An Impact Analysis Of Covid-19 On The Sales Of Passenger Vehicles In India

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Abstract

The COVID-19 (Corona Virus Disease) pandemic has had a major affect all over the world. Even the government and public faced its negative after effects in the import export, manufacturing segment, service sector which had led to financial crisis and other difficulties. Governments had taken several precautionary measures to overcome these adversities. Meanwhile, the deterioration in Gross Domestic Product (GDP) showed a decline in the growth of automobile companies. This article aims to investigate the cause and effects of COVID-19 on the Indian automobile industry. The study conducted involves analysis of the sales data from Fiat, Ford, Honda, Hyundai, Mahindra, Maruti Suzuki, Nissan, Renault, Skoda, Tata, Toyota, Volkswagen. This research examines the crucial trend changes and consequences of the pandemic on the industry by taking a macroscopic viewpoint. This perspective involved the market share analysis and trend analysis. The former provided the best form of information both microscopically by describing the changes in market share over the years and the significant causality and macroscopically by depicting the industry grip of all Original Equipment Manufacturers (OEMs) in India. The analysis of the data in this case study shows that the correlation factors returned with high significance stating that the effect of COVID-19 was only temporary. Based on the experiment results, the authors were able to determine which OEMs (R-squared value >0.5) had consistency in regards to their time sequence sales and were able to determine the best fit curve with as much minimum error as possible.

Keywords: Automobiles industries, COVID-19, Curve fitting, Coefficient of correlation, Passenger vehicles, Regression.

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1. Introduction

India now being a global economy member and having incredible influence with the rest of the world in terms of import and export. India is one of more than 200 nations affected by the COVID-19 Pandemic and also was on the list of most impacted economies. Automotive industry has major contribution on the economic development with 3 % of all GDP output; with emerging markets having even higher share. Indian industries contribute nearly 7% of GDP and also responsible for 7-8% of employed population [1]. A majority of Indian population belongs to Middle class categories; hence their major attention was primarily on household goods which directly affected the sales of other non-essential commodities like cars and bikes. This resulted in drastic decrease in sales of passenger vehicles and which in turn effected the GDP of the country. For this reason, the study and analysis of effect and causes is of paramount importance in the growth of automobile Industry. The market share and trends of the sales data were analysed and have made relevant inferences regarding what has been observed. So far significant information in regard to the effect of COVID-19 have been noted such as significant market share changes and actions taken by OEMs to combat the pandemic.

The goal is to conduct a correlation analysis along with regression analysis to understand the pattern of the data. In a way, the variance of the data and the relationship between the OEMs with these objectives were understood. Once the tests are conducted, the result based on the values obtained are described. With respect to achieving this objective, the methods such as the coefficient of correlation, regression/curve fitting along with additional ANOVA (analysis of variance) parameters as well as general population parameters are adopted. With these methods, the effects of COVID-19 could be analysed on a much more mathematical perspective. Authors have utilized different ways to deduce any form of relevant patterns in the data, the patterns in general are to be supportive of the attributions provided in previous reports. The most efficient ways to manage to bring forth a formidable explanation is by conducting different statistical experiments with well-known methods which can produce the best possible results.

The visual form of statistics with the help of bar and pie charts to help understand crucial aspects with respect to changes in market share were considered. The other form was to basically support the visual forms of data with attributions which help describe a certain causality of the change in data. The advanced statistical modelling phase which comprises of mathematical methods to describe variation in data and the relationship between datasets were used. Knowing that the success of these experiments depends on the quality of data, authors have employed strategies to obtain sales data sets from proper sources which were at most 3rd party data sets, but in order to ensure the legitimacy of data, the method of financial statements verification of the OEMs directly used. In this process author verified the sales quantity of 3 years and did not proceed for the full 6-year period in order to reduce the time taken for the executions of the experiments. The obtained data were arranged in OEM wise and setup monthly cumulative data along with yearly cumulative data for better appropriation of the visual phase. According to the literature, the market share analysis revealed the true nature of the pandemic on the OEMs where each OEM faced unique problems related to the supply chain and the outcomes of the pandemic were different for each OEM, where the outcomes varied from discontinuation of OEMs to the rebirth of some. Major market share changes were observed and through that one can easily understand the true effects of COVID-19. Authors also understand how the data patterns between OEMs behaved relative to each other using correlation matrices and conclude that the market had a cyclical nature before the pandemic and a random nature post pandemic, through this it was understood yet again that each OEM had a unique outcome which supports the market share changes as well. For regression plots, the best nature of the curve that can be fitted along with the understanding that the data was highly scattered. With the help of additional population parameters and comparison of error values, the best possible fits were deduced. The motivation for this article is to basically understand on a mathematical level, the effects of COVID-19 on the Indian automobile industry. In this way one can truly understand from an analytical perspective about the natural effects of such unprecedented events. Often times the human actions or at least on the industry level are considered as the causality of a course of action on supply chain efficiency, but in this case the effects of COVID-19 on a time perspective are considered. A time series analysis based on a statistical model is considered.

The organization of the rest of the article is, Section 2 includes the literature that had been reviewed for this research. Section 3 gives a methodology analyse the sales data based on regression/curve fitting and correlation. In Section 4, an overview of the presented work is discussed along with the results, discussions, achievements, and limitations. This is followed by the conclusion in Section 5.

2. Related Work

The economic factors such as investment inflows affect a certain industry, with respect to the automobile industry, it states that the inflow patters are cyclical in nature where the factors affecting the cycles are on the basis of economic cycles. These cycles are used synonymously with seasonality where supply and demand patterns change based on factors like weather, recessions and other external causes. In [2], the automobile undergoes a partial seasonality where most vehicle sales are fluctuating based on the tax dates and often times also can be explained by the correlative nature. Ever since the inflow of foreign money began in India, the automobile sector benefited the most as most assets formed, were for those in the automobile sector, companies setup manufacturing plants and provided jobs for the local public, this resulted in a stable automobile market as the cash cycles allowed consumers to purchase vehicles, this in turn provided a broad market formidability for India and led to increased competition and better vehicles for consumers [3].

During COVID-19 the oil prices were affected due to the confused state of demand in many nations, ever since the lockdowns were put in place, transportation decreased and led to the reduction in demand, but many political factors led to a decrease in oil prices, this in turn enabled consumers to take advantage and purchase vehicles. This observation is crucial in understand why consumers kept buying at normal levels even though the period of COVID-19 was stated as a recession in the financial world [4]. The effects of COVID-19 in the economy wasn't similar to that of an ordinary financial caused crisis. The pandemic exhibited effects similar to that of pandemic like influenza and a mixture of the 2008 financial crisis, even though context with respect to the automobile industry is not provided here, the paper gives us flexibility in providing an explanation on what happened in the automobile industry [5]. In [6], several government decisions like stimulus programs for MSMEs and large enterprises lead to an instant stabilization and in a way lead to a quick resurrection of the automobile industry. In a macro-economic perspective, every nation had a similar pattern of problems where first, due to lockdowns, many businesses suffered, secondly, many commodities like oil underwent massive price changes, but the automobile industry was temporarily affected and in turn gave way to incorporation of brand-new strategies and OEM comebacks [7].

A case study in [8] states that the incorporation of a curve fitting procedure in a real experiment and its true relevance in determining results. The significance of the Karl Pearson's coefficient in regards to how this methodology can benefit an ongoing statistical experiment. The points discussed here are the idea of defining a relationship between different types of variables and how an established relationship could help draw out crucial inferences and conclusions [9]. The incorporation of ANOVA values in the experiment where values like standard error and R-squared values to basically determine a best fit curve when carrying out the regression experiments [10]. Authors in [11] guide on how to basically set up different regression tests in regards to how to arrange the data and how the variables are supposed to act in accordance with each other.

Objective of this article is to obtain relationship parameters by using a correlation coefficient test by constructing a correlation matrix which shows the correlation of all OEMs against each other and also to describe best fit line on the basis of ANOVA values such as R-squared and standard error.

3. Methodology

The COVID-19 pandemic has caused the global devastation, due to which the governments had forced a nationwide lockdown. As a result of this lockdown, economies were adversely affected especially the automobile sector which led to reduction in outcomes of original equipment manufacturers (OEM). Moreover, the demand for passenger vehicles also declined which in turn caused a severe liquidity crisis and a loss in revenue. A negative growth was observed in sales of all vehicle categories during the FY21 (2.24% decline in sales of passenger vehicles, 13.19% fall in sales of two wheelers, 0.77% fall in sales of commercial vehicles, and 66.06% fall in the sales of three wheelers) [1]. Maruti Suzuki, the largest automobile manufacturer-imposed layoff of 6%, following the drop-in car sales.

This article puts forward the sales analysis of Fiat, Ford, Honda, Hyundai, Mahindra, Maruti Suzuki, Nissan, Renault, Skoda, Tata, Toyota, Volkswagen for which the data is collected from different sources like websites, journals, articles, newspapers, etc. have been utilized for impact analysis and challenges faced due to COVID-19.

3.1 Regression/curve fitting

Regression or curve fitting is a way to understand the trend of scattered data, or non-scattered data by constructing a line which accommodates all points on the plot to the least square distance. In simple terms, curve fitting is the method of fitting a line which best describes the trend of the data. Commonly used methods are Linear curve fit, Quadratic curve fit, Cubic curve fit, Logarithmic curve fit. In Linear curve method, the variable relationship is formed by the equation, $y = a + bx$. This method used is the least squares method where the residual distance of $R_i = y_i - (a + bx_i)$, and values a and b are kept of a minimum.

