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Editorial Message

Happy New Year!!!

It is a great pleasure for me to make available to you the 2nd issue of Volume 8 in this year 2020.

We are continuously putting our effort in developing the alliance between academia, industry practitioners to bring various perspective of data science, exchanging research insights, analytical techniques and knowledge in various functional areas which include but are not limited to a destination, yet we emphasis on constant journey.

In this issue, we have come with topics like automation, to detect fraudulent behavior to minimize risk in banking sector, determine efficient mutual fund and performance of two major Indian airlines.

It's an immense pleasure to present Prof. Arnab Kumar Laha from IIM Ahmedabad with his paper on Causal effect. He brought a perspective to determine the changes occurred on a subject due to certain interventions.

In uncertain times, enterprises don't have resources to waste. That's why more organizations are turning to process mining for detailed, actionable insights on where and how to improve with automation. Armed with detailed insights on mission-critical processes, where process mining helps leaders create operational resilience. In the era of automation, the methods of recording and analysis of business transactions are also becoming automated and thus various disruptive technologies have emerged in field of accounting. Robotic accounting is one of them, which reduces mundane and repetitive tasks. In a research paper, an attempt has been made to study the awareness about use of robotic process automation (RPA) in accounting by three academicians from Udaipur, Rajasthan.

Since almost a decade, the problem of Non-Performing Asset (NPA) in the Indian banking system has been a subject of concerned so for investigation as well. It is a major impact and detrimental to the financial health of the banking system, and this willful default indicates 'intend of fraud'. The researchers constructed an Artificial Neural Network model to predict the "willful default" with an accuracy rate 92.2%.

In a study on the Identification of the Efficient Mutual Funds - A Data Envelopment Analysis approach is depicted by two eminent academicians from Karnataka, India. The paper attempts to identify the efficient mutual funds analyzed based on Data Envelopment Analysis (DEA) it's an endeavor to study the impact of various financial parameters.

In our last paper depicts the performance of two domestic airlines viz. Indigo and Spice jet with the help of DuPont analysis. Four ratios related to DuPont analysis have been used for the performance evaluation.

I would like to thank the researchers and renowned data science practitioners who have honored us by choosing our young journal to publish some of their research. I am sure that our readers will enjoy and learn a lot from the present issue. Do let us know your wish, suggestions, and views to enrich our journal.

Sincerely Yours,

Madhumita Ghosh
Joint Editor-in-Chief
&
Tuhin Chattopadhyay
Editor-in-Chief

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Column

Research Papers

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The Cause of the Effect

Arnab Kumar Laha*

Introduction

In many problems of science and social science we encounter situations in which we have to determine whether an intervention has been effective or not. In other words we want to ascertain whether the observed effect is really due to the intervention or has just happened by chance. For example, suppose a new diet, say Diet X, is proposed by its manufacturers as an effective way for losing weight for obese individuals. How does one check whether the claim of the manufacturer is correct or not?

Consider an individual who has agreed to adopt Diet X. We measure his weight just before he starts on the Diet X and find his weight to be W_B. Then after a month on Diet X we measure his weight again and find that his weight is W_A. Thus, $D = W_B - W_A$ is the change in his weight during this one-month period when he was on Diet X. Note that $D > 0$ indicates a loss of weight whereas $D < 0$ indicates a gain in weight. Suppose we observe $D > 0$. Can we ascribe this loss of weight to Diet X? If we do not think carefully, the answer is apparently 'Yes'. However, on a little reflection, we would recognise that the loss of weight could have been due to various other reasons such as an illness or a disease which is unknown to the individual. Unless such possibilities are ruled out, it would be incorrect to ascribe the loss of weight of this individual to his adoption of Diet X.

Can we do better? One approach could be that we look at the change in the person's weight when he is on Diet X, say D_X and also when he is on normal Diet, say D_N, and compare D_X and D_N. If $D_X > D_N$, then we can say that the loss of weight is due to Diet X. However, we face an insurmountable problem here- the individual at a time can either be on Diet X or on normal diet. He cannot be simultaneously on Diet X as well as on normal diet. Thus, if a person is on Diet X we can find D_X but it is impossible for us to know what would have happened had he been on normal diet i.e. we cannot obtain D_N. Similarly, for another person who is on normal diet we can obtain D_N but it is impossible for us to tell what would have happened had he been on Diet X i.e. we cannot obtain D_X for this person. Thus, the above plan for comparing D_X and D_N cannot be executed in the absence of simultaneous measurements of D_X and D_N.

You may have realised by now establishing causality is not an easy endeavour except in the simplest of circumstances. This stems from the fact that the same subject, cannot be simultaneously on both the 'treatment' (Diet X) as well on 'control' (normal diet). This allows for the possibility of factors other than the treatment, being responsible for the observed effect. How do we resolve such claims of causality? In this article we briefly discuss a few of these approaches.

Sir Ronald Fisher suggested the use of specially designed experiments for dealing with this problem. Suppose that we have a group of individuals on whom we want to test the effect of Diet X. Specifically, let us assume that all these individuals are men having above average BMI but are otherwise healthy. We want to know the impact of Diet X on this group in terms of reduction of weight after following the Diet X regimen for a month. A possible way to do this is to carry out the following experiment. We randomly allocate the men into two groups - Group X and Group N. All individuals in Group X follow the Diet X regimen for one month and all the individuals in Group N follow their normal diet. Suppose both the groups contain k men each. The weights of the k men in the Group X before the commencement of the Diet X regime is noted and suppose they are $W_{BX,1}, W_{BX,2}, \ldots, W_{BX,k}$. Likewise, the weight of the k men who are on the normal diet group are also noted and let these be $W_{BN,1}, W_{BN,2}, \ldots, W_{BN,k}$. During the month we take actions

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that ensure that the men in Group X sticks to the Diet X and do not deviate. After the one-month period is over, the weights of all the individuals are again noted. Let, the weights of the individuals in Group X after the one-month period be $W_{AX,1}, W_{AX,2}, \ldots, W_{AX,k}$ and those in Group N be $W_{AN,1}, W_{AN,2}, \ldots, W_{AN,k}$. From these data we compute the change in the weight of all the individuals in Group X in the one-month period as $D_{X,1} = W_{BX,1} - W_{AX,1}, \ldots, D_{X,k} = W_{BX,k} - W_{AX,k}$ and those in Group N as $D_{N,1} = W_{BN,1} - W_{AN,1}, \ldots, D_{N,k} = W_{BN,k} - W_{AN,k}$. Since the allocation of the men taking part in this study to the two groups were done randomly, we expect that no systematic bias would be present that may lead to erroneous conclusions. In general, random allocation ensures that the two groups are homogeneous in all other respects except the treatment. If the average value of the $D_{X,i}$'s () is significantly larger than the average value of $D_{N,i}$'s () we can conclude, with reasonable degree of confidence, that the Diet X regimen is effective in reducing weight in the study group. In other words, we say that Diet X is the cause of the weight loss of individuals in Group X.

Design of Experiments (DoE) is a large field of study that has contributed significantly in improving products and processes in different areas such as agriculture, engineering product and process design, drug development, healthcare process improvement and many more. DoE is often used in the 'Improve' step of DMAIC in Six Sigma for identifying the best alternative among many potential alternatives. The Japanese quality guru, Genechi Taguchi used DoE for product quality improvement. His ideas, known as Robust Quality or Taguchi Methods, focus on using DoE for designing products that can withstand wide variations in field operating conditions.

One of the key questions raised during the ongoing COVID-19 pandemic has been the question of efficacy of the different vaccines proposed by the manufacturers. This raises the question: How does one know whether a vaccine is effective in preventing a COVID-19 infection? It is not ethical to expose vaccinated individuals to COVID-19 infection intentionally. If the vaccine doesn't work then the exposed person can become sick and may even die due to the infection. Thus a different method is required for dealing with this situation. In what is commonly known as the Phase-III clinical trial, a large group of individuals who meet the pre-specified health conditions that make the vaccine safe for administration is identified. All these individuals are given an injection which can either be the vaccine or a placebo (such as distilled water). Half the supplied injections are of the vaccine while the remaining half contains the placebo. The injections look identical in all other respects so that neither the doctor nor the patient can figure out whether s/he received the vaccine or the placebo. (Such clinical trials are called double blind trials). All the individuals are tracked for a pre-specified period of time (say, three months) and all the instances of COVID-19 infection during this period are recorded. An analysis is done comparing the number of cases of COVID-19 in the vaccine group and in the placebo group. If the number of cases in the vaccine group is significantly less than that of the placebo group we conclude that the vaccine is effective in preventing COVID-19 infection.

You may be wondering about the need for administering the placebo. This is important since it might happen that after administration of the injection the behaviour of some of the individuals may change. Some of them may feel that they have received the vaccine and are now immune to the infection. This can make them lax about maintaining the norms of safe behaviour such as wearing of mask, social distancing and frequent hand washing. As a result, they may get exposed to the infection more frequently than others. Since with more exposure the chance of catching the infection increases, this makes the vaccine appear less effective than actual. With a control group that has been administered the placebo it would be possible to identify the impact of such behaviour and a correct understanding of the efficacy of the vaccine can be obtained.

Alternatively, it may happen that due to some reason such as development of herd immunity or the weakening of the infectivity of the virus the chance of catching the infection reduces in the general population. Then most of the vaccinated persons would not catch the infection making the effectiveness of the vaccine look better than actual. Here also the presence of a control group is critical as it would allow for estimation of the impact of these changes which would lead to accurate understanding of the vaccine efficacy.

In some instances it may not be possible to have a random allocation of individuals into different groups. Say for example, we are interested to know the impact of smoking on certain health parameters such as occurrence of mini brain-stroke. It is not possible to ask individuals

to smoke a certain number of cigarettes every day for a prolonged period of time knowing fully well that it may have detrimental effects, such as occurrence of cancer in different parts of the body. So how does one, figure out the impact of smoking on the occurrence of mini brain-stroke? One way to proceed is to create a treatment group by choosing individuals meeting the inclusion criterion (such as smoking a certain number of cigarettes per day but having no history of hypertension, diabetes or heart disease) from the group of all the individuals who are smokers. Similarly, a control group can be created by "judiciously" choosing individuals from the group of all non-smokers. These individuals then need to be tracked for a pre-defined period, say five years and incidents of occurrence of mini brain-strokes are recorded. At the end-of the study period the number of mini brain-stroke events in the two groups are compared to check if the number of such events in the smoking group is significantly larger than in the control group.

However, such observational studies, can encounter many difficulties as events such as mini brain-stroke can happen due to many reasons such as age, daily calorie consumption, stress level etc. Such variables are often called confounding variables. To avoid the problems created by the presence of confounding variables, while creating the control group we attempt to match the attributes of the individuals in this group with the attributes of the individuals in the treatment group, to the extent possible. Without careful matching of individuals in the control group and treatment group we would not be able to draw valid conclusions.

There are many ways of matching individuals for creating the control group. A simple way of matching participants, is to match them on their attributes. We can define a distance between any two individuals, based on the attributes of importance for the researchers. If all the features under consideration are numerical then the Euclidean distance can be used. For example, let A be a smoker in the treatment group whose age, daily calorie consumption and stress level values are x_1, x_2 and x_3 respectively. Suppose we have a group of non-smokers who meet the inclusion criteria and for each of whom we have information about their age, daily calorie consumption and stress level. For the i-th individual let these values be y_{1i}, y_{2i} and y_{3i} respectively. Who among these would be chosen in the control group to match with A? For each individual i, we compute the Euclidean distance of A with the i-th individual as

The individual with the lowest value of D_i is chosen as the match of the individual A in the control group. In this way we attempt to make the treatment and control groups as similar as possible with respect to the confounding variables. Now, if we compare the results of these two groups and observe a significant difference we can be reasonably confident that the difference is caused by the treatment.

Another widely used approach for matching uses the 'propensity score'. This approach of allocation is useful in situations where one or more variables impact the chance of an individual being included in the treatment group. For e.g. it may be the case that higher proportion of individuals with high stress levels are smokers compared to individuals with lower stress levels. In such cases a choice model such as a logistic regression model, is used to estimate the probability of a person with the observed characteristics being in the treated group. Now, consider an individual in the treatment group with propensity score P_i. Among all the probable individuals who are not in the treatment group, the individual with the propensity score closest to P_i is chosen to be included in the control group.

The subject of Causal inference has made great progress in the recent times with development of many exciting new techniques. A very readable introduction to this intriguing subject is the book by Pearl and Mackenzie (2018).

Reference

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Awareness about Emerging Trends of Robotics in Accounting: An Empirical Research

Shilpa Vardia*, Ritu Soni, Rimpi Saluja*****

Abstract

In the era of automation, the methods of recording and analysing business transactions are becoming automated, thus leading to the emergence of various disruptive technologies in the field of accounting. Robotic accounting is one such technology. The daily, repetitive data are automated using Bot software. In the present research, an attempt has been made to study the awareness about the use of robotic process automation (RPA) in accounting. The sample selected for the study consists of students, academicians, accountants, entrepreneurs, and auditors. The research analysed how this disruptive technology affects the work of accountants. Cronbach's alpha test was applied to test the consistency of the items. Factor analysis was done to identify the factors that affect the use of robotics accounting. Factor analysis extracted three major components. The chi-square test was applied to measure the relationship between the respondents' understanding of robotic process automation in accounting and their demographics. From the results, it can be inferred that the respondents' understanding of robotic process automation in accounting differs significantly with respect to their gender, age, qualification, and profession.

Keywords: Robotics Accounting, Robotic Process Automation, RPA Software, Exploratory Factor Analysis, Chi-Square

Introduction

In the era of automation, various disruptive technologies have emerged in the field of accounting, such as robotics accounting, cloud accounting, block chain accounting, big data analytics, Internet of things, artificial intelligence, and so on. In turn, the methods of recording and analysing business transactions are changing. Traditional or tally accounting is transforming into automated accounting. The monotonous, repetitive data are being automatically recorded with the latest software. The process of using automated applications (SAP, Blue Prism, UiPath) in accounting is known as robotics process automation (RPA). The daily, repetitive data are automated using Bot software. The RPA software are efficient, cost-effective, user-friendly, time-saving, and error-free. The software is similar to Excel, but has potential beyond Excel. Thus, RPA refers to configuring software to do the work previously done by humans, in a more efficient and accurate way. On the basis of the survey of ICAI in India, RPA has been used by several large organisations and in financial functions. In large organisations, automated loading of data can reduce sub-ledger cycle time, and with centralised operation, the operating cost can be reduced. In addition, automation can help in invoice reconciliation, which is highly intensive and prone to errors if done manually. The report observed that with automation, the audit will be done in a more efficient way, and auditors can provide clients a better, error-free, and faster service. Furthermore, automation will increase the efficiency of accountants. Besides, RPA can be helpful in direct and indirect tax assessment. In India, RPA has great potential, and by using the software, value-added services can be delivered efficiently.

