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International Review of Business and Economics

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Mr. FAGIN & U

- Is there any relationship between Child labour, crime rates and country income per capita?

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Abstract

Child labour exists in varying degrees in virtually all countries aspiring to reach high income status. The prevalence of child labour and associated criminal activities have been portrayed in the 19th century novels of Charles Dickens, perhaps most vividly in the character 'Fagin' in the novel 'Oliver Twist'. It seems clear that the early years of the industrial revolution in Britain gave rise to demand for increased child labour and also provided fertile ground for criminal activities. However, it is also evident from the experience of the high-income countries that the hallowed peaks of the development process witness an end to such activities representing the dark side of income creation. This paper examines whether there is a definite relationship between country income per capita and the prevalence of crime and child labour. The presumption is that as incomes grow there is an increase in the use of child labour as well as in crime, with a tapering- off after a certain income level. This paper presents evidence for such an inverted 'U' relationship between child labour and income per capita as well as between the crime index and income. These findings may also throw some light on the puzzle of the sudden fall in U.S crime rates in the 1990s.

Keywords: *Income-Child labour, urban inequalities, crime rates, Inverted-U theory*.

JEL Classification Codes: F5, O25, O25, J11

I. Introduction

Despite concerted efforts by international organizations such as the ILO and the promise of the passage of strict laws to ban the scourge by national governments, child labour in economic activities exists to varying degrees in all the developing nations in the low- and middle-income categories. So tenacious is its presence in these countries that very often efforts have been redirected to ameliorating the suffering of child workers, by regulating the conditions and hours of their employment, and ensuring that they do not drop out of school.

Child workers do contribute to the family purse, but their conditions of work are indeed harsh: for the little girl who sells you flowers on the streets and curtsies saying, ‘your own girl, sir’, as for the nimble-fingered child worker in a matchbox factory. Their lot has changed little from that portrayed vividly in the nineteenth century novels, ‘Oliver Twist’, ‘A Christmas Carol’ etc., of the celebrated writer Charles Dickens. Also, it does seem that the same factors that draw children out of their homes and schools to work also serve to provide a fertile soil for the breeding and thriving of criminal activities. Such a phenomenon is personified in the character, Mr. Fagin, the organizer of child pickpockets in Dicken’s book. ‘Oliver Twist’.

Charles Dickens had been born in the stagecoach era but lived to experience the steamship and railways era. In his lifetime, the industrial revolution was increasing demand for labour, creating urban conglomerates with unsavoury living conditions. Efforts of social reformers such as Robert Owen to improve living and working conditions of child workers could not make a decisive impact. Owen, a philanthropist industrialist and manager had been pained by the conditions of children in British poorhouses that bred crime and vice, and had tried to pass a resolution in a meeting of manufacturers in 1817 to limit the number or hours of work of children – but to no avail. It would take several decades of industrial expansion that also increased aggregate incomes before the living conditions of the masses improved.

Thus, there seems to be grounds for a premise of a changing relation, as a country industrializes and develops, between income levels and the incidence of child labour as well as that of crime. In this paper we examine this relationship in a cross-section sample of a large number of countries. Specifically, the cross-section data will be examined to see if an inverted 'U' relationship exists between income per capita and the extent of child labour, as well as between income per capita and the incidence of crime captured by a crime index.

In the next section we first look at some relationships between phenomena in management and economics that have been shown to have an inverted 'U' relation. Then we proceed to present arguments that indicate that such a relation is also likely between income, child labour and levels of crime. Section III examines cross-country data for the presumed income-child labour relation, using an interrupted regression technique, and section IV does the same for the income-crime link. There is a final, concluding section.

II. Inverted 'U' s in economics and allied sciences

As the literature in social sciences contain a number of examples – sometimes untested presumptions as well – of an inverted 'U' relation, it may be appropriate to mention a few of those before proceeding with our tests. It may be added that these relationships have been mostly pinned down with the initial fillip coming from actual observation of the phenomena; that is, as was the case with the Phillips Curve, where actual observation of the phenomena in the British context led to the formulation of the theory and the graphical representation.

In economics, perhaps the most celebrated example of an inverted U relation is the Laffer Curve which shows that as tax rates rise tax revenue rises, but falls after a certain tax rate level – so that then it is a tax cut that would increase revenue further (see Firouz 1989). Another example is economics is that presented by Calmfors and Driffil (1988), who perceive an inverted 'U' relationship between the centralization of wage bargaining and the growth of wages. A similar result is seen in industrial organization theory, with an intermediate level of competition auguring best for innovation (Aghion et.al, 2005). Dating further back is the Kuznets Curve (1955) which presents the hypothesis that a society develops and becomes richer, income inequality first rises, but falls later.

Inverted U relationships have also caught the interest of researchers in other areas of social science. In political science, increasing democracy first increases the chances of engaging in warfare, but reduces the chance of this possibility at a higher degree of democracy – so that a toddler-democracy is more prone to war than both a dictatorship and a mature democracy (Hegre et.al, 2001). Psychologists have noted such a relation between satisfaction with one's lot, i.e, life satisfaction, and income five to fifteen years later (Oishi et.al., 2007). Extremely satisfied people earned less than the moderately satisfied, and also achieved lower levels of education. A similar result is seen in the area of sports training: Berman et.al.,(2002) studied the training programs and outcomes of the NBA teams and found that while the basketball teams won more when they played together for a number of years, this effect tended to be mitigated after some four years or so. Too much of training in teams or at the same job as an individual may be self-defeating after a certain level; this could be why, for instance, John McEnroe did not wear himself out in training on tennis courts or in the gym – to avoid losing his magic touch (he chose, instead, to play doubles as well, perhaps to be open to varied impulses and stroking angles)!

As mentioned in the beginning of this section, much work on the inverted U has had its triggering motivation in the observation of actual world phenomena. The writings of a novelist two centuries ago gave the initial impulse for this paper, but the same phenomena may be seen now in the newly industrializing nations.

III Factors influencing child labour: a role for income?

Demand-side as well as supply-side factors are seen to influence the extent of child labour used in an economy. And, income growth in developing nations can affect the extent of usage of child workers can be seen to affect both the demand for, and the supply of. Child labour.

There is a blatantly obvious reason for demanding child labour as children are more obedient, easier to control and manipulate than adults. Family business owners often prefer to employ their own children instead of outsiders. Also, this gives their children a hands-on experience of the business. They don't have to be given regular money payments, unlike outsiders, can be trusted more, and will also be getting trained to carry on the family tradition. Microfinance meant to increase rural family incomes may have the unintended effect of increasing child labour in family businesses, especially where skill is involved, as in tailoring etc. Wyydick (1999) notes that microloans have a negative effect on school attendance and child labour if skilled labour for tailoring is used in the family business. Menon (2005) found negative effects of microfinance on schooling in Pakistan. A $17 microloan was seen to reduce the likelihood of attending schooling by 9%. And, apart from the advantage of being easy to control, another blatantly obvious reason for employing child workers is their endowment of small, nimble fingers suited for industries manufacturing matchboxes, crackers etc. Thus, there are plenty of arguments in favour of economic growth and rise in incomes increasing the demand for child labour.

