hypothesis and accept the alternative hypothesis at a 95 percent of confidence level since its p-value of 0.467 is greater than the critical value of 0.05. The second model is the inverse model which has a positive lambda coefficient of 1.000, a non-linear pairing determination coefficient of 1.000 (perfect correlation) and a constant value of 1.000, with a p-value of 0.000 which is less than a recommended critical value of the significant level of 0.05. Hence, we reject the null hypothesis and accept the alternative hypothesis at a 95 percent of confidence level since its p-value of 0.000 is less than the recommended critical value of 0.05. The third model is the S-curved model which has a positive lambda coefficient of 1.00, a constant value of 3.014E-12, a non-linear pairing determination coefficient of 1.000(perfect correlation) and the p-values of 0.000, which is less than the recommended critical value of the significant level of 0.05. Hence, we reject the null hypothesis and accept the alternative hypothesis at a 95 percent of confidence level.

The two significant models-inverse and S-curve models are described in non-linear pairing classes; the PPP class and NPP class. The classes are explained by the homo-hetero scattering plots established by curve estimation (Figure 7). The curve estimation plots the scattering of the

relative price homo-pairing changes in the daily trading volume relative to the change of daily closing stock price and the homo pairing changes in daily closing stock price relative to daily trading volume in to reveal the classes that are described by the non-linear pairing function; the inverse and S-curve models.

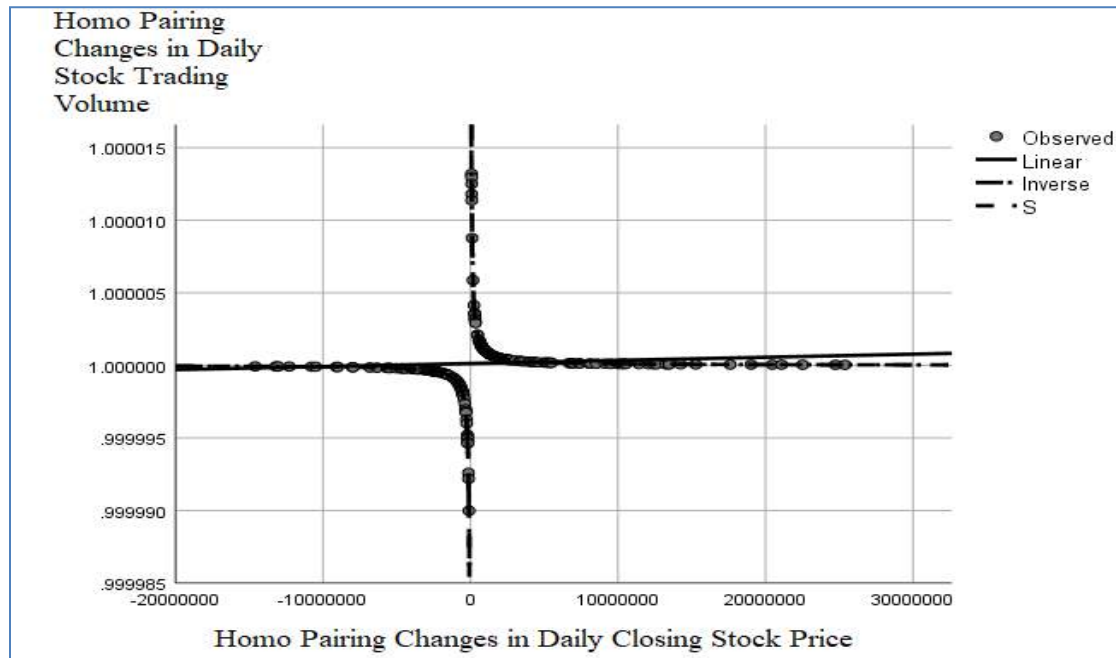


Figure 7: Curve estimation of homo pairing changes in stock price and stock trading volume
Source: Author (2022).

