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Visualization of Quantitative Thresholds in Stocks

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***Abstract*—**Technical analysis comprised by various technical indicators is a holistic way of representing price movement of stocks in the market. Various forms of indicators have evolved from the primitive ones in the past decades. There have been many attempts to introduce volume as a major determinant to determine strong patterns in market forecasting. The law of demand defines the relationship between the volume and price. Most of the traders are familiar with the volume game. Including the time dimension to the law of demand provides a different visualization to the theory. While attempting the same, it was found that there are different thresholds in the market for different companies. These thresholds have a significant influence on the price. This article is an attempt in determining the thresholds for companies using the three dimensional graphs for optimizing the portfolios. It also emphasizes on the magnitude of importance of volumes as a key factor for determining of predicting strong price movements, bullish and bearish markets. It uses a comprehensive data set of major companies which form a major chunk of the Indian automotive sector and are thus used as an illustration.

***Keywords*—**Technical Analysis, Expert System, Law of demand, Stocks, Portfolio Analysis, Indian Automotive Sector.

I. Introduction

STOCK market charting is conventionally done in a two dimensional plane using stock prices as the y variable and time stamp as the x variable. One of the variables which characterize a stock is the total traded quantity which is usually compared with the stock price or time stamp using separate two dimensional visualizations. In this study, visualization of a three dimensional step-wise surface with the total traded quantity as the third dimension has been done. This can also be visualized as a three dimensional law of demand where the fluctuation of a stock price due to the change in quantity of shares of that stock traded can be analyzed in time series and various regions like common trading quantity region and the threshold trading quantities can be identified. The study presents examples of such three dimensional plots and infers the relationship between trading volume and price.

II. Review of Literature

Wright W. (1997) [1], in his research paper, commented on the power of expression of three-dimensional computer graphics and how it can be used to quickly and easily comprehend large amounts of information. He said that three dimensional plots convey better information than two dimensional plots or rows or columns of numbers. In his article, he quoted various examples of application of three-dimensional visualization in representation of information in various industrial domains including the capital markets, retail banking, manufacturing, and consumer product goods.

K. H. Lee et al. (1999) [2] in his research work, developed a candle stick chart analysis expert system for predicting the stock market momentum and making investment decisions. The expert system provides patterns and movements which can be used to predict stock market future movements. The experimental results signified that the system provided an average hit ratio of 72% to help investors get high returns from their equity investments.

Martin Wattenberg (1999) [3] in his article, described a new 2-dimensional visualization algorithm capable of presenting detailed information on hundreds of items while emphasizing overall patterns in the data. This display method, which builds on tree map technique, makes use of both hierarchy and similarity information.

Christopher Westphal et al. (1998) [4] in their book introduce a brand new approach to data mining analysis. They elaborated upon techniques to discover patterns on inside training in the stock market, evaluate the utility of marketing campaigns, analyze retail services patterns over geographical areas, identify money laundering operations

Hilol Kargupta et al. (2002) [5] in their article, describe an experimental mobile data mining system that allows intelligent monitoring of time-critical financial data from a hand-held PDA and works using data mining techniques. They describe the data mining component of the system that employs a novel Fourier analysis-based approach to efficiently represent, visualize, and communicate decision trees over limited bandwidth wireless networks. They also discuss about a quadratic programming-based personalization module that runs on the PDAs and the multi-media based user-interfaces

Nesbit K. V. et al. (2009) [6] in their article describes our design and evaluation of a multisensory human perceptual tool for the real-world task domain of stock market trading. The data mined in this case study was the bid-and-ask data from the Australian Stock Exchange. Their design incorporated a 3D visual and a 2D sound display thus developing a visual-auditory bid-ask landscape.