On the supply side, child labour fills an important 'consumption smoothing' function, reducing vulnerability to family income shocks. Child labour can be used for consumption smoothing, as it is not affected by the shocks impinging on parents' income. So, children may be supplied for work during a reduced income period – but may continue to work even when incomes have risen (Guarcellon et.al., 2003). The financial scenario is also important; in developing countries financial markets lag behind income expansion and there are credit constraints. In the presence of credit constraints, parents cannot take credit against the expected future income of their children who are still at school. Hence child labour becomes an alternative for consumption smoothing.

There are a number of other studies in a similar vein. Child labor may reduce with a rise in family income. Nielsen and Dubey (2002) find in a case study of India that covering – low – household expenses is a main reason for the prevalence of child labour. Edmond (2005) gets a similar result for Vietnam. In a study on Ethiopia, Cockburn (2001) finds that ownership of assets like oxen and water is likely to substitute for child labour - perhaps, the necessity to send children out to fetch water and so on is reduced. But child labour could still be involved in the maintenance of such assets. However, there is evidence to the contrary from Pakistan and Ghana (Bhalotra and Heady, 2003): daughters of richer land-owner households are seen to be more likely to work. There are instances of increased child labour and reduced enrolment in Indonesia due to participation in microcredit programs designed to increase family incomes. Islam amd Chongwood (2013) find a negative effect, with especially younger children and girls being forced to drop out of school and work.

What transpires from the above analysis of demand and supply factors arising from income expansion translating into actual child labour in the economy is that there is, indeed, a case for more children being put to work a country industrializes and incomes rise. There are some jobs, besides those requiring small, nimble fingers, such as that of rushing out to clean car windshields at traffic signals, which can be done by children alone. But the verdict rests on actual testing, which is achieved in this paper through a cross-country analysis.

IV. Crime and incomes: the case for a linkage

When the offence is a crime of passion, it is, of course, useless to search for a logical explanation linking it to income or any other variables. But, when such is not the case, it may be amenable to logical analysis. There are two points of view about the effect of income growth on crime. One perspective is that lack of adequate income pushes people into crime. This would be particularly true when then are large inequalities, not when everyone is uniformly poor, with little inequality, as could be the case in primitive societies. The opposing view, which economists tend to favour, is that crime increases with a rise in the general income level; the increased visibility of luxury goods is an incentive for crime, and there could be also a rise in crime linked to drugs and alcohol.

In the literature, more attention has been paid to the effects of crime on output and growth, not vice versa. But there are studies on the determinants of crime both at the individual and the macro-level. Becker (1968) argues that economic incentives have an influence on criminal activities just as they have on law-abiding citizens, and that the probability of detection and the kind of enforcement and punishment also play an important role. At the macro-level, a study by the U.S Department of Justice found that states that were hurt worst by the 2007 -2010 recession experienced the largest fall in crime rates (The Economist, 2011). At an individual country level, Mulok et.al., (2016) find that economic growth in Malaysia has had a positive effect on crime.

Our observations in the introduction about the activities of the “benevolent” (!) Fagin who is portrayed to have lived in the industrialization era of Britain, the first country to industrialize, is still relevant today for developing and industrializing nations. Economic growth draws people from the villages into large urban centres, the urban – rural wage differential functioning as a catalyst for migration (Harris and Todaro, 1970). The high and institutionalized urban wages rates attract rural labour even when urban unemployment prevails. The ensuing urban inequalities can breed crime; a positive relation between inequalities and crime has been noted by Ehlrich (1973).

Income growth may also lead to increased competition for the available output pie and inter-group conflicts. Ray and Esteban (2017) argue that growth is not ‘a tranquil paradigm’, but is, rather, intrinsically uneven, with winning and losing sectors and groups – so that social conflicts may accompany growth.

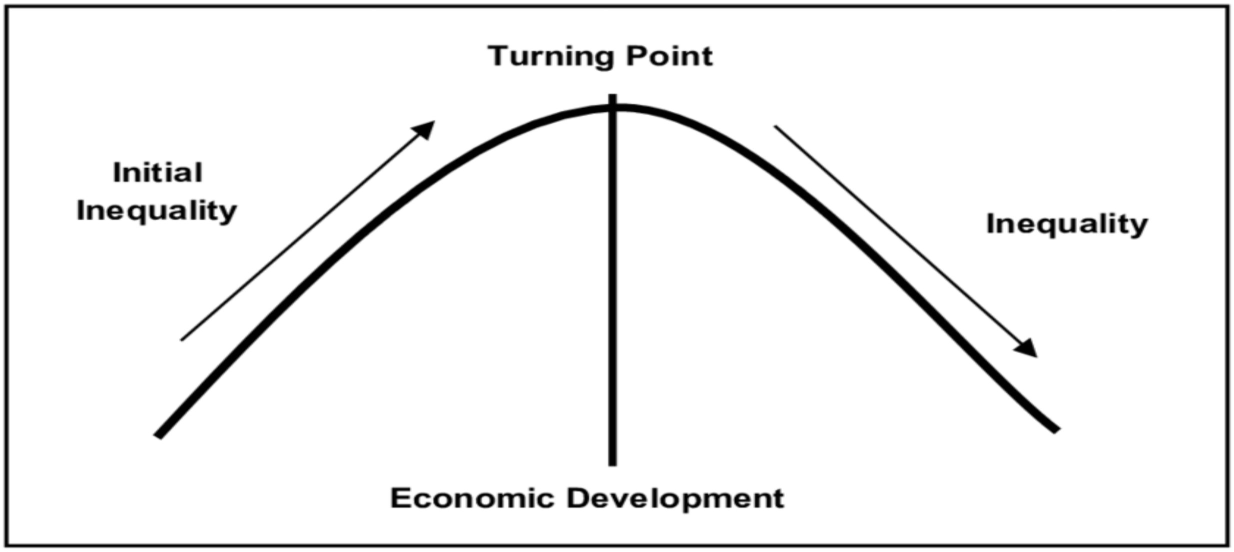
Thus, the likelihood of income growth leading to social unrest and crime does loom large. The attempt in this paper is to explore this possibility using a cross-country approach using a sample of eighty-six nations comprising of low income as well as medium and high-income categories.

V. Empirical Analysis

V.1 An inverted “U’ for child labour

The earlier studies exploring inverted U relationships have tended to rely on the quadratic regression method. But that test in isolation has been now deemed to be insufficient in drawing definite conclusions about such relationships (see Lind & Mehlum, 2010; Simonsohn, 2018). Hence, in this paper the two lines approach proposed by Simonsohn (2018) is used. Since an inverted U or a hump has opposing slopes on the two sides of the peak or turning point, the slope of a line fitted in the first part of the curve would be positive, turning negative in the part of the curve after the peak. See figure 1 below.

Figure 1. The Two Lines Approach



Thus, it makes sense to estimate two slopes up to the turning point at the peak, in two separate regression tests. But, alternately, as in Simonsohn (2018), an interrupted regression can be run instead of the two separate tests. Such an approach is adopted in this paper, and it is deemed unnecessary to run preliminary tests using a quadratic regression, inasmuch as that provides no conclusive evidence.

To run the interrupted regression, first an appropriate peak should be chosen to run the regression around it, so to say. One obvious choice is the maximum value, $x_{peak,}$ corresponding to the peak value of the dependent child labour variable along the Y axis, in figure 1. Simonsohn (2018) describes the approach to another, perhaps more suitable turning point for the regression if it works well. The choice works like this: fits run two regressions using the maximum peak up to and beyond that peak. Then the choice of the turning point for the interrupted regression is made using the ratio, $t_2 / (t_1 + t_2)$, of the test statistics; such a procedure is adopted to give additional allocations of observations to the statistically weaker line. For details of the procedure, please refer to Simonsohn (2018).