In case of Quadratic curve fit, the variable relationship is formed by the equation $y = ax^2 + bx + c$ where $a \neq 0$. This method is similar where squared distances of residuals for values a, b and c. The Cubic curve fit method shows the variable relationship using the equation, $y = a + bx + cx^2 + dx^3$. This method is similar as squared distances of residuals of values a, b, c and d. A Sequence chart is a form of line graph which provides a clear depiction of a trend for extended time series data. This chart is often used as a reference to compare towards regression trends and also provides visual cues from which in the context of this project, also offers supporting claims to the attribution made previously. Fig 1 shows the Methodology flowchart for Regression/Curve fitting.

3.1.1 Procedure for Curve fitting

1) Firstly, authors produce sequence charts to plot a complete trend for companies which existed from January 2017 till March 2022.

2) Understand that the sequence chart will only be used to compare with the regression plots.
3) The data as mentioned will be in a continuous time series format.
4) The curve plots will be for linear, quadratic and cubic only.
5) Authors mentioned which curve fits best based on the lowest significance value obtained in the background process.

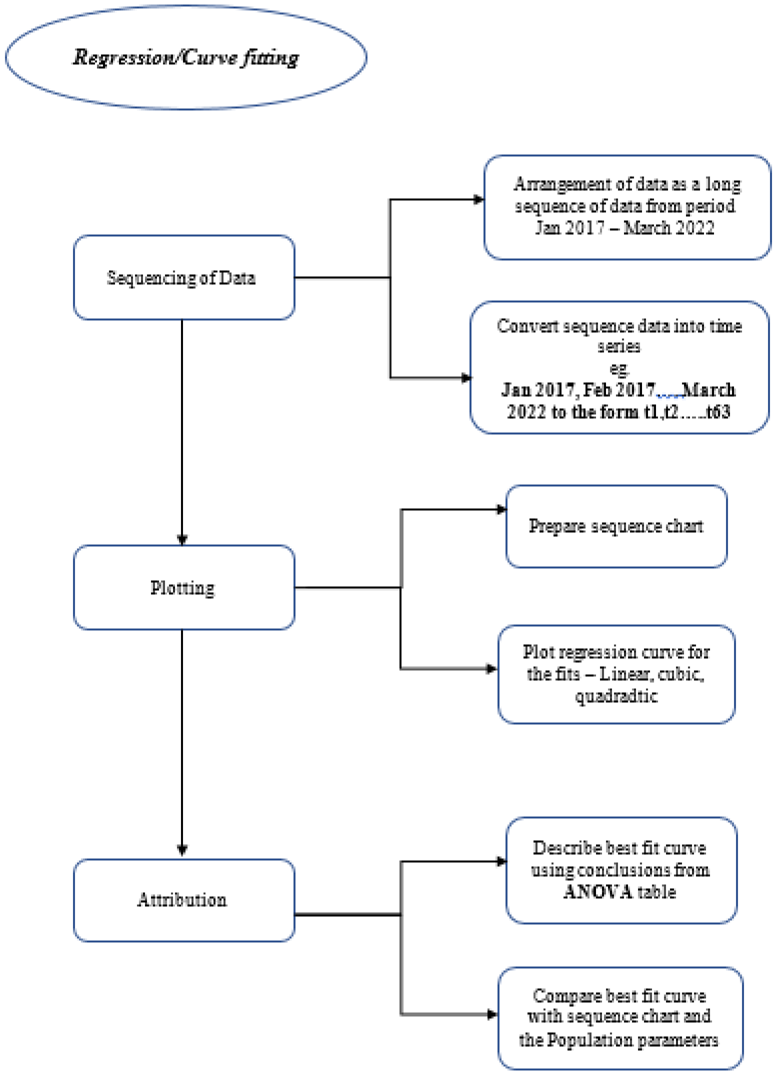


Fig 1 – Methodology flowchart for Regression/Curve fitting

3.2 Karl Pearson's coefficient

The Karl Pearson's coefficient also known as the coefficient of correlation is a mathematical method to understand the relationship between two sets of variables such that the output is a number $-1 < r < 1$. The coefficient indicated whether the relationship is negatively related or positively related. The formula for the correlation coefficient is $= \frac{\sum(x-\bar{X})(y-\bar{Y})}{\sqrt{\sum(x-\bar{X})^2}\sqrt{\sum(y-\bar{Y})^2}}$. $r = (0,1]$ is Positive correlation, $r = [-1,0)$ is Negative correlation and $r = 0$ is Zero-correlation/Uncorrelation.

In this article, authors used significance levels as a supporting factor for the correlations where significance will take on values such that, the Significance is great at values <0.05 and also Significance is good at level 0.05.

3.2.1 Procedure for Coefficient of correlation

1) The data set will be partitioned into 3 parts –Pre-COVID-19, Post-COVID-19, All time relation.

2) Authors constructed correlation matrix for all companies which existed from dates January 2017 till March 2022 for all partitions.

3) The coefficient of correlation for the will be further supported by the significance ratings.

4) The partitions will further be divided to 3 parts – Double star, single star, no star.

Significance ratings are, ** (Double Star) Significance rating at 0.01 level – high correlation, *(Single Star) Significance rating at 0.05 level – moderate correlation, No star – no significance and no correlation. Fig 2 shows the Methodology flowchart for correlation.

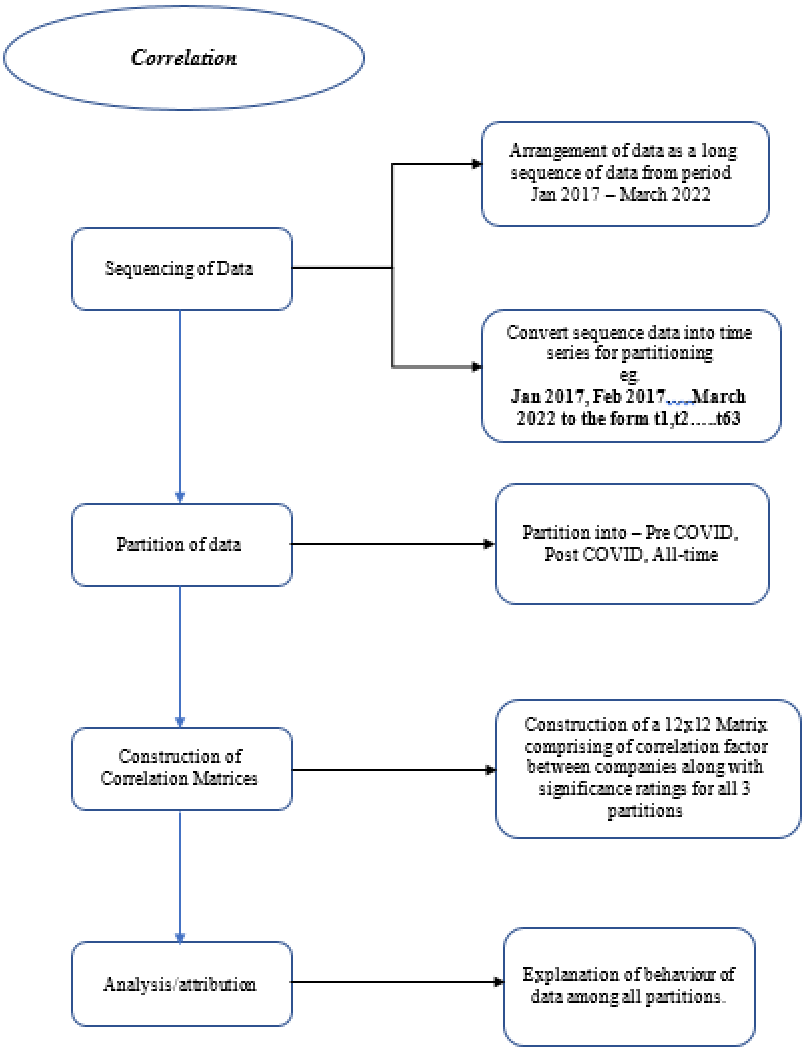


Fig 2 – Methodology flowchart for Correlation

4. Results and Discussions

The results obtained and present it in simple terms such that mathematical complexity is put to a minimum. The analysis of the data in this impact study shows that the correlation factors returned with high significance stating that the effect of COVID-19 was only temporary. Based on the experiment results, the authors were able to determine which OEMs (R-squared value >0.5) had consistency in regards to their time sequence sales and were able to determine the best fit curve with as much minimum error as possible.

