A New Modus Operandi for Determining Post - IPO Pricing : Analysis of Indian IPOs Using Artificial Neural Networks

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Abstract

The objective of this study was to identify different factors useful in determining post-IPO pricing and test their relative significance by comparing stock performance across 3-, 6-, and 12-months post listing.To do so, the study analyzed data from 299 non-financial companies that had their IPOs listed on the Bombay Stock Exchange from 2005 – 2018 in India. The data collected were used to train a neural network, called the multilayer perceptron model. The study grouped all factors into four categories viz-a-viz macroeconomic, issue-specific, technical, and fundamental. Analysis of the results generated from 20 iterative constructions of the neural network revealed that the highest relative relevance in prediction was attributed to technical factors. It was also observed that the importance of fundamental factors increased with the investment horizon. The results are country-specific and found that the importance of "underpricing" and "listing gains" as factors reduced within a year post-listing and thus, provide a helpful addition to the present knowledge of financial gains resulting to investors from IPOs.

Keywords : **initial public offering, artificial neural networks, multi-layer perceptron, Post-IPO performance**

JEL Code : C45, G11, G12, G14

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The price of an IPO can be based on the fundamental valuation, a discount, other explainable, and numerous inexplicable factors related to expectations. While deciding for an investment in an IPO, the investors usually are in a dilemma about the post-listing performance as well as the long-term performance of a company because generally, no substantial information and analysis are readily available about the past performance of a firm. The investors, especially retail, have to depend only on the limited financial data, news that is publicly available, and the moves of the institutional investors. It is quite difficult for them to focus and analyze

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different factors of an IPO and simultaneously control for exogenous variables. With this study, we evaluate the predicting power of 20 factors on post-IPO pricing, thus simplifying the investment decision-making process for the investors. The conclusions of this study will allow investors to identify the most important decision points and reduce the time and labour spent in the process.

Amidst high volatility and the management commentary surrounding the issue, traditional linear and non-linear models can prove to be insufficient. On the basis of some given information, even if the investors are able to use a statistical model, the results generated from them, generally, tend to have huge errors (or less accuracy) owing to the non-conformity of assumptions required to run them. Understanding these limitations, Haykin (1998) found if interpretability of a model is not important, artificial neural networks (ANN) can generate better and quick results. Thus, we utilized the machine learning technique of artificial neural networks to analyze data from 299 non-financial and non-MSME Indian companies that had their IPOs on the BSE from 2005 – 2018.

This study has been divided into three parts and it tries to fill the gap in existing literature by taking into account 20 factors related to the macroeconomic, technical, fundamental, and issue-specific trends, which are readily available to the investors for analysis, and finding their relevance in determining the performance for up to a year post listing using ANN. In the first part, existing literature is reviewed and hypotheses to be tested are developed. The second part trains a neural network on the data of 299 firms that had their IPOs between 2005 and 2018 on BSE, which is then used in the final part for analyzing up to a year of performance as shown by 3, 6, and 12-months prices for the IPOs. Finally, the findings and observations are represented graphically and conclusions are drawn to aid investors in their investment decision making.

Literature Review

An enormous amount of research has been done in the field of IPOs, especially in the areas of forecasting and underpricing. This helped the IPO market gain traction with investors in the previous decades. However, there are multiple studies, which have produced results that create apprehensions in the minds of investors, especially those of the retail investors, before investing in the IPO market. In one such study, Bhanu Murthy and Singh (2008) found that the listing gains were not sustainable and were wiped out by the end of a particular day, and that can happen on any day between one and three weeks post the IPO after which the true price is established. This was further supported by Deepak and Gowda (2014), who also found that a significant number of retail investors in India do not perform any market research before investing and rather follow the institutional investors while investing in an IPO. For aiding investors, IPO grading was introduced, however, Trivedi and Sheth (2013) concluded that IPO grading turned out to be a myth as higher graded IPOs failed to perform, one-year post listing. Thus, IPO grading failed to deliver intended results.

Forecasting IPO market returns has been a difficult process, especially for retail investors, and hence, to bring clarity, researchers have tried to identify the factors which can help in predicting the IPO performance. For instance, Pandey and Pattanayak (2018) found that in the Indian IPO market, macro-economic factors played a critical role in initial IPO pricing. Factors such as firm age and issue price significantly impacted underpricing, while factors such as inflation, market volatility, and economic activity had a higher degree of explanatory power in forecasting. In the Indian markets, it was found by Singh and Shrivastav (2017) that about 12% of day listed gain was earned by 152 IPOs and they posted a loss of 3.78% for one-month return. Singh and Maurya (2018) concluded that there are multiple inexplicable factors that affect IPO returns. Bhullar and Bhatnagar (2014) concluded that issue size, issue prize, listing date, and number of times an issue is oversubscribed impacts the IPO short term performance. Investment Bank Goldman Sachs in 2019 researched 4,481 IPOs and concluded that the most important factors are industry, firm age, sales growth, valuation, and path to profitability (Strauss, 2019).