Pak Chung Wong et al. (2004) [7] in their article, defined visual analytics as the formation of abstract visual metaphors in combination with a human information discourse (interaction) that enables detection of the expected and discovery of the unexpected within massive, dynamically changing information spaces. They also stated that visual analytics is an outgrowth of the fields of scientific and information visualization but includes technologies from many other fields, including knowledge management, statistical

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analysis, cognitive science, decision science, and many more. The processes and goals of analysis dominate the approach, but it's enabled by the wide-band visual interface to the brain and a dynamic interaction style of communication and discourse.

Šimunić et al. (2003) [8] in their research proposed a visualization system for stock market charts. They focus on clustering existing chart shapes which represent a set of similar charts. They generated a 2D map of these representative charts and implemented tools like zooming, levels of details and selection. Thus, they present a new approach of automatically generating the whole picture of the stock market dynamics.

Blume Lawrence at al. (1994) [9] in their work investigated the informational role of volume and its applicability for technical analysis. They showed that volume provides information on quality that cannot be deduced from the price statistic. They showed how volume, information precision, and price movements relate, and demonstrate how sequences of volume and prices can be informative. They also show that traders who use information contained in market statistics do better than traders who do not. They concluded that technical analysis thus arises as a natural component of the agents' learning process.

A. Antoniou et al. (1997) [10] in their analysis stated that, although there is a widespread belief that stock markets are weak-form efficient, technical analysis is a pervasive activity. The extent is examined to which this apparent paradox can be explained by conditioning the past sequence of prices on the past sequence of volume. They used a unique data set from an emerging market which revealed that, for a number of companies in the sample, returns appeared to conform to the weak-form version of the efficient markets hypothesis. However, when returns were conditioned on past levels of volume, current returns on over half of the companies exhibited predictability, particularly for low trading volume companies.

Daniella Acker et al. (2002) [11] in their research examined the determinants of inside spreads and their behavior around corporate earnings announcement dates, for a sample of UK firms over the period 1986–94. They found that closing daily inside spreads are affected by order processing costs (proxied by trading volumes), inventory control costs (trading volumes and return variability) and asymmetric information (unusually high trading volumes), thus quoting trading volumes as an important determinant. They also state that inside spreads start to narrow 15 days before an earnings announcement, narrow further by the end of the announcement day and remain sluggish after the announcement day thus signifying the importance of announcement news in the spread as well.

Tim Bollerslev et al. (2012) [12] in their article examines the behavior of equity trading volume and volatility for the individual firms composing the Standard & Poor's 100 composite index. Using multivariate spectral methods, they find that fractionally integrated processes best describe the long-run temporal dependencies in both series. Consistent with a stylized mixture-of-distributions hypothesis model in which the aggregate news-arrival process possesses long-memory characteristics, the long-run hyperbolic decay rates appear to be common across each volume-volatility pair.

Charles M.C. Lee et al. (2002) [13] in their study showed that past trading volume provides an important link between ‘momentum’ and ‘value’ strategies. They added that past trading volume also predicts both the magnitude and persistence of price momentum. Specifically, price momentum effects reverse over the next five years, and high volume winners experience faster reversals. Collectively, their findings show that past volume helps to reconcile intermediate-horizon under reaction and long-horizon over reaction effects.

Hendrik Bessembinder et al. (1993) [14] in their research examined the relations between volume, volatility, and market depth in eight physical and financial futures markets. Their study suggested that linking volatility to total volume does not extract all information. When volume is partitioned into expected and unexpected components, the paper finds that unexpected volume shocks have a larger effect on volatility. Further, the relation is asymmetric; the impact of positive unexpected volume shocks on volatility is larger than the impact of negative shocks. Finally, consistent with theories of market depth, the study showed large open interest mitigates volatility.

A. W. Lo at al. (2000) [15] in their study examined the implications of portfolio theory for the cross-sectional behavior of equity trading volume. Their two-fund separation theorems suggested a natural definition for trading activity. They asserted that, if two-fund separation holds, share turnover must be identical for all securities. If (K + 1)-fund separation holds, they showed that turnover satisfies an approximately linear K-factor structure. These implications were examined by them empirically using individual weekly turnover data for NYSE and AMEX securities from 1962 to 1996. They finally find strong evidence against two-fund separation, and principal-components decomposition suggested that turnover is well approximated by a two-factor linear model.