4.1 Analysis of Coefficient of Correlation

Table 1 – 12x12 Correlation matrix for Pre COVID-19 partition

Correlations

		Fiat_Sales	Ford_Sales	Honda_Sales	Hyundai_Sales	Mahindra_Sales	Maruti_Suzuki_Sales	Nissan_Sales	Renault_Sales	Skoda_Sales	TATA_Sales	Toyota_Sales	Volkswagen_Sales
Fiat_Sales	Pearson Correlation	1	.711**	.452**	.601**	.410**	.523**	.274	-.091	.524**	.740**	.551**	.253
	Sig. (2-tailed)		<.001	.004	<.001	.009	<.001	.091	.583	<.001	<.001	<.001	.120
	N	39	39	39	39	39	39	39	39	39	39	39	39
Ford_Sales	Pearson Correlation	.711**	1	.750**	.657**	.509**	.529**	.634**	.128	.511**	.721**	.711**	.527**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001	<.001	<.001	.436	<.001	<.001	<.001	<.001
	N	39	39	39	39	39	39	39	39	39	39	39	39
Honda_Sales	Pearson Correlation	.452**	.750**	1	.437**	.472**	.444**	.603**	.014	.486**	.695**	.665**	.593**
	Sig. (2-tailed)	.004	<.001		.005	.002	.005	<.001	.932	.002	<.001	<.001	<.001
	N	39	39	39	39	39	39	39	39	39	39	39	39
Hyundai_Sales	Pearson Correlation	.601**	.657**	.437**	1	.617**	.659**	.412**	.234	.614**	.718**	.573**	.495**
	Sig. (2-tailed)	<.001	<.001	.005		<.001	<.001	.009	.152	<.001	<.001	<.001	.001
	N	39	39	39	39	39	39	39	39	39	39	39	39
Mahindra_Sales	Pearson Correlation	.410**	.509**	.472**	.617**	1	.591**	.555**	.191	.281	.599**	.378*	.528**
	Sig. (2-tailed)	.009	<.001	.002	<.001		<.001	<.001	.245	.083	<.001	.018	<.001
	N	39	39	39	39	39	39	39	39	39	39	39	39
Maruti_Suzuki_Sales	Pearson Correlation	.523**	.529**	.444**	.659**	.591**	1	.365*	.274	.390*	.706**	.546**	.291
	Sig. (2-tailed)	<.001	<.001	.005	<.001	<.001		.022	.092	.014	<.001	<.001	.072
	N	39	39	39	39	39	39	39	39	39	39	39	39
Nissan_Sales	Pearson Correlation	.274	.634**	.603**	.412**	.555**	.365*	1	.352*	.348*	.485**	.307	.785**
	Sig. (2-tailed)	.091	<.001	<.001	.009	<.001	.022		.028	.030	.002	.057	<.001
	N	39	39	39	39	39	39	39	39	39	39	39	39
Renault_Sales	Pearson Correlation	-.091	.128	.014	.234	.191	.274	.352*	1	.350*	-.028	.034	.483**
	Sig. (2-tailed)	.583	.436	.932	.152	.245	.092	.028		.029	.866	.837	.002
	N	39	39	39	39	39	39	39	39	39	39	39	39
Skoda_Sales	Pearson Correlation	.524**	.511**	.486**	.614**	.281	.390*	.348*	.350*	1	.611**	.381*	.494**
	Sig. (2-tailed)	<.001	<.001	.002	<.001	.083	.014	.030	.029		<.001	.017	.001
	N	39	39	39	39	39	39	39	39	39	39	39	39
TATA_Sales	Pearson Correlation	.740**	.721**	.695**	.718**	.599**	.706**	.485**	-.028	.611**	1	.614**	.368*
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	.002	.866	<.001		<.001	.021
	N	39	39	39	39	39	39	39	39	39	39	39	39
Toyota_Sales	Pearson Correlation	.551**	.711**	.665**	.573**	.378*	.546**	.307	.034	.381*	.614**	1	.318*
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	.018	<.001	.057	.837	.017	<.001		.048
	N	39	39	39	39	39	39	39	39	39	39	39	39
Volkswagen_Sales	Pearson Correlation	.253	.527**	.593**	.495**	.528**	.291	.785**	.483**	.494**	.368*	.318*	1
	Sig. (2-tailed)	.120	<.001	<.001	.001	<.001	.072	<.001	.002	.001	.021	.048	
	N	39	39	39	39	39	39	39	39	39	39	39	39

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 2 - Significance ratings frequency by company for Pre COVID-19 partition.

COMPANY	DOUBLE STAR	SINGLE STAR	NO STAR
Fiat	8	0	4
Ford	10	0	2
Honda	10	0	2
Hyundai	10	0	2
Mahindra	8	1	3
Maruti Suzuki	7	2	3
Nissan	6	3	3
Renault	1	2	9
Skoda	6	4	2
Tata	9	1	2
Toyota	6	3	3
Volkswagen	7	2	3

In the pre-COVID-19 era, most cases of OEM vs OEM correlation had high significance ratings indicating that the correlation coefficients are closely accurate to the actual patterns of the data of OEMs when compared against each other. From Table 2, No. of Double star ratings (0.01 level significance) are 88 coefficients or 66.67%. No. of Single star ratings (0.05 level significance) are 18 coefficients or 13.63%. and the No. of No star ratings (>0.05 level significance) are 26 coefficients or 19.7%. The no. of single/double star ratings are greater and can be considered together as a low significance data since the difference is only that of 5% between the star ratings. Since: single star rating is <= 0.01 level significance, double star rating is 0.05 < alpha < 0.01. Both the no. of coefficients to 106 coefficients is 80.3%. Therefore, meaning that about 80.3% of the data can be correlated from the pre-COVID-19 sample.

From Table 1, No. of Strong correlations (r>0.7) is 17 or 16.03%, No. of Moderate correlations (0.3 < r < 0.7) is 88 or 83.01%. No. of Weak correlations (r<0.3) is 1 or 0.96%. From the above evaluations, it is understood that about 17 OEM vs OEM cases had a strong correlation therefore translating to the fact that during pre-COVID-19 a good number of OEMs followed a strong cyclical pattern with each other. Around 88 OEM vs OEM cases followed moderate correlation which is a strong indication of moderate cyclical behaviour between the OEMs. In the overall conclusion of the pre-COVID-19 data set, that most of the OEMs from the period Jan 2017 till Mar 2022 followed a close relation in the rising and dropping trend on a relative scale is observed.

Table 3 – 12x12 Correlation matrix for Post COVID-19 partition.

Correlations

		Fiat_Sales	Ford_Sales	Honda_Sales	Hyundai_Sales	Mahindra_Sales	Maruti_Suzuki_Sales	Nissan_Sales	Renault_Sales	Skoda_Sales	TATA_Sales	Toyota_Sales	Volkswagen_Sales
Fiat_Sales	Pearson Correlation	1	.111	.220	.200	-.013	.240	.213	.256	-.044	-.043	.272	-.285
	Sig. (2-tailed)		.614	.313	.360	.952	.270	.329	.239	.840	.846	.209	.187
	N	23	23	23	23	23	23	23	23	23	23	23	23
Ford_Sales	Pearson Correlation	.111	1	.294	.565**	-.178	.305	-.037	.542**	-.597**	-.274	.158	-.571**
	Sig. (2-tailed)	.614		.174	.005	.416	.157	.866	.008	.003	.206	.472	.004
	N	23	23	23	23	23	23	23	23	23	23	23	23
Honda_Sales	Pearson Correlation	.220	.294	1	.838**	.457*	.656**	.371	.776**	.216	.525*	.538**	.207
	Sig. (2-tailed)	.313	.174		<.001	.028	<.001	.081	<.001	.323	.010	.008	.342
	N	23	23	23	23	23	23	23	23	23	23	23	23
Hyundai_Sales	Pearson Correlation	.200	.565**	.838**	1	.562**	.778**	.388	.883**	.122	.507*	.638**	.088
	Sig. (2-tailed)	.360	.005	<.001		.005	<.001	.067	<.001	.580	.014	.001	.690
	N	23	23	23	23	23	23	23	23	23	23	23	23
Mahindra_Sales	Pearson Correlation	-.013	-.178	.457*	.562**	1	.608**	.525*	.368	.667**	.858**	.599**	.626**
	Sig. (2-tailed)	.952	.416	.028	.005		.002	.010	.084	<.001	<.001	.003	.001
	N	23	23	23	23	23	23	23	23	23	23	23	23
Maruti_Suzuki_Sales	Pearson Correlation	.240	.305	.656**	.778**	.608**	1	.382	.648**	.196	.548**	.500*	.249
	Sig. (2-tailed)	.270	.157	<.001	<.001	.002		.072	<.001	.370	.007	.015	.252
	N	23	23	23	23	23	23	23	23	23	23	23	23
Nissan_Sales	Pearson Correlation	.213	-.037	.371	.388	.525*	.382	1	.408	.393	.714**	.679**	.385
	Sig. (2-tailed)	.329	.866	.081	.067	.010	.072		.053	.063	<.001	<.001	.070
	N	23	23	23	23	23	23	23	23	23	23	23	23
Renault_Sales	Pearson Correlation	.256	.542**	.776**	.883**	.368	.648**	.408	1	.139	.445*	.698**	.041
	Sig. (2-tailed)	.239	.008	<.001	<.001	.084	<.001	.053		.526	.034	<.001	.854
	N	23	23	23	23	23	23	23	23	23	23	23	23
Skoda_Sales	Pearson Correlation	-.044	-.597**	.216	.122	.667**	.196	.393	.139	1	.784**	.523*	.765**
	Sig. (2-tailed)	.840	.003	.323	.580	<.001	.370	.063	.526		<.001	.010	<.001
	N	23	23	23	23	23	23	23	23	23	23	23	23
TATA_Sales	Pearson Correlation	-.043	-.274	.525*	.507*	.858**	.548**	.714**	.445*	.784**	1	.717**	.816**
	Sig. (2-tailed)	.846	.206	.010	.014	<.001	.007	<.001	.034	<.001		<.001	<.001
	N	23	23	23	23	23	23	23	23	23	23	23	23
Toyota_Sales	Pearson Correlation	.272	.158	.538**	.638**	.599**	.500*	.679**	.698**	.523*	.717**	1	.426*
	Sig. (2-tailed)	.209	.472	.008	.001	.003	.015	<.001	<.001	.010	<.001		.043
	N	23	23	23	23	23	23	23	23	23	23	23	23
Volkswagen_Sales	Pearson Correlation	-.285	-.571**	.207	.088	.626**	.249	.385	.041	.765**	.816**	.426*	1
	Sig. (2-tailed)	.187	.004	.342	.690	.001	.252	.070	.854	<.001	<.001	.043	
	N	23	23	23	23	23	23	23	23	23	23	23	23

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 4 - Significance ratings frequency by company for Post COVID-19 partition.