However, all these studies were not able to identify an exhaustive list of factors affecting post-IPO pricing and compare their predictive powers. One of the main reasons for this problem is the limitation of the traditional statistical models used for forecasting – they can be designed with only a limited number of explanatory variables as input. In this study, we try to bridge this gap and establish a mechanism for evaluating IPO performance based on 20 factors using a machine learning technique called artificial neural network (ANN).

ANN has found a wide applicability in finance, however, its use with regards to the IPO and stock listings has been limited vis-à-vis other studies. Suitability of neural network models in IPO analysis was studied by Jain and Nag (1997), who concluded that neural networks consistently outperformed similar logit models in terms of predictive accuracy of the successful ventures. Esfahanipour, Goodarzi, and Jahanbin (2015) compared the regression analysis (fuzzy regression) with ANN for forecasting for IPO withdrawal and underpricing and found that ANN was a better method of forecasting the IPOs' pricing. Similarly, Quah and Wong (2006) used the radial basis function (RBF) network, which is a type of ANN, to predict the closing price of the IPOs for the first six months of their listing. Their model was able to predict the first 30 days prices quite accurately, however, with the increase in the prediction time, the error increased, and the predictions became less accurate. The relative importance generating mechanism of ANN was studied by Colak, Fu, and Hasan (2018), who concluded that similar models can not only handle a greater number of variables, but also are more suitable for using variables with large skewness and kurtosis.

Based on these findings, it is apparent that the machine learning techniques have an enormous edge over the traditional ones. Henceforth, our study uses the multilayer perceptron model under ANN, which has been a major gap in the existing literature of the Indian IPO markets. This technique, unlike traditional forecasting techniques, allows us to incorporate the vast multitude of factors in our analysis and generate results with a low error rate.

Objectives, Research Gap, and Hypotheses

The objective of this study is to overcome the limitations of traditional techniques in examining the set of factors most relevant in determining post-IPO pricing by using artificial neural networks. The next objective is to find how the relative importance of these factors change till one-year post-listing.

The research gap that our study addresses is the inability of traditional forecasting models to incorporate a large number of explanatory variables, which was a critical requirement for predicting the relative importance of factors influencing the post-IPO performance till one year. We abridge it by using artificial neural networks under machine learning. Further, such a study has not been done on the companies listed on Indian stock exchanges, and thus, by focusing solely on the Indian market, we aim to test the following hypotheses :

- **H_{01} :** Fundamental, technical, issue-specific, and economic factors have equal importance in determination of post-IPO performance.

- **H_{a1} :** Fundamental, technical, issue-specific, and economic factors do not have equal importance in determination of post-IPO performance.

- **H_{02} :** Relevance of factors, once determined, remains the same across different investment horizons viz-a-viz 3 months, 6-months, and 12-months of listing.

- **H_{a2} :** Relevance of different factors, once determined, vary across different investment horizons viz-a-viz 3 months, 6-months, and 12-months of listing.

Research Methodology

Neural networks form the base for deep learning, which is a sub-field of machine learning (ML), where the algorithms are inspired by the structure of the human brain, and thus, can help us in solving compound problems by replicating the brain processes.

McClelland, Rumelhart, and Hinton (1986) found that ANNs are a favoured tool for many predictive applications because of their flexibility, power, and ease of use. These statistical tools are known to use a learning process for acquiring knowledge and then storing it in the form of interneuron connection strengths called as synaptic weights, thus resembling the human brain.

A multilayer perceptron model has been used for the purpose of this study. It is a network of three or more layers (the input layer, the hidden layer, and the output layer) consisting of interconnected nodes called neurons. Neurons in a particular layer do not have any connections between them if they belong to the same layer, but each neuron in a particular layer is linked to every other neuron in the next layer.

The input layer includes the input variables that we enter and is simply used to transmit information to the hidden layer, which then processes the information. It then subsequently transfers the results to the output layer, which predicts continuous values or produces the class label depending on the type of data used.

The neurons react to their input values and their reaction depends on their activation state. This activation state defines the activity of a neuron and the results from an activation function. Every neuron is assigned a particular value called the threshold value near which neurons become sensitive. In an ANN, an activation function also helps us to introduce non-linearity into the output of a neuron. Thus, an activation function is defined as :

$$A_j(t) = f_{act}(net_j(t), a_j(t-1), _j$$

A neural network is just a simple regression model in the absence of an activation function, and thus, the non-linear transformation of the activation function is required for performing complex tasks.