Figure 7 shows the curve estimation of the homo pairing changes in the daily trading volume relative to the change in daily closing stock price and the homo pairing changes in daily closing stock price relative to the change in trading volume in the NASDAQ stock exchange market. The figure exhibits two classes that are described by the non-linear pairing functions; the inverse and S-curved models. Each model is described by two non-linear pairing classes, the PPP and NPP classes. Therefore, since the inverse model has a lambda coefficient is one, and the constant value is one, the NASDAQ stock exchange market technical model is described as;

$$\partial_{VP} = 1 + \frac{1}{\partial_{PV}} ; \text{ PPP class model}$$

$$\partial_{VP} = 1 - \frac{1}{\partial_{PV}} ; \text{ NPP class model}$$

On the other hand, the NASDAQ stock exchange market technical model can be determined by the S-curved function. Since the S-curved model has a unit lambda coefficient and the constant value is 3.014E-12, NASDAQ stock exchange market technical model is described as;

$$\ln \partial_{VP} = 3.014 \times 10^{-12} + \frac{1}{\partial_{PV}} ; \text{PPP class model}$$

$$\ln \partial_{VP} = 3.014 \times 10^{-12} - \frac{1}{\partial_{PV}} ; \text{NPP class model}$$

In conclusion, both empirical models- inverse and S-curved models that represent the NASDAQ stock exchange market technical models, proved that the homo pairing changes in daily trading volume relative to change in daily closing stock price are non-linear related to the homo pairing changes in daily closing stock price relative to the change in daily trading volume in the NASDAQ stock exchange market.

4.5 Fundamental analysis in the NASDAQ Stock exchange market

The fundamental analysis in the NASDAQ stock exchange market was done by regressing the homo-pairing change of the daily closing stock price relative to the change in daily stock information, ∂_{PD} , and the homo pairing changes in daily stock information relative to the change in the daily closing stock price, ∂_{DP} . The study hypothesis (alternative hypothesis) is that the homo pairing changes in daily closing stock price relative to the change in daily stock information have a non-linear pairing impact on the homo pairing changes in daily stock information relative to the change in the daily closing stock price in the NASDAQ stock exchange market. The HHP regression model was run using SPSS software and the model summary and parameter estimates were provided (Table 7).

Table 7: Model Summary and Parameter Estimates in the NASDAQ Stock Exchange Market

Dependent Variable: Relative-days homo pairing changes of daily closing stock prices, ∂_{PD} ,							
Model Summary						Parameter Estimates	
Equation	Ψ^2	F	df1	df2	Sig.	Constant (λ_0)	λ_1
Linear	0.030	6.576	1	216	0.011	1.001	1.896E-5
Inverse	0.990	20628.300	1	216	0.000	1.001	0.986
S	0.997	82132.046	1	216	0.000	0.000	0.991

The independent variable is relative-price homo pairing changes of daily stock information, ∂_{DP} ,

Source: Author (2022).

Table 7 shows the HHP regression summary and parameter estimates for the NASDAQ stock exchange market fundamental model. The table described three fundamental models in the NASDAQ stock exchange market- the linear, inverse and S-curved models. The linear model has a positive lambda coefficient of 1.896E-5, a constant value of 1.001, and a linear pairing coefficient of 0.030, with a p-value of 0.011, which is less than the recommended critical value of the significant level of 0.05; therefore, we reject the null hypothesis and accept the study hypothesis at a 95 percent of confidence level; although, the linear model is poorly determined at 0.030. The second model is the inverse model that has a positive lambda coefficient of 0.986 and constant value of 1.001, with a non-linear pairing determination coefficient, Ψ^2 of 0.990, and a p-value of 0.000, which is less than the recommended critical value of a significant level of 0.05. Hence, the stud rejects the null hypothesis and accepts the alternative hypothesis at a 95 percent

of confidence level. The third model is the S-curved model which has a positive lambda coefficient of 0.991, a constant value of 0.000(3dp), and a non-linear pairing coefficient, Ψ^2 of 0.997, with a p-value of 0.000 which is less than the recommended critical value of the significant level of 0.05, hence, the study rejects the null hypothesis and accepts the alternative at a 95 percent of confidence level.

The two significant models- inverse and S-curve models are described in non-linear pairing classes; the PPP class and NPP class. The classes are explained by the homo-hetero scattering plots established by curve estimation (Figure 8). The curve estimation plots the scattering of homo pairing changes in the daily closing stock price relative to the changes in daily stock information and the homo pairing changes in daily stock information relative to the change in the daily closing stock price in the NASDAQ stock exchange market. The classes are described by the non-linear pairing function-the inverse and S-curve models.