COMPANY	DOUBLE STAR	SINGLE STAR	NO STAR
Fiat	0	0	12
Ford	4	0	8
Honda	4	2	6
Hyundai	6	1	5
Mahindra	6	2	4
Maruti Suzuki	5	1	6
Nissan	2	1	9
Renault	5	1	6
Skoda	4	1	7
Tata	6	3	3
Toyota	6	3	3
Volkswagen	4	1	7

From Table 4, No. of Double star ratings (0.01 level significance) are 52 or 40%, No. of Single star ratings (0.05 level significance) are 16 or 12% and the No. of No star ratings (>0.05 level significance) are 64 or 48%. It is observed that majority observation tallying upto 48% or the cases are with bad significance ratings. Yet as per rule of significance made, the cases with the single/double star ratings can be summated and can tally upto 52% of the cases with good significance ratings. In conclusion, about 52% of the data can be correlated, and with great importance mentioning that the no of significant cases has dropped from 80.3% to 52% post COVID-19 is recorded.

From Table 3, No. of Strong correlations (r>0.7) is 20 or 30%, No. of Moderate correlations (0.3 < r < 0.7) is 46 or 67% and the No. of Weak correlations (r<0.3) is 2 or 3%. From the set of significant cases extrapolated from the post COVID-19 dataset, that around 30% of significant cases have strong correlation along with 67% having moderate correlation. In comparison to the pre COVID-19 data set around 105 cases of correlation with good strength compared to the 66 cases in the post COVID-19 dataset were observed, in conclusion the COVID-19 indeed decrease the correlation between OEMs and also reduced the cyclical nature of the patters present before COVID-19.

Table 6 – Significance ratings frequency by company for all time partition.

COMPANY	DOUBLE STAR	SINGLE STAR	NO STAR
Fiat	5	3	4
Ford	8	1	3
Honda	8	0	4
Hyundai	9	1	2
Mahindra	8	2	2
Maruti Suzuki	9	1	2
Nissan	9	2	1
Renault	4	2	6
Skoda	5	1	6
Tata	6	1	5
Toyota	10	1	1
Volkswagen	5	5	2

Table 5 – 12x12 Correlation matrix for All-Time partition.

Correlations

		Fiat_Sales	Ford_Sales	Honda_Sales	Hyundai_Sales	Mahindra_Sales	Maruti_Suzuki_Sales	Nissan_Sales	Renault_Sales	Skoda_Sales	TATA_Sales	Toyota_Sales	Volkswagen_Sales
Fiat_Sales	Pearson Correlation	1	.632**	.574**	.388**	.331**	.417**	.326**	.059	.013	-.013	.499**	.304*
	Sig. (2-tailed)		<.001	<.001	.002	.008	<.001	.009	.644	.922	.917	<.001	.015
	N	63	63	63	63	63	63	63	63	63	63	63	63
Ford_Sales	Pearson Correlation	.632**	1	.765**	.519**	.270*	.442**	.382**	.269*	-.351**	-.338**	.513**	.359**
	Sig. (2-tailed)	<.001		<.001	<.001	.033	<.001	.002	.033	.005	.007	<.001	.004
	N	63	63	63	63	63	63	63	63	63	63	63	63
Honda_Sales	Pearson Correlation	.574**	.765**	1	.555**	.486**	.540**	.546**	.275*	.043	.004	.647**	.618**
	Sig. (2-tailed)	<.001	<.001		<.001	<.001	<.001	<.001	.029	.738	.977	<.001	<.001
	N	63	63	63	63	63	63	63	63	63	63	63	63
Hyundai_Sales	Pearson Correlation	.388**	.519**	.555**	1	.664**	.821**	.459**	.681**	.233	.429**	.680**	.401**
	Sig. (2-tailed)	.002	<.001	<.001		<.001	<.001	<.001	<.001	.066	<.001	<.001	.001
	N	63	63	63	63	63	63	63	63	63	63	63	63
Mahindra_Sales	Pearson Correlation	.331**	.270*	.486**	.664**	1	.688**	.591**	.394**	.480**	.542**	.580**	.620**
	Sig. (2-tailed)	.008	.033	<.001	<.001		<.001	<.001	.001	<.001	<.001	<.001	<.001
	N	63	63	63	63	63	63	63	63	63	63	63	63
Maruti_Suzuki_Sales	Pearson Correlation	.417**	.442**	.540**	.821**	.688**	1	.455**	.573**	.242	.423**	.619**	.417**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001		<.001	<.001	.056	<.001	<.001	<.001
	N	63	63	63	63	63	63	63	63	63	63	63	63
Nissan_Sales	Pearson Correlation	.326**	.382**	.546**	.459**	.591**	.455**	1	.426**	.292*	.380**	.561**	.672**
	Sig. (2-tailed)	.009	.002	<.001	<.001	<.001	<.001		<.001	.020	.002	<.001	<.001
	N	63	63	63	63	63	63	63	63	63	63	63	63
Renault_Sales	Pearson Correlation	.059	.269*	.275*	.681**	.394**	.573**	.426**	1	.237	.309*	.453**	.366**
	Sig. (2-tailed)	.644	.033	.029	<.001	.001	<.001	<.001		.062	.014	<.001	.003
	N	63	63	63	63	63	63	63	63	63	63	63	63
Skoda_Sales	Pearson Correlation	.013	-.351**	.043	.233	.480**	.242	.292*	.237	1	.755**	.377**	.406**
	Sig. (2-tailed)	.922	.005	.738	.066	<.001	.056	.020	.062		<.001	.002	<.001
	N	63	63	63	63	63	63	63	63	63	63	63	63
TATA_Sales	Pearson Correlation	-.013	-.338**	.004	.429**	.542**	.423**	.380**	.309*	.755**	1	.382**	.244
	Sig. (2-tailed)	.917	.007	.977	<.001	<.001	<.001	.002	.014	<.001		.002	.054
	N	63	63	63	63	63	63	63	63	63	63	63	63
Toyota_Sales	Pearson Correlation	.499**	.513**	.647**	.680**	.580**	.619**	.561**	.453**	.377**	.382**	1	.491**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	.002	.002		<.001
	N	63	63	63	63	63	63	63	63	63	63	63	63
Volkswagen_Sales	Pearson Correlation	.304*	.359**	.618**	.401**	.620**	.417**	.672**	.366**	.406**	.244	.491**	1
	Sig. (2-tailed)	.015	.004	<.001	.001	<.001	<.001	<.001	.003	<.001	.054	<.001	
	N	63	63	63	63	63	63	63	63	63	63	63	63

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Interpreting an all-time correlation matrix will be difficult since the pre/post COVID-19 data sets provided clear lines of difference between the data. From Table 6, No. of Double star ratings (0.01 level significance) are 86 or 65%, No. of Single star ratings (0.05 level significance) are 20 or 15%, and the No. of No star ratings (>0.05 level significance) are 26 or 20%. The all time correlation matrix shows that about 80% of the cases are significant, one way to understand the difference against pre/post COVID-19 datasets is the difference in time periods. The pre COVID-19 datasets has recorded cases for 39 months and the post COVID-19 dataset has 24 months, therefore the skew in results.

From Table 5, No. of Strong correlations (r>0.7) is 6 or 6%, No. of Moderate correlations (0.3 < r < 0.7) is 100 or 94% and the No. of Weak correlations (r<0.3) is 0. All the cases return a correlation of high strength even after the incorporation of the post COVID-19 dataset, therefore in a clear basis it understood that the effect of COVID-19 in terms of cases with low correlation occurred only during the post COVID-19 dataset, by which in simple words the effect of COVID-19 was only temporary and on the overall timeseries data.

4.2 Result analysis of Curve fitting/Regression

In this section, the best fit curve with the help of visual cues and statistical parameters are determined. The main parameters considered for the study are population parameters (Mean, Standard variation, Coefficient of variation), ANOVA (analysis of variance) (R-squared value, Standard error values of linear, quadratic and cubic curves). The population parameters will only be used as a comparison between the normal mean line and the curve fit line. The ANOVA will help us pick the optimal curve fit which can hold maximum degree of predictability. The optimum ANOVA parameter conditions are R-squared that should be higher on the mentioned tables, standard error which also should be the lowest on the table, and must be lesser than the population parameter of standard deviation. In the Regression and Best fit data table, the green colour shows the best fit.