The databank for this exercise consists of 83 countries, both low income and middle income and a few upper income nations. More high-income nations will not serve the purpose of the study as they have virtually no child workers. The appendix lists the countries in the sample for this estimation. Both the child labour data and the figures for income per capita for all the countries in the sample are from the World Bank databank.

The equation estimated as an interrupted regression is as follows:

(1) $CL = \alpha_0 + \alpha_1 X_{low} + \alpha_2 X_{high} + \alpha_3 HIGH$

Where CL = percentage of child labour in total child population 7-14 years of age,
$X_{low} = (X_{peak} - X)$ for $X \leq X_{peak}$ and $X_{low} = 0$ for $X \geq X_{peak}$;
$X_{high} = o$ for $X \leq X_{peak}$ and $X = (X_{peak} - X)$ for $X \geq X_{peak}$;
HIGH = 0 for $X \leq X_{peak}$ and HIGH =1 for $X \leq X_{peak}$

An inverted U is seen to be present when the coefficients α_1 and α_2 are significant with differing signs, coming out negative and positive respectively, indicating that a change of slope occurs after the peak.

For the initial estimation, the peak was chosen using the procedure presented in Simonsohn (2018); the corresponding income level was 1409 dollars. The results of the estimation are presented in table 1.

Table 1. Interrupted Regression Estimates of equation (1) for Child Labour

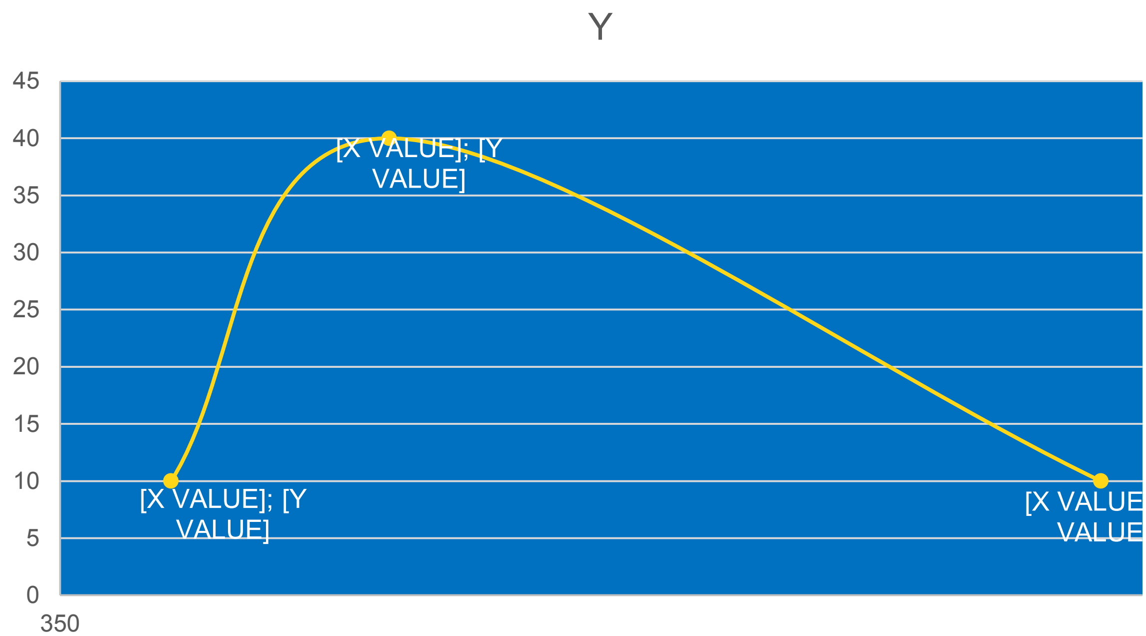
Dependent Variable	Chosen peak	α_0	α_1	α_2	α_3	R_2 adj
(1) CL	At X = 1409	27.1366**	.00144	-.00089**	-11.453*	0.374
(2) CL	At X = 1197.7	22.363***	.0132*	-.00137*	-1..8827*	0.351

- Three stars represent significance at 1% level for the t statistic and two and one stars at 5 and 10 percent respectively.

In estimation (1) presented in the table, as can be seen, the regression coefficient for X_{high} is significant and negative. But while that for X_{low} has a positive sign, it is not significant. Hence, though the two coefficients have differing signs, are of the same sign, the presence of an inverted U relation cannot be ascertained.

For the second run, the peak chosen was that available in the data itself, a value of 1197.7, corresponding to the highest child labour usage of 45.6% in the sample. When the equation is re-run as (2), a confirmation of the inverted U relationship between child labour and income per capita becomes evident: the coefficients for both X_{low} and X_{high} are, significant at the ten percent level, with a positive and negative sign respectively. This relationship is depicted in figure 2 below:

Figure 2. Lopsided Inverted U: Child Labour Vs. Country Income per Capita



The curve relating child labour and income per capita for the cross-section sample first rises, up to the income level of 1197.7, and then turns downwards, clearly an inverted U or hump--shaped relation. As child labour use is less in the highest income than the countries in the lowest income category, a *lopsided inverted U* curve is obtained, with the right-side tail loner than the left-side tail.

V.2. Charting the crime rate – income per capita relationship

As the choice of the peak for the analysis using initial t statistics did not compare favourably in eventual results with the choice of the peak directly from data, we proceed with the latter approach here for the crime rate part of the study. The data for the Crime Index for the 88 countries in the sample, obtained from *World Population Review*, is given in the appendix. The sample is not the same as that for the child labour analysis as high-income countries have been added.

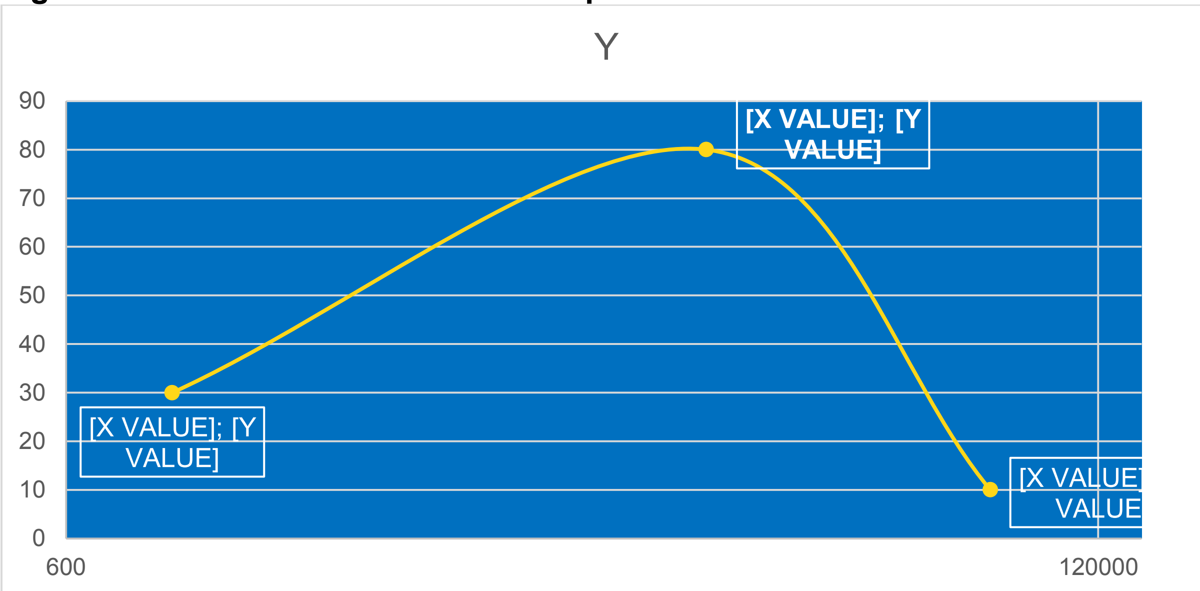
Now we proceed to undertake the interrupted regression for the crime rate – incomes relation. The peak used is the income of 16054.5 dollars per capita corresponding to the highest country crime index of 84. The estimation is obtained as follows:

(2) $CRIME = 59.22734^{***} + 0.000504^{*} X_{low} - 25.5213^{**} X_{high} - 0.00004\ HIGH$
Adj. R_2 for the regression = 0.5133.

It can be seen from (2) that the coefficients for X_{low} and X_{high} emerge with opposing signs as required for an inverted U relation between crime and income per capita. The coefficient for X_{low} is positive and significant at the 10 percent level, while that for X_{high} is negative (indicating a reversed relation, a tapering down after the peak) and significant at the five percent level.

The relation between the variables will, as in the case of the child labour-income relation, takes the shape of a lopsided inverted U. The curve is lop-sided in the sense the right-side tail reaches lower down than the left-side tail, as the crime index in the richest countries tends to be lower than that in the poorest.

Figure 3. Crime Rate and Incomes: Lopsided Inverted U Curve



Thus, our analysis does point to a discernible inverted U relation between crime and country income levels, with a rise in crime up to the higher-income echelons among the middle-income nations.

The insights gained from the multi-country; cross-sectional study conducted here can provided some understanding of individual country experiences as well. Levitt & Dubner (2020) discuss the long-standing riddle of a sudden drop in U.S crime rates in the 1990s – and come up with an innovative explanation based on changed abortion laws. This paper may be providing an alternative explanation for the sudden drop in U.S crime rates in the 1990s. Our analysis indicates that crime rates may drop after the country reaches a per capita real GDP level of around 17,000 dollars; in the U.S, crime rates started dropping in the 1990s after reaching a per capita income level of around 24,000 dollars, not too distant from the figure projected by us.

V Concluding observations

The British dilemma of increasing child labor use and crime during the period of rapid economic growth during industrialization has been vividly portrayed in the novels of Charles Dickens, both the vices personified in the character of Fagin in 'Oliver Twist". However, such a concomitance between crime and growth is clearly not time-invariant, as crime rates and child labor usage are at historically low levels in the post-industrial Nordic societies – and even in modern Britain. Such an observation leads to the premise that crime rates and income per capita may have an inverted U relationship. The analysis in this paper confirms an inverted U relation, between child labor use as well as crime rates with country income per capita. These inverted 'U's are found to be lopsided in shape, with the right-side tail longer than the left. Finally, the analysis in this paper may well provide an explanation for the sudden drop in U.S crime rates in the 1990s, after a steady increase in the previous decades.

APPENDIX

List of 83 countries used for the child labor-income relationship estimation:

Albania, Algeria, Angola, Azerbajan, Argentina, Belarus, Benin, Bolivia, Bosnia, Brazil, Cambodia, Cameroon, Central African Republic, Colombia, Congo Democratic Republic, Cote D'Ivoire, Dominican Republic, Ecuador, Egypt, El Salvador, Ethiopia, Fiji, Gabon, Gambia, Georgia, Ghana, Guatemela, Guinea, Haiti, Honduras, India, Indonesia, Iraq, Jamaica, Jordan, Kazaksthan, Kenya, Kyrgyz Republic, Laos, Madagascar, Namibia, South Africa, Moldova, Pakistan, Syria, Mali, Mauritania, Morocco, Mozambique, Liberia, Nepal, Senegal, Nicaruga, Paraguay, Peru, Philippines, Nigeria, Serbia, Somalia, Sri Lanka, Sudan, Mexico, Lesotho, Uganda, Thailand, Togo, Tunisia, Panama, Tanzania, Uzbekistan, Vietnam, Zambia, Mongolia, Zimbabwe, Turkey, Rwanda, Rumania, Ukraine, Trinidad, Venezuela, Uruguay, Chile, Portugal.

Table A.1: Crime Index*

Country	Crime Index	Country	Crime Index
Venezuela	84.86	**Libya**	61.26
South Africa	77.02	**Malaysia**	60.66
Honduras	75.84	**Tanzania**	59.83
Brazil	69.48	**Uganda**	56.47
El Salvador	68.63	**Guatamela**	56.05
Namibia	68.14	**Costa Rica**	55.77
Jamaica	65.26	**Algeria**	54.41
Bangladesh	64.98	**Bolivia**	54.31
Nigeria	64.64	**Zimbabwe**	53.84
Peru	64.58	**Botswana**	52.89
Kazakstan	64.23	**Colombia**	52.54
Argentina	62.96	**Mexico**	52.51
Kenya	62.38	**Uruguay**	52.33
Cambodia	51.8	**Greece**	39.29
Ghana	51.57	**Germany**	34.6
Morocco	49.53	**Norway**	33.51
Ukraine	49.04	**Malta**	37.73
Iran	49.03	**Spain**	31.07
Ecuador	48.91	**Israel**	30.71
Egypt	48.53	**Bahrain**	30.18
Vietnam	48.22	**Luxembourg**	30.17
Mauritius	47.34	**South Korea**	29.24

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Country	Crime Index	Country	Crime Index
Sweden	47.21	**The Netherlands**	28.54
Chile	47.12	**Saudi Arabia**	28.22
USA	46.73	**Singapore**	27.7
France	46.45	**Czech Republic**	25.99
Indonesia	46.26	**Denmark**	24.72
Ireland	45.43	**Austria**	23.23
Italy	44.35	**Iceland**	23.15
The UK	43.64	**Finland**	22.75
Australia	42.7	**Oman**	21.55
Belgium	42.5	**Switzerland**	21.18
India	42.38	**Japan**	15.9
Russia	41.7	**UAE**	15.52
Thailand	41.29	**Qatar**	12.0
The Philippines	41.089	**Slovenia**	22.01
New Zealand	40.89	**Fiji**	58.9
Canada	39.48	**Somalia**	58.5
Mongolia	57.9	**Serbia**	37.8
Maldives	53.2	**Nepal**	34.56
Pakistan	44.08	**Sri Lanka**	40.22
Lebanon	43.36		
Tunisia	41.88		
Nicaruga	44.44		

Jordan	40.83	

Source: World Population Review, 2020, index including all categories of crime

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Thailand's Trade Policies: Short Review of Successes and Shortcomings

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Abstract:

While Thailand is often considered a bastion of free trade, the Southeast Asian country has deployed a multitude of different policies that has led to Thailand's current economic success. Thailand has generally always sought to be a modern, liberal country. Before the Asian Financial Crisis of the 1990's Thailand saw unprecedented economic growth before the crisis and has since focused on even more liberalization measures. The paper aims to explore some of the different parts of economic theory that Thailand has implemented (both liberal and protectionist), in order to explain some of Thailand's economic success and some possible shortcomings. The first section of the paper explores various parts of economic theory such as different obstructions to free trade and Standard Trade theory. The next part of the paper applies these concepts to Thailand to see how the country implements these theories and policies. Major protectionist policies that Thailand follows are tariffs and resistance to international IPRs. Another critical aspect that is discussed for Thailand's economic success is the gravity model. The research concludes that while some protectionist policies have certainly helped Thailand in the short term, their desire to continue liberalizing will help the country in the long run.