Tarun Chordia et al. (2002) [16] in a study on trading volume and cross-autocorrelations in stock returns sound that trading volume is a significant determinant of the lead-lag patterns observed in stock returns. Daily and weekly returns on high volume portfolios lead returns on low volume portfolios, controlling for firm size. Nonsynchronous trading or low volume portfolio autocorrelations cannot explain these findings. These patterns were evident because returns on low volume portfolios responded more slowly to information in market returns. The speed of adjustment of individual stocks confirmed these findings. Overall, the results indicated that differential speed of adjustment to information was a significant source of the cross-autocorrelation patterns in short-horizon stock returns.

Thus, through an extensive literature survey, it was clearly evident that volumes contribute significantly to the prices of stocks. However, representation of volumes along with stock prices and time stamps using a holistic visualization in the form of a technical indicator which could signify relevant inferences is what forms the basis for this study.

III. Data and Analysis Methodology

Since, the dynamics of every economic sector may be different, thus this study focuses on automobile sector bu using a data consisting of daily stock variables of 8 major automotive sector firms namely Ashok Leyland, Bajaj Auto, Eicher Motors, Hero Motors, Hindustan Motors, Mahindra & Mahindra, Maruti Suzuki India, Tata Motors. The time duration of the data is 8th January, 2013 to 9th January, 2014 i.e. for a year consisting of 250 trading days. This historical data was extracted from the National Stock Exchange (NSE) of India's online database. The date/time stamp has beenconverted to a numerical variable of trading day varying from 1-250. To study the central tendencies of that data collected,the descriptive statistics were calculated and thus, have been presented in Table I.

The analysis revolves around plotting a three dimensional nearest neighbor interpolation plot also known as a piecewise plot using 'MATLAB Surface Fitting Toolbox' with the total traded quantity, date and the closing price of a specific stock as *x, y* and *z* variable respectively.

The plot can be expressed as a three-dimensional function:

$$z = f(x, y)$$

where *x* and *y* are normalized by mean and standard deviation values. '*z'* can be termed as a piece-wise surface interpolation plot. The color distinction is the graph represents the different stages of the graph such that visualization is clear. Thus, these three dimensional graphs were analyzed for major price movements and quantitative thresholds.

TABLE I
DATA DESCRIPTIVE STATISTICS

	Mean	Std. Deviation	Variance
AL Close Price	19.1754	4.200	17.64347876
AL Quantity	6783753.29	5294260.66	2.80292E+13
Bajaj Close Price	1925.9846	120.271799	14465.30553
Bajaj Quantity	394467.804	247966.314	61487293068
Eicher Close Price	3497.613	689.088984	474843.6279
Eicher Quantity	23455.592	25752.052	663168182.5
Hero Close Price	1829.0576	196.287385	38528.73763
Hero Quantity	343865.892	245495.181	60267883874
HML Close Price	8.3754	1.18305678	1.399623333
HML Quantity	249956.96	414539.53	1.71843E+11
Mahindra Close Price	901.3642	52.4146153	2747.291896
Mahindra Quantity	1236427.19	643992.443	4.14726E+11
Maruti Close Price	1520.1288	145.618614	21204.78079
Maruti Quantity	693449.14	477811.38	2.28304E+11
Tata Close Price	167.8608	20.379936	415.3417905
Tata Quantity	2131173.31	1220997.4	1.49083E+12

IV. Results and Discussions

The three dimensional graphs for all the stock prices plotted using the piece-wise surface fitting interpolation technique are presented in Figs. 1 to 8.