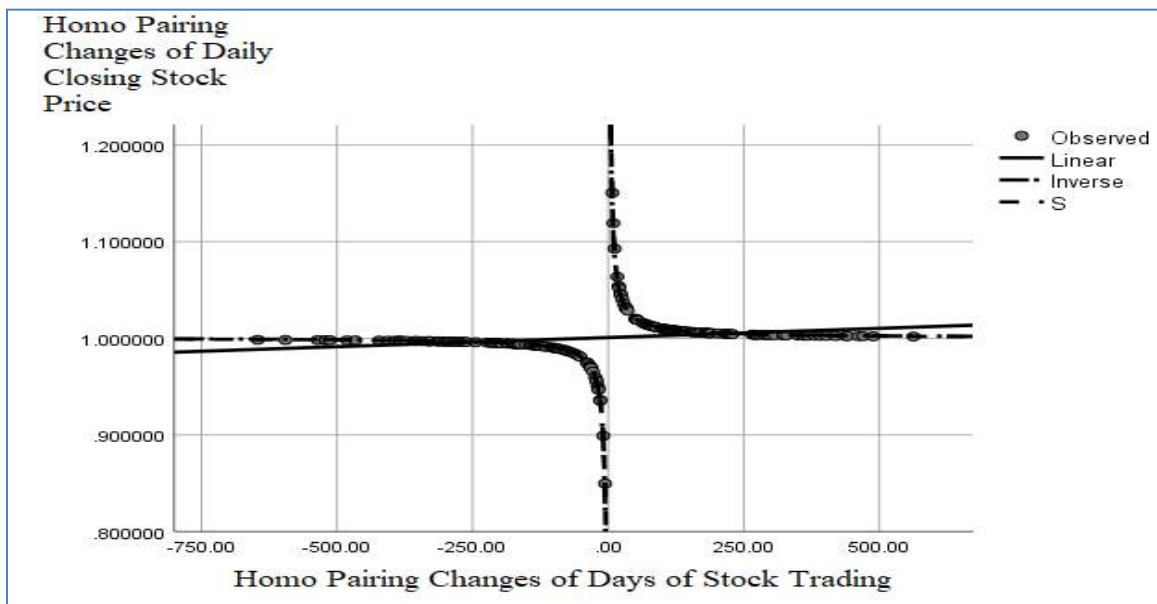


Figure 8: Curve estimation of homo pairing changes in stock price and days of stock trading

Figure 8 shows the curve estimation of the homo pairing changes of the daily closing stock price relative to the change of daily stock information and the homo pairing changes in daily stock information relative to the change in the daily closing stock price in the NASDAQ stock exchange market. The figure exhibits two classes that are described by the non-linear pairing functions- the inverse and S-curved models. Each model is described by two non-pairing classes, the PPP and NPP classes. Therefore, since the inverse model has a lambda coefficient is 0.986, and the constant value is 1.001, the NASDAQ stock exchange market fundamental model is described as;

$$\partial_{PD} = 1.001 + \frac{0.986}{\partial_{DP}} ; \text{ PPP class model}$$

$$\partial_{PD} = 1.001 - \frac{0.986}{\partial_{DP}} ; \text{NPP class model}$$

On the other hand, the NASDAQ stock exchange market fundamental model can be determined by the S-curved function. Since the S-curved model has a λ coefficient of 0.991 and the constant value is 0.000(dp), the NASDAQ stock exchange market fundamental model is described as;

$$\ln \partial_{PD} = 0.000 + \frac{0.991}{\partial_{DP}} ; \text{PPP class model}$$

$$\ln \partial_{PD} = 0.000 - \frac{0.991}{\partial_{DP}} ; \text{NPP class model}$$

In conclusion, both empirical models- inverse and S-curved models that represent the NASDAQ stock exchange market fundamental models proved that the homo pairing changes in the daily closing stock price relative to the daily stock information are non-linearly related to the homo pairing changes in daily stock information relative to the daily closing stock price.

4.6 Technical analysis in the NYSE market

The technical analysis in the NYSE market was done by regressing the homo-pairing changes in daily trading volume relative to the change in the daily closing stock price, ∂_{VP} , and the homo pairing changes daily closing stock price relative to the change in the daily trading volume, ∂_{PV} . The study hypothesis (alternative hypothesis) is that the homo pairing changes in daily trading volume relative to the change in daily closing stock price have a non-linear pairing impact on the homo pairing change in daily closing stock price relative to the daily trading volume in the NYSE market. The HHP regression model was run using IBM SPSS software and the model summary and parameter estimates were provided (Table 8).