The MLP also includes a bias neuron in both the input as well as the hidden layer. It is always activated and has a value 1. It acts alike to the intercept in classical linear regression models, thereby improving the efficacy of the neural networks.

Ripley (1996) said ANNs differ from conventional statistical methods in their application, but also are similar in nature to them. Say, a linear regression model is a rigid model structure because of numerous assumptions required to run it, while ANNs can approximate a wide range of statistical models without hypothesizing in advance a particular relationship between the independent and dependent variables. An ANN can even introduce non-linearity in computation. However, a drawback of this is that the synaptic weights in ANN cannot be interpreted easily.

Data Methodology and Description of Variables

Financial data of 299 companies that had their IPOs between 2005 & 2018 on BSE were used in the study. The time period of the study is from January 2005 – December 2018.This time period is selected because the research began in the year 2019, and hence, the complete verified and audited data of the listed corporations were obtainable till the year 2018, while 2005 was the earliest period for which complete and consistent data across all 20 variables was available for a maximum of 299 firms in the databases used for the purpose of research. The databases used for finding the data are 'Prime Database' and 'ProwessIQ'. The data for macroeconomic factors were collected from the Ministry of Statistics and Programme Implementation website. The following list defines the variables used to build the ANN model :

Macroeconomic Factors

(1) Inflation Rate (INF) : Last closing year inflation rate (Consumer Price Index) from the year of IPO.

(2) GDP Growth Rate (GDP) : Previous quarter GDP growth rate has been used.

(3) Market Hotness of Previous Month (MH) : S&P BSE IPO index data from the month prior to listing is used to measure the performance of the IPO companies listed on BSE post their IPO.

(4) Shocks (S) : Two international shock years have been taken in the year of study, that is, of 2008 (The Global Financial Crisis) and 2013 (Taper Tantrums caused shocks across the emerging economies due to the stopping of quantitative easing by US Federal Reserve).

$S = 1$, if yes, $S = 0$, if no.

Issue Specific Factors

(5) Price Band (PB) : The firms that used fixed price method were assigned a value of 0, while for the remaining firms, those who used price band method, their value has been incorporated as the deviation of the final price from the average price.

(6) Issue Expenses to Total Issue Amount (I_EXP) : It is taken as a percentage of the total issued amount.

(7) Capital Issued to Total Capital (CAP_ISS) : It captures how much percentage of total authorized capital has been unlocked by a company for free trading and is offered in the IPO for raising funds from the market.

(8) Underwritten (U) : The companies have been classified based on whether they have been underwritten or not. $U = 1$, if yes, $U = 0$, if not.

(9) Valuation (Val) : There are two methods of valuation, fixed price and book-building. $Val = 1$, if book building, $V = 0$, if fixed price.

(10) Years till Date (L_YRS) : Years since the IPO has been listed on the exchange.

(11) Age (AGE) : Time taken by the firm from the year of incorporation to the year of listing.

Technical Factors

The reason for limiting the scope to 12 months is that post 12 months, the stock becomes fairly stable and its market value converges with the true value, and also, as per the study of Reilly and Hatfield (1969) on IPO performance, strong returns persist only up to a year.

(12) Issue Price (I_PR) : The price at which the IPO was issued.

(13) Issue Gain (I_GN) : The issue gain has been recorded in the percentage terms on the issue date over the issue price of the closing price of that stock.

(14) 1-week price (P_1WK), 1-month price (P_1MO), 3-month price (P_3MO), 6-month price (P_6MO), 12-month price (P_12MO).

Fundamental Factors

These factors have been taken from the previous financial year closing data of the firms from the year in which they did their IPO.

(15) Return on Equity (ROE) : It is calculated as PAT divided by the paid-up capital for the annual year.

(16) Net Sales (N_SALES), Profit after tax (PAT), Total assets (TA), Borrowings (BORR).

Research Design

The multilayer perceptron module of IBM SPSS Statistics 21 was used to build the neural network model and to evaluate how factor importance changes for predicting IPO prices across a time frame of 3 months, 6 months, and 12 months after listing.

The data were randomly assigned to training (70%) and testing (30%) subsets. The training dataset are used to build the model and find the weights ; whereas, the testing data are used to test the model on the remaining sample and find errors and prevent overtraining during the training mode. Before training, all variables were rescaled using a standardized measure which subtracts the mean and divides by the standard deviation, *(x−mean)/standard deviation* (refer to Table 1).