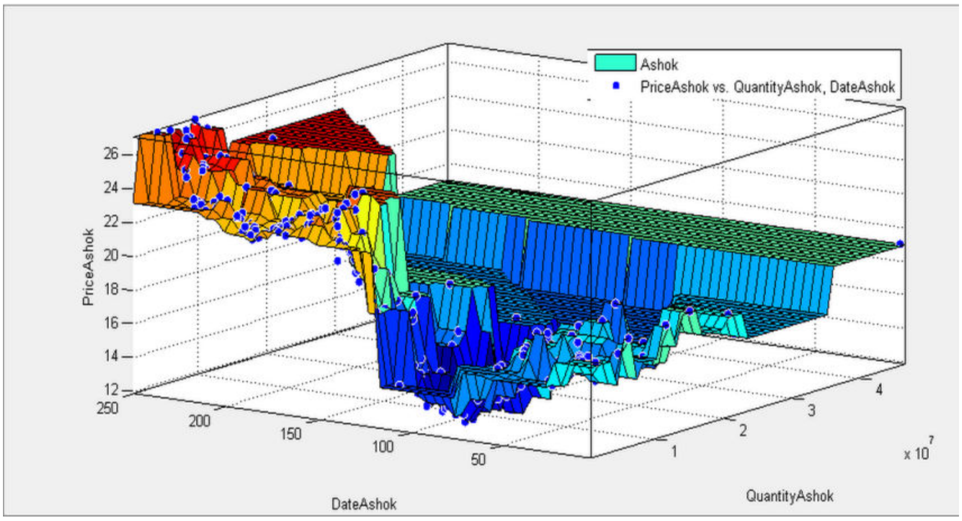

Fig. 1 Piece-wise three dimensional plot for Ashok Leyland stocks

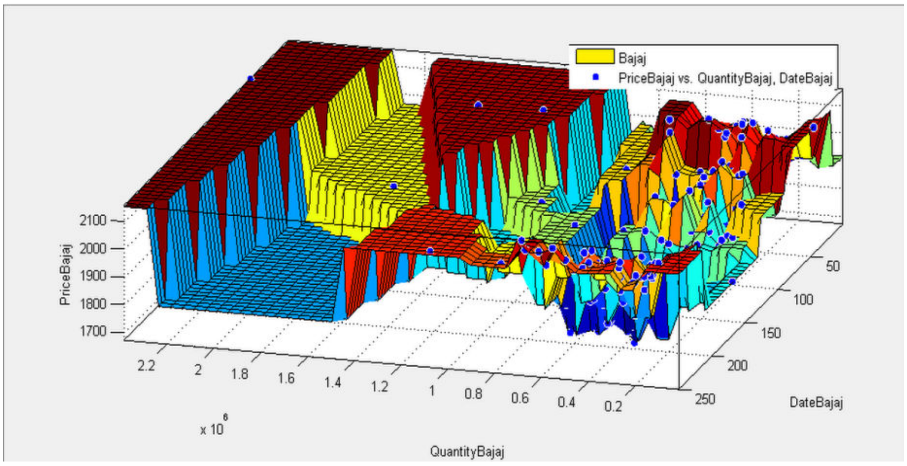

Fig. 2 Piece-wise three dimensional plot for Bajaj Auto stocks

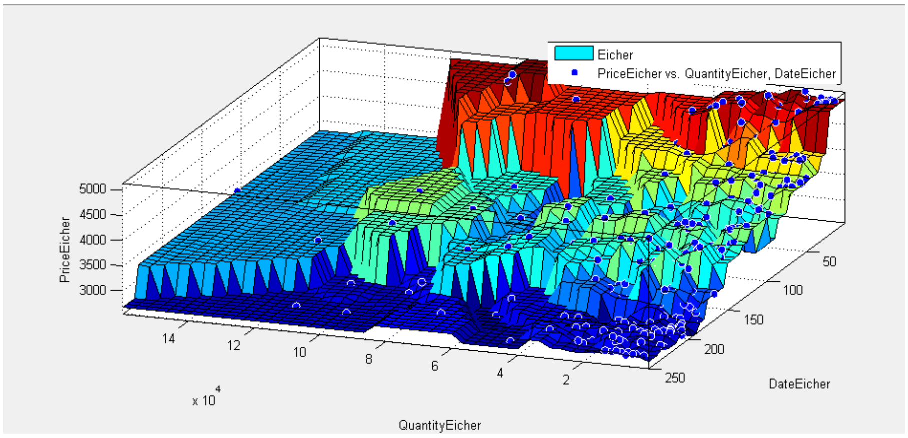

Fig. 3 Piece-wise three dimensional plot for Eicher Motors stocks

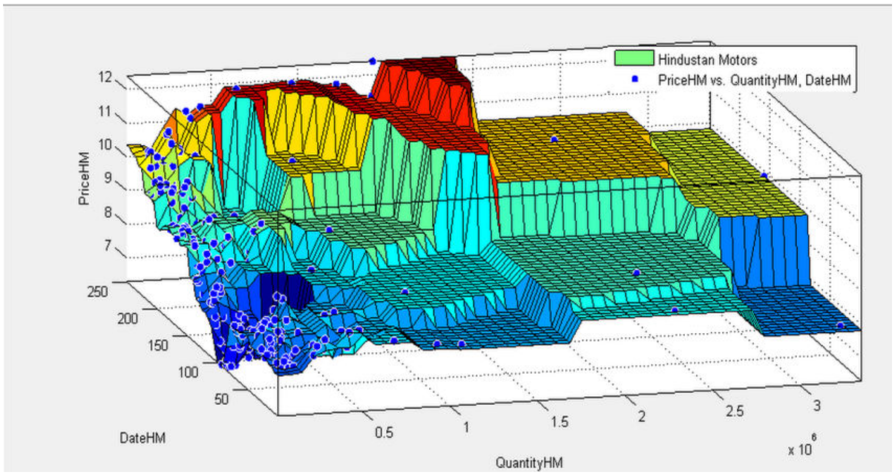

Fig. 4 Piece-wise three dimensional plot for Hindustan Motors stocks

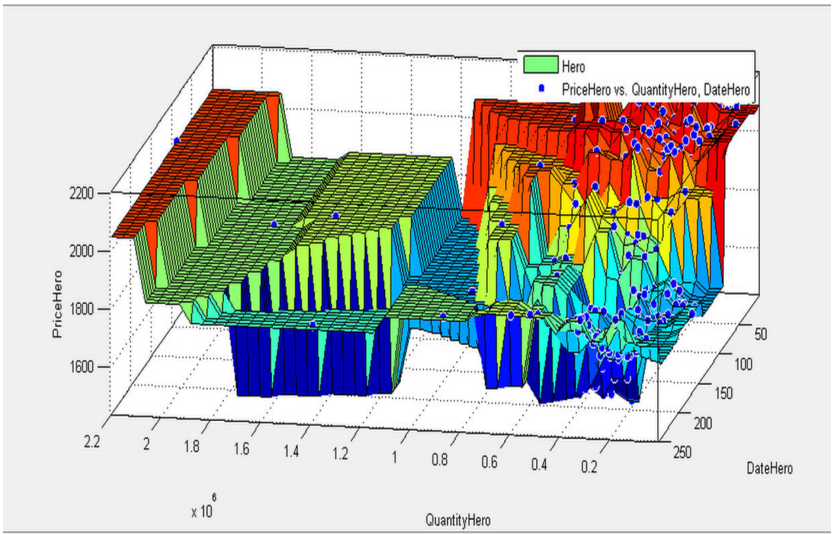

Fig. 5 Piece-wise three dimensional plot for Hero Motors stocks

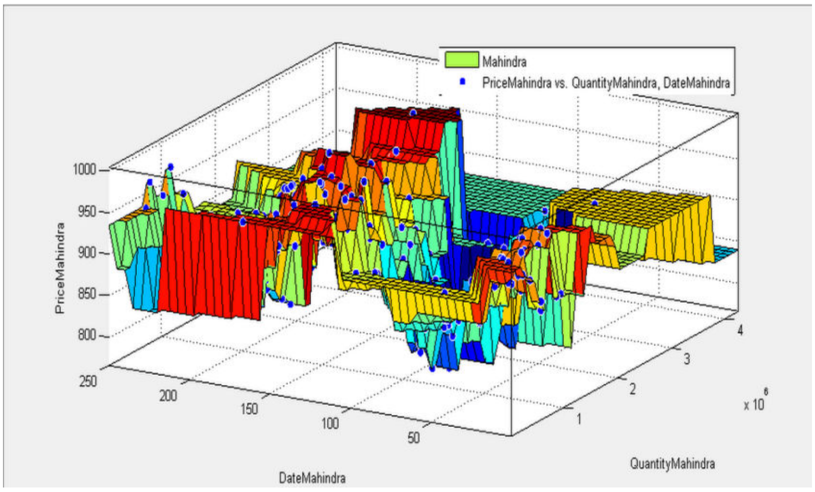

Fig. 6 Piece-wise three dimensional plot for Mahindra & Mahindra stocks

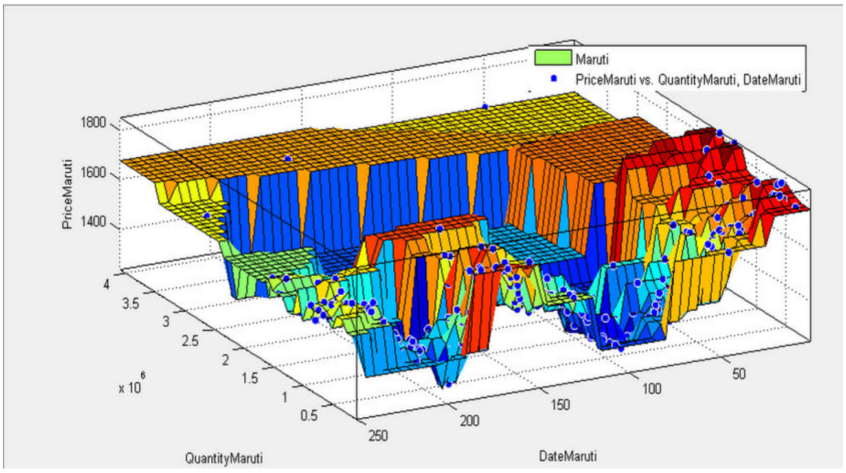

Fig. 7 Piece-wise three dimensional plot for Maruti Suzuki stocks

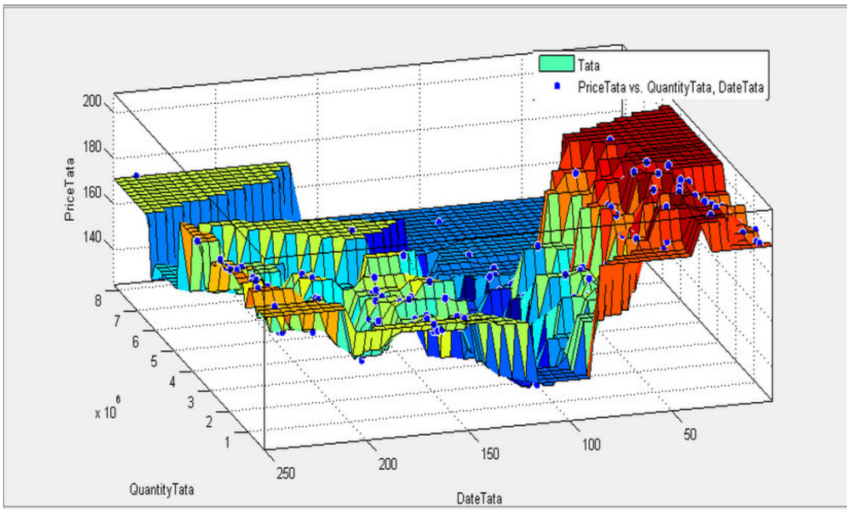

Fig. 8 Piece-wise three dimensional plot for Tata Motors stocks

In Fig. 1, the three dimensional graph for the Ashok Leyland indicates that there is a threshold limit for the Ashok Leyland stock in the first 150 days of the year and the share prices have downward pressure. Beyond 150 days there has been room for variance. Similarly, the quantity of Ashok Leyland expands more than 20-30 million. The prices see a plateau signifying stagnation in trade. In Fig. 2, while the Bajaj shares did not have a segment of the year for the spread, the