Table 8: Model Summary and Parameter Estimates NYSE market

Dependent Variable: Relative –price homo pairing changes in daily stock trading volume (∂_{VP})							
Equation	Model Summary					Parameter Estimates	
	Ψ^2	F	df1	df2	Sig.	Constant (λ_0)	λ_1
Linear	0.002	0.467	1	237	0.495	1.000	6.370E-15
Inverse	1.000	8106027854060.792	1	237	0.000	1.000	1.000
S	1.000	32425588956436.074	1	237	0.000	1.451E-12	1.000

The independent variable is relative-volume homo pairing changes in daily closing stock price (∂_{PV})

Source: Author (2022).

Table 8 shows the HHP regression model summary and its parameter estimates. The table provides the three parameters of the three models; the linear, inverse and S-curved models. The linear model has a positive λ coefficient of 6.370E-15 and a constant value of 1.000, a p-value of 0.495 which is greater than the recommended critical value of a significant level of 0.05. The model is poorly determined as it has a linear pairing determination coefficient, Ψ^2 of 0.002. Therefore, we reject the null hypothesis and accept the alternative hypothesis at a 95 percent of confidence level since its p-value of 0.467 is greater than the critical value of 0.05. The second

model is the inverse model which has a positive lambda coefficient of 1.000, a non-linear pairing coefficient, Ψ^2 of 1.000 (perfect correlation) and a constant value of 1.000, with a p-value of 0.000 which is less than the recommended critical value of the significant level of 0.05. Hence, we reject the null hypothesis and accept the alternative hypothesis at a 95 percent of confidence level since its p-value of 0.000 is less than the recommended critical value of 0.05. The third model is the S-curved model which has a positive lambda coefficient of 1.00, a constant value of 1.451E-12, a non-linear pairing coefficient, Ψ^2 of 1.000(perfect correlation) and the p-values of 0.000, which is less than the recommended critical value of the significant level of 0.05. Hence, we reject the null hypothesis and accept the alternative hypothesis at a 95 percent of confidence level.

The two significant models- inverse and S-curve models are described in non-linear pairing classes; the PPP class and NPP class. The classes are explained by the homo-hetero scattering plots established by curve estimation (Figure 9). The curve estimation plots the scattering of homo pairing changes in the daily trading volume relative to the change in daily the closing stock price and the homo pairing changes in the daily closing stock price relative to the change in the daily trading volume in the NYSE market. The classes are described by the non-linear pairing function-the inverse and S-curve models.

Figure 9 shows the curve estimation of the homo pairing changes of the daily trading volume relative to the daily closing stock price and the homo pairing changes in the daily stock trading volume relative to the change in the daily trading volume in the NYSE market