Review of Literature

The purpose of this review is to understand the concept of disruptive technologies with reference to robotic

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accounting. A summary of the previous studies would be helpful to understand the concept.

- Lauren Cooper (2018) investigated the adoption and use of robotic process automation (RPA) software, often referred to as bots, in the public accounting industry. Accounting firms use RPA software to automate the input, processing, and output of data across computer applications, in order to streamline repetitive and mundane business processes. They identified and discussed the potential benefits, opportunities, and challenges of implementing RPA in the accounting profession.
- Dahlia Fernandez (2018) studied the impact of robotic process automation (RPA) on global accounting services (GAS) using the institutional logic lens. The author used an in-depth case study approach in one of the largest global business services firms that provides global accounting services. The study showed that RPA technology has a significant impact on the individual and organisations, resulting in a change and reduction in work, thus decreasing the number of employees. Nevertheless, the introduction of new technology in an organisation creates unnecessary competition between humans and robots. Although RPA technology could solve issues involving humans, such as disciplinary problems, employee productivity, and human resource shortages, higher level of work, such as analytical aspects, can only be done by humans.
- Severin Lemaignan (2016) identified individual and collaborative cognitive skills: geometric reasoning and situation assessment based on perspective-taking, and affordance analysis; acquisition and representation of knowledge models for multiple agents (humans and robots, with their specificities); situated, natural, and multi-modal dialogue; human-aware task planning; and human-robot joint task achievement. Each of these abilities were analysed and presented as working implementations, explaining how they combine in a coherent and original deliberative architecture for human-robot interaction.
- Karippur Nanda Kumar (2018) focused on factors influencing customer experience in retail banking services delivered by RPA. The study theorises the role of various factors influencing the adoption of RPA in the retail banking industry, and highlighted factors such as security, privacy, reliability, and usefulness as significant in advancing RPA in the retail banking industry. Implications for research and practice are also discussed.
- Somayya Madakam (2019) discovered that robots and robotic process automation technologies are becoming compulsory to conduct business operations in organisations across the globe. Robotic process automation can bring immediate value to the core business processes, including employee payroll, employee status changes, recruitment and onboarding, accounts receivable and payable, invoice processing, inventory management, report creation, software installations, data migration, vendor onboarding, and so on, to name a few. Besides, robotic process automation has abundant applications in various sectors, including healthcare and pharmaceuticals, financial services, outsourcing, retail, telecom, energy and utilities, real estate, FMCG, and so on.
- Marianne Chrisos (2018) focused on how robotics can help the finance and accounting industries. The author studied how robotics will impact finance and accounting. The study suggested that increasingly, robotic process automation or RPA has been considered a beneficial addition to the areas of accounting and finance. These industries and departments are often highly regulated and require a great attention to detail. Because of these factors, namely, the need for reduced errors and quick output to meet the needs of clients, as well as the rules of regulation, the sectors of accounting and finance lend themselves well to the influence and assistance of robotics, especially automation.

Research Gap

After a study of the existing literature, it was found that very less work has been done on the awareness of robotic accounting software and their use in accounting. This study is an attempt to study the factors which influence enterprises to move towards the adoption of RPA in accounting.

Objectives

The present study is based on the following objectives.

- To study the respondents' opinion of robotic accounting.
- To find out various reasons for adopting and not adopting robotic process automation in accounting.
- To explore the factors affecting the use of robotics accounting.
- To study if respondents' understanding of robotic process automation in accounting is indifferent, with respect to their demographics.

Hypothesis

Present research proposed to test the following hypothesis.

H_0: Respondents' understanding of robotic process automation in accounting is indifferent, with respect to their demographics.

Data and Methodology

This study is descriptive in nature. The study is based on primary data collected through a close-ended structured questionnaire. The respondents of the present study were students, academicians, accountants, entrepreneurs, and auditors in the city of Udaipur. Non-probability purposive sampling technique has been used for data collection. The hypothesis was tested with the help of various statistical techniques, viz., statistical descriptive analysis, factor analysis, and chi-square.

Data Analysis and Interpretation

Reliability of Data Collection Instrument

Researchers commonly use the Cronbach's alpha coefficient for establishing scale reliability. The Cronbach's alpha coefficient is an indicator of internal consistency of the scale. A value of Cronbach's alpha above 0.60 can be used as a reasonable test of scale reliability. The reliability results for the questionnaire are presented in Tables 1 and 2.

Table 1: Case Processing Summary

		N	*%*
Cases	Valid	156	100.0
	Excludeda	0	.0
	Total	156	100.0

a. List-wise deletion based on all variables in the procedure.

Table 2: Reliability Statistics

Dimensions	*Number of Items*	*Cronbach's Alpha*
Advantages of Robotics Accounting	5	0.614
Limitations of Robotics Accounting	5	0.621
Approaches to Robotics Accounting	20	0.871

Table 2 shows that the value of the Cronbach's alpha ranges from 0.614 to 0.871. As suggested by previous researchers, an acceptable level of reliability for psychometric test starts from 0.60. This indicates a good internal consistency of the items in the scale.

Demographic Profile of Respondents

Descriptive statistics are illustrated in Table 3, which indicates demographic-wise distribution of respondents. About 51.92% respondents are male and the remaining (N = 75, Percentage = 48.08) are female. A majority of the respondents belong to the age group 30 to 40 years (N = 57, Percentage = 36.54), followed by respondents in the age group 20 to 30 years (N = 39, Percentage = 25). It was observed that a majority of the respondents (N = 45, Percentage = 28.85) held a Ph.D. and most of them (N = 51, Percentage = 48.57) have work experience of more than ten years.

Table 3: Demographic Profile of Respondents

Gender	*N*	*Percentage*	*Qualification*	*N*	*Percentage*
Male	81	51.92	Degree	33	21.15
Female	75	48.08	Graduate	15	9.62
Total	156	100	Post Graduate	18	11.54
Age (In Years)	N	Percentage	PhD	45	28.85
Below 20	18	11.54	CA/CS	39	25.00
20 to 30	39	25.00	Other	6	3.85
30 to 40	57	36.54	Total	156	100
40 to 50	33	21.15	Work Status	N	Percentage
Above 50	9	5.77	Working	105	67.31
Total	156	100.00	Student	51	32.69
Profession	N	Percentage	Total	156	100
Academician	42	26.92	Years of Experience	N	Percentage
Accountant	9	5.77	Less than 5 Years	33	31.43
Auditor	36	23.08	5 to 10 Years	21	20.00
Entrepreneur	18	11.54	More than 10 Years	51	48.57
Student	51	32.69	Total	105	100.00
Total	156	100			

Respondents' Opinion of Robotics Accounting

A majority of respondents (N = 90, Percentage = 57.69) indicated that they understand robotic process automation in accounting. About 57.69% respondents (N = 90) opined that robotics accounting will replace accountants, while 30.77% respondents (N = 48) believe that it may or may not happen. The respondents were asked if they had heard about the applications of robotics in accounting; it was found that a majority of the respondents (N = 78, Percentage = 50) had heard about SAP, followed by UiPath (N = 36, Percentage = 23.08), and Blue Prism (N = 27, Percentage = 17.31). Around 30.77% respondents (N = 48) indicated that they had not heard about any of the automation applications of robotics in accounting.

Table 4: Technology Trends of Future

Understand Robotic Process Automation in Accounting	*N*	*Percentage*
Yes	90	57.69
No	66	42.31
Total	156	100
Robotics accounting will replace accountants	N	Percentage
Yes	90	57.69
No	18	11.54
Maybe	48	30.77
Total	156	100
Heard about the automation applications of robotics in accounting	N	Percentage
UiPath	36	23.08
Blue Prism	27	17.31
SAP	78	50.00
Cathy	9	5.77
Others	3	1.92
Not Heard	48	30.77

Advantages of Robotics Accounting

Respondents were asked to indicate the advantages of robotics accounting. The results received are presented in Table 5. According to the results, the major advantage of robotics accounting is multiple-tasking (Mean = 3.94, Rank = 1), followed by consistency and reduced error (Mean = 3.85, Rank = 2), and non-stop performance (Mean = 3.62, Rank = 3). The last two ranked advantages of robotics accounting were cost saving (Mean = 1.98, Rank = 4) and lower employee turnover (Mean = 1.62, Rank = 5).

Table 5: Advantages of Robotics Accounting

Weight	*5*	*4*	*3*	*2*	*1*	*Total*	*Weighted Total*	*Weighted Average*	*Rank*
Rank / *Advantages*	*1*	*2*	*3*	*4*	*5*				
Non-stop performance	36	48	57	6	9	156	564	3.62	3
Multiple tasking	54	60	24	15	3	156	615	3.94	1
Consistency and reduced error	60	27	54	15	0	156	600	3.85	2
Cost saving	6	12	12	69	57	156	309	1.98	4
Lower employee turnover	0	9	9	51	87	156	252	1.62	5

Limitations of Robotics Accounting

Table 6 presents the limitations of robotics accounting. According to respondents' opinion, the major limitation of robotics accounting is that it is expensive (Mean = 3.44). Other limitations were security concerns (Mean = 3.37, Rank = 2), threat to accountants' jobs (Mean = 3.13, Rank = 3), lack of technical knowledge (Mean = 2.56, Rank = 4), and non-readability electronic data (Mean = 2.50, Rank = 5).

Table 6: Limitations of Robotics Accounting

Weight	*5*	*4*	*3*	*2*	*1*	*Total*	*Weighted Total*	*Weighted Average*	*Rank*
Rank / *Limitations*	*1*	*2*	*3*	*4*	*5*				
Cannot read non-electronic data	30	27	3	27	69	156	390	2.50	**5**
Security concerns	39	30	51	21	15	156	525	3.37	**2**
Lack of technical knowledge	6	18	57	51	24	156	399	2.56	**4**
Expensive	39	51	18	36	12	156	537	3.44	**1**
Threat to accountants' jobs	42	30	27	21	36	156	489	3.13	**3**

Major Factors Affecting the Use of Robotics Accounting

Respondents were asked to indicate main concerns in their approach to robotics accounting. To reduce the number of variables in terms of relatively few new categories, factor analysis is performed. These new categories are termed as factors, which also indicate the percentage of variance explained. The results are presented in Table 7. The results show that the total variance explained is 60.291%. This is appropriate for factor analysis. The 60.291% variance is explained by three extracted components.

Table 7: Total Variance Explained

Total Variance Explained						
Component	*Initial Eigenvalues*			*Extraction Sums of Squared Loadings*		
	Total	*% of Variance*	*Cumulative %*	*Total*	*% of Variance*	*Cumulative %*
1	7.817	39.087	39.087	7.817	39.087	39.087
2	2.612	13.062	52.149	2.612	13.062	52.149
3	1.628	8.142	60.291	1.628	8.142	60.291
4	1.206	6.029	66.32			
5	1.041	5.204	71.524			
6	0.923	4.616	76.141			
7	0.862	4.309	80.45			
8	0.745	3.726	84.176			
9	0.63	3.149	87.325			
10	0.537	2.685	90.01			
11	0.448	2.24	92.25			
12	0.344	1.721	93.972			
13	0.304	1.518	95.49			
14	0.228	1.139	96.629			
15	0.2	0.999	97.628			
16	0.141	0.705	98.333			
17	0.133	0.665	98.998			
18	0.093	0.465	99.463			
19	0.072	0.359	99.822			
20	0.036	0.178	100			

The most important tool in interpreting factors is factor rotation. The term rotation means the reference axes of the factors are turned about the origin until some other position has been reached. Factor rotation assists in the interpretation of the factors by simplifying the structure through maximising significant loadings of a variable on a single factor.

Table 8 explains that factor analysis has grouped the 20 variables into three factors. Factor 1 has 14 variables, factor 2 has five, and factor 3 has only one variable.

Table 8: Rotated Component Matrix

Component	*Factor*		
	1	*2*	*3*
1	0.569		
2	0.824		
3	0.555		
4		0.582	
5		0.636	
6		0.544	
7		0.629	
8	0.514		
9	0.73		
10	0.74		
11	0.915		
12	0.555		
13	0.77		
14		0.564	
15	0.739		
16	0.632		
17			0.448
18	0.821		
19	0.817		
20	0.796		

Extraction Method: Principal Component Analysis; Rotation Method: Varimax with Kaiser Normalisation.

On the basis of loading of the variables, the extracted factors are explained in Table 9. Based on the nature of the maximum number of variables included in factors, they are renamed as shown in Table 9.

Table 9: Factors Extracted

Factor	*Variable*	*Loading*
Factor 1 (Easy and Efficient)	Easy to use	0.569
	Improves accuracy	0.824
	Improves efficiency	0.555
	Improves productivity	0.514
	Scalability and expertise	0.73
	Fewer errors	0.74
	Independent auditing and testing	0.915
	High predictability	0.555
	Flexibility	0.77
	More informed decision making	0.739
	Saves time	0.632
	Better control	0.821
	Better account and bank reconciliation	0.817
	Better financial review	0.796
Factor 2 (Better control)	Reduces overall cost	0.582
	Reduction in monotonous work	0.636
	Cost saving	0.544
	Skill up-gradation of employees	0.629
	Beneficial in controlling human resources	0.564
Factor 3 (Better customer services)	Better customer services	0.448

Factor 1 (Easy and Efficient)

This factor is responsible for 39.087% variance of the total variance. Fourteen variables are grouped in this factor; they are related to the benefits of robotics accounting, i.e. easy to use, improves accuracy, improves efficiency, improves productivity, scalability and expertise, fewer errors, independent auditing and testing, high predictability, flexibility, more informed decision making, saves time, better control, better account and bank reconciliation, and better financial review.

Factor 2 (Better Control)

This factor explains 13.062% variance of the total variance. Four variables, which indicate the benefits in terms of cost and increase in efficiency of human resources, are grouped under this factor. The variables include reduces overall cost, reduction in monotonous work, cost saving, skill up-gradation of employees, and beneficial in controlling human resources.