4.2.1 Fiat

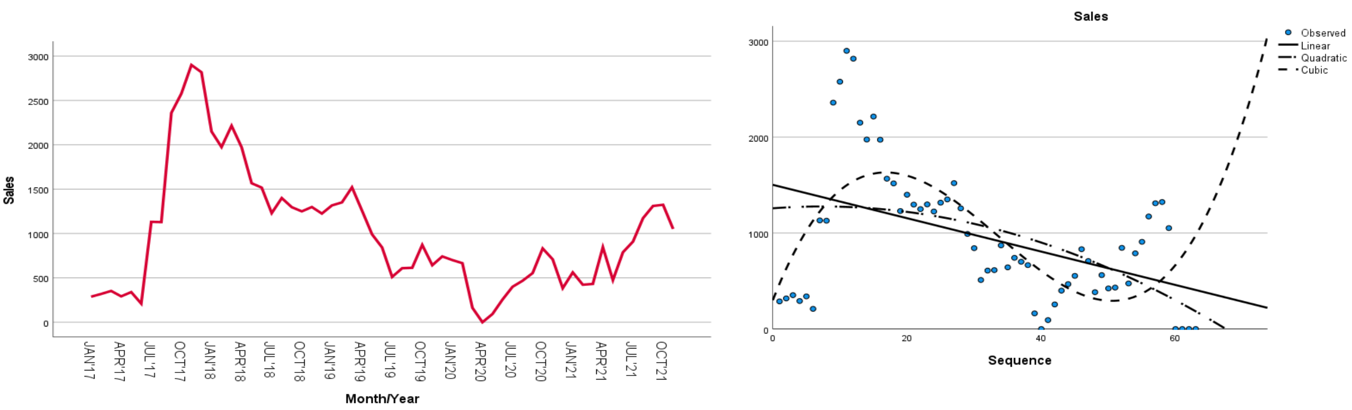


Fig 3 – (a) Sequence chart for Fiat (b) Regression lines for Fiat.

Table 7 – Regression table and best fit for Fiat.

Fit	R-squared	Std. error	Best fit
Linear	0.202	639.196	
Quadratic	0.224	635.566	
Cubic	0.443	543.185	

The obtained Standard deviation is 674.279, Mean is 1027.81 and the Coefficient of variance is 65.6%. The sequence chart in Fig 3 shows that sales rise constantly from the period January 2017 till November 2017, and then a sudden decline trend till the period March 2020, following the 0 sales point on period April 2020, the trend begins to rise with moderate variance from the mean line. The population metrics in Table 7 shows an average sales of 1028 units with a standard deviation of 674.279, as the CV is around 66% at stating that every data point has a high probability of varying from the mean indicating that the population parameters are supportive of the sequence chart behaviour. The best fit based on the ANOVA results where R-squared is 0.433 and the standard error is 543.185, the best fit is the cubic curve. The cubic curve is able to fit the sequence chart pattern from period January 2017 till November 2017 with a sinusoidal shape and replicate the decline and partial rise along the sequence chart. When comparing the standard error and standard deviation, the cubic curve yet again returns a lower error value when compared to the deviation, therefore suggesting that the cubic fit is perfect.

4.2.2 Ford

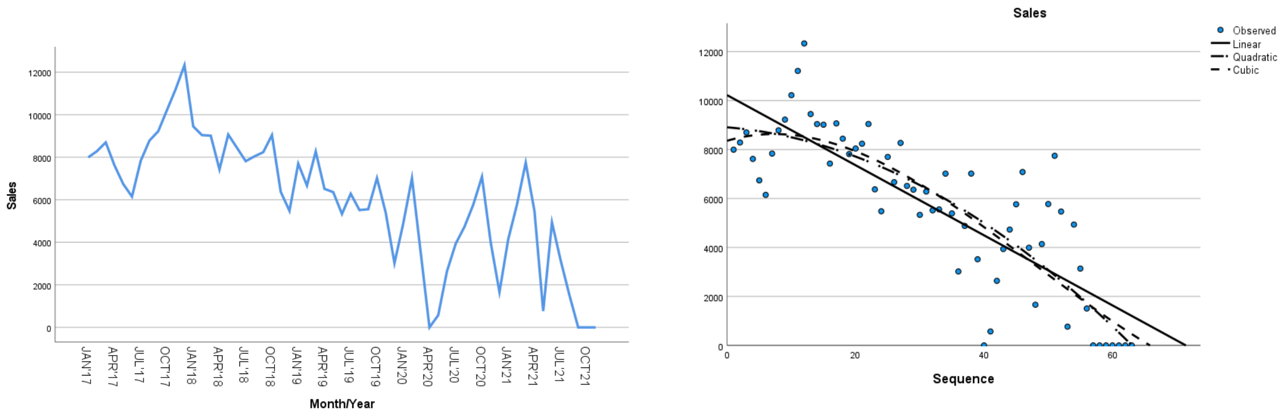


Fig 4 – (a) Sequence chart for Ford (b) Regression lines for Ford.

Table 8 – Regression table and best fit for Ford.

Fit	R-squared	Std. error	Best fit
Linear	0.668	1866.421	
Quadratic	0.698	1792.287	
Cubic	0.702	1796.878	

The obtained Standard deviation is 2513.195, Mean is 6462.982 and the coefficient of variance is 39%. The sequence chart in Fig 4 shows that the data follows a random cyclical pattern throughout the periods till March 2022. Based on visual cues, the overall trend is downwards with major variance from the period November 2019. The population parameters show an average sale of 6463 units with a standard deviation of 2513 units, as the CV is low giving an indicating of data points being less scattered. The best fit based on the ANOVA results where R-squared is 0.698 and the standard error is 1792.287 in Table 8, the best fit is the Quadratic curve. Authors have chosen the quadratic curve even though the cubic curve has an R-squared value of 0.702 because the standard error for the quadratic curve is lower along with the fact that the difference in R-squared values between both is only 0.004. In sequence chart, based on the cyclical downward trend, the quadratic curve acts as the perfect mean line. The population parameters along with the ANOVA values, authors observed that the R-squared is high and can be further supported by the moderately low CV value and the reduced error value with the quadratic mean line.

4.2.3 Honda

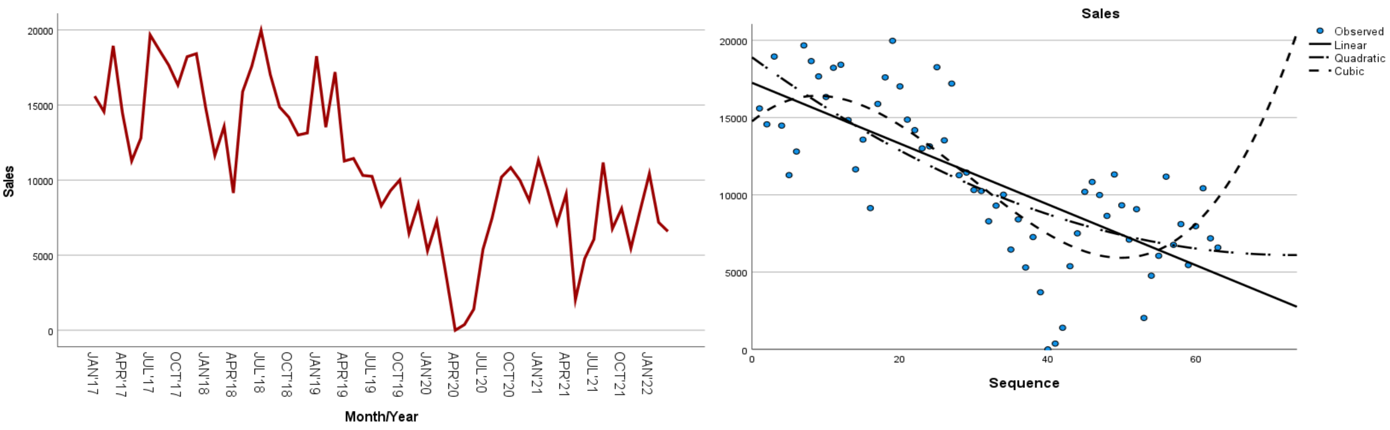


Fig 5 – (a) Sequence chart for Honda (b) Regression lines for Honda.

Table 9 – Regression table and best fit for Honda.

Fit	R-squared	Std. error	Best fit
Linear	0.520	3491.893	
Quadratic	0.540	3446.412	
Cubic	0.622	3149.309	

The obtained Standard deviation is 4798.589, Mean is 11132.34 and Coefficient of variance is 43.10%. The sequence chart in Fig 5 shows that there is a constant cyclical pattern for sales till the period April 2019 followed by a downward cyclical trend till the 0 sales point. Soon after the trend is an upward cyclical trend with moderate variance. The population parameters show an average sale of 11132 units with a standard deviation of 4799 units, as observed the CV is at a moderately high level at 43%. The best fit based on the ANOVA results in Table 9, where R-squared is 0.622 and the standard error is 3149.309, the best fit is the cubic curve. The cubic curve has a high R-squared value of 0.622, and also the standard error value are at high levels of >3000 because the distance of the peaks to valleys and vice versa are higher when they occur at a higher frequency compared to the previous 2 companies.

4.2.4 Hyundai

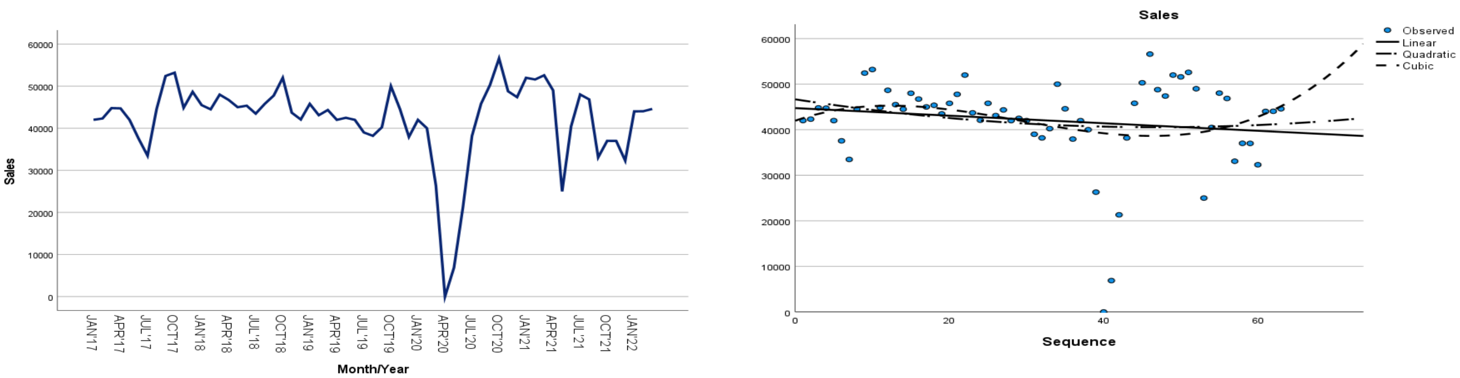


Fig 6 – (a) Sequence chart for Hyundai (b) Regression lines for Hyundai.