Introduction:

Since the Asian Financial Crisis of the 1990's Thailand has become an increasingly important and strong economy in Asia and the rest of the world. In Asia, Thailand is a founding member of the Association of Southeast Asian Nations (ASEAN) and has since joined several bilateral and multilateral trade agreements (Trade.gov, 2019). Thailand has long strived to integrate into the international economy and pursue liberal and outward-oriented trade policies (Talerngrsi, 2005). Thailand currently stands as a beacon of free trade and development for developing countries and has a considerably higher GDP(PPP) per capita than most of its immediate neighbors including Myanmar, Laos, and Cambodia (CIA, 2018). This paper aims to explain why Thailand has been so economically successful especially relatives to these neighbors.

The research will first go over some economic theory before applying it to the case of Thailand in the next part. The theoretical section will explain key parts of Standard Trade Theory such as comparative advantage, and Heckscher-Olin Samuelson theorem and will also look at obstructions as well as reasons against free trade such as infant industry, tariff, and non-tariff trade barriers. The second part will seek to apply these concepts to the case of Thailand and how it implemented some of these theories and how it did not. By the end of the paper, Thailand's economic success will be better understood by applying these economic concepts.

Theoretical Section:

Part One: Reasons for Free Trade:

According to Dominick Salvatore, International Trade Theory is a crucial component to development, and remains critical in modern economics despite critiques (Salvatore, 2020). One of the most foundational aspects of International Trade Theory is Comparative Advantage, first coined by David Ricardo. Comparative Advantage Theory is a critique of Absolute Advantage Theory and has become a fundamental argument for free trade. Comparative Advantage can be explained using a simple example where two countries, country A and country B both produce two goods, good X and good Y. In Comparative Advantage, even if country A was more efficient at producing both goods, Ricardo argued that the countries could still trade. The key is that the countries would aim to specialize in one good more than the other after determining the opportunity cost. If states follow Standard Trade Theory, then free trade will act as an engine of growth (Salvatore, 2020).

Beyond Ricardo's contribution to economics, the Heckscher-Olin Samuelson theorem expanded on how trade could still be conducted between countries that have the same technological capabilities. The theorem holds that states should specialize in goods that they have factor abundance in, therefore countries with a labor abundance should specialize in goods whose production is labor intensive. While countries that have capital abundance should specialize in capital intensive goods. The Samuelson aspect of the theorem looked at how post trade between countries and determined that after trade, the labor abundant country will likely see an increase in wages and the capital abundant country will likely see an increase in rent.

Next, the gravity model of international trade is another major reason for why countries trade. It is rational that large economies that are geographically close to each other are more likely to trade than other countries that are farther apart due to smaller costs, closer proximity, and similar demands.

Part Two: Obstructions to Free Trade and Arguments Against Free Trade:

According to Neoclassical economists, following the Standard Trade Model is an important part of development. But there are also people who argue for obstructions to free trade and argue for protectionist policies. Tariffs are one of the most common ways that countries obstruct free trade but there are other non-tariff trade barriers implemented such as quota policies, Intellectual Property Rights, and dumping. Tariffs and Quotas have the same effect on a countries economy when implemented because they increase the domestic producer's surplus but decrease the Consumers'' surplus. IPR's are important for International Trade because most countries want their products and ideas to be protected so they can make a profit. Countries that do not closely follow IPR rules may receive pressure from the international community to start following the rules.

Less Developed Countries or LDC's and newly developed countries such as Thailand may seek to obstruct free trade in the name of protection. Protectionist arguments that are most widely used are the National Defense argument and the Infant Industry argument. The National Defense argument has been in economics from the beginning because countries have always sought ways to have power over their competitors. If countries can implement tariffs on their enemies then they will do so if it is meant to help protect their sovereignty and economy. Infant Trade Industry was a common argument used by developing countries but has been heavily criticized because it leads to the monopolization of domestic markets and ruins the incentive to be competitive and increase both quality and efficiency.

Thailand's Policies for Success:

Protectionist Policies in Thailand:

Thailand continues to be a strong advocate for liberalization and free trade. Therefore, it has more recently implemented free trade policies except on rare occasion. Before the crisis, Thailand did implement important protectionist policies despite being known as more open (Warr, 2000). According to Warr, Thailand should not be considered a low protection country even after the crisis because they still favor exports over imports through protectionism. One of the main things that Thailand usually seeks to resist from other countries is IPR rules (Talerngsri, 2005). Tourism is a major industry in Thailand. Much of the appeal for tourists in Thailand is the availability of cheap "knockoff" goods that support much of the informal economy. Liberalization in Thailand has deepened since the financial crisis which has also meant less regulation on work so a weakening of unions, low wages, and more contract work (Hewison, 2013). Because many people earn their living in Thailand by selling the knockoffs, Thailand continues to resist IPR rules.

However, besides resisting IPR rules, Thailand has increasingly implemented free trade policies which started before the economic crisis. Since the economic crisis of the 1990's Thailand has focused on rebalancing because of their reliance on exports (Sussangkarn, 2012). Sussangkarn et al recommended that Thailand seeks balancing through diversifying trade and trading more with its region rather than primarily exporting to the west. However, the paper does not mention the need for protectionist policies. So, Thailand has historically followed liberal economics even until the Asian Financial Crisis, where Thailand liberalized further, but it should be considered that Thailand still had important tariff policies as mentioned by Warr above. Thailand has sought to balance its economy through more investment and diversity and has not utilized many obstructions to free trade. Nor has Thailand made arguments for free trade, the literature has not mentioned any arguments for infant industry. Thailand does not actively seek any obstructionist policies such as the use of tariffs, quotas, or VERs. Thailand has pursued anti-dumping measures, but the one of the most important anti-free trade rules Thailand still follows is resisting IPR rules (Talerngsri, 2005).

Free-Trade Policies in Thailand:

Because Thailand has consistently followed liberalization. It is rational that they would follow liberal economic theory. Comparative advantage has been an important part of Thailand's economic policy. Thailand exports a wide range of exports such as meat, fish, rubber, cereals, tin, and sugar which all have a strong comparative advantage, and Thailand has correctly specialized in many of these products and even more (Karimi, 2018). The implications of Thailand's specialization and liberalization are nuanced, however. After joining ASEAN Free Trade Agreement (AFTA), there appeared to be more trade diversion than creation between the original five AFTA members because of more competitive rather than complimentary goods between the countries before the Asian Financial Crisis (Maule, 1996). Instead, Thailand's goods were more complimentary to the US and Japan.