Factor 3 (Better Customer Services)

This factor is responsible for 8.142% variance of the total variance. It has only a single variable, i.e. better customer services.

Hypothesis Testing

H_0 *Respondents' understanding of robotic process automation in accounting is indifferent, with respect to their demographics.*

H_1 *Respondents' understanding of robotic process automation in accounting is significantly different, with respect to their demographics.*

To measure the relationship between the respondents' understanding of robotic process automation in accounting and their demographics, chi-square test is applied. The results are presented in Table 10.

Table 10: Chi-square Test Results to Measure Relationship Between Respondents' Understanding of Robotic Process Automation in Accounting and their Demographics

Demographic		*Understanding*		*Total*	*Calculated Value*	*p-Value*	*Result*
		Yes	*No*				
Gender	Male	39	42	81	6.288	0.012	Significant
	Female	51	24	75			
Total		90	66	156			
Age	Below 20	0	18	18	47.612	0.000	Significant
	20 to 30	24	15	39			
	30 to 40	39	18	57			
	40 to 50	27	6	33			
	Above 50	0	9	9			
Total		90	66	156			
Qualification	Degree	18	15	33	36.758	0.000	Significant
	Graduate	0	15	15			
	Postgraduate	6	12	18			
	PhD	30	15	45			
	CA/CS	30	9	39			
	Other	6	0	6			
Total		90	66	156			
Profession	Academician	18	24	42	18.244	0.001	Significant
	Accountant	3	6	9			
	Auditor	27	9	36			
	Entrepreneur	6	12	18			
	Student	36	15	51			
Total		90	66	156			
Experience	Less than 5 Years	21	12	33	4.343	0.227	Not Significant
	5 to 10 Years	15	6	21			
	More than 10 Years	18	33	51			
Total		54	51	105			

Level of Significance = 5%

From the results, it can be inferred that the respondents' understanding of robotic process automation in accounting is significantly different, with respect to their gender, age, qualification, and profession, while their understanding of robotic process automation in accounting is significantly indifferent, with respect to their experience.

Conclusion

The present study attempted to study the application of robotic process automation in accounting. The respondents for the study were from different fields of accounting. The researchers attempted to study the effect of disruptive technology in the field of accounting. It was found that most of the respondents understand the phenomenon of RPA in accounting. However, many respondents felt that robotic accounting would replace the accountants. In addition, it was found that RPA is a cost- and time-saving process, resulting in error-free accounting. Factor analysis was done to analyse the factors for which RPA should be used in accounting. It was found that RPA will make accounting easy and accountants more efficient, management will have better control, the monotony of the work will be reduced, and the financial statements will be error-free. Chi-square test was applied to measure the relationship between respondents' understanding

of robotic process automation in accounting and their demographics. It was found that their understanding is significantly different, with gender, age, qualification, and profession. Thus, it can be concluded that RPA is an emerging technology, and to increase its implementation in the field of accounting, organisations should enhance the skills of accountants and auditors to prepare them for this emerging technology. To conclude, RPA will not replace the accountants. It will, however, improve their skills and make them more efficient, helping them to serve their client and organisation in a more effective way.

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Application of Artificial Neural Network to Predict Wilful Default for Commercial Banks in India

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Abstract

Since 2014, the problem of the rise of Non-Performing Assets (NPA) in the Indian banking system has been a subject of investigation. A major impact of mounting NPA has tested the bank's ability to recover bad loans and its capacity to lend in the short run. Among others, wilful default has been a significant category of NPA; it is detrimental to the financial health of the banking system. The share of wilful default in the total NPA for the year 2018 stands at 44%. By and large, wilful default indicates 'intend of fraud'. As declared by various banks, around 106 companies are identified as wilful default companies from those listed between 2000 and 2018. The research paper constructs a model to predict the wilful default using an artificial neural network. The model is based on 106 wilful default companies and 106 non-default companies. The model predicts an accuracy rate of 92.2% and the variables with the highest degree of importance are found to be Profit before Interest and Taxes/Total Assets, followed by Enterprise Value/Total Assets, Operating Profit Margin, Cash Flow Financing/ Cash Flow Investing, Total Debt/Total Asset, Sales/ Capital Employed, Retained Earnings/Total Assets, Return on Shareholders' Funds, PBIT/Sales, and others..

Keywords: Artificial Neural Network, Wilful Default, Non-Performing Assets, Bankruptcy Prediction Model

Introduction

As per RBI's Master Circular on wilful defaulter, a "wilful default" is deemed to have occurred if any of the following events is noted. When the unit has:

- Capacity to repay but still defaulted in meeting its repayment.
- Diverted the funds for purposes other than specified in the loan terms.
- Siphoned off the funds, that is, the funds are neither used in buying assets specified in the loan terms nor other assets.
- Disposed of or removed the movable fixed assets or immovable property given by the borrower to secure a term loan without the knowledge of the bank/lender. (RBI, Master Circular, 2014) (RBI, NOTIFICATIONS-Master Circular on Wilful Defaulters, 2015).

Among other measures that can be taken to moderate the risk of default, a centralised information infrastructure plays a significant role for banks to appraise lending. With the introduction of credit information companies, India is moving towards better lending space. The cases are reported in public by the lender through credit information companies (CIC) like Experian Credit Information Company of India Private Limited, Equifax Credit Information Services Private Limited, CRIF High Mark Credit Information Services Private Limited, and Credit Information Bureau (India) Limited (CIBIL). It provides details, quarterly, from both banks and financial institutions. In 2019, RBI launched a new web-based Central Information System for Banking Infrastructure (CISBI). These initiatives and efforts using digital information will simplify data sharing in the Indian banking system, leading to better coordination among banks and monitoring authorities.

The magnitude of wilful default data about non-performing assets justifies the scope of the study.

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Table 1: Bank Group-Wise Gross Non-Performing Assets, Gross Advances, and Gross NPA Ratios of Scheduled Commercial Banks 2018

Banks	*Gross NPAs (Rs. Billion)*	*% Gross NPA of Total*	*Gross Advances (Rs. Billion)*	*% Gross Advances of Total*	*Gross NPAs to Gross Advances Ratio (%)*
1	*2*	*3*	*4*	*5*	*6*
Nationalised	8956.01	86.43	61416.98	66.53	14.58
Private Sector	1258.63	12.15	27258.90	29.53	4.61
Foreign	13830	1.33	3633.04	3.94	3.81
Small Finance	8.93	0.09	353.16.	0.38	2.53
Total	10361.87	100	92308.94	100	11.18

Source: Department of Supervision, Reserve Bank of India

As per Table 1, RBI claims that with 86.43% of GNPA and 14.58% of GNPA to Lending Ratio, the financial health of public sector banks is dismal, followed by private sector and foreign banks in India.

Data on wilful default as presented in Table 2, as of 31 March 2018, will help us consider the problem in its severity. The table includes the wilful default number of cases classified as accounts wilful with more than Rs. 1 crore and more than Rs. 25 lakhs. A comparison among schedule commercial banks, nationalised, private sector, and foreign banks indicates the dominance of public sector banks in hosting wilful default accounts.

Table 2: Suit-Filed Accounts-Wilful Default as on 31 March 18 Summary (Column 2 and 5 in Rs. Billion)

Banks	*More than Rs. 1 Crore (Amount)*	*Share of Total (%)*	*No. of Cases*	*Rs. 25 Lakhs and Above (Amount)*	*Share of Total (%)*	*No. of Cases*
1	*2*	*3*	*4*	*5*	*6*	*7*
Nationalised	2543.92	80.58	15284	1125.95	87.51	8058
Private Sector	500.66	15.86	2964	152.19	11.83	1399
Foreign	112.33	3.56	390	846.80	0.66	43
Total	3156.92	100	18638	1286.62	100.00	9500
Grand Total	4443.53					

Source: Transunion and Cibil

With reference to Tables 1 and 2, more than 40% of the total NPA of Rs. 10 trillion falls under the category of wilful default. Public sector bank have the maximum share of not only NPA, but also wilful default. Interestingly, wilful defaults increased dramatically by 78% from 2017 to 2018, amounting to Rs. 44 trillion from the earlier Rs. 25 trillion.

The problem of wilful default is a serious cause for concern of the overall health of the banking system. Hence, an attempt to predict wilful default in advance can be of great help. With technological advancement and awareness, use of Artificial Intelligence (AI) in solving serious economic problems specific to big data is gaining impetus. It would not be wrong to comment that AI is the 'Future of Banking'. A process-driven AI, along with the advanced level of data analytics in the banking industry, can be a boon to identify and restrict fraudulent transactions. In addition, AI will play an important role in enhancing compliances in the banking industry, by managing large volumes of data and information, process them speedily, and share the information among all the stakeholders for efficient decision-making, including credit lending.

Review of Literature

NPL (non-performing loan) or NPA are those loans in which interest (or principal) is overdue by 90 days (RBI,

Master Circulars, 2001). The NPA-qualifying definition may vary a bit in the US, UK, Japan, Korea, Taiwan, China, or any other country (Golin & Delhaise, 2013) (Khan, 2009) (Bloem & Freeman, 2005) (Inaba, Kozu, & Sekine, 2017) (Bank C. C., 2004) (Bank H. S., 2015) (Taiwan, 2014) (Bholat, Lastra, Markose, Miglionico & Sen, 2016).

It is significantly important to study the nature and causes of NPA as it is an important key performance indicator of the banking system, especially related to safety and soundness (Throsten & Cull, 2005) (Lin & Zhang, 2009) (Siraj & Pillai, 2013). A significant branch of research stresses the central role of assets quality as a predictor of bank failures (Berger, 1997) (Abdelkader, Boulila Taktak & Jellouli, 2009). Apart from endogenous and exogenous factors, the impact of banking regulation and poor supervision can be one of the major causes of NPA (Abdelkader, Boulila Taktak & Jellouli, 2009) (Barth, Caprio & Levine, 2004).

The bank contemplates the entire risk exposure at the international and national level through the central bank and Basel Norms. The comprehensive set of risk includes operational, currency, interest rate, market, and credit risks. A bank is exposed to multiple risks just in one profile of the prospective borrower (Rousse, 2002). For mitigating and identifying credit risk, prediction models undergo a process which verifies the relationship through the classification of the tools or techniques employed, the sector or the domain of application, and lastly, the products on which the models shall be applicable. The most commonly used technique is from econometrics, neural networks, optimisation models, rule-based, or expert and hybrid systems (Caouette, Altman, Narayanan & Nimmo, 2008).

Artificial Neural Network (ANN) is a computer-programming-based model and works on the same lines as a human brain (Bishop, 1995). It is interconnected with many algorithms set up through econometric models. It provides flexibility in building a non-linear association between the dependent and independent variables. One of the types of ANN, viz., multilayer perceptron (MLP), consists of three layers: inner, hidden, and outer. Each layer is connected to the other and the interconnection is very strong; it works as a wire mesh to transmit the information and calculate it further (Brown, 2014). This technology helps in higher iterations and minimal error in the outcome. Accuracy comparison with various bankruptcy prediction models, like traditional techniques, and linear and logistic regression, finds ANN and Genetic Programming from Advance tool is consistently accurate in prediction. "Early warning system" with probability-based neural networks using Bayes' classification theory was developed thereafter (Yang, 2001). A set of data tested on small Italian businesses by using ANN showed positive results in prediction. Two ANN models were developed in the research; one with Standard Feedforward Network and the other with special Architecture (Angelini, Tollo, & Roli, 2008). Another interesting research based on the experimental method suggested that both emotional and neural network can be used effectively for evaluating credit risk. However, emotional models outperformed in terms of speed and accuracy of decision making (Khashman, 2011).

For the application of artificial neural network, parameters of Z-Score, one of the widely used bankruptcy prediction models, were used. Artificial neural network techniques resulted in better accuracy than MDA. ANN resulted in 90% and MDA in 85% accuracy rate for the USA companies (Wilson & Sharda, 1994). In a comparative study of various bankruptcy prediction models for Korean companies, viz., case-based reasoning, MDA, and ANN, 51 financial ratios across six industries were used, resulting in accuracy ranging between 81 and 83% in all the methods–ANN with 82.98%, MDA at 82.43%, and case-based reasoning at 81.88% (Jot, Han & Lee, 1997). A study on model comparison of 1,139 banks in all the regions of the USA used ANN, Logit, and MDA for three years before the bankruptcy resulting from ANN had better accuracy and cost less in comparison to other methods (Etheridge & Sriram, 1997). Various branches of computer-programming-based methods became famous among the financial fraternity and grabbed the attention of the computer science, financial, and banking sectors. Support Vector Machine (SVM) method was used for 1,160 bankrupt and non-bankrupt Korean companies, each with ten financial ratios as the variables. The method of optimising was used to discover where SVM has the highest level of accuracies and better generalisation performance than Back-Propogation Neural Network as the training set size was becoming smaller. Overall accuracy was more than 73% at the optimum level

(Shin, Lee & Kim, 2005). The study used two methods to predict the failure: neural network and multivariate statistical methods. In the case of neural networks, four different architectures, namely multi-layer perceptron, competitive learning, self-organising map, and learning vector quantisation were employed, while in multivariate statistical methods, multivariate discriminant analysis, cluster analysis, and logistic regression analysis were tested. Learning vector quantisation (LVQ) resulted in a phenomenal 100% accuracy, followed by multi-layer perceptron with 95% and support vector machines (SVM) with 91% accuracy (Boyacioglu, Kara & Bayken, 2009).

In yet another attempt to find a better technique for bankruptcy prediction, 32 bankrupt and 45 non-bankrupt companies in England comprised the sample with ratios regarding management inefficiency, capital structure, insolvency, adverse economic conditions, and income volatility for the Logit model and the quadratic interval logit model. Multi-layered perceptron and radial basis function network resulted in an accuracy ranging from 91.5% to 77.05%, where the best method was proved to be radial basis function network (Tseng & Hu, 2010). A study on bankruptcy models for UK companies used 18,589 company-years and selected 12 variables covering accounting, market, and macroeconomy. Three methods were tested: ANN, Altman's Z-Score, and logistic regression. ANN had the maximum accuracy of 84.7%, Altman's only 65%, and logistic regression 84% (Tinoco & Wilson, 2013).