Table 10 – Regression table and best fit for Hyundai.

Fit	R-squared	Std. error	Best fit
Linear	0.025	9622.960	
Quadratic	0.032	9666.244	
Cubic	0.060	9603.953	

The obtained Standard deviation is 8024.084, Mean is 41435, and the Coefficient of variance is 19.36%. The sequence chart in Fig 6 shows a constant sales trend with moderate cyclical variance throughout the period except for the 0 sales point. The post COVID-19 trend as observed is an upward curve. The population parameters show an average sale of 41435 units along with a standard deviation of 8025 units, as observed the returned CV value is at a lower range of 19.36%. The best fit based on the ANOVA results in Table 10, where R-squared is 0.060 and the standard error is 9603.953, the best fit is the cubic curve. The curve chosen is cubic, but the R-squared value is majorly low at levels < 0.1 and very high standard error. This is due to the fact that a constant mean line trend as described by the cubic curve, the outlier data points below the 30,000 sales levels and the ones above the 50,000 sales levels skew the data, another way to explain this is by observing the frequency of the cycles, the higher the no of cycles, the lower the R-squared value. When using the population parameters as a difference, a low CV value which is contradictory of the error values obtained for regression is observed.

4.2.5 Mahindra

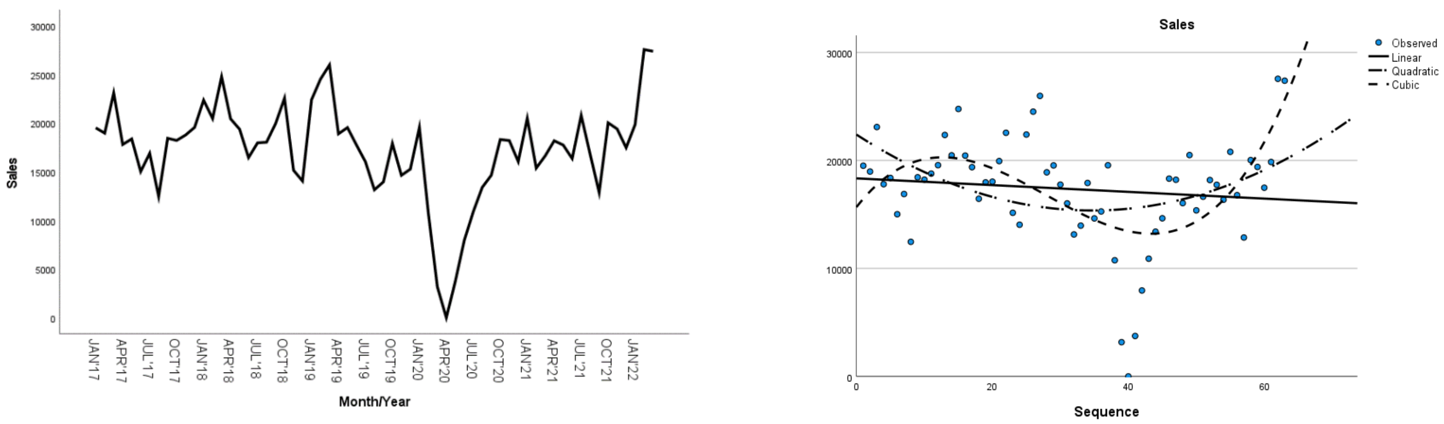


Fig 7 – (a) Sequence chart for Mahindra (b) Regression lines for Mahindra.

Table 11 – Regression table and best fit for Mahindra.

Fit	R-squared	Std. error	Best fit
Linear	0.013	5087.542	
Quadratic	0.130	4814.133	
Cubic	0.340	4228.560	

The obtained Standard deviation is 4567.775, Mean is 17261, and the Coefficient of variance is 26.46%. The sequence chart in Fig 7 shows that a constant cyclical trend throughout the whole period except for the 0 sales point, and there is a sudden rise at the end point of the sequence period. The population parameters show an average sale of 17261 units with a standard deviation of 4568 units, as observed a CV value of 26.46% indicating closely varying values above and below the mean. The best fit based on the ANOVA results in Table 11, where R-squared is 0.340 and the standard error is 4228.560, the best fit is the cubic curve. The cubic curve was chosen as it best fits the sequence of data as the best mean line, but the R-squared values lies at a lower point of 0.340 level with a moderately high variance of 4228.560, the reason for the low R-squared value is due to the large no. of outlier data points away from the cubic mean line resulting in a skewing of data. As explained before the frequency of cycles is higher hence the lower value. When referring to the population parameters, the standard deviation value is 4567.775, but the cubic mean line reduces the error values to 4228.560 therefore proving the cubic fit is perfect in these high frequency cycles.

4.2.6 Maruti Suzuki

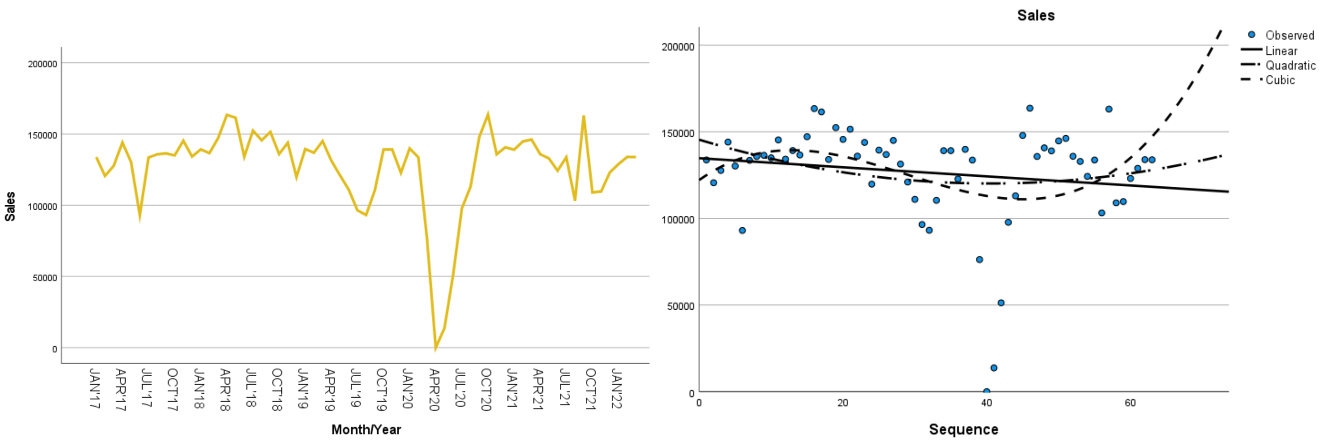


Fig 8 – (a) Sequence chart for Maruti Suzuki (b) Regression lines for Maruti Suzuki.

Table 12 – Regression table and best fit for Maruti Suzuki.

Fit	R-squared	Std. error	Best fit
Linear	0.026	29672.698	
Quadratic	0.050	29552.676	
Cubic	0.123	28631.459	

The obtained Standard deviation is 25052.53, Mean is 128421, and the Coefficient of variance is 19.5%. The sequence chart in Fig 8 shows a constant cyclical trend similar to that of Mahindra and Hyundai where the trend is constantly cyclical except for the 0 sales point, expected the same level of values to that of the mentioned companies. The population parameters show an average sale of 128421 units with a standard deviation of 25053 units, the CV is returned at the lower ranges of 19.5%. The best fit based on the ANOVA results in

Table 12, where R-squared is 0.123 and the standard error is 28631.459, the best fit is the cubic curve. The curve chosen is cubic since the R-squared values and std error values are optimal on the table, the low levels are due to the outlier data points and the high cyclical frequency which skews the data. The Maruti Suzuki line faces a similar case to Hyundai where the pattern or shape is the same and the CV levels are the same, also similar are the rising error values on the curve fits, on a similar basis to Hyundai, it is better to fit a mean line of 128421 units to best describe the line.