Table 1. ***Descriptive Statistics***

Variables	*N*	Minimum	Maximum	Mean	Std. Deviation
L_YRS	299	1	15	9.90	4.175
AGE	299	1	100	17.06	13.185
INF	299	0.02	0.12	0.0649	0.02893
GDP	299	0.00	0.11	0.0817	0.02294
PB	299	–0.11	0.08	0.0068	0.01838
I_GN	299	–0.71	1.51	0.0193	0.24445
I_EXP	299	0.00	0.18	0.0711	0.02410
CAP_ISS	299	0.10	0.66	0.2682	0.10710
MH	299	–0.33	0.21	0.0087	0.08611
ROE	299	–1.46	3.01	0.2823	0.31239
N_SALES	299	5.90	523504.00	9324.9077	33242.18222
PAT	299	–3455.50	96224.50	1048.7361	5800.23264
TA	299	116.00	731027.10	14563.1585	53567.08422
BORR	299	0.00	374219.20	5569.0559	26365.03381
I_PR	299	10.00	1766.00	264.8194	273.03673
P_1WK	299	5.26	2615.35	312.0790	339.65859
P_1MO	299	9.13	2648.85	306.4181	339.27180
P_3MO	299	3.90	3494.85	308.4808	369.96029
P_6MO	299	3.69	3451.00	318.2739	383.60531
P_12MO	299	0.00	2729.00	311.1517	387.07013

For both the hidden and output layer, hyperbolic tangent functions are used as activation function. This function has the form :

$$\gamma(x) = tanh(x) = \frac{(1 - e^{-2x})}{(1 + e^{-2x})}$$

or

$$\gamma(x) = tanh(x) = \frac{(e^{-x} - e^{-x})}{(e^{-x} + e^{-x})}$$

It takes real-valued arguments and transforms them to the range (–1, 1).

As ANNs are learning models and results can differ from each learning iteration to other, hence 20 iterations for each of the periods were conducted and results have been averaged to better present the results.

Analysis and Results

One of the objectives of this study is to evaluate how factor importance changes in predicting IPO performance over time. For this purpose, three different models, each utilizing a different period from 3 months, 6 months, and 12 months from listing date were made.

For the model summary, since scale measurement variables are used, relative error is displayed. It is the sum of squares error and is the average overall relative error (relative to the mean model). Relative errors are calculated in both the training and testing phases. The training phase has a relative error of .076 for the 12-month period, .048 for the 6-month period, and .039 as relative error for the 3-month period. The error measure increases with the time, that is, from 3 to 6 to 12-months, and this is consistent with the literature as provided by Quah and Wong (2006). Similarly, for the testing phase, relative errors for 12-month, 6-month, and 3-month periods are .232, .128, and .160.

It can be concluded that the models are a good fit due to low relative error levels, as shown in Table 2. This is also evident from Figures 1, 2, and 3 in the plot of observed v/s predicted values. The average results of 20 iterations of tests have been summarized in Table 2.

Table 2. ***Model Summary & Prediction Errors***

		12 Months	6 Months	3 Months
Training	Sum of Squares Error	.575	.289	.386
	Relative Error	.076	.048	.039
	Stopping Rate Used	Max Epochs	Max Epochs	Max Epochs
	Training Time	0:00:00.08	0:00:00.11	0:00:00.07
Testing	Sum of Squares Error	1.018	.163	1.118
	Relative Error	.232	.128	.160

The results in Figures 1, 2, and 3 show that model forecasts are reliable and that accurate values can be predicted using the same.