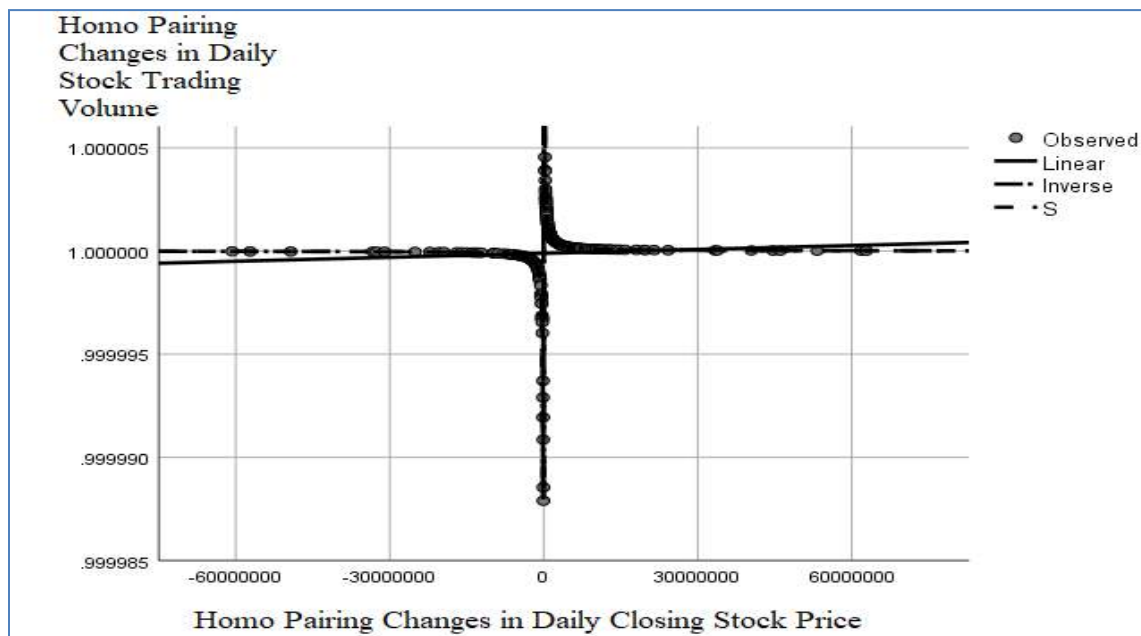


Figure 9: Curve estimation of homo pairing changes in stock price and stock trading volume
Source: Author (2022).

The figure exhibits two classes that are described by the non-linear pairing functions- the inverse and S-curved models. Each model is described by two non-pairing classes, the PPP and NPP classes. Therefore, since the inverse model has a lambda coefficient is 1, and the constant value is 1 the NYSE market technical model is described as;

$$\partial_{VP} = 1 + \frac{1}{\partial_{PV}} ; \text{ PPP class model}$$

$$\partial_{VP} = 1 - \frac{1}{\partial_{PV}} ; \text{ NPP class model}$$

On the other hand, the NYSE market technical model can be determined by the S-curved function. Since the S-curved model has a lambda coefficient of 1 and the constant value is 1.451E-12, therefore, the NYSE market technical model is described as;

$$\ln \partial_{VP} = 1.451 \times 10^{-12} + \frac{1}{\partial_{PV}} ; \text{ PPP class model}$$

$$\ln \partial_{VP} = 1.451 \times 10^{-12} - \frac{1}{\partial_{PV}} ; \text{ NPP class model}$$

In conclusion, both empirical models- inverse and S-curved models that represent the NYSE market technical models, proved that the homo pairing changes in the daily trading volume relative to the change in the daily closing stock price are non-linearly related to the homo pairing changes in the daily closing stock price.

4.7 Fundamental analysis in the NYSE market

The fundamental analysis of the NYSE market was done by regressing the homo-pairing changes in the daily closing stock price relative to the change in daily stock information, ∂_{PD} , and homo pairing changes in daily stock information relative to the change in daily closing stock price, ∂_{DP} . The study hypothesis (alternative hypothesis) is that the homo pairing change in daily closing stock price relative to the change in daily stock information has a non-linear pairing impact on the homo pairing changes in daily stock information relative to the change in the daily closing stock price in the NYSE market. The HHP regression model was run using SPSS software and the model summary and parameter estimates were provided (Table 9).

Table 9: Model Summary and Parameter Estimates in the NYSE market

Dependent Variable: Relative-Days homo pairing changes of daily closing stock price (∂_{PD})							
Model Summary						Parameter Estimates	
Equation	Ψ^2	F	df1	df2	Sig.	Constant (λ_0)	λ_1
Linear	0.014	3.322	1	237	0.070	0.994	3.513E-5
Inverse	0.939	3646.785	1	237	0.000	1.000	0.639
S	0.984	14448.241	1	237	0.000	7.334E-5	0.785

The independent variable is the Relative price- homo pairing changes of daily stock information(∂_{DP})

Source: Author (2022).

Table 9 shows the HHP regression model summary and its parameter estimates. The table provides the three parameters of the three models; the linear, inverse and S-curved models. The linear model has a positive lambda coefficient of 3.513E-5 and a constant value of 0.994, a p-value of 0.070 which is greater than the recommended critical value of a significant level of 0.05. The model is poorly determined as it has a linear pairing determination coefficient, Ψ^2 of 0.014. Therefore, we reject the null hypothesis and accept the alternative hypothesis at a 95 percent of confidence level since its p-value of 0.070 is greater than the critical value of 0.05. The second model is the inverse model which has a positive lambda coefficient of 0.639, a non-linear pairing determination coefficient, Ψ^2 of 0.939 and a constant value of 1.000, with a p-value of 0.000 which is less than the recommended critical value of the significant level of 0.05. Hence, we reject the null hypothesis and accept the alternative hypothesis at a 95 percent of confidence level since its p-value of 0.000 is less than the recommended critical value of 0.05. The third model is the S-curved model which has a positive lambda coefficient of 0.785, a constant value of 7.334E-5, a non-linear pairing determination coefficient, Ψ^2 of 0.984 and the p-values of 0.000, which is less than the recommended critical value of the significant level of 0.05. Hence, we reject the null hypothesis and accept the alternative hypothesis at a 95 percent of confidence level.