By using 98 unique ratios across various parameters, including cash flow, liquidity, profitability, turnover, balance structure, indicators from previously constructed models and Russian Legislations to compute using LR, MDA, ANN, and Classification and Regression Tree (CRT). A unique method of combining various models was decided based on significance, intersection, and CRT+LR. The basis of intersection by using ANN provided the best results with an accuracy of 88.8%, while MDA, CRT, and LR resulted in accuracies of 74.5%, 86.7%, and 87.8%, respectively (Fedorova, Gilenko, & Dovzhenko, 2013). An extension to the study on bankruptcy prediction models by Phillippe Jardin focuses on retail, construction, and service sectors in France from 2005-2010, with 50 financial ratios. The failure prediction one, two, and three years before default was computed using a new failure-based model to compute LR, Cox model, MDA, and ANN techniques. The accuracy rate ranged from 75 to 85% across the period. The failure-based model provided the best results in predicting accuracy three years before the default for all the years for all the techniques. However, the average accuracy rate for all the methods was 80% (Jardin, 2014).

In the Indian context, the study on wilful default is limited; it includes research from 2002-2016 focusing on wilful default, which used a total of 558 sample companies with an equal number of bankrupt and non-bankrupt firms, 279 in each category used logistic regression and resulted in an overall accuracy of 87.5% (Karthik, Subramanyam, Shrivastava & Joshi, 2018). Concerning artificial neural network, 1,460 listed companies were taken as a sample to test Altman's, Zmijemski's, Springate's, and IN05 models. It was further computed using the decision-tree model, where the accuracy rate was a meager 54.6% and ANN was just 43% (Kapil & Agarwal, 2019).

The review from literature across countries like the US, UK, Korea, Italy, India, and France indicates that artificial neural network has been used widely. It concludes that the accuracy rate has maximum ANN in most cases. In addition, it indicates a gap in research in the Indian context, especially in wilful default.

Objective

To construct bankruptcy prediction models for wilful default public limited companies listed from the year 2000 by using artificial neural network.

Research Methodology

The research is categorised as analytical. The research is based on the financial performance data of the companies. It critically examines and tries to draw a relationship among the variables. It is primarily a statistical compilation and follows many computations. It is applied research since it focuses on banking business-related problems. The entire research is quantitative; it takes only the financial performance data. It is further classified as empirical research since it is based on past data (*post ante*). The approach is deductive, where conclusions are drawn using various statistical techniques.

Over 900 IPOs were launched between 2000 and 2017, out of which 106 have been declared as wilful defaulters.

These 106 companies constitute the entire population of the study. Further, non-default companies of equal number, that is, 106, are shortlisted based on the highest market capitalisation in India.

Population: It comprises all the public limited listed companies in India. There are more than 5,000 listed companies.

Sampling Unit: It considers the public limited listed companies listed after 2000 till 2018, which comprises around 900 companies.

Sampling Method: The method of sampling is purposive as the sample selected is based on the pre-decided defined objective.

Size of Sample: The entire population of the defined scope is 106 public limited wilful default companies. In addition, for model creation, the top 106 companies from BSE 200 index are shortlisted based on their market capitalisation, excluding the companies in the banking and financial sectors.

Parameters of Interest: Financial performance from 2000 to 2018 in the years falling relevant for the companies covers the following parameters.

Table 3: Variables-Ratios

1	Liquidity Ratios
1.1	Current Ratio
1.2	Net Working Capital/Total Assets
2	Profitability Ratios
2.1	Net Profit Margin
2.2	Operating Profit Margin
2.3	PBIT Margin
2.4	Return on Assets
2.5	Return on Shareholders' Fund
2.6	Return on Capital Employed
3	Solvency and Valuation Ratios
3.1	Interest Service Coverage Ratio
3.2	Total Debt/Total Assets
3.3	Retained Earnings/Total Assets
3.4	EBIT/Total Assets
3.5	Sales/Total Assets
3.6	Debt/Enterprise Value
3.7	Profit After Tax/Enterprise Value
3.8	Enterprise Value/Total Assets
4	Cash flow Ratios
4.1	Increase (Decrease) Loan Funds/Cash-flow from Loan
4.2	Cash-flow Financing/Cash-flow Investing
5	Miscellaneous
5.1	Market Capitalisation/Outstanding Debt
5.2	Sales/Capital Employed
5.3	Minority Interest/PAT

Collecting the Data: The data is extracted from the Software Ace Equity powered by Accord FinTech. The statistical computations are on IBM SPSS and Microsoft Excel.

Data Size: Table 4 shows the details of the research data computed.

Table 4: Details of Data Selection

Sr. No	*Parameter*	*Total Observations*
1	Total Companies	106+106 = 212 (Default and Non-Default)
2	Number of Years	18 (2000-2018)
3	Number of Years and Companies (Company Years)	3,319
4	Total Parameters	21 (Financial Ratios)
5	Wilful Default–Years and Parameters	28917
6	Non-Default–Years and Parameters	40782
7	All Companies, All Years, All Parameters	69699

Variable consists of five categories of financial ratios: liquidity, profitability, solvency, valuation, cash flow, and miscellaneous. A total of 21 financial ratios from five categories have been considered for the construction of ANN models.

Using the above-stated methodology, all the data has been extracted from Ace Equity Software and computed on IBM SPSS. The analysis and results are discussed below.

ANN Model Building

An artificial neural network is an attempt to replicate the brain's neural network. It has been used extensively for programming Artificial Intelligence Softwares. As per the

literature review, this method has the highest accuracy rate. The data is studied using IBM SPSS software to construct the ANN model. The model is processed under multi-layer perceptron (MLP), a class of feed-forward ANN. The model is built through various steps, starting with the processing of data. It divides the data in the ratio of 70:30, where 70% is training and 30% is testing data (Table 5). After various simulations on 70% of the data, the same is tested on the remaining 30% to provide the importance of variables. It provides the outcome in terms of accuracy (Classification-Table 8).

From Table 5 on Case Processing, 2161 was taken as training input and 962 as testing input to process the data.

Table 5: Case Processing Summary

		N	*Percent*
Sample	Training	2161	69.2%
	Testing	962	30.8%
Valid		3123	100.0%
Excluded		196	
Total		3319	

ANN is constructed using a single hidden layer, where the input layer consists of 21 variables and its hidden layer six units. For the hidden layer, the Activation function is a hyperbolic tangent and the output layers are two units (default and not) with activation function Softmax.

Table 6: Network Information

Input Layer	Covariates	1	Current Ratio
		2	Net Profit Margin
		3	Operating Profit Margin
		4	PBIT Margin
		5	Return on Assets
		6	Return on Shareholders' Fund
		7	Return on Capital Employed
		8	Interest Service Coverage Ratio
		9	Net Working Capital/Total Assets
		10	Retained Earnings/Total Assets
		11	PBIT/Total Assets
		12	Market Capitalisation/BV of Total Debt
		13	Sales/Total Assets
		14	Inc Dec Loan Funds/CF from Loan
		15	Sales/Capital Employed
		16	Total Debt/Total Assets
		17	CF Financing/CF Investing
		18	Minority Interest/PAT
		19	Debt/EV
		20	PAT/EV
		21	EV/Total Assets
	Number of Units		21
	Rescaling Method for Covariates		Standardised
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1a		6
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	DEFAULT
	Number of Units		2
	Activation Function		Softmax
	Error Function		Cross-entropy

Excluding the bias unit

The most important aspect of model building in bankruptcy prediction lies in accuracy. As per the results in Table 6, training data predicted accurately is 93.8%, while testing is 92.2% accurate.

Table 7: Model Summary

Training	Cross-Entropy Error	372.757
	Percent Incorrect Predictions	6.2%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[s]
	Training Time	0:00:00.78
Testing	Cross-Entropy Error	181.972
	Percent Incorrect Predictions	7.8%

Dependent Variable: DEFAULT

Overall, the results of the function have an accuracy of 92.2%. Details are provided in Table 8. Training data has an overall accuracy rate of 93.8% and testing data has 92.2%.

Table 8: Classification

Sample	*Observed*	*Predicted*		
		NO	*YES*	*Percent Correct*
Training	NO	1908	50	97.4%
	YES	85	118	58.1%
	Overall Percent	92.2%	7.8%	93.8%
Testing	NO	839	30	96.5%
	YES	45	48	51.6%
	Overall Percent	91.9%	8.1%	92.2%

The visual outcome of an artificial neural network with one hidden layer structure is shown in Fig. 1.

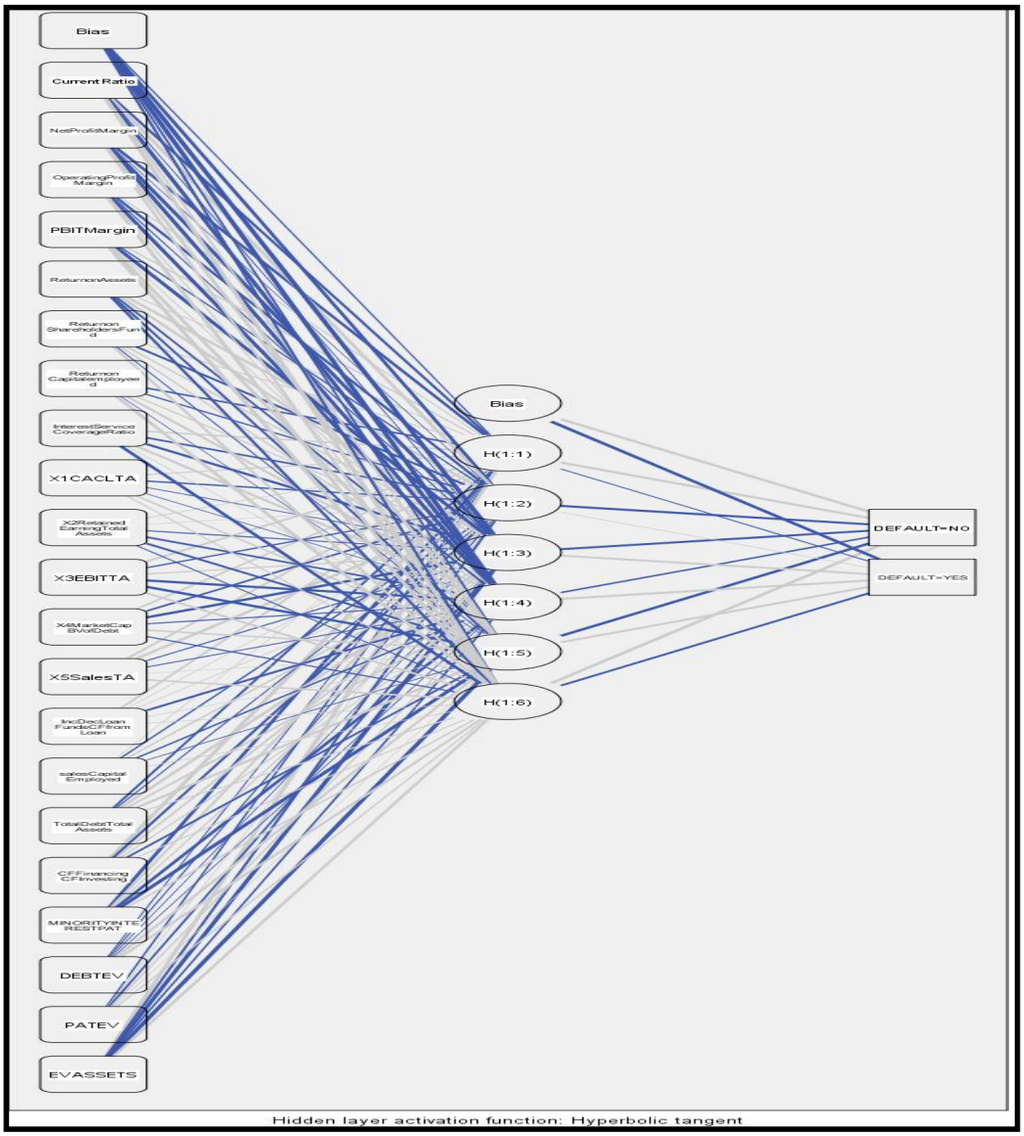

Fig. 1: Artificial Neural Network One Layer Structure

The function provides independent variable importance in Table 9. Highest is PBIT/Total Assets, followed by Enterprise Value/Total Assets, Operating Profit Margin, Cash Flow Financing/Cash Flow Investing, Total Debt/Total Asset, Sales/Capital Employed, Retained Earnings/Total Assets, Return on Shareholders' Funds, PBIT/Sales, and others.

Table 9: Independent Variable Importance

Ratios	*Importance*	*Normalised Importance*
PBIT/Total Assets	0.096	100.00%
EV/Total Assets	0.086	89.20%
Operating Profit Margin	0.065	67.70%
Cash-flow Financing/Cash-flow Investing	0.063	65.50%
Total Debt/Total Assets	0.06	62.30%
Sales/Capital Employed	0.058	60.10%
Retained Earnings/Total Assets	0.058	60.00%
Return on Shareholders' Funds	0.051	52.90%
PBIT Margin	0.049	51.40%
Net Working Capital/Total Assets	0.045	46.40%
Increase (Decrease) Loan Funds/ Cash-flow from Loan	0.044	46.30%
Return on Assets	0.043	45.00%
Net Profit Margin	0.04	41.90%
Minority Interest/PAT	0.037	38.90%
Sales/Total Assets	0.035	36.70%
Debt/EV	0.032	33.70%
Return on Capital Employed	0.031	32.00%
PAT/EV	0.029	30.10%
Current Ratio	0.027	28.50%
Interest Service Coverage Ratio	0.025	26.20%
Market Capitalisation/BV of Total Debt	0.025	26.20%

Conclusion

This is a modest attempt to study the given data and find that with the use of artificial neural network, commercial banks in India can predict if the loan account will become a wilful default or not, with 92.2% accuracy. It provides meaningful insight on variables to be considered before disbursing and for monitoring purposes. Utmost importance should be given to PBIT/Total Asset ratio. Bankers should consider the insights seriously in case of a downward trend or major negative fluctuation in this ratio. Bankers can thereafter investigate the loan account and take action as per the guidelines of the central bank. Other variables to be equally considered include variables of importance: Enterprise Value/Total Assets, Operating Profit Margin, Cash Flow Financing/Cash Flow Investing, Total Debt/Total Asset, Sales/Capital Employed, Retained Earnings/Total Assets, Return on Shareholders' Funds, PBIT/Sales, and others.

The amount of NPA and NPA to Advance ratio are dreadful for public sector banks. The study indicates that public sector banks should give more emphasis on predicting the default using ANN instead of going for a cumbersome process of filing a post-default lawsuit. Artificial Intelligence has been used by banks across the globe and public sector banks should invest in this direction.