Figure 1. *ANN Predictions v/s Observed Values for 12 Months*

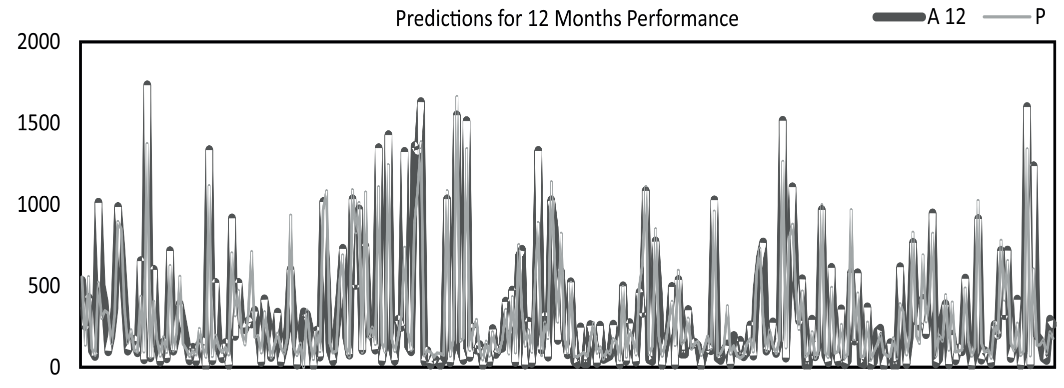


Figure 2. *ANN Predictions v/s Observed Values for 6 Months*

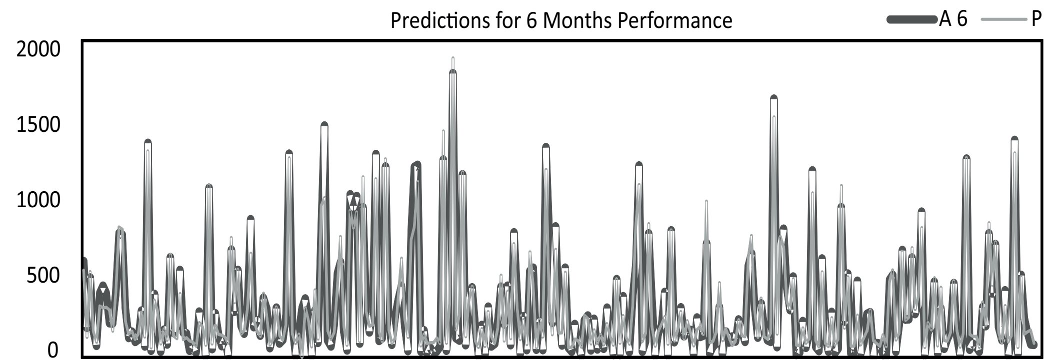
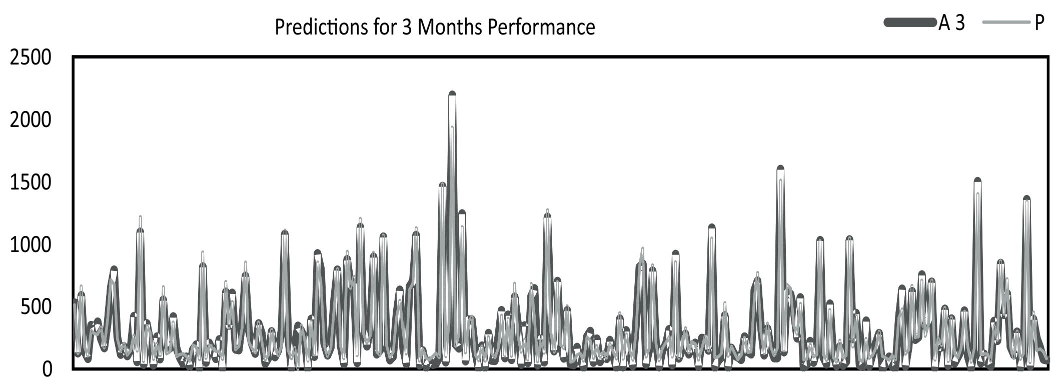


Figure 3. *ANN Predictions v/s Observed Values for 3 Months*



Discussion

The next objective of the study is identification of relative importance of variables. As importance kept on changing with iterations, 20 iterations were used, and average importance has been calculated for the different time periods. For graphical representation of the results of the relative factors' importance, Sankey diagrams have been used. They represent the independent variable importance analysis obtained from SPSS for the 20 iterations. The independent variable importance analysis performs a sensitivity analysis, which determines the importance of each predictor or independent variable in determining the neural network. This analysis is based on the testing and training samples in the ANN architecture and displays importance and normalized importance in output. As shown in Figures 4, 5, 6, and 7, the Sankey charts for each category have been separately analyzed. The left side of the chart shows different variables classified under that category and the right side includes the three output variables that is 3-, 6- and 12-months IPO prices. Each variable on left side is linked to output variables on the right side by lines of varying thickness, which are linearly proportional to their respective factor importance, expressed in % obtained as an average of importance in the 20 iterations for that variable.

Importance of Macroeconomic Factors

From the macroeconomic factors, as shown in Figure 4, it can be understood that market shocks have a very little impact on IPO prices across periods, which is consistent with the findings of Ali and Afzal (2012) who concluded that BSE-100 was mildly impacted by the financial crisis. Inflation and GDP growth rates prior to the issue date have the most impact on 12-month prices as compared to the 3- & 6-months prices. Similarly, IPO market hotness prior to IPO impacts 3-month prices more as compared to 6- & 12-months prices. This is consistent with the study results of Alim, Ramakrishnan, and Khan (2016), who concluded that long term underpricing was significantly impacted by the hot market vis-à-vis the cold market IPOs. Thus, it can be concluded that macroeconomic factors, as a subset of total variables, have a relative importance of less than 10%, making them least useful for investors.