Next, beyond following comparative advantage, Thailand has continued a tradition of emphasis on exports and increasing liberalization by increasing trade partners in bilateral and multilateral FTAs. Exports were critical to Thailand's unprecedented GDP growth in the late

1980's and early 1990's (Herderschee, 1993). Focusing on exports is important to Thailand for maintaining a trade surplus to build wealth. In the Thailand-Australia Free Trade Agreement or TAFTA, trade has increased considerably between the two countries but more in exports from Thailand to Australia (Athukorala, 2011). That suggests that Thailand could still be following export-oriented industrialization. Which means that by focusing on exports Thailand can continue to have a trade surplus to grow the economy. However, while Thailand has been at the forefront in Asia for pursuing FTAs, its developmental rather than neoliberal strategy and lack of institutionalization of trade policies has led to cronyism and corruption (Koo, 2014). In addition to trade diversion, and cronyism, there may be other unintended consequences of all the FTAs that Thailand and other countries have implemented. The recent growth of FTAs in Southeast Asia has been created for the competition of receiving Foreign Direct Investment or FDI at the expense of the working class and especially labor-intensive industries (Arnold, 2006). So, FTAs could derail Thailand's pursuit of sustainable development.

The last important policies that are affecting Thailand's economy is how its trade is impacted through gravity theory. AFTA has considerably increase trade between its member countries and countries follow the logic of the gravity theory with trading more with countries the closer they are to each other (Nguyen, 2015). As well as trade increasing between Thailand and its close neighbors, labor migration is an important aspect of Thailand's economy. Many people migrate to Thailand for work, but many are also coerced or forced into forced labor on sex trafficking (CIA, 2020). However, Thailand has a lot of potential to develop its trade relations even more with its immediate neighbors. The countries have already seen much economic growth along the borders with more movement of commerce and people (Krainara, 2015). However, the relationship could continue and strengthen in Thailand and its neighbors develop more on the borders.

Conclusion:

Thailand is an interesting country for economics. The only Southeast Asian country to never be directly colonized by Europeans, Thailand has had the advantage of relative peace compared to its immediate neighbors of Myanmar, Laos, and Cambodia. Because of Thailand's historical desire to remain positive and friendly with the west, they have long continued a tradition of liberalism. Before the 1990's Thailand pursued mostly free trade policies and some protectionist policies such as tariffs and resisting IPRs, and in turn had the highest GDP growth rate before the Asian Financial Crisis. Since the crisis, Thailand sought to liberalize further and focus on export-oriented trade to try to continue high growth rates. Since joining ASEAN and AFTA, Thailand has pursued several FTAs with multiple countries to garner more FDI. However, its Asian neighbors have been important contributors to increasing trade and growth with migrants and proximity being an important part of the Thai economy. Thailand is an important contributor to the Asian and world economy. Its desire for sustainable development has perhaps hampered its economic development but remains an inspiration for its poorer neighbors. While still successful, Thailand holds much potential through continued liberalization and interaction with its neighbors.

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Efficiency Ranking of IT Services Producing Firms: Case of Indian Multinationals

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Abstract

Production functions often study the output of physical products with capital and labor inputs. Instead, we use 2004 to 2016 data for 55 Indian multinational companies to assess the production of services. Our estimates of flexible production functions yield estimates of scale elasticity (SCE) and elasticity of substitution (EOS) for pooled data. A subset of 31 companies with relatively complete data yields their individual SCE and EOS values, revealing their heterogeneity. Sorting the 31 companies by their SCE help name scale-efficient (high SCE) and scale inefficient (low SCE) multinationals. Similarly, a listing of 31 companies sorted by EOS allows us to name companies that are (and are not) robust to input price shocks. Using stock market data on these publicly traded companies, we report the values of three stock market criteria for top ranking companies by SCE. We also study empirical causal paths from the market criteria to EOS and SCE, suggesting that SCE and EOS do drive stock market indicators implying efficient markets. Our pooled and detailed results are relevant for government policy toward the IT sector and corporate governance issues.

1 Introduction

A production function helps measure the contribution of individual inputs to the creation of output. Consider the production of a tangible product such as bushels of corn by a farm. If we have data on farmer's revenue (quantity × price) and the price of corn per bushel, a deflated revenue [(quantity × price) /(price)], readily gives the desired output quantity. A modern firm produces several products and services whose quantities cannot be directly aggregated.

Hence, economists define a firm's 'value-added' (V a) as the difference between its total sales revenue and the total cost of components, materials, and services purchased from other firms. Now, a firm's high V a in a year might have been so because the firm raised the prices. If a firm produces mostly tangible products, it is customary to remove the effect of output price inflation by deflating the V a by a price index as specific to the firm's output as possible to yield its output quantity. Unfortunately, service-output-specific price index for deflating value-added numbers is unavailable.

In this paper, we are concerned with the production of intangible services by Indian multinational firms who sell those services mostly to developed countries. Using a suffix R for rupees, we let V aR stand for the value-added in millions of rupees, deflated by the consumer price index (CPI) in India. Now we define logs of capital and labor inputs, K = log(Asst), where Asst represents total assets in millions of Rupees, making K the log of capital input. Similarly, L = log(Emp), where Emp means the number of employees, making L the log of labor input.

Three popular functional forms for a production function with two inputs include the Cobb-Douglas,

$$y = \alpha_0 + \alpha_1 K + \alpha_2 L, \tag{1}$$

which is linear in parameters. The trans-log functional form with cross product and square terms is

$$y = \alpha_0 + \alpha_1 K + \alpha_2 L + \alpha_3 K\,L + \alpha_4 K^2 + \alpha_5 L^2. \qquad (2)$$

The constant elasticity of substitution (CES) production function is defined as

$$y = \gamma[\delta K^{-\rho} + (1 - \delta)L^{-\rho}]^{-\nu/\rho}, \qquad (3)$$

where γ measures the efficiency, δ measures input intensity, ν measures the scale elasticity (SCE) and ρ measures elasticity of substitution (EOS).

The highly nonlinear functional form (3) makes the estimates depend on the optimization algorithm used, which searches in the neighborhood of some starting values for unknown coefficients. In addition to such nonlinear estimation difficulties, there is little theoretical or empirical justification for assuming, as the functional form (3) does, that SCE= ν and EOS= ρ should be fixed constants for all firms and years.

Unfortunately, all three functional forms listed above are not suitable for our purposes. The Cobb-Douglas is too restrictive in assuming without evidence that SCE is a fixed constant and EOS=1. For our data the matrix of correlation coefficients $\{r_{ij}\}$ reported in Table 1 between (K, L, KL, K^2, L^2) has all correlations large, $\{r_{ij}\} > 0.858$, suggesting collinearity. The ordered vector of eigenvalues $\lambda_i, i = 1, 2, \ldots 5$, for the regressors in (2) are: (4.710, 0.269, 0.018, 0.002, 0.000). Note that the smallest eigenvalue $\min(\lambda) \approx 0$ for these data suggest a near-zero determinant and a very high condition number, $(\max(\lambda_i)/\min(\lambda_i)) \to \infty$, implying a very ill-conditioned matrix of regressors. Numerical mathematicians have long warned against inverting ill-conditioned matrices.