The two significant models- inverse and S-curve models are described in non-linear pairing classes; the PPP class and NPP class. The classes are explained by the homo-hetero scattering plots established by curve estimation (Figure 10). The curve estimation plots the scattering of homo pairing changes in daily closing stock price relative to the changes in the daily stock information and the homo pairing changes in daily stock information relative to the change in the daily closing stock prices in the NYSE market. The classes are described by the non-linear pairing function-the inverse and S-curve models.

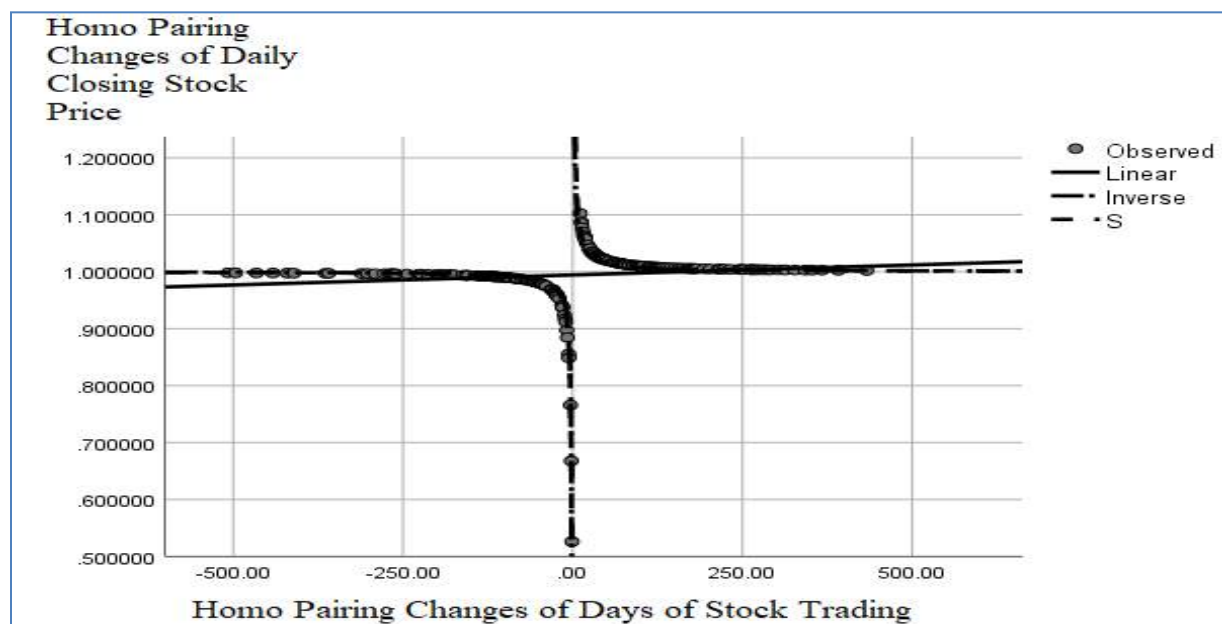


Figure 10: Curve estimation of homo pairing changes in stock price and daily stock information

Source: Author (2022).

Figure 10 shows the curve estimation of the homo pairing changes in the daily closing stock price relative to the daily stock information and the homo pairing change in daily stock information relative to the change in the daily closing stock price in the NYSE market. The figure exhibits two classes that are described by the non-linear pairing functions- the inverse and S-curved models. Each model is described by two non-pairing classes, the PPP and NPP classes. Therefore, since the inverse model has a lambda coefficient is 0.639, and the constant value is 1 the NYSE market fundamental model is described as;

$$\partial_{PD} = 1 + \frac{0.639}{\partial_{DP}} ; \text{ PPP class model}$$

$$\partial_{PD} = 1 - \frac{0.639}{\partial_{DP}} ; \text{ NPP class model}$$

On the other hand, the NYSE market fundamental model can be determined by the S-curved function. Since the S-curved model has a lambda coefficient of 0.785 and the constant value is 7.334E-5, therefore, the NYSE market fundamental model is described as;

$$\ln \partial_{PD} = 7.334 \times 10^{-5} + \frac{0.785}{\partial_{DP}} ; \text{ PPP class model}$$

$$\ln \partial_{PD} = 7.334 \times 10^{-5} - \frac{0.785}{\partial_{DP}} ; \text{ NPP class model}$$

In conclusion, both empirical models- inverse and S-curved models that represent the NYSE market fundamental models proved that the homo pairing changes in daily closing stock price relative to the changes in the daily stock information are non-linearly related to the homo pairing changes in daily stock information relative to the daily closing stock price.