Importance of Issue Specific Factors

For within the issue-specific factors, as shown in Figure 5, valuation method and whether the IPO has been underwritten or not have the least importance and the same is consistent across different time periods. Age of the

Figure 4. ***Relevance of Macroeconomic Factors (in %)***

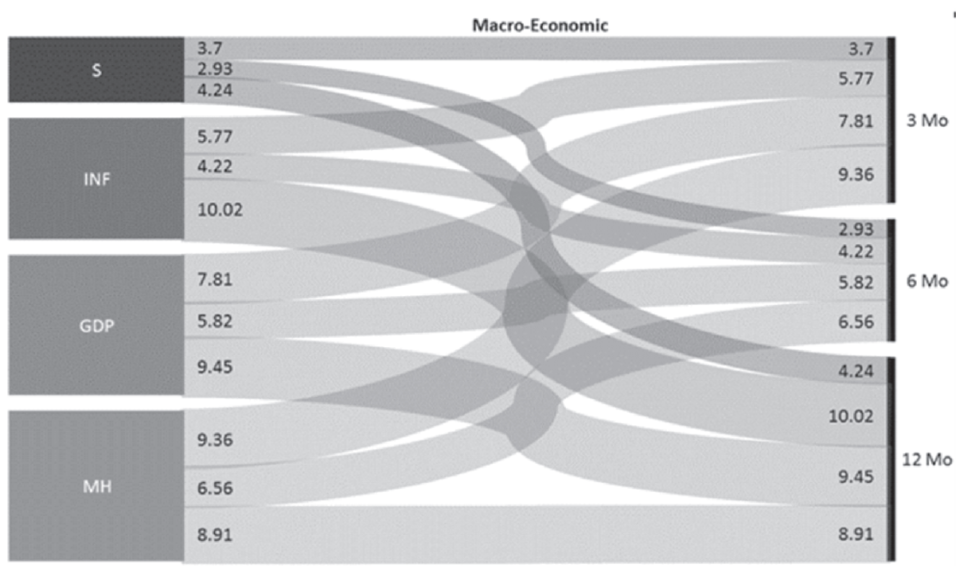
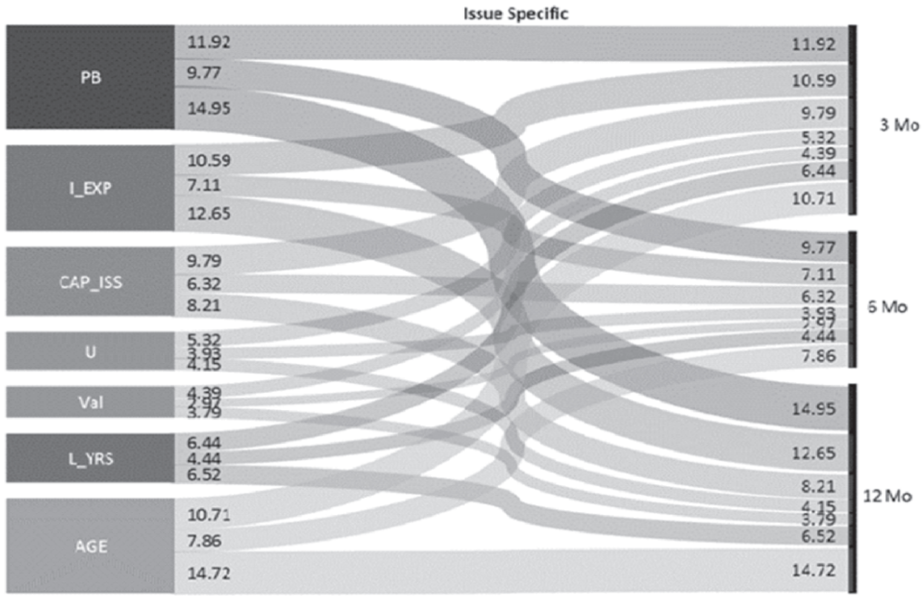


Figure 5. ***Relevance of Issue Specific Factors (in %)***



firm is most important in the 12-month period and it can be understood from the perspective that markets incorporate all available information, and hence, volatility reduces. This result is consistent with the findings obtained by Goldman Sachs after examining 4,481 IPOs over 25 years, in which it was concluded that firm age was a significant factor for the long run IPO-performance. Kar and Jena (2019) and Pandey and Pattanayak (2018) also concluded that firm age had a significant impact on the performance. The capital issued in the IPO is of equal importance across time and expenses incurred at the time of issue, which matter least in the 6-month period and most in the 12-month period.