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A Study of the Identification of Efficient Mutual Funds - A Data Envelopment Analysis Approach

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Abstract

This paper attempts to identify efficient mutual funds, analysed on the basis of Data Envelopment Analysis (DEA). This is an endeavour to study the impact of parameters like expense ratio, asset under management, standard deviation, Sortino ratio, Sharpe ratio, beta, alpha, and R-Squared, on the performance of the mutual fund, and to identify efficient mutual funds which lie on the efficient frontier according to DEA. To specify the scope of the study, the above parameters of the open-ended equity schemes of the top 15 mutual funds were considered. A relationship between the funds' parameters was found using the linear programming methodology, which is the DEA. It was observed that only 37 mutual fund schemes implementing the constant return to scale (CRS) and 61 mutual fund schemes implementing the variable return to scale (VRS), out of the 188 mutual fund schemes under consideration, were efficient, as per the DEA approach.

Keywords: Data Envelopment Analysis, Efficient Mutual Fund

Introduction

Assessing the performance of mutual funds has been an important concern for mutual fund managers and financial sector investors. Credible metrics have emerged for assessing the performance of mutual funds. Investment managers have huge responsibilities, and their incentives in the future will be fantastic.

Professionally managed funds, global diversification risks, and market attractiveness are some of the developments experienced by global investors in recent decades. Due to the growing requirements in the financial services industry, organisations like Morningstar have developed their own fund performance metrics.

Three of the most primitive performance metrics in use today are the Treynor index, which measures the excess return per unit of systemic risk; the Sharpe index, which measures the excess return per unit of overall risk; and the Jensen's α index, which measures the gap between the estimated return on the portfolio and the anticipated benchmark return. Groundbreaking studies have focused on calculating efficiency into two dimensions, namely risks and returns on the grounds of the Capital Asset Pricing Model (CAPM).

The Data Envelopment Analysis, unlike other performance metrics, incorporates multiple variables related to mutual fund performance. This approach enables the development of performance indices for mutual funds that take different investment risk measures and expenses into account. The DEA method includes other output measures, in addition to the mean return considered by conventional indices. The DEA Portfolio Efficiency Index (DPEI), which incorporates transaction costs, was thus introduced by Murthi et al. (1997). In comparison with the best fund set, the DEA measures the performance of a mutual fund in the given target zone. It solves the problem of transaction cost endogeneity, by simultaneously taking account of transaction costs and returns in the analysis.

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A more recent, more modern risk assessment should be put in place to calculate the risk of the fund, and thereby assess the performance of the fund. The plethora of methods, on the other hand, often show that several risk indicators may be necessary to accurately assess its performance, this being the advantage of using the DEA method for determining the fund's benefit over other techniques. In addition, DEA demonstrates an efficient argument on how to get the mutual fund to its optimum performance. To date, most research on the framework of the DEA model was carried out by using mutual funds located in the United States, as the Indian market is still growing. Over a period, DEA-based studies of the Indian mutual fund will increase.

Literature Review

Murthi et al. (1997) analysed the mutual funds based on the CRS DEA model and used standard deviation, expense ratio, turnover, and loads as the inputs.

Morey and Morey (1999) analysed the mutual funds based on quadratic-constrained DEA and used variance as the input.

Choi and Murthi (2001) analysed the mutual funds based on CRS and VRS DEA model and used standard deviation, expense ratio, turnover, and loads as the inputs.

Galagedera and Silvapulle (2002) analysed the mutual funds based on the VRS DEA model and used standard deviation, operating expenses, and minimum initial investment as the inputs.

Wilkens and Zhu (2005) analysed the mutual funds based on the VRS DEA model and used standard deviation and lower partial moments of order 0 as the inputs.

Joro and Na (2006) analysed the mutual funds based on cubic restriction DEA and CRS, and used variance as the input.

Briec, Kerstens and Jokung (2007) analysed the mutual funds based on quadratic restriction DEA (extended) and used variance as the input.

Briec and Kerstens (2009) analysed the mutual funds based on cubic restriction DEA and used variance as the input.

Zhao et al. (2011) analysed the mutual funds based on quadratic restriction DEA and used standard deviation and variance as the inputs.

Matallín, Soler and Tortosa-Alsina (2014) analysed the mutual funds based on DEA and used beta, returns, expense ratio, and standard deviation as the inputs.

Need for the Study

It is observed that mutual fund investors are constantly looking for the well-performing mutual funds. Generally, the investors observe the returns of the mutual fund and take a decision. To have a better understanding of the well-performing mutual funds, it is necessary to identify efficient mutual funds based on various parameters, also called the input factors, that affect mutual fund performance, rather than blindly following the mutual fund performance over a period. In the search for such mutual funds, the need for the study was observed. The study was planned to be implemented using the data envelopment analysis model. This model indicates that efficient mutual funds lying on the efficient frontier are worth investing in, based on the various input parameters of the mutual fund considered in the study.

Objective of the Study

- To identify efficient mutual funds based on the data envelopment approach.

Methodology

The technique used is the DEA (Data Envelopment Analysis), which was essentially developed by Charnes, Cooper, and Rhodes (CCR) to determine the relative effectiveness of output units. This technique is proficient in using several inputs and outputs; the approach is non-parametric and is used to approximate the production frontiers in operational research and economics. It is used to calculate the performance of DMUs (decision-making units) and to benchmark operations management. Effective DMUs lead to a frontier of best practice. Based on the function of production, the maximum output that is achievable for any possible input combination can be displayed.

Mutual funds are considered production units in this research work. As the DEA technique can handle several inputs and outputs, it is beneficial. It incorporates multiple characteristics of investment and fund behaviours, which impact the performance of the mutual fund in addition to normal return and risk. The DEA technique generally reflects the effectiveness of the mutual fund by its position on the boundary of the mutual fund's best returns, numerically based on the proportion of the weighted output to the weighted input. The approximate edge of the best performance is also known as the wrapping surface.

The DEA model has the potential to be evaluated in two ways, namely the input and output orientations. The input orientation provides information as to how much input decrease is essential for an inefficient mutual fund to become DEA-efficient, while retaining its existing output levels. Similarly, an evaluation of the output orientation provides information on how much a DEA-inefficient mutual fund needs to considerably raise its output level such that the mutual fund is efficient.

Data Analysis and Interpretation

To find out the effect of various mutual fund parameters like expense ratio, asset under management, standard deviation, Sharpe ratio, Sortino ratio, beta, alpha, and R-Squared (input factors) on the returns of the mutual fund (out factor), the DEA model was applied on the open-ended Indian equity schemes of the top 15 mutual funds. The top 15 mutual funds houses, in terms of overall asset under management, were ABSL MF, AXIS MF, DSP MF, Franklin MF, HDFC MF, ICICI MF, IDFC MF, Kotak MF, L&T MF, Mirae MF, Nippon India MF, SBI MF, Sundaram MF, TATA MF, and UTI MF. The total schemes under consideration were 188. Secondary data with regards to mutual funds was taken from https://www.valueresearchonline.com/ and the data was collected in terms of five-year returns, with the term ending on January 11, 2020.

The Max DEA 7 basic model was used to implement the linear programming methodology, based on the factors mentioned earlier. Some of the data were negative in nature and were converted to positive numbers by the addition of a constant positive value as per the findings of Bowlin (1998). The 188 mutual funds under consideration formed the decision-making units (DMUs) of the DEA model. The total number of input factors considered was eight, and the five-year return was considered as the output factor. These factors were fed into the Excel sheet, which was subsequently imported into the Max DEA model; the envelopment model distance considered was Radial (CCR 1978, BCC 1984), input orientation, and both return to scale were considered separately, namely the constant return to scale (CRS) and variable return to scale (VRS). As shown in Table 1, when the model was run in the constant return to scale mode, we observed that 37 mutual funds were efficient and had a score of 1; in addition, the table contains a few of the mutual funds having a high score of above 0.9.

Besides the efficiency score, the results are identified by the benchmark lambdas. These are the raw weights assigned to the peer units while solving the DEA model. They are interpreted through the dual formulation of the DEA model. These statistics identify the relative efficiency score so that a mutual fund can achieve the highest optimum level of performance. The table provides information about the relative benchmark lambdas for every mutual fund, except the efficient ones. Efficient mutual funds have a score of 1. Let us consider the 8th mutual fund as mentioned in Table 1, which is the DSP Midcap fund. It has an efficiency score of 92.9%. The last column shows the benchmark lambdas of the efficient mutual funds that are closest in terms of input and output to the DSP Midcap fund. Each percentage indicated with a mutual fund is a statistic. The statistics, on the other hand, are multiplied by the entries for the same reference lambdas. A smaller number is generated throughout. This process is repeated for each input and output benchmark, leading to separate inputs and outputs. These new inputs and outputs will give nearly 100% efficient rectified input variables at the same output level.

This model was executed with VRS, a variable return to scale DEA model. Accordingly, 61 mutual fund schemes were found efficient. On using the CRS, a constant return to scale DEA model, 37 mutual fund schemes were found to be efficient. The difference in the number of efficient mutual funds based on CRS and VRS is because the envelopment surface will differ depending on the assumptions underlying the model.

Table 1: Showing the Sample DEA Output with a Constant Return to Scale

DEA_Results		
DMU (Name of the Mutual Fund)	*Score*	*Benchmark (Lambda)*
ABSL Digital India	1	ABSL Digital India (1.000000)
ABSL Dividend Yield	1	ABSL Dividend Yield (1.000000)
ABSL India GenNext	1	ABSL India GenNext (1.000000)
ABSL Infrastructure	1	ABSL Infrastructure (1.000000)
ABSL Midcap	1	ABSL Midcap (1.000000)
ABSL Nifty ETF	1	ABSL Nifty ETF (1.000000)
Axis Small Cap	1	Axis Small Cap (1.000000)
DSP Midcap	0.929566	DSP Natural Rsrcs and New Energy (0.213084); L&T Midcap (0.504005); Mirae Asset Emerging Bluechip (0.163760)
DSP Natural Rsrcs and New Energy	1	DSP Natural Rsrcs and New Energy (1.000000)
Franklin Prima	1	Franklin Prima (1.000000)
Franklin Technology	1	Franklin Technology (1.000000)
ICICI Pru Dividend Yield Eqt	0.914528	DSP Natural Rsrcs and New Energy (0.403835); Kotak Infra & Eco Reform (0.024287); Nippon India Consumption (0.018690)
ICICI Pru FMCG	0.979984	ABSL Digital India (0.348687); DSP Natural Rsrcs and New Energy (0.153277); ICICI Pru Sensex ETF (0.078687); Mirae Asset Great Consumer (0.297124)
ICICI Pru Nifty 100 ETF	1	ICICI Pru Nifty 100 ETF (1.000000)
ICICI Pru Nifty ETF	1	ICICI Pru Nifty ETF (1.000000)
ICICI Pru Sensex ETF	1	ICICI Pru Sensex ETF (1.000000)
ICICI Pru Value Discovery	1	ICICI Pru Value Discovery (1.000000)
IDFC Infrastructure	1	IDFC Infrastructure (1.000000)
Kotak Banking ETF	1	Kotak Banking ETF (1.000000)
Kotak Emrgng Eqt	0.9912	DSP Natural Rsrcs and New Energy (0.181175); L&T Midcap (0.588769); Mirae Asset Emerging Bluechip (0.133572); Nippon India ETF Junior BeES (0.041156)
Kotak India EQ Contra	1	Kotak India EQ Contra (1.000000)
Kotak Infra & Eco Reform	1	Kotak Infra & Eco Reform (1.000000)
Kotak Sensex ETF	1	Kotak Sensex ETF (1.000000)
L&T Midcap	1	L&T Midcap (1.000000)
Mirae Asset Emerging Bluechip	1	Mirae Asset Emerging Bluechip (1.000000)
Mirae Asset Great Consumer	1	Mirae Asset Great Consumer (1.000000)
Nippon India Consumption	1	Nippon India Consumption (1.000000)
Nippon India ETF Bank BeES	1	Nippon India ETF Bank BeES (1.000000)
Nippon India ETF Consumption	1	Nippon India ETF Consumption (1.000000)
Nippon India ETF Dividend Opp	1	Nippon India ETF Dividend Opp (1.000000)
Nippon India ETF Junior BeES	1	Nippon India ETF Junior BeES (1.000000)
Nippon India ETF Nifty 100	1	Nippon India ETF Nifty 100 (1.000000)
Nippon India ETF Sensex	1	Nippon India ETF Sensex (1.000000)
Nippon India ETF Shariah BeES	1	Nippon India ETF Shariah BeES (1.000000)
SBI Consumption Opportunities	1	SBI Consumption Opportunities (1.000000)
SBI ETF Sensex	1	SBI ETF Sensex (1.000000)
Sundaram Large & Midcap	1	Sundaram Large & Midcap (1.000000)
Sundaram Mid Cap Inst	1	Sundaram Mid Cap Inst (1.000000)
Sundaram Midcap	1	Sundaram Midcap (1.000000)
Sundaram Select Focus Inst	1	Sundaram Select Focus Inst (1.000000)
Templeton India Value	1	Templeton India Value (1.000000)

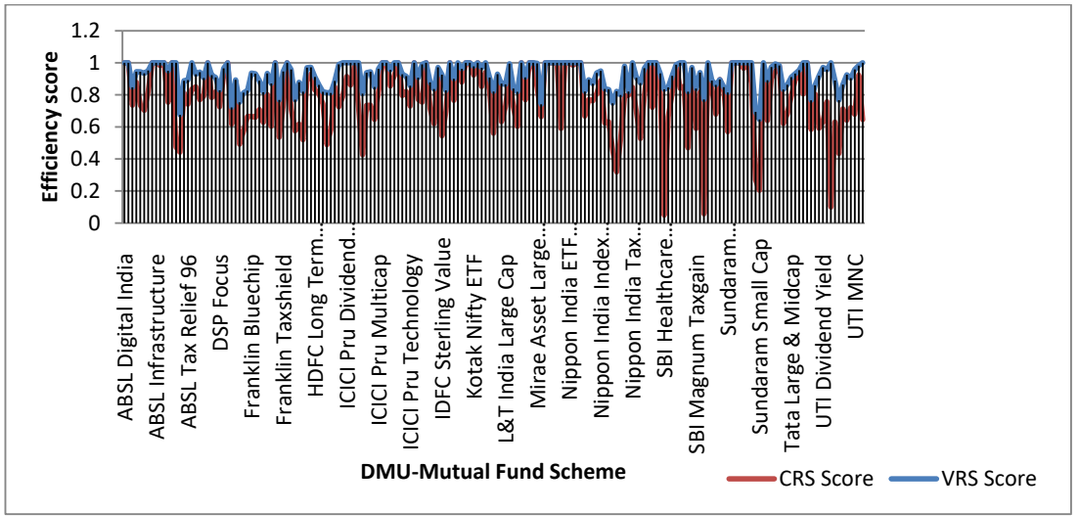

Fig. 1: Chart Showing the Output Graph using CRS and VRS

Conclusion

Out of 188 mutual fund schemes under study, only 37 mutual funds were found to be efficient as per the CRS-DEA model and 61 mutual funds were found to be efficient according to the VRS-DEA model. Since this was an input-oriented model, mutual funds were classified and generally evaluated based on comparable outputs and inputs charged. Hence, it can be assumed that all mutual fund schemes that are below the efficiency boundary need to be compared with industry benchmark efficient mutual funds. To achieve an optimal and high-efficiency score for these inefficient mutual funds, fund managers can inspect all inputs to evaluate the slack they can allow to decrease the input without reducing the outcome.