4.2.7 Nissan

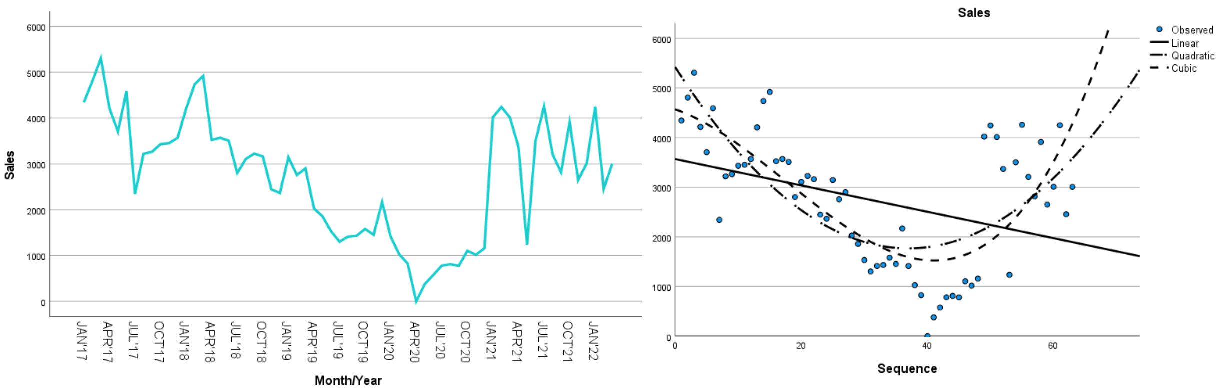


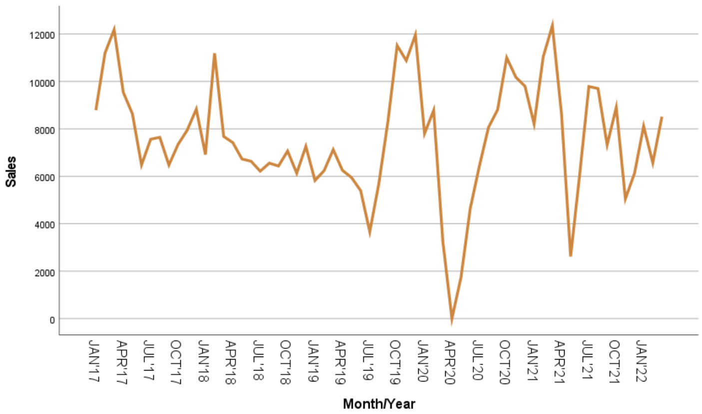
Fig 9 – (a) Sequence chart for Nissan (b) Regression lines for Nissan.

Table 13 – Regression table and best fit for Nissan.

Fit	R-squared	Std. error	Best fit
Linear	0.136	1240.122	
Quadratic	0.499	952.315	
Cubic	0.548	911.342	

The obtained Standard deviation is 1276.468, Mean is 2762, and the Coefficient of variance is 46.21%. The sequence chart in Fig 9 shows an erratic downward cyclical trend till the zero-sales point followed by an upward cyclical trend with high variance. The population parameters show an average sales of 2762 units with a standard deviation of 1276 units, the CV value returned is at moderately high levels at 46%. The best fit based on the ANOVA results in Table 13, where R-squared is 0.548 and the standard error is 911.342, the best fit is the cubic curve. The cubic fit is chosen because the the ANOVA values are optimal with respect to the table, the R-squared value and the std. error values are high and low respectively when compared to the previous 3 companies, this is due to the cubic mean line following the scattered data points closely with low variance and low frequency of cycles. As observed with the pattern the CV stands at 46% with a deviation of 1276 units, but with the cubic line, the error is reduced to 911 units with a good enough R-squared value of 0.548.

4.2.8 Renault



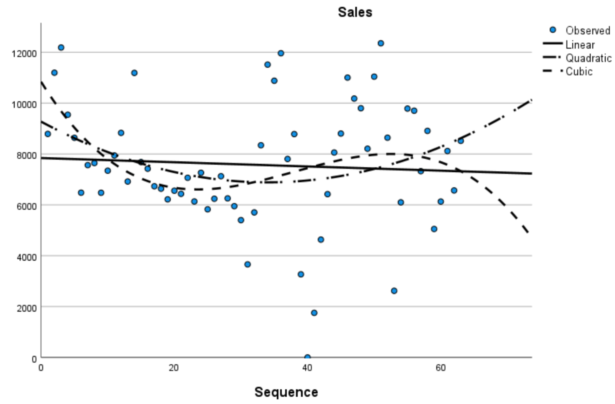


Fig 10 – (a) Sequence chart for Renault (b) Regression lines for Renault.

Table 14 – Regression table and best fit for Renault.

Fit	R-squared	Std. error	Best fit
Linear	0.004	2483.836	
Quadratic	0.066	2425.158	
Cubic	0.114	2381.463	

The obtained Standard deviation is 2269.797, Mean is 7700, and the Coefficient of variance is 29.47%. The sequence chart in Fig 10 shows a high form of erratic cyclical pattern which is inconsistent throughout the whole periods, but when observed closely the variance or the distance between the peaks and valleys have a constant variance due to which a mean trend line which is constant is observed. The population parameters show an average sale of 7700 units with a standard deviation of 2270 units, as observed the CV value is at a lower level of 30%. The best fit based on the ANOVA results in Table 14, where R-squared is 0.114 and the standard error is 2381.463, the best fit is the cubic curve. The fit chosen is cubic since the ANOVA values are optimal in result in accordance to the table, but the sequence pattern is similar to that of Maruti Suzuki and Hyundai, and the proof lies in the similarities of the ANOVA value where the low R-squared value of 0.114 and increased error values show the best fit line would be a constant mean line at 7700.

4.2.9 Skoda

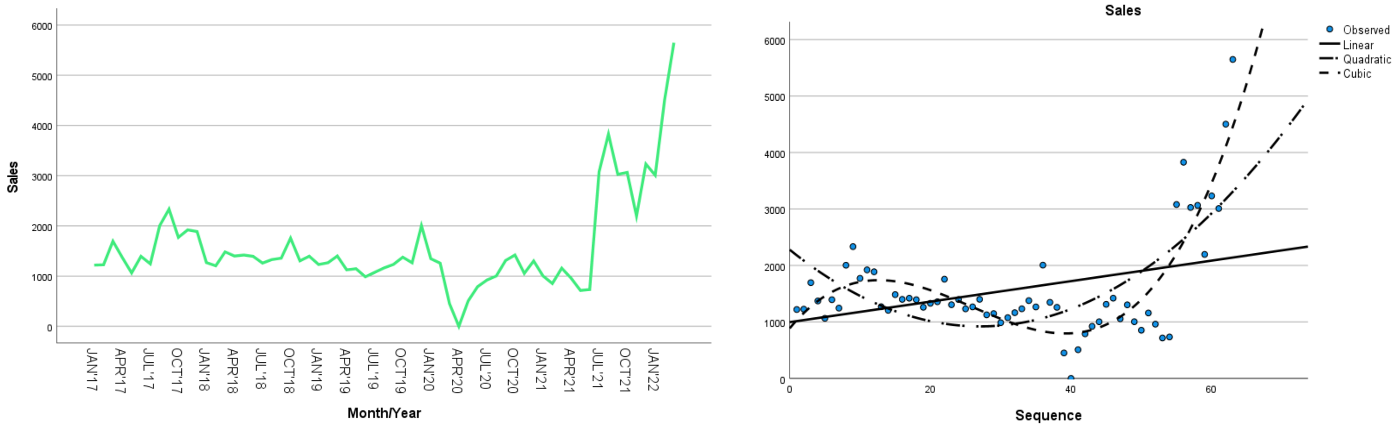


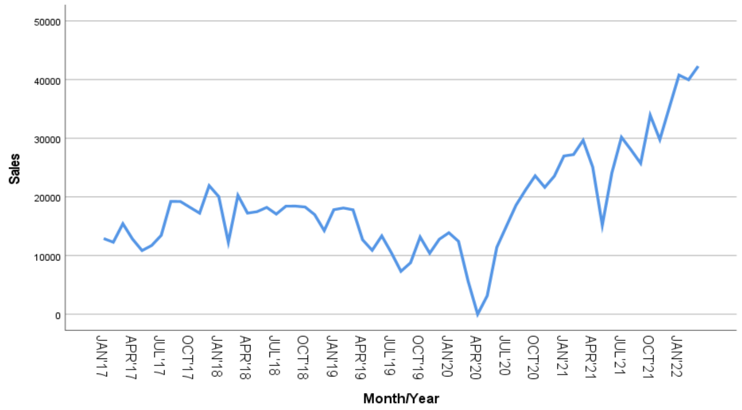
Fig 11 – (a) Sequence chart for Skoda (b) Regression lines for Skoda.

Table 15 – Regression table and best fit for Skoda.

Fit	R-squared	Std. error	Best fit
Linear	0.123	896.877	
Quadratic	0.460	709.750	
Cubic	0.717	517.743	

The obtained Standard deviation is 928.136, Mean is 1603, and the Coefficient of variance is 57.89%. The sequence chart in Fig 11 shows a constant cyclical trend till the 0 sales point with minimum variance, after the 0 sales point an abrupt upward trend with changing variance on the peaks and valleys are observed. The population parameters show an average sales of 1603 units with a standard deviation of 928 units, as observed the CV is moderately high. The best fit based on the ANOVA results in Table 15, where R-squared is 0.717 and the standard error is 517.743, the best fit is the cubic curve. The table returned a high R-squared value along with a reduced standard error of 518 units, surprisingly the CV value stands at 58% with 928 standard deviation on the basis of mean value obtained, but the cubic mean line reduces the error significantly hence authors chose the cubic fit.

4.2.10 TATA



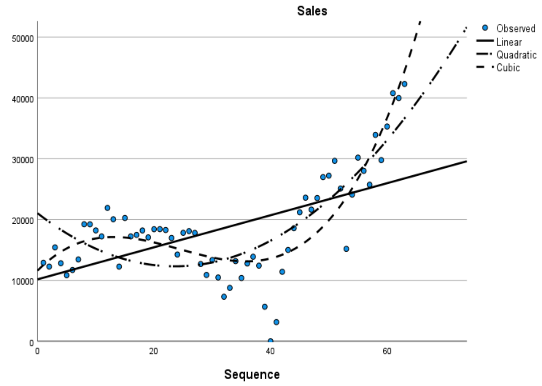


Fig 12 – (a) Sequence chart for TATA (b) Regression lines for TATA.