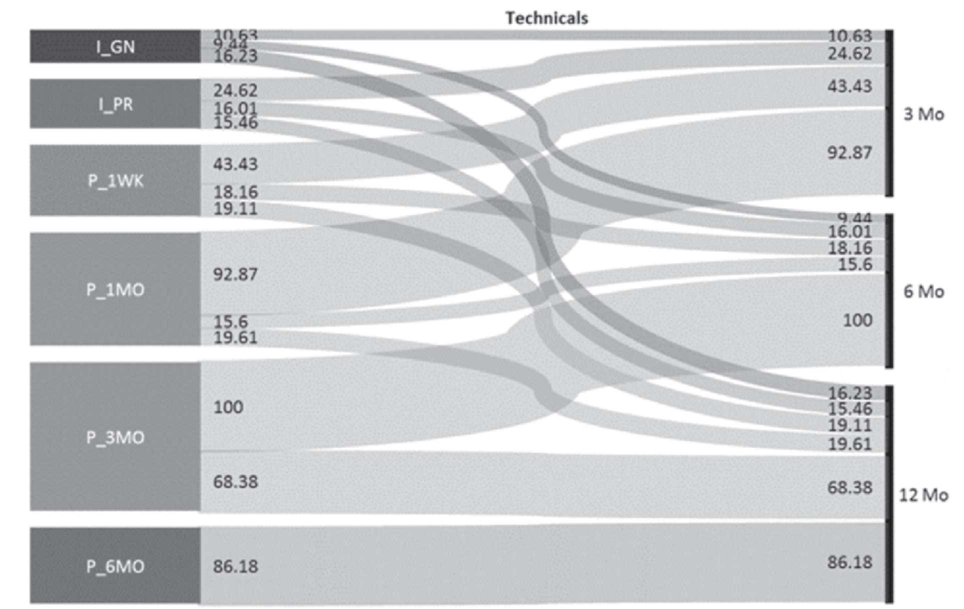
The issue-specific factors, as a subset of total variables, have a higher relative importance on average as compared to the macroeconomic factors. Thus, it can be concluded that more than the macroeconomic environment surrounding the timing of IPOs, investors should focus on the age of the company going for IPO, the price band, and expenses incurred while looking for the 12 months performance.

Importance of Technical Factors

As per Figure 6, within the technical factors, it is the recent price data which is most important. Thus, for 12-month prices, 6-month prices, and similarly for 6- & 3-months, it is the 3- & 1-month prices that are most important. One-month prices do not play a very significant role in 6- & 12-month prices. Likewise, the 1-week prices impact the 3-month performance the most with an equivalent, if not lesser, impact on the 6-& 12-month performance.

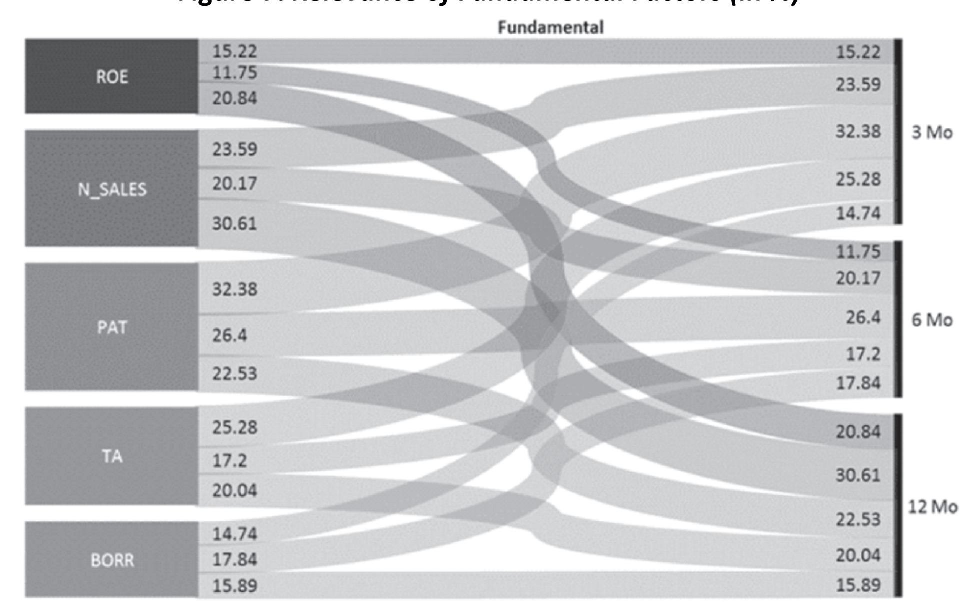
The results reveal that the short-term price fluctuations might be due to underpricing and do not play a significant role in determining future performance. Hence, investors should not be blindsided to make investments in firms with high listing gains and this is also in line with the previous literature. Also, it is found that the issue price has a major impact only until the 3-month performance, which is consistent with the findings of Bhanu Murthy and Singh (2008). Post that has a lower as well as an equal impact on the 6- & 12-months performance of the IPOs. Listing gains are of least importance in determining IPO performance, and hence, it can

Figure 6. *Relevance of Technical Factors (in %)*



be said that the initial price volatility has little to no impact on prices in time horizons greater than 3-months. Hence, the technical factors, as a subset of total variables, have the highest relative importance on an average as compared to the rest of the factors.