Table 1: Correlation matrix between variables in a translog production function

	y	K	L	KL	K^2	L^2
y	1.000	0.938	0.928	0.957	0.931	0.928
K	0.938	1.000	0.858	0.952	0.991	0.867
L	0.928	0.858	1.000	0.960	0.860	0.991
KL	0.957	0.952	0.960	1.000	0.964	0.974
K^2	0.931	0.991	0.860	0.964	1.000	0.880
L^2	0.928	0.867	0.991	0.974	0.880	1.000

The mean squared error, $MSE(\hat{\alpha}) = E(\hat{\alpha} - \alpha)^2$, is the expected value of the squared Euclidean distance between the $p \times 1$ vector of estimates and true values (α). When ($E(\hat{\alpha}) = \alpha$), we have an unbiased estimator. Since the ordinary least squares (OLS) estimator is unbiased, it can be shown that the $MSE(\hat{\alpha}) = Var(\hat{\alpha}) = \sigma^2(\lambda_1^{1} + \lambda_2^{1} \ldots + \lambda_p^{1})$. When we have collinear data, the smallest eigenvalue ($\min(\lambda_i)$) of the covariance (or correlation) matrix is very small, close to zero. Then, $1/\min(\lambda_i) \to \infty$ implying a very high MSE suggesting a highly unreliable OLS estimate ($\hat{\alpha}$). Our data analysis reveals that the full trans-log form of equation (2) has $\min(\lambda_i) \approx 0$.
We also find that omitting the square terms (K^2, L^2) of the trans- log helps reduce the condition number from near infinite to 16.073, solving the collinearity problem.
This avoids the use of ridge regressions or other biased estimators, Vinod (1976).

We choose a version of the trans-log production function, which remains linear in parameters but includes KL term allowing for limited nonlinearity while omitting (K^2, L^2) causing the collinearity. It can be proved that the following form is non-homogenous and exhibits variable EOS, (VES). We estimate:

$$y = \alpha_0 + \alpha_1 K + \alpha_2 L + \alpha_3 (K L) + , \tag{4}$$

where the notation already uses logs of output, capital, and labor. The Cobb-Douglas production function (1) is a particular case when the coefficient of the cross-product term $\alpha_3 = 0$ in (4).

This production function is non-homogeneous and hence flexible in the sense that it lets data determine various elasticities described in the sequel, rather than simply fixing their values as known constants. For example, the Cobb-Douglas form sets the elasticity of substitution (EOS) to be unity, irrespective of the data. Similarly, constant elasticity of substitution (CES) production function sets EOS = η, some constant. Instead, the formulation in equation (4) lets the data estimate variable EOS. If the estimated EOS values are indeed nearly constant, one can always simplify the specification and use a CES functional form. We shall see later that our data on Indian multinationals exhibit a considerable range of EOS values, far from being a constant.

1.1 Marginal and scale elasticity

Output per unit of labor (per employee) VaR/Emp, is a crude but straightforward measure of labor productivity. The limitation of (VaR/Emp) ratio is that it ignores the contribution of capital, falsely pretending that all output can credited to the labor input. Similarly, one can define $(VaR/Asst)$ ratio as a crude measure of capital efficiency. The input productivity is better measured by the marginal productivity of capital and labor (MP_K, MP_L), defined by the partial derivative of the output with respect to an input. Unfortunately, the MP_K, MP_L values are sensitive to the units of measurement for assets and employees and we cannot conveniently compare MP_K with MP_L over time, nor can we compare their values across firms.

The marginal elasticities of capital and labor, denoted by MEK, MEL, respectively measure the percent change in the output as an effect of a 1% change in capital or labor input, one at a time. Now, percent changes are not sensitive to units of measurement and are readily compared over time and across firms. In fact, we can compute MEK, MEL as the partial derivatives of the log of output with respect to (wrt) the log of one input. For the specification in equation (4) the MEK $(=\partial y/\partial K)$ values are defined as:

$$MEK = \alpha_1 + \alpha_3(L) \tag{5}$$

An empirical estimate of these marginal elasticities requires regression coefficient estimates. The term (L) or log of labor appearing in the last right-hand side terms of (5) represent data on the input, which varies with each observation. Hence, MEK estimates will vary with each L. Since one cannot report so many (750 values for 55-firm 13-year data) pooled data MEK estimates, it is customary to estimate MEK values at the sample mean or $\bar{L}$. That is, one replaces L in the formula (5) by a single number $\bar{L}$ for average L in the data.

Analogous marginal elasticities of labor (MEL) are also readily computed from estimated coefficients and the known sample mean, $\bar{K}$. The scale elasticity SCE measures the percentage change in output from a one percent increase in the scale of operations measured by a one percent change in all inputs. Thus, we have:

$$SCE = MEK + MEL, \tag{6}$$

which is a summary measure of the efficiency of the Indian multinational entity.

1.2 Elasticity of substitution

The ratio of marginal productivities of capital and labor, MP_K/MP_L, is called the marginal rate of transformation (MRT). J. R. Hicks first defined elasticity of substitution (EOS) as the percent change in MRT in response to a one percent change in input ratio K/L. It is best expounded in Ferguson (1971) and partially covered in many economics textbooks. Here we are interested in the sign of EOS(K,L) between inputs K and L. Assuming the corporate entity producing the output is on an output-maximizing 'expansion path,' Hicksian theory implies that whenever the EOS(K,L) is positive, the gains in output remain positive despite adverse input price changes. There is, however, no reason to assume that EOS remains constant, EOS = η, for each observation, which is done by constant elasticity of substitution (CES) production functions. If our marginal elasticities already vary with each observation, CES' constancy assumption is all the more unrealistic, and hence avoided here.

The non-homogeneous production function (4) has the advantage that its elasticity of substitution is given by a simple expression

$$EOS = SCE/(SCE + 2\alpha_3). \qquad (7)$$

Since the scale elasticity SCE defined in (6) is easy to estimate, estimating EOS merely needs one to plug in $\hat{\alpha}_3$, an already estimated regression coefficient.

The Cobb-Douglas production function is obtained by setting the coefficients of the cross-product term ($\alpha_3 = 0$). A quick check on the validity of (7) is that EOS for Cobb-Douglas should be unity. Now, EOS is indeed unity, since it becomes $EOS = SCE/SCE = 1$ for the special case when $\alpha_3 = 0$.

2 Pooled data production function estimation

Using the data pooled together for all 55 Indian multinational companies for years 2004 to 2016 on logs of outputs and inputs, we first estimate a few versions of the non-homogeneous production function:

$$y = \alpha_0 + \alpha_1 K + \alpha_2 L + \alpha_3 (K L) + \alpha_4 Year + \varepsilon, \qquad (8)$$

where we have an additional regressor for time ($Year = 2004, 2005....2016$) represents a proxy for technological change, commonly used in the related literature. Our results in Table 2 use pooled data, which makes no distinction between individual companies. One way to assess whether pooling is appropriate is to check the quality of its statistical fit. We use the usual F test and a newer exogeneity test for this purpose here.

Recall that our value-added output variable VaR uses CPI to correct for inflation. Since the Cobb-Douglas scale elasticity, $SCE = \alpha_1 + \alpha_2$, is $0.596 + 0.531 = 1.127$, is above unity, these corporations as a whole in pooled data enjoy increasing returns to scale, implying general efficiency. All models are statistically significant from the reported large F statistics.