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Appendix

A brief explanation of the mutual fund parameters used as inputs in the DEA model:

1. Expense Ratio: An expense ratio is an annual fee expressed as a percentage of the investment — or, like the term implies, the ratio of the investment that goes toward the fund's expenses.
2. Asset under management: Assets under management are the overall market value of assets/capital that a mutual fund holds. The fund manager manages these assets and makes all investment-related decisions on behalf of the investors. AUM is an indicator of the size of a given fund house.
3. Standard deviation: Standard deviation is a statistical measurement that shows how much variation there is from the arithmetic mean, Investors, describe standard deviation as the volatility of past mutual fund returns.
4. Sharpe Ratio: The Sharpe Ratio is calculated by subtracting the risk-free return from the portfolio return; which is known as the excess return. Eventually, the excess return is divided by the standard deviation of the portfolio returns.
5. Sortino Ratio: The Sortino ratio measures the risk-adjusted return of an investment asset, portfolio, or strategy. It is a modification of the Sharpe ratio but penalizes only those returns falling below a user-specified target or required rate of return, while the Sharpe ratio penalizes both upside and downside volatility equally.
6. Beta: Beta, concerning mutual fund investing, is a measure of a particular fund's movement (ups and downs) compared to the overall market.
7. Alpha: Alpha is a measure of an investment's performance on a risk-adjusted basis. It takes the volatility (price risk) of a security or fund portfolio and compares its risk-adjusted performance to a benchmark index. The excess return of the investment relative to the return of the benchmark index is its alpha.
8. R-Squared: R-squared is a measure of the percentage of an asset or fund's performance as a result of a benchmark. ... A hypothetical mutual fund with an R-squared of 0 does not correlate its benchmark at all. A mutual fund with an R-squared of 100 matches the performance of its benchmark precisely.

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DuPont Analysis of IndiGo (Inter Globe Aviation Ltd.) and SpiceJet: A Study of Domestic Airlines in India with the Help of Two-Tailed T-test

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Abstract

The aviation industry in India is one of the fastest growing industries in our economy. In the present paper, the performance of two domestic airlines, viz. IndiGo and SpiceJet, have been analysed with the help of DuPont analysis. Four ratios related to DuPont analysis have been used for the performance evaluation—profit margin, asset turnover ratio, equity multiplier, and return on equity (ROE will show the overall impact). The study is based on secondary data drawn from the annual reports of respective companies. Data of five years, i.e. 2012-13 to 2016-17, is analysed by calculating four ratios related to DuPont analysis. The statistical tool 'two-tailed t-test' has been used for evaluating the financial performance of these two companies. Data is analysed manually without using any software. The results show that the financial performance of IndiGo is better than SpiceJet.

Keywords: Aviation Industry, DuPont Analysis, Financial Performance, IndiGo, SpiceJet

Introduction

The mobility of men and material by air is called air transport. It is the fastest means of transport and very useful for long distances; it is time saving. It is known for its high speed, strategic importance, ease of transport of expensive and light goods, free from physical barriers, and useful in natural calamities. The Indian air industry is one of the fastest growing industries in India. The aviation industry plays a significant role in the development of an economy. However, it involves high costs and huge investments. India is expected to become the world's largest domestic civil aviation market in the next 10 to 15 years. According to the International Air Transport Association (ITAI), India will displace the UK to reach third place in 2025, and by 2036, India will have nearly 478 million air passenger traffic, which will be more than that of Japan and Germany, combined.

About IndiGo

IndiGo is a low-cost domestic airline headquartered in Gurugram, Haryana, India. It was set up by Rahul Bhatia of Inter Globe Enterprises and Rakesh Gangwal, a United States-based NRI. Inter Globe holds 51.12% stake in IndiGo, and Caelum Investments, Gangwal's Virginia-based company, holds 48%. It is the largest airline in India by passengers carried and fleet size. It has 41 domestic and seven international destinations, which includes Kathmandu, Muscat, Doha, Singapore, Bangkok, Dubai, and Sharjah. To date, no deadly incidents have been recorded related to IndiGo aircraft.

About SpiceJet

SpiceJet is a low-cost domestic airline headquartered in Gurugram, Haryana, India. It was earlier known as Royal Airways. In May 2005, SpiceJet was being promoted by Ajay Singh and the Kansagra family. In March 2018, SpiceJet was awarded India's Best Domestic Airline award at the Wings India Awards for Excellence in the Aviation Sector organised by the Government of India, Ministry of Civil Aviation, and FICCI. As yet, no deadly incidents have been recorded related to SpiceJet aircraft. This airline commenced its international operations in October 2010 and now provides services to Afghanistan, Maldives, Nepal, Oman, Saudi Arabia, Sri Lanka, and the UAE.

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About DuPont Analysis

DuPont analysis is a performance measurement method started by DuPont Corporation in the 1920s. DuPont analysis breaks return on equity (ROE) into components to determine which component is most responsible for changes in ROE. There are three components of ROE, viz. profit margin, asset turnover ratio, and equity multiplier. Thus, we can represent DuPont in mathematical form, i.e. Return on Equity = Profit Margin x Asset Turnover Ratio x Equity Multiplier. Therefore, four ratios have been selected for this research paper, and the explanation of these ratios is as follows.

Ratios	*Meaning*	*Formula*	*Interpretation*
Profit Margin	Profit margin or net margin is expressed as a percentage. It is the margin that remains after deducting all operating expenses, taxes, interest, and preferred stock dividends.	Net Income / Net Sales or Revenue (as per annual reports of airline industries, the term revenue is used instead of sales)	This ratio shows how much the company earns in relation to its sales. Generally, higher the ratio, the better the earnings.
Asset Turnover Ratio	This ratio helps in determining how effectively a company uses its assets to generate revenue.	Net Sales or Revenue / Average Total Assets (average total assets means total assets at the beginning and end of the year divided by two; total assets means current + non-current as shown in the balance sheet)	Higher the ratio, better the company's performance, which shows that the company is generating more revenue per rupee of its total assets.
Equity Multiplier	This ratio measures financial leverage. It compares average total assets to average total equity, and indicates whether the company finances its assets from debt or equity.	Average Total Assets / Average Total Equity (shareholders equity can be expressed as the total of a company's share capital and retained earnings)	A high equity multiplier indicates that the company is using more debt than equity to finance its assets; higher the ratio, higher the financial burden on the company.
Return on Equity	ROE is the result of the above mentioned ratios. When we multiply the ratios with each other, the result we get is ROE.	Return on Equity = Profit Margin x Asset Turnover Ratio x Equity Multiplier	It measures the profitability of the concern. It shows how much profit a company generates with the shareholders' money. Higher the ratio, the better the profitability.

Objectives of the Study

The main objectives of the study are as follows.

- To analyse and compare the financial position and performance of IndiGo and SpiceJet.
- To describe the DuPont analysis of these companies with the help of ratios.
- To interpret the statistical results drawn from the research, and evaluate the usefulness of DuPont analysis in doing so.
- To suggest measures on the basis of the results to further improve the financial performance of the companies under study.

Research Methodology

In order to conduct the research, data has been taken from the annual reports of IndiGo and SpiceJet (from the websites of the respective airlines). A time period of five financial years have been covered, i.e. 2012-13 to 2016-17. Four ratios have been taken into consideration, viz. profit margin, asset turnover ratio, equity multiplier, and return on equity (ROE will show the overall impact and it is the crux of the previous ratios). Statistical tool t-test (two-tailed-test with $\alpha = 0.05$) has been used in order to evaluate results. Data is analysed manually without using any software.

Hypothesis

For hypothesis testing, T-test is applied. Various ratios are tested under the following hypothesis.

Profit Margin

Null Hypothesis (Ho): There is no significant difference between the profit margin ratios of IndiGo and SpiceJet.

Alternative Hypothesis (Ha): There is significant difference between the profit margin ratios of IndiGo and SpiceJet.

Asset Turnover Ratio

Null Hypothesis (Ho): There is no significant difference between the asset turnover ratios of IndiGo and SpiceJet.

Alternative Hypothesis (Ha): There is significant difference between the asset turnover ratios of IndiGo and SpiceJet.

Equity Multiplier

Null Hypothesis (Ho): There is no significant difference between the equity multiplier ratios of IndiGo and SpiceJet.

Alternative Hypothesis (Ha): There is significant difference between the equity multiplier ratios of IndiGo and SpiceJet.

Return on Equity

Null Hypothesis (Ho): There is no significant difference between the return on equity ratios of IndiGo and SpiceJet.

Alternative Hypothesis (Ha): There is significant difference between the return on equity ratios of IndiGo and SpiceJet.

Analysis and Interpretation

In this section, we will analyse the different ratios of DuPont analysis and interpret the results.

Profit Margin Ratio: Earning quality mainly measures the profitability and productivity of the company, and explains the growth and sustainability of future earning capacity. Profit margin ratio shows how much a company earns in relation to its sales. Generally, higher the ratio, the better the earnings.

Table 1: Showing Profit Margin Ratio of IndiGo and SpiceJet

Years / *Companies*	*2012-13*	*2013-14*	*2014-15*	*2015-16*	*2016-17*
IndiGo Airlines (in per cent)	8.32	2.77	9.11	11.99	8.55
SpiceJet Airlines (in per cent)	-3.32	-15.68	-12.77	8.61	6.83

Source: Annual Reports of IndiGo and SpiceJet of respective years from their websites

Table 2: Showing Two-tailed T-test of Profit Margin Ratio of IndiGo and SpiceJet

Companies	*Ratio*	*Mean*	*Standard Deviation*	*Standard Error*	*T-Test Value*	*Table Value*	*P-Value*	*Accept and Reject Criteria*
IndiGo Airlines	Profit Margin	8.148	3.347	1.673	-2.213 Or | T | 2.213	2.306	0.0578	2.213 < 2.306 Hypothesis Accepted 0.0578 ≥ 0.025 Result is not significant
SpiceJet Airlines		-3.266	11.039	5.519				

Findings: As we know, the higher the ratio, the better the earnings. In this case, the position of IndiGo is far better than SpiceJet during all the years. In the first three years, SpiceJet has incurred a loss and in the last two years, although it has earned a profit, the ratio is less compared to IndiGo. IndiGo's profitability is good, except in the year 2013-14, i.e. just 2.77%, but it is positive. As far as the hypothesis is concerned, the result reveals that 2.213 < 2.306 (calculated value is less than table value) and 0.0578 ≥ 0.025 [p-value is greater than value of α (in the case of the two-tailed t-test, we will take α/2 for calculation purpose, i.e. 0.05/2 = 0.025)]. Therefore, the result is not significant and the hypothesis is accepted. (We are using two-tailed T-test, therefore | T | modulus defines a real number regardless of its sign).

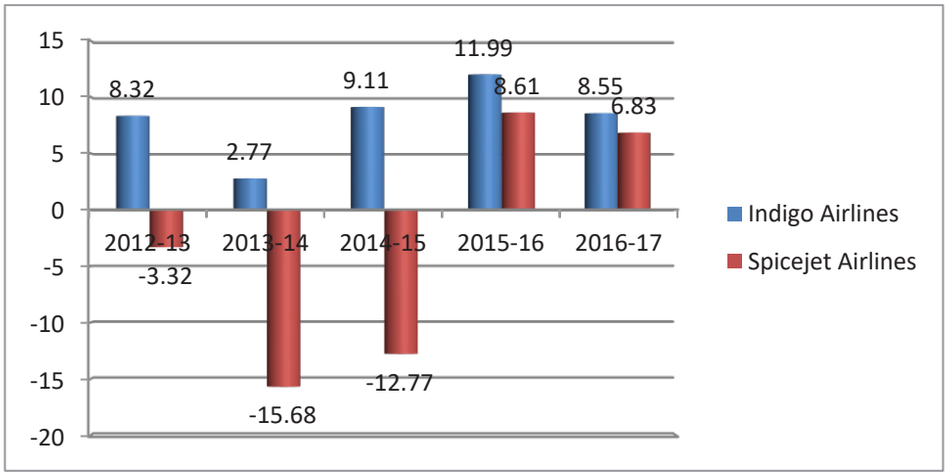

Fig. 1: Showing Trend in Profit Margin Ratio of IndiGo and SpiceJet

Asset Turnover Ratio: Investment in assets is the main and starting point of every company. Airlines have to invest huge amounts in purchasing fixed assets, and current assets are a part of the working capital, without which the performance of operations will become impossible. This ratio helps in determining how effectively a company uses its assets to generate revenue.

Table 3: Showing Asset Turnover Ratio of IndiGo and SpiceJet

Years / Companies	2012-13	2013-14	2014-15	2015-16	2016-17
IndiGo Airlines (in times)	1.93	1.51	1.44	1.40	1.37
SpiceJet Airlines (in times)	2.29	2.13	1.94	1.91	2.15

Source: Annual Reports of IndiGo and SpiceJet of respective years from their websites

Table 4: Showing Two-tailed T-test of Asset Turnover Ratio of IndiGo and SpiceJet

Companies	Ratio	Mean	Standard Deviation	Standard Error	T-Test Value	Table Value	P-Value	Accept and Reject Criteria
IndiGo Airlines	Asset Turnover Ratio	1.53	0.230	0.115	4.4435	2.306	0.0022	4.4435 > 2.306 Hypothesis Rejected 0.0022 ≤ 0.025 Result is significant
SpiceJet Airlines		2.084	0.1581	0.0790				

Findings: As we know, the higher the ratio, the more effective the company. In this case, position of SpiceJet is better than IndiGo during all the years. This means that SpiceJet has generated more revenue per rupee of its total assets compared to IndiGo. As far as the hypothesis is concerned, the result reveals that 4.4435 > 2.306 (calculated value is greater than table value) and 0.0022 ≤ 0.025 [p-value is less than value of α (in the case of the two-tailed t-test. we will take α/2 for calculation purpose, i.e. 0.05/2 = 0.025)]. Therefore, the result is significant and the hypothesis is rejected.