4.8 Discussion

The study aimed to examine the technical and fundamental hypotheses in NYSE, NASDAQ and S&P 500 stock exchange markets by application of the homo-hetero regression model. The main determinants (variables) that were examined are stock trading volumes, stock closing prices and stock information available in the stock exchange market about the specific stock. The study evidenced that both the technical and fundamental features of the markets are defined by the inverse and S-curved relations. The inverse and S-curved relationships are evidenced in all stock exchange markets. Furthermore, the study evidenced that the homo pairing change in the daily trading volume relative to the change in the daily closing stock price has an inverse and S-curved relationship with the homo pairing changes in the daily closing stock price relative to the change in the daily trading volume. Moreover, the homo pairing change in the daily closing stock price relative to the change in the daily stock information has an inverse and S-curved impact with the homo pairing change in the daily stock information relative to the change in daily closing stock price. The inverse and S-curved models evidenced in the study are described in two distinctive pairing classes, namely positive-positive pairing (PPP) class and negative-positive pairing (NPP) in both fundamental and technical analysis. In the technical analysis, the study evidenced the

empirical relationship /model of $\partial_{VP} = 1 \pm \frac{1}{\partial_{PV}}$. This means that the ∂_{VP} in the NYSE, NASDAQ and S&P 500 stock exchange markets vary inversely to the ∂_{PV} . In other words, we conclude that the homo pairing changes in the daily stock trading volumes relative to the changes in daily closing stock price are reciprocally related to the homo pairing changes in the daily closing stock price relative to the changes in the daily trading volume. This can be interpreted that, a unit homo pairing change of daily closing stock price relative to changes in the daily trading volume resulting in two effects in the markets. Some investors will lose (getting zero returns), but other investors will gain (2), that $\partial_{VP} = 1 \pm 1$, when $\partial_{PV} = 1$, then $\partial_{VP} = 0$ or 2. This phenomenon evidenced the nature of volatility of the market, that there is no assurance of the investor to gain or lose when the unit homo pairing changes in daily closing stock price relative to the changes in daily trading volume happened. This is why the stock prediction becomes harder and more complex as suggested by some scholars (Karin et al., 2021; Gharehchopogh et al., 2013; Bhuriya et al., 2017; Teachman, 1995; Srivinary et al., 2022). This can be explained that when a unit homo pairing changes happened in daily closing stock price the investors can expect to profit (gain) or loss. This means some investors will not have relevant information about the stock price; hence they will underprice or overprice the stock's valuation. From this aspect, we confirmed that the technical hypothesis does not fully capture the investor buying or selling (trading) decisions in the stock markets. It does not offer reliable predictive information; it can forecast both the gain and loss at the same time. This finding confirms the studies of Wang (2014), Mpofu (2012), and Alhussayen(2022).

On the other hand, the study examined the fundamental hypothesis in the NYSE, NASDAQ, and S&P 500 stock exchange markets. The empirical study found that the fundamental analysis in the markets is described by the general inverse model