Table 16 – Regression table and best fit for TATA.

Fit	R-squared	Std. error	Best fit
Linear	0.315	7185.104	
Quadratic	0.609	5471.354	
Cubic	0.753	4383.439	

The obtained Standard deviation is 8273, Mean is 18908, and the Coefficient of variance is 43.75%. The sequence chart in Fig 12 shows a constant cyclical trend with a gradual decline till the 0-sales point followed by an abrupt upward trend till the end. The population parameter shows an average sale of 18908 units with a standard deviation of 8273 units, as observed the CV value is moderately high at 43.75%. The best fit based on the ANOVA results in Table 16, where R-squared is 0.753 and the standard error is 4383.439, the best fit is the cubic curve. As the table shows a high R-squared value of 0.753 as the pattern has lower cyclical frequency and constant levels of variance. From the population parameters, the standard deviation lies at 8273 units, but the cubic mean line significantly reduced the error and gave lower levels of variance by which cubic line chosen as the perfect fit.

4.2.11 Toyota

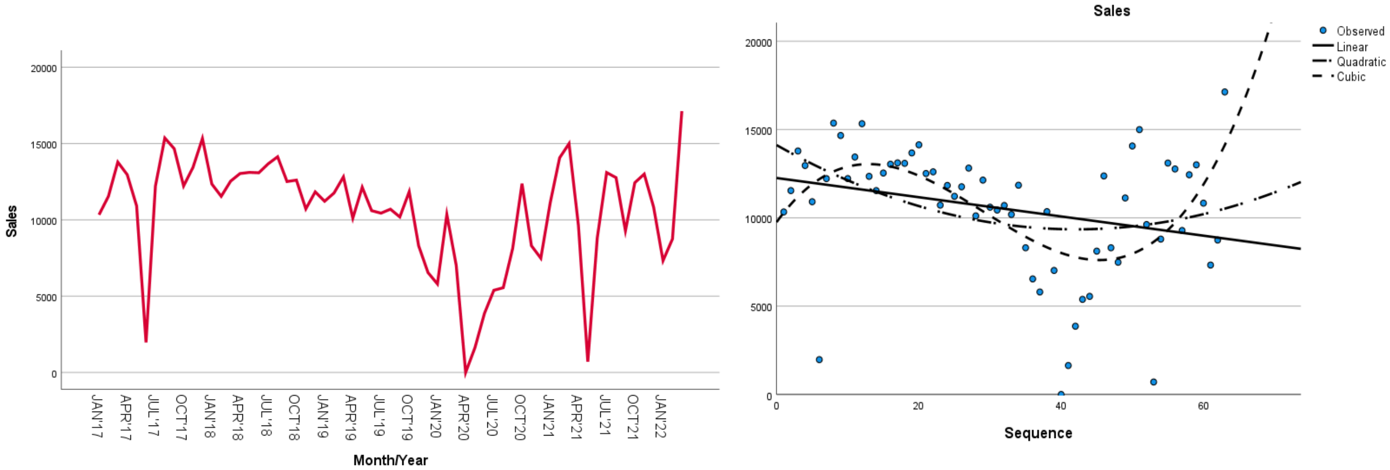


Fig 13 – (a) Sequence chart for Toyota (b) Regression lines for Toyota.

Table 17 – Regression table and best fit for Toyota.

Fit	R-squared	Std. error	Best fit
Linear	0.075	3523.439	
Quadratic	0.124	3458.118	
Cubic	0.297	3124.553	

The obtained Standard deviation is 3375.945, Mean is 10685.07, and the Coefficient of variance – 31.59%. The sequence chart in Fig 13 shows an erratic cyclical pattern with abrupt declines during the period May 2019 and May 2021. Apart from the 0 sales point, the cyclical trend continues with high levels of variance. The population parameters show an average sale of 10685 units with a standard deviation of 3376 units, as observed the CV values lies at the moderately low levels of 32%. The best fit based on the ANOVA results in Table 17, where R-squared is 0.297 and the standard error is 3124.553, the best fit is the cubic curve. Based on the table values, the cubic mean line returns a relatively low R-squared value but still high than the other curves, in these cases that Toyota's sequence trend has high cyclicality and is also inconsistent, but when compared with the population parameters, the standard deviation is 3376 units, and in the cubic fit it is considerably reduced, hence the cubic fit is chosen.

4.2.12 Volkswagen

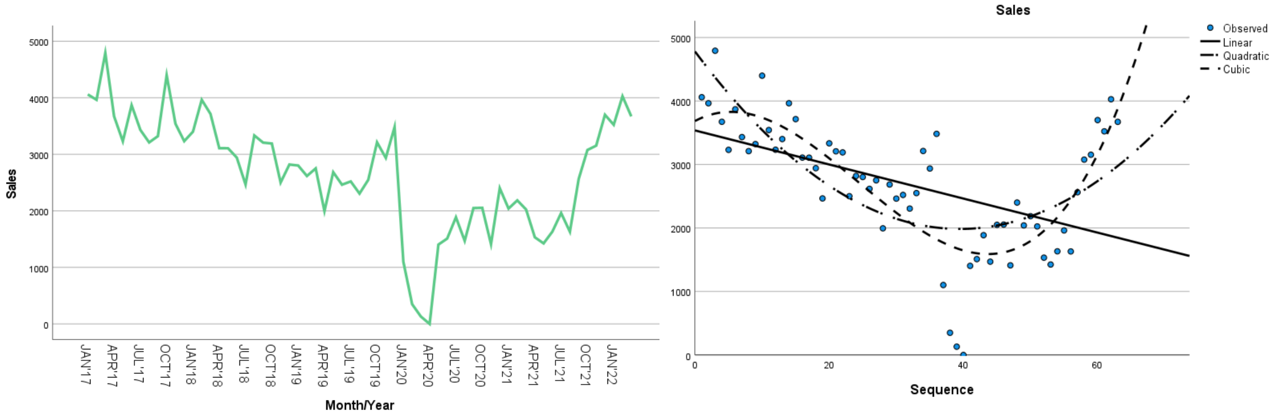


Fig 14 – (a) Sequence chart for Volkswagen (b) Regression lines for Volkswagen.

Table 18 –Regression table and best fit for Volkswagen.

Fit	R-squared	Std. error	Best fit
Linear	0.237	889.397	
Quadratic	0.517	713.566	
Cubic	0.658	605.593	

The obtained Standard deviation is 949.989, Mean is 2721.597, and the Coefficient of variance is 34.90%. The sequence chart in Fig 14 shows a constant cyclical downward trend till the 0 sales point with minimum variation, after which it is followed by an upward trend till the endpoint remaining lower than the initial point. The population parameters show an average sales of 2722 units with a standard deviation of 950 units, and the CV to be at moderately low levels of 35%. The best fit based on the ANOVA results in Table 18, where R-squared is 0.658 and the standard error is 605.593, the best fit is the cubic curve. The cubic fit returns a good enough R-squared value as the sequence pattern to be consistent with even though it has higher frequency of cycles, the variance is at low levels, when compared with the population parameters, a standard deviation of 950 units, but the cubic mean line significantly reduces the error therefore the cubic fit is chosen.

4.3 Overall result discussion for curve fitting

The results vary across OEM to OEM as most sequence patterns hold a level of uniqueness. The R-squared value gives information about the correlation of the data points on the best fit curve to the scattered points, and the other parameter like the standard error helps to navigate the choice on which curve to pick. The population parameters help to understand and compare the values between the normal mean line and the curve fitted line. All OEMs errors and variance are relative to their sales volume. The coefficient of variation helps to understand the average variance of the data points from the normal mean line and gives a perspective on the volatility of each individual OEM. From the collection of results, OEMs like Fiat and Skoda had coefficient of variance percentages >50% showing high volatility on the overall timeseries. OEMs like Hyundai, Maruti Suzuki and Renault had similar sequence patterns and identical parameters in relation to each other, where the curve fitting process achieved low R-squared values and increased error values in comparison to the normal mean line, this suggested that the best fit curve for such companies is the normal mean line. This occurrence was due to the inconsistent cycles which had shifting variance values. OEMs like Volkswagen, TATA, Skoda, Nissan and Ford returned good R-squared values >0.5, which indicated these OEMs had a good level of predictability pre COVID and post COVID. In overall conclusiveness with the curve fitting authors were able to deduce the best fit curve which offers the best form of predictability with as much minimum error as possible.

5. Conclusion

The sales data were analysed to understand the closeness of relation between OEMs on the post vs pre COVID-19 level. In true significance, the authors were able to understand that the OEM market follow a moderate to strong correlation in the pre COVID-19 era and resulted in a low correlation market due in the post pandemic era. But the overall all-time correlation showed that the correlation factors returned with high significance stating that the effect of COVID-19 was only temporary. Based on the experiment results, authors were able to determine which OEMs had consistency in regards to their time sequence sales and were able to determine the best fit curve with as much minimum error as possible. OEMs with R-squared value >0.5 were considered to have a good degree of predictability as compared to those lesser than that. The ones below that level would have to considered having low level of predictability, but if observed most cases like Mahindra, Maruti Suzuki have a consistent number of cycle variance, which in turn indicates that the ones with R-squared values less than 0.5 can be best fit with the normal mean line. Major market share changes were observed and through that one can easily understand the true effects of COVID-19. The regression plots revealed that best nature of the curve that can be fitted along with the understanding that the data was highly scattered, but with the help of additional population parameters and comparison of error values, authors were able to deduce the best possible fits.

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