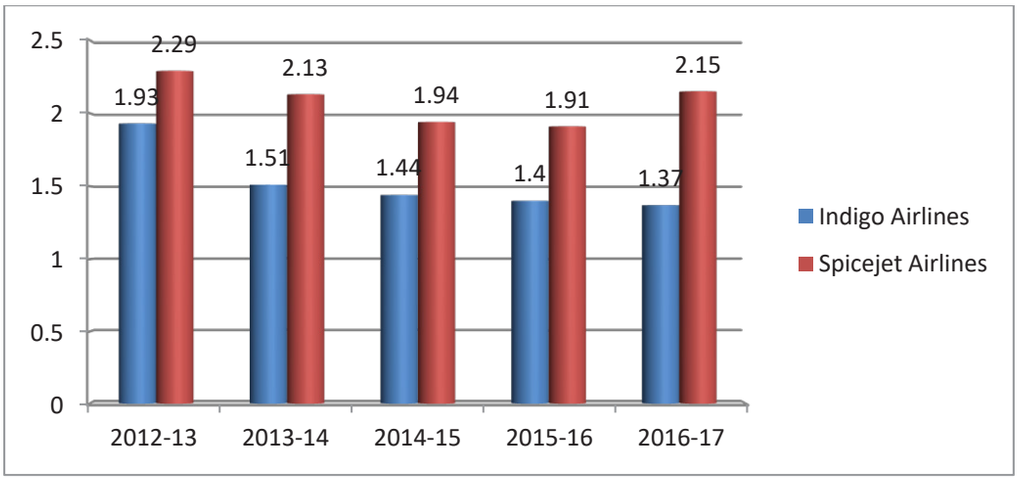

Fig. 2: Showing Trend in Asset Turnover Ratio of IndiGo and SpiceJet

Equity Multiplier Ratio: This ratio measures financial leverage. It compares average total assets to average total equity and indicates whether the company finances its assets from debt or equity. A high equity multiplier indicates that the company is using more debt than equity to finance its assets. Higher the ratio, higher the financial burden on the company.

Table 5: Showing Equity Multiplier Ratio of IndiGo and SpiceJet

Years / *Companies*	*2012-13*	*2013-14*	*2014-15*	*2015-16*	*2016-17*
IndiGo Airlines	10.73	16.08	23.99	10.55	5.03
SpiceJet Airlines	-13.56	-4.94	-2.46	-2.37	-3.54

Source: Annual Reports of IndiGo and SpiceJet of respective years from their websites

Table 6: Showing Two-tailed t-test of Equity Multiplier Ratio of IndiGo and SpiceJet

Companies	*Ratio*	*Mean*	*Standard Deviation*	*Standard Error*	*T-Test Value*	*Table Value*	*P-Value*	*Accept and Reject Criteria*
IndiGo Airlines	Equity Multiplier	13.276	7.151	3.576	-4.876 Or |T| 4.876	2.306	0.0012	4.876 > 2.306 Hypothesis Rejected 0.0012 ≤ 0.025 Result is significant
SpiceJet Airlines		-5.374	4.692	2.346				

Findings: As we know, higher the ratio, higher the financial burden on the company. This ratio is negative in the case of SpiceJet, because of its negative equity (due to heavy losses) during all the years, whereas it is positive in the case of IndiGo. However, the position is not satisfactory in the case of both the companies, thus indicating that both the companies are a financial burden. As far as the hypothesis is concerned, the result reveals that 4.876 > 2.306 (calculated value is greater than table value) and 0.0012 ≤ 0.025 [p-value is less than value of α (in the case of a two-tailed t-test, we will take α/2 for calculation purpose, i.e. 0.05/2 = 0.025)]. So, the result is significant and the hypothesis is rejected. (We are using two-tailed T test. Therefore, |T| modulus defines a real number regardless of its sign.)

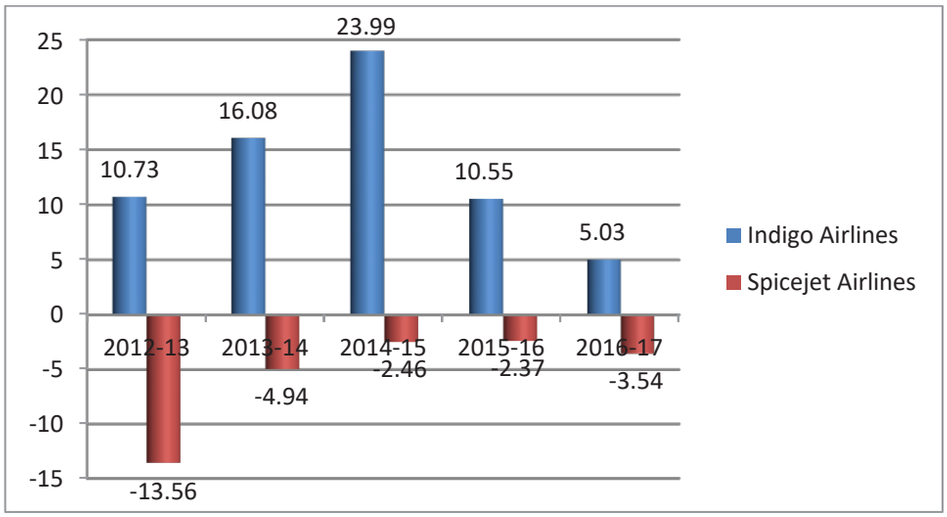

Fig. 3: Showing Trend in Equity Multiplier Ratio of IndiGo and SpiceJet

Return on Equity: Return on Equity = Profit Margin x Asset Turnover Ratio x Equity Multiplier. It measures the profitability of the concern. It shows how much profit a company generates with the shareholders' money. Higher the ratio, better the profitability.

Table 7: Showing Return on Equity Ratio of IndiGo and SpiceJet

Years / Companies	2012-13	2013-14	2014-15	2015-16	2016-17
IndiGo Airlines	172.30	67.26	314.71	177.09	58.92
SpiceJet Airlines	103.09	164.99	60.94	-38.97	-51.98

Source: Annual Reports of IndiGo and SpiceJet of respective years from their websites

Table 8: Showing Two-tailed t-test of Return on Equity Ratio of IndiGo and SpiceJet

Companies	Ratio	Mean	Standard Deviation	Standard Error	T-Test Value	Table Value	P-Value	Accept and Reject Criteria
IndiGo Airlines	Return on Equity	158.06	103.896	51.948	-1.773 Or |T| 1.773	2.306	0.1142	1.773 < 2.306 Hypothesis Accepted 0.1142 ≥ 0.025 Result is not significant
SpiceJet Airlines		47.614	92.801	46.400				

Findings: As we know, higher the ratio, better the profitability for the concern. In this case, the position of IndiGo is better than that of SpiceJet. IndiGo has incurred a profit in all the years, as shown in profit margin ratio, with positive equity in all the years. However, in the case of SpiceJet, the position is not good. SpiceJet has incurred losses in the first three years and a profit in the last two years, with negative equity during all the years. It is only because of mathematical calculations that we have found a positive return on equity in the first three years and a negative return in the last two years, as shown in the annexure, in the case of SpiceJet. As far as the hypothesis is concerned, the result reveals that 1.773 < 2.306 (calculated value is less than table value) and 0.1142 ≥ 0.025 [p-value is greater than value of α (in the case of a two-tailed t-test, we will take α/2 for calculation purpose, i.e. 0.05/2 = 0.025)]. Therefore, the result is significant and the hypothesis is rejected. (We are using a two-tailed T-test. So, |T| modulus defines a real number regardless of its sign.)

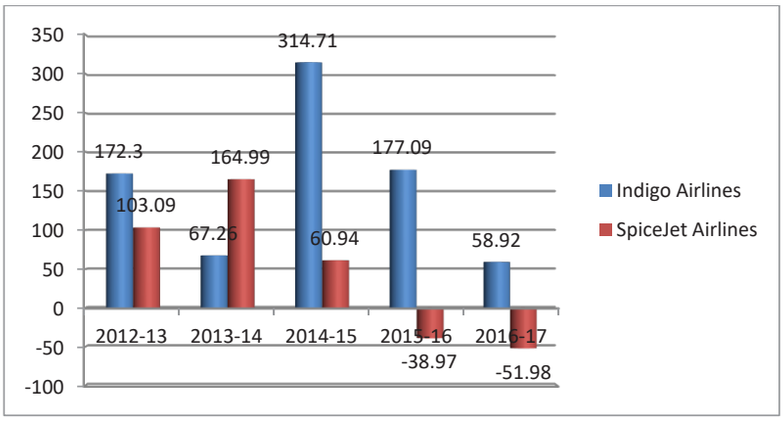

Fig. 4: Showing Trend in Return on Equity Ratio of IndiGo and SpiceJet

Summary of Findings

The ratio analysis has shown that the performance of IndiGo is much better compared to that of SpiceJet, except in the case of asset turnover ratio. SpiceJet is utilising its assets much better than IndiGo. However, in the case of other ratios, the position of SpiceJet is not satisfactory. It has incurred losses in the first three years of the time period under consideration, and has a negative equity during all the years. It needs great improvement. And as far as hypothesis is concerned, the following is a summary of the findings.

Ratios	*Significance Level*	*Results*
Profit Margin	There is no significant difference between the profit margin ratios of IndiGo and SpiceJet.	Null hypothesis has been accepted and alternative hypothesis has been rejected.
Asset Turnover Ratio	There is significant difference between the asset turnover ratios of IndiGo and SpiceJet.	Null hypothesis has been rejected and alternative hypothesis has been accepted.
Equity Multiplier	There is significant difference between the equity multiplier ratios of IndiGo and SpiceJet.	Null hypothesis has been rejected and alternative hypothesis has been accepted.
Return on Equity	There is no significant difference between the return on equity ratios of IndiGo and SpiceJet.	Null hypothesis has been accepted and alternative hypothesis has been rejected.

Suggestions

The airlines industry is one of the fastest growing industries in India. It involves infrastructural development. There are many airline companies in India, but for the purpose of this study, two companies have been taking into consideration, viz. IndiGo and SpiceJet. As far as financial performance is concerned, DuPont analysis is used for financial analysis. The results reveal that the performance of IndiGo is better than SpiceJet. The latter needs improvement in profitability. Return on equity is the main indicator of profitability, and SpiceJet has incurred losses in the first three years, and has a negative equity during all the years, which is bad. The company should try to earn profits; only then can it convert its negative equity into a positive one, making SpiceJet a growing organisation. As far as IndiGo is concerned, it needs improvement in asset turnover ratio and equity multiplier as a higher multiplier ratio indicates higher financial burden on the concern.

Concluding Remarks

To uplift the economy of the country, the infrastructural sector is required to be developed. With this in mind, the aviation sector must be given priority to attain sustainability. Therefore, the smooth and efficient operation of the aviation sector helps reduce the risk of failure of an economy. The performance of the aviation sector has always been a source of interest for researchers to judge the economic condition of the country. Towards this purpose, to know the financial condition of any sector or industry, the DuPont analysis is commonly used all over the world.

Limitations of the Study

The study is based on secondary data collected from a secondary data source, viz. the Internet and websites of

the companies under study. Therefore, the quality of the study depends on the accuracy, reliability, and quality of secondary data source. In addition, a time period of only five years has been researched.

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Annexure

Table 1: Profit and Loss Account of Inter Globe Aviation Ltd. or IndiGo Airlines for Relevant Years Ending in March (Rupees in millions)

Particulars	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*
Revenue						
Revenue from operations	55646.60	92.030.80	111,165.84	139,253.36	161,399.09	185,805.00
Other income	1,534.09	2552.34	3,304.39	3,945.83	4,613.93	7,890.70
	57,180.69	**94,583.14**	**114,470.23**	**143,199.19**	**166,013.02**	**193,695.70**
Expenses						
Aircraft fuel expenses	28,735.91	43,126.26	55,133.50	57,484.86	47,793.24	63,415.13
Aircrafts and engines rentals	8,007.15	13,561.48	16,703.14	19,522.38	26,121.52	31,253.73
Purchase of stock-in-trade	346.57	559.94	593.27	817.10	1,147.82	1,238.32
Change in inventories of stock	(6.83)	(18.65)	7.06	(31.72)	(11.32)	(2.94)
Employee benefits	5,218.07	6,972.33	9,289.40	11,886.91	17,899.23	20,481.90
Finance costs	514.27	578.01	1,225.77	1,155.32	1,348.53	3,307.80
Depreciation and amortisation	665.23	856.20	2,260.08	3,022.14	5,030.79	4,572.53
Other expenses	13,061.28	19,015.34	24,480.46	30,876.97	38,393.71	47,985.83
	56,541.65	**84,650.91**	**109,692.68**	**124,733.96**	**137,723.52**	**172,252.30**
Profit before tax (charge)/benefit	**639.04**	**9,932.23**	**4,777.55**	**18,465.23**	**28,289.50**	**21,443.40**
Tax(charge)/benefit						
Current tax						
Current period						
Minimum alternate tax (MAT)	---	---	---	---	(7,303.93)	(4,911.51)
Current period						
Less: MAT credit entitlement	(55.89)	(1,936.06)	(938.63)	(3,889.77)	---	---
Less: MAT recoverable written off	55.89	1,079.55	938.63	2,014.85	---	---
Deferred tax credit/(charge)	---	---	(1,602.03)	---	---	---
Profit for the year						
	639.72	(1,202.25)	(5.61)	(3,548.59)	(1,088.37)	59.99
Other comprehensive income for the year (Net of Tax)	**1278.76**	**7,873.47**	**3,169.91**	**13,041.72**	**19,897.20**	**16,591.88**
	---	---	---	---	---	(21.72)
Total comprehensive income for the years	1278.76	**7,873.47**	**3,169.91**	**13,041.72**	**19,897.20**	**16,570.16**

Source: Annual reports of Inter Globe Aviation Ltd.