quantity threshold was clearly visible at 8 million. In Fig. 3, in the case of the Eicher Shares, they are traded very actively in the first 50 days of the year and offer a good spread. In the case of quantitative thresholds, Eicher shares reached a plateau after 80,000. In Fig. 4, the Hindustan motor shares are higher after the first 100 days in a year. The threshold quantity is 5 lakhs. After the threshold, the prices tend to be higher. In Fig. 5, Hero motor shares trade the most in the first 100 days of the year. However when the quantity reaches the threshold of 8 lakhs, they reach a plateau. In Fig. 6, Mahindra reaches the peak between 150th to the 200th day of the year. Similarly when the Mahindra quantity is between 20-30 lakhs they are highly traded. It is the ideal quantity to have a good spread. In Fig. 7, the threshold limit for Maruti shares is 2 million, that is, Maruti stock prices offer better variance within the threshold. In Fig. 8, in the case of Tata Motors the first 100 days offer the highest prices in the year. Further, Tata Motor stocks offer better spread before the volume reaches 3 million. If there is an increase in volume above three million, the price of Tata Motors stocks hit the plateau.

In order to understand the portfolio better, the price quantity ratio of all the equities were estimated. The ratios were estimated using the mean quantities and the mean prices for the year 2013.

This study also suggests that the price volume ratio can be used in indexing the thresholds of a segment in the stock market. Higher the ratio, it means that the company is closely held and lowers the ratio it offers higher spread. The ratio is inversely related to the spread.

TABLE II
STOCK PRICE TO QUANTITY RATIO

Company	Price / Quantity Ratio
Ashok Leyland	0.00000282667
Bajaj	0.00488248871
Eicher	0.14911638129
Hero	0.00531910155
HML	0.00003350737
Mahindra	0.00072900710
Maruti	0.00219212731
Tata	0.00007876450

V. CONCLUSION

The time dimension to the law of demand dramatically changes the view of the movement of the price and it explains when one can reach the optimal returns. From, the stated above examples, it is clearly evident that volume of trade of a particular stock is also an important consideration for making an investment decision. The three dimensional graph is a helpful technical indicator for traders who follow the stock trend to formulate their trading strategies. It would help them to decide the probability of the market being bullish or bearish and would thus help confirming a price movement. When prices rise or fall, an increase in volume is strong confirmation that the rise or fall in price is real and that the price movement had strength. When prices rise or fall and there is a decrease in volume, then this is interpreted as being a weak price move, because the price move had very little strength and interest from traders. Thus, volumes signify the nature of market capitalization and indicate the buying or selling pressures in the market from equity spot, futures and options trading. Thus, this study helps to determine the volume dimension specifically in the India automotive sector. The nature of volume peaks in different sector may be different due to different dynamics of investment and other macro-economic factors.

Another lesson is that the three dimensional charting should be available in other analytical tools for the analysts to advise the brokers or clients. This can also be a good tool for the regulators in monitoring the manipulations of the market. The whole forecasting process would become more accurate with the multidimensional charting. Further, it can be substituted with the price volume ratio to obtain a better picture of the quantitative thresholds in equity investments. Such three dimensional charting can be incorporated in high frequency/automated trading and analysis systems where in these quantity thresholds can be algorithmically set in order to limit trade beyond them.

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