Figure 7. *Relevance of Fundamental Factors (in %)*



Importance of Fundamental Factors

Here, we analyze how information related to fundamental factors available at the time of IPO launch impacts the performance, valuation, and thereby prices. As shown in Figure 7, within the fundamental factors, ROE has a higher impact on the 12-month performance as compared to shorter durations. This shows that investors looking for issues with sustainable performance and a longer investment horizon prefer those new issues that have a stronger RoE and not only high initial gains. Similarly, net sales are considered more important for 12-month prices as compared to shorter time spans. Borrowings of the firm have an almost equivalent impact across durations. It can also be concluded that profit margins are given a higher priority for the 3-month performance, but in the longer term, it is not just margins, but the overall growth that drives performance. This is consistent with a study conducted by Goldman Sachs, where it was concluded that profitability and reduction in losses (if any) were significant factors for the IPO success determination. The total assets of a firm, which can be taken as a proxy for firm size, are of higher importance in the 3-month prices. This can be attributed to the expectation that a bigger firm going public will generate higher and consistent returns. However, for the 12 - month prices, the returns for equity investors that a firm generates are given higher importance.

Thus, it can be concluded that fundamental factors, as a subset of total variables, have a higher relative importance in contrast to macroeconomic and issue-specific factors, but lower relative importance than the technical factors. Also, importance of some of the fundamental factors fluctuates over investment horizon and also increases with time once initial volatility and returns stop playing a bigger role in their investment decisions.

Practical and Managerial Implications

The proposed results can effectively help retail investors in their investment decision-making while laying keen focus on relevant factors. This class of investors is always in a conundrum regarding their investments, given the perplexity surrounding the valuations, inundation of information, difficulty in gathering data, and effectively analyzing it using a forecasting model. Our study will, thus, help them in deciding factors towards which they should pay more attention while investing in a new public issue. The technique of ANN used for analysis herein is not common in IPO related research, despite its superiority to traditional methods of forecasting. Thus, our study will also stimulate interest in this direction of machine learning (ANN) and IPO research, which will further help in bettering the process of forecasting of IPO performance.

Conclusion

Understanding factors influencing the performance of an IPO is a difficult task due to the innate complexity of the IPO market and various econometric challenges. This paper employs ANN to investigate the key determinants for a successful IPO in the Indian market. It is then used to test the predictive power of 20 factors for 299 Indian companies. The empirical findings from this study conclude that the significance of fundamental factors fluctuates across investment horizons, however, their relative importance increases overtime and that the technical factors are the most important in determining the post-IPO performance of the stocks. Across all investment horizons up to a year, the latest available technical data is of most importance in prediction, thus rejecting both the null hypotheses that technical, fundamental, macroeconomic, and issue specific factors have an equal importance (H_{01}) and their importance remains the same across different periods, once determined (H_{02}). This is consistent with the generally accepted proposition of stock prices reflecting the true value. It is also found that the initial price behavior and volatility of returns (underpricing) do not have much impact in determining 6-

and 12-months performance. Thus, investors should not base their investment decisions solely on it. Consistent results have been obtained in relation to whether there were financial shocks, the valuation method, and whether the issue is underwritten or not. These factors are of least importance across all horizons.

Limitations of the Study and Scope for Further Research

The study is limited to the non-financial and non-MSME Indian companies. Moreover, there are limits on variables, stock exchange (BSE), and time horizon of investment used. Therefore, future research can conduct a comparative study on a global level. There is a need to account for other significant variables like the auditor's and underwriter's prestige and a need to examine the changing determinants of post-IPO pricing over a period longer than 12 months.

Authors' Contribution

Dr.Amit Kumar Singh extracted research papers of high repute, filtered these based on keywords, verified the analytical methods, supervised the research & critical revision of the paper, and helped in final approval of the version to be published. Bhavesh Gupta and Saksham Jain conceived the idea and developed the qualitative and quantitative design to undertake the empirical study. They together worked on acquisition of the data, conducting numerical analysis using SPSS 20.0, analysis & interpretation of the work, and drafting the manuscript in consultation with both the authors. Dr. Mukesh Kumar Jain helped in the language and grammar review for the manuscript.

Conflict of Interest

The authors certify that they have no affiliation with or involvement in any organization or entity with a financial interest, or non-financial interest in the subject matter, or materials discussed in the manuscript.

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