Table 2: Balance Sheet of Inter Globe Aviation Ltd. or IndiGo Airlines of Relevant Years Ending in March (Rupees in millions)

Particulars	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*
EQUITY AND LIABILITIES						
Shareholder's funds						
Share capital	343.72	343.72	343.72	343.72	3,603.57	3,614.68
Reserves and surpluses	3,483.09	4,980.15	3,732.58	3,863.23	14,739.20	34,177.49
	3,826.81	**5,323.87**	**4,076.30**	**4,206.95**	**18,342.77**	**37,792.17**
Non-current liabilities						
Long-term borrowings	9,055.48	16,173.32	30,807.40	35,884.02	29,498.61	23,957.08
Deferred tax liability (net)	---	537.15	542.76	4,091.35	5,179.72	1,618.06
Other long-term liabilities	2,793.79	7,234.82	12,957.85	20,169.51	24,722.47	22,760.34
Long-term provisions	158.31	231.64	368.32	522.91	810.64	1,223.94
Deferred incentives	8,748.39	11,677.54	13,654.32	13,317.44	11,778.16	16,899.90
	20,755.97	**35,854.47**	**58,330.65**	**73,985.23**	**71,989.60**	**66,459.32**
Current liabilities						
Short-term borrowings	305.58	814.34	---	---	---	---
Trade payables	1,793.39	2,797.41	3,935.38	4,754.75	7,412.28	7,745.94
Other current liabilities	8,149.01	11,383.29	16,149.40	19,007.99	21,509.21	34,495.28
Short-term provisions	153.23	307.85	4,645.06	1,528.51	6,883.18	667.06
Deferred incentives	3,055.37	3,626.58	3,878.42	4,199.02	4,054.07	4,937.83
	13,456.58	**18,929.47**	**28,608.26**	**29,490.27**	**39,858.74**	**47,846.11**
TOTAL	**38,039.36**	**60,107.81**	**91,015.21**	**107,682.45**	**130,191.11**	**152,097.60**
ASSETS						
Non-current assets						
Fixed assets						
Tangible fixed assets	8,813.12	17,547.89	39,407.20	48,664.02	46,755.15	37,474.72
Intangible fixed assets	46.99	96.70	152.46	96.37	282.05	482.52
Capital work in progress	---	68.47	---	4.53	237.34	233.03
	8,860.11	**17,713.06**	**39,559.66**	**48,764.92**	**47,274.54**	**38,190.27**
Deferred tax assets (net)	665.10	---	---	---		---
Non-current investments	---	0.35	0.47	0.46	0.25	0.28
Long-term loans & advances	4,541.84	6,829.86	7,992.91	1,1181.34	11,930.62	15,796.65
Other non-current assets	885.30	4,857.72	14,315.23	16,055.60	14,977.84	3,646.34
Current assets	**6,092.24**	**11,687.93**	**22,308.61**	**27,237.40**	**26,908.71**	**19,443.27**
Current investments	5,234.18	11,383.42	12,714.84	5,167.52	9,741.20	37,134.10
Inventories	373.88	522.75	672.86	1,305.54	1,267.20	1,631.50
Trade receivables	389.20	685.22	891.22	1,045.50	1,571.14	1,587.02
Cash & bank balances	13,088.26	13,405.88	11,015.33	1,9993.80	37,186.70	46,325.35
Short-term loans & advances	3,179.45	3,586.59	2,231.34	1,555.61	2,248.75	4,140.86
Other current assets	822.04	1,122.96	1,621.35	2,612.16	3,992.87	3,645.23
	23,087.01	**30,706.82**	**29,146.94**	**31,680.13**	**56,007.86**	**94,464.06**
TOTAL	**38,039.36**	**60,107.81**	**91,015.21**	**107,682.45**	**130,191.11**	**152,097.60**

Source: Annual reports of Inter Globe Aviation Ltd.

Table 3: Calculation of Ratios of IndiGo Airlines

Ratios / *Years*	*Profit Margin Ratio = Net Income / Net Sales or Revenue*	*Asset Turnover Ratio = Net Sales or Revenue / Average Total Assets*	*Equity Multiplier Ratio = Average Total Assets / Average Equity*	*Return on Equity Ratio= Profit Margin Ratio x Asset Turnover Ratio x Equity Multiplier Ratio*
2012-13	7873.47 / 94583.14 x 100 = 8.32%	94583.14 / (38039.36+60107.81)/2 = 1.93	(38039.36+60107.81)/2 / (3826.81+5323.87)/2 = 10.73	8.32 x 1.93 x 10.73 = 172.30
2013-14	3169.91 / 114470.23 x 100 =2.77%	114470.23 / (60107.81+91015.21)/2 =1.51	(60107.81+91015.21)/2 / (5323.87+4076.30)/2 = 16.08	2.77 x 1.51 x 16.08 = 67.26
2014-15	13041.72 / 143199.19 x 100 9.11%	143199.19 / (91015.21+107682.45)/2 =1.44	(91015.21+107682.45)/2 / (4076.30+4206.95)/2 = 23.99	9.11 x 1.44 x 23.99 = 314.71
2015-16	19897.20 / 166013.02 x 100 = 11.99%	166013.02 / (107682.45+130191.11)/2 = 1.40	(107682.45+130191.11)/2 / (4206.95+18342.77)/2 = 10.55	11.99 x 1.40 x 10.55 = 177.09
2016-17	16570.16 / 193695.70 x 100 = 8.55%	193695.70 / (130191.11+152097.60)/2 = 1.37	(130191.11+152097.60)/2 / (18342.77+37792.17)/2 = 5.03	8.55 x 1.37 x 5.03 = 58.92

Table 4: Profit and Loss Account of SpiceJet Ltd. for Relevant Years Ending in March (Rupees in millions)

Particulars	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*
Income						
Revenue from operations	39,432.62	56,006.78	63,042.33	52,015.25	50,880.72	61,912.66
Other revenue	547.10	1,618.03	943.60	1,803.05	1,309.35	801.34
	39,979.72	**57,624.81**	**63,985.93**	**53,818.30**	**52,190.07**	**62,714.00**
Expenses						
Operating expenses	37,079.00	48,104.77	60,081.98	48,057.59	35,941.02	44,325.14
Employee benefit expenses	4,028.72	5,267.99	5,756.95	5,374.66	4,924.51	6,735.39
Selling expenses	2,704.20	2,791.45	3,521.47	2,793.61	1,637.05	2,092.90
Other expenses	1,604.35	1,805.33	2,193.82	2,371.65	3,003.19	3,326.42
	45,416.27	**57,969.54**	**71,554.22**	**58,597.51**	**45,505.77**	**56,479.85**
Earnings before interest, tax, depreciation and amortisation	**(5,436.55)**	**(344.73)**	**(7,568.29)**	**(4,779.21)**	**6,684.30**	**6,234.15**
Depreciation and amortisation	(309.98)	(835.45)	(1,482.60)	(1,266.25)	(1,798.07)	(1,986.05)
Interest income on bank deposit	211.42	426.60	384.60	196.76	211.21	324.04
Finance costs	(522.57)	(1,157.18)	(1,366.15)	(1,635.39)	(1,236.50)	(650.40)
Profit / (Loss) for the years before extraordinary items	**(6,057.68)**	**(1,910.76)**	**(10,032.44)**	**(7,484.09)**	**3,860.94**	**3,921.74**
Extraordinary items	---	---	---	613.55	636.94	385.54
Profit / (Loss) for the years	**(6,057.68)**	**(1,910.76)**	**(10,032.44)**	**(6,870.54)**	**4,497.88**	**4,307.28**
Other comprehensive loss	---	---	---	---	(5.47)	(21.22)
Total comprehensive income for the year	**(6,057.68)**	**(1,910.76)**	**(10,032.44)**	**(6,870.54)**	**4,492.41**	**4,286.06**

Source: Annual reports of SpiceJet Ltd.

Table 5: Balance sheet of SpiceJet Ltd. of Relevant Years Ending in March (Rupees in millions)

Particulars	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*
EQUITIES AND LIABILITIES						
Shareholder's funds						
Share capital	4,414.50	4,843.50	5,352.81	5,994.50	5,994.50	5,994.50
Reserves and surpluses	(5,886.82)	(7,223.63)	(15,880.61)	(22,144.67)	(16,383.13)	(12,085.43)
Money received against share warrants	---	135.68	---	---	---	---
Advance money received against securities issued	---	---	583.04	3,504.97	---	---
Non-current liabilities	**(1,472.32)**	**(2,244.45)**	**(9,944.76)**	**(12,645.20)**	**(10,388.63)**	**(6,090.93)**
Long-term borrowings						
Trade payables	6,504.35	14,299.62	12,362.83	11,198.65	9,209.22	7,759.84
Other long term liabilities	718.73	1,003.37	1,103.55	1,681.50	537.94	209.51
Long-term provisions	135.18	225.28	291.18	254.78	220.04	461.22
	84.68	116.76	160.22	152.95	2,634.02	2,897.25
Current Liabilities	**7,442.94**	**15,645.03**	**13,917.78**	**13,287.88**	**12,601.22**	**11,327.82**
Short-term borrowings						
Trade payables	2,050.00	2,481.52	2,800.00	2,985.92	1,050.00	2,522.45
Other current liabilities	4,701.27	6,887.01	10,515.09	10,105.22	7,209.87	5,845.15
Short-term provisions	6,915.83	7,886.79	12,068.99	8,979.23	14,310.26	14,886.67
	65.67	54.20	113.05	3,352.85	3,684.34	1,417.92
TOTAL	**13,732.77**	**17,309.52**	**25,497.13**	**25,423.22**	**26,254.47**	**24,672.19**
ASSETS	**19,703.39**	**30,710.10**	**29,470.15**	**26,065.90**	**28,467.06**	**29,909.08**
Non-current assets						
Fixed assets						
Tangible assets						
Intangible assets	8,496.65	17,925.45	18,728.45	17,114.38	16,265.49	16,188.79
Capital work in progress	5.47	9.77	38.19	23.87	10.10	9.02
Investments in subsidiaries	0.64	12.05	7.73	---	---	---
Long-term loans and advances	---	---	---	---	---	0.20
Non-current tax assets	4,701.32	2,279.04	3,335.56	2,314.47	3,342.00	3,108.07
Other non-current assets	---	---	---	---	292.77	211.54
	2,156.28	2,627.05	2,664.50	344.36	1,753.88	2,127.27
Current assets	**15,360.36**	**22,853.36**	**24,774.43**	**19,797.08**	**21,664.24**	**21,644.89**
Inventories						
Trade receivables	316.53	456.23	451.52	451.17	665.46	869.94
Cash and bank balances	204.09	1,050.32	1,557.35	1,216.76	433.74	617.69
Short-term loans and advances	2,359.07	2,170.82	50.56	235.84	1,059.02	2,011.65
Other current assets	1,334.57	1,905.04	1,057.28	4,138.06	1,848.33	3,195.45
	128.77	2,274.33	1,579.01	226.99	2,796.27	1,569.46
TOTAL	**4,343.03**	**7,856.74**	**4,695.72**	**6,268.82**	**6,802.82**	**8,264.19**
	19,703.39	**30,710.10**	**29,470.15**	**26,065.90**	**28,467.06**	**29,909.08**

Source: Annual reports of SpiceJet Ltd.

Table 6: Calculation of Ratios of SpiceJet Airlines

Ratios / *Years*	*Profit Margin Ratio = Net Income / Net Sales or Revenue*	*Asset Turnover Ratio = Net Sales or Revenue / Average Total Assets*	*Equity Multiplier Ratio = Average Total Assets / Average Equity*	*Return on Equity Ratio= Profit Margin Ratio x Asset Turnover Ratio x Equity Multiplier Ratio*
2012-13	(1910.76) / 57624.81 x 100 = -3.32%	57624.81 / (19703.39+30710.10)/2 = 2.29	(19703.39+30710.10)/2 / ((1472.32)+(2244.45))/2 = -13.56	-3.32 x 2.29 x -13.56 = 103.09
2013-14	(10032.44) / 63985.93 x 100 = -15.68%	63985.93 / (30710.10+29470.15)/2 = 2.13	(30710.10+29470.15)/2 / ((2244.45)+(9944.76))/2 = -4.94	-15.68 x 2.13 x -4.94 = 164.99
2014-15	(6870.54) / 53818.30 x 100 = -12.77%	53818.30 / (29470.15+26065.90)/2 = 1.94	(29470.15+26065.90)/2 / ((9944.76)+(12645.20))/2 = -2.46	-12.77 x 1.94 x -2.46 = 60.94
2015-16	4492.41 / 52190.07 x 100 = 8.61%	52190.07 / (26065.90+28467.06)/2 = 1.91	(26065.90+28467.06)/2 / ((12645.20)+(10388.63))/2 = -2.37	8.61 x 1.91 x -2.37 = -38.97
2016-17	4286.06 / 62714.00 x 100 = 6.83%	62714.00 / (28467.06+29909.08)/2 = 2.15	(28467.05+29909.08)/2 / ((10388.63)+(6090.93))/2 = -3.54	6.83 x 2.15 x -3.54 = -51.98

Note 1: Balance sheet Performa of IndiGo in 2017 is vast. Hence, some items are to be clubbed together. For example, in the asset side, intangible assets under development are clubbed with intangible assets, loans and other financial assets are clubbed with long-term loans and advances, and income tax assets are clubbed with other assets. Under current assets, loans and other financial assets are included in short-term loans and advances. And in the liability side, under non-current liabilities, other financial liabilities are included in other long-term liabilities, and under current liabilities, other financial liabilities and current tax liabilities are included in other current liabilities. Similar to IndiGo, some items in SpiceJet have also been clubbed together in the year 2017.

Note 2: IndiGo had 0.00% convertible preference shares of Rs.1,000 fully paid up from FY 2012, which are now converted into equity shares. The company is not paying any dividend to the shareholders. The value of these shares, therefore, are included in the shareholder's funds in these years because of their convertibility nature, and as shown in the schedules of the company's accounts. SpiceJet does not have preference shares.

Note 3: Return on Equity Ratio = Profit Margin Ratio x Asset Turnover Ratio x Equity Multiplier Ratio has to be taken into account. However, ROE can be calculated with the help of another formula, i.e. Net Income/Average Equity x 100. The results will be slightly different.

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