$$\partial_{PD} = 1.008 \pm \frac{0.909}{\partial_{DP}} \text{ in S\&P 500,}$$

$$\partial_{PD} = 1.001 \pm \frac{0.986}{\partial_{DP}} \text{ in NASDAQ and}$$

$$\partial_{PD} = 1 \pm \frac{0.639}{\partial_{DP}} \text{ in NYSE.}$$

The general meaning is that the relationship between the homo pairing change in daily closing stock price relative to the changes in daily stock information, ∂_{PD} , and homo pairing changes in the daily stock information relative to the change in the daily closing stock price, ∂_{DP} , is described by the inverse model. The unit change of the ∂_{DP} , i.e., $\partial_{DP} = 1$, the fundamental empirical equation becomes, $\partial_{PD} = 1.008 \pm 0.909$ in S&P 500, $\partial_{PD} = 1.001 \pm 0.986$ in NASDAQ and $\partial_{PD} = 1 \pm 0.639$ in NYSE. This means, that investors relying on the daily stock information (fundamentalist) reduced the vulnerability or risks of the stock underpricing or overpricing his financial asset (stock). For example investor in S&P500 who used the fundamental hypothesis to predict the impact of the unit change of stock information on the price of the stock the next day, he will have a pay-off of the range of 1.008 ± 0.909 ; that is, the stock price predicted to raise by a ratio of 1.909 (higher) or 0.099 (lower). Therefore, the fundamental analysis is more reliable than the technical analysis. Moreover, the investor in NYSE used the fundamental analysis/model, his returns (pay-off) have a range of 1 ± 0.639 , that is he expected

his return or price to raise by a ratio from 1.639 (higher) to 0.361 (lower) for each change of the day of stock information in the market. In using the fundamental analysis an investor can expect or predict to get higher or lower returns (pay-off). This approach is the best as an investor can expect no loss from the investment. The approach is more reliable than the technical analysis which predicts loss and gains only. This finding goes in line with Huang, et al., 2021, Mahajan and Singh (2008), and Wu et al., (2022).

In addition, the study confirms the non-linear and volatility of the stock exchange market since we found both technical analysis and fundamental analysis are described with gain and loss (PPP class and NPP class). One question to ask is why the three markets are defined with the same technical models and slightly differ in fundamental models. Purposely, the study collected data from the three largest stock exchange markets in the world to have a comparison of facts/findings. Generally, the findings are the same for each stock exchange. Do we conclude that technical and fundamental analysis in all the stock markets in the world can be defined by inverse and S-curved models? The answer is no! Bajzik(2020) contented that one cannot rely on the general conclusion on the stock exchange market, this is because the predictability of the stock price(returns) varies with different markets and the nature/type of the stock. Now we conclude the S&P500, NASDAQ and NYSE markets have similar or share a lot of empirical characteristics of the technical and fundamental determinants/factors. However, we call up more research in this area by using this HHP regression model in other stock exchange markets to enhance the empirical cross-validity of the general conclusion of this study.

Specifically, the use of the HHP regression in analysing both the technical and fundamental hypothesis at the stock exchange market is valued as the model can able to detect/capture both linear and non-linearity behaviour of the determinants of the stock exchange markets. The use of traditional linear regression could not detect the non-linearity (Cai and Gao, 2017; Sahoo and Charlapally, 2015; Chaudhary et al. 2018; Gupta and Wagalakshmi, 2019).

5. Conclusion and recommendation

The paper aimed to examine the impact of homo pairing changes in daily closing stock price relative to the change in daily stock information on homo pairing changes in the daily stock information relative to change in daily closing stock prices (fundamental analysis); and the impact of homo pairing changes in the daily trading volume relative to daily closing stock price and the homo pairing changes in daily closing stock price relative to the daily trading volume (Technical analysis) in S&P 500, NASDAQ and NYSE markets. The study applied the Homo-Hetero Pairing Regression Model, simply the HHP regression model. This model was developed to identify the linear and non-linear behaviour of data, hence being an appropriate econometric predictive model for homo paired data such as stock prices. The study found that both the technical and fundamental hypotheses are defined by the inverse and S-curved models in the three stock exchange markets. This means that the non-linearity relationship between the changes in stock information and closing stock price (fundamental hypothesis) and the changes in closing stock price and stock trading volume (technical hypothesis) is confirmed. Moreover, the study confirmed that the fundamental analysis is more reliable that can predict accurately more than technical analysis. Therefore the study concluded that the optimal prediction of the stock price or return is achieved by the fundamentalists in the stock exchange markets. However,

the expected returns range from higher to lower gains (profits). The study recommends that the stock investors prioritise the use of fundamental hypothesis /analysis to make their stock investment decision. In other words, the study recommends that stock investors be fundamentalists.

On the other hand, the study found that the homo-hetero pairing regression model is the best analysis to study the homo-paired data such as the stock prices. This is because the models capture the non-linearity and linearity behaviour of the homo-paired data such as stock price. Hence the study recommends the application of this regression model to the study of financial markets, economics, psychology, and medicine. Specific recommendations for the application of the HHP regression model are the prediction of water waves in the investigation of hydrodynamic and erosion-accretion processes on shallow depths.

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