The statistically significant estimates of ($\hat{\alpha}_4 = -0.017$) in columns (2) and (3) suggests that as time increases the output mildly decreases. Since the coefficients of Y ear is rather small it is convenient to exclude the Year as a regressor in the sequel. Although the coefficient of the cross-product, K L, is even smaller,we need to retain it in our VES specification. Otherwise, we are implicitly using a Cobb-Douglas functional specification, which fixes the elasticity of substitution to be unity and SCE to be a fixed constant. The pooled data estimates in Table 3 continue to support our model specifications and continue to suggest

Table 2: Cobb-Douglas and non-homogeneous production functions: Indian multinationals producing services output measured by 'Value added' deflated by CPI using pooled data, eq. (8)

	Dependent variable:		
		y	
	(1)	(2)	(3)
K	0.596***	0.604***	0.677***
	(0.028)	(0.028)	(0.062)
L	0.531***	0.526***	0.609***
	(0.029)	(0.029)	(0.069)
K L			−0.009
			(0.007)
Year		−0.017**	−0.017**
		(0.008)	(0.008)
Constant	−1.816***	32.006**	31.691**
	(0.126)	(15.367)	(15.353)
Observations	374	374	374
R^2	0.937	0.937	0.938
Adjusted R^2	0.936	0.937	0.937
Resid. Std. Err	0.543 (df = 371)	0.540 (df = 370)	0.539 (df = 369)
F Statistic	2,736***(df=2; 371)	1,844***(df=3; 370)	1,387***(df=4; 369)

Note:*p<0.1; **p<0.05; ***p<0.01

that Indian multinationals are generally efficient (all $SCE \approx 1$) and robust with respect to price shocks ($EOS > 0$). The estimates along rows 1 to 3 in Table 3 are computed from the coefficients reported in columns 1 to 3 of Table 2.

Table 3: Pooled data various elasticities

Row	Type	ME-K	ME-L	SCE	EOS
1	CobbD	0.596	0.531	1.127	1.000
2	CobbD-Yr	0.604	0.526	1.130	1.000
3	VES-Yr	0.607	0.537	1.144	1.016

2.1 Exogeneity assessment of model regressors

This subsection hopes to learn whether the VES model specification (4) might suffer from the so-called "endogeneity problem," Koopmans (1950). Generally speaking, we want the right-hand side (RHS) variables in our models illustrated by eq. (4) to be exogenous, in the sense that they should have independent variation and drive the variation in the dependent variable. Correlation coefficients between output variable (y) on the left-hand and inputs (K, L) are fairly large and positive, implying that when the companies increase the number of employees, their 'value-added' output increases. However, exogeneity assessment requires deeper analysis discussed next.

We use the R package called 'generalCorr' from Vinod (2016), which contains decision rules based on a unanimity index summarizing three criteria (Cr1 to Cr3). The theory is explained in software vignettes and Vinod (2019). The software readily compares flipped models where one model has an output (y) on the one hand and inputs K, L on the other. The decision rules help name the variable in the column entitled 'cause' and also name the flipped variable in the column entitled 'response.' Koopmans showed long ago that regressors should approximately 'cause' the dependent variable. Otherwise, the model suffers from the so-called 'endogeneity problem.'

2.2 Description of headings in causal path tables

We describe the headings of all causal path tables in this paper in this subsection for easy reference based on the theory in Vinod (2019).

1. cause = name of the causal variable.

2. response = name of the response variable.

3. strength = absolute value of the unanimity index (UI) in the range [0,100]. If strength is less than 5% the causal path is bidirectional.

4. corr = the usual correlation coefficient between the two flipped variables.

5. p-value = p-values for testing the null hypothesis that the population correlation coefficient is zero. We generally reject the null if p-value < .05.

Table 4 has our causal path results relevant for assessment of exogeneity of variables on the right-hand side of (4). The p-values are all near zero in Table 4, suggesting highly significant correlations. Since the input variables K and L are in the 'response' column, we do have the endogeneity problem for pooled data problems.

Table 4: Causal paths for exogeneity assessment for pooled data

	cause	response	strength	corr.	p-value
1	y	K	37.008	0.9076	0
2	y	L	100	0.9277	0

We conclude subsection 2.2 by noting that Indian multinationals appear to hire their inputs of K, L in response to their profitability measured by their value-added output. Since three regression models reported in Tables 2 are statistically significant with plausible coefficients, we can conclude Section 2 by noting that pooled data are providing a reasonable picture of the production of services by Indian multinationals. Despite the endogeneity problem, the overall conclusion is that $SCE \approx EOS \approx 1$ along all rows of Table 3. The pooled results refer to multi- nationals as a group and are of interest for economic policy toward them as a group. We study individual company performance in the next section.

3 Cobb-Douglas function estimates for individual companies

We estimate separate Cobb-Douglas production functions for each Indian multinational to assess the nature of heterogeneity between the Indian multinationals. Only 31 companies out of 55 are selected for reporting. They have at least five years of non-missing data for all variables.

Table 5 reports two marginal elasticities and their sum as scale elasticity using the formulas given in (5) to (6) earlier. Of course, in the absence of the cross-product term in a Cobb-Douglas specification, we are implicitly fixing $\alpha_3 = 0$. That is, the scale elasticity for Cobb-Douglas is analytically known to be $SCE = \alpha_1 + \alpha_2$.

The column entitled 'rank' reports the sorted rank of the company measured by its scale elasticity, with rank=1 indicating the company with the largest SCE. Since we have some negative slope estimates, $MEK=\alpha_1 < 0$, and $MEL=\alpha_2 < 0$, in Table 5, it is tempting to conclude that measured capital or labor is an unproductive input in producing services of those companies. We need a deeper review of possible data errors, nonlinearities missed by the Cobb-Douglas form, and of circumstances faced by these companies before we can say that some inputs are "unproductive." Any identification of relatively inefficient firms based on $SCE = \alpha_1 + \alpha_2$ alone is subject to limitations, simply because the Cobb-Douglas form arbitrarily assumes that SCE is a constant and EOS=1.

Table 5: Cobb-Douglas Model elasticities for 31 firms sorted by SCE

rank	n	MEK	MEL	SCE	EOS	R^2	Name
1	6	4.9527	0.6792	5.6319	1	0.9894	TRIG
2	11	1.622	0.5158	2.1378	1	0.3624	APTE
3	8	-0.0362	2.095	2.0588	1	0.3837	FINT
4	7	0.4079	1.2289	1.6368	1	0.9126	NITT
5	13	-0.0412	1.5722	1.531	1	0.1225	TIMK
6	10	-0.5765	2.0469	1.4704	1	0.905	MPHA
7	12	0.3776	1.0316	1.4093	1	0.6425	CSS
8	9	1.076	0.2561	1.3321	1	0.9468	ALLS
9	12	0.4343	0.8681	1.3024	1	0.4403	MIT
10	13	0.2167	0.9983	1.215	1	0.9069	ASMT
11	12	-0.1443	1.2473	1.103	1	0.9505	SONA
12	6	0.8365	0.1952	1.0317	1	0.89	MAST

13	7	0.2394	0.7518	0.9912	1	0.9359	OMNI
14	13	0.3276	0.5802	0.9078	1	0.9271	HCLT
15	8	0.2032	0.7043	0.9075	1	0.9923	MINT
16	10	0.2241	0.6357	0.8598	1	0.7445	MIND
17	13	-0.2418	1.0919	0.8501	1	0.9622	KPI
18	11	0.1886	0.6455	0.8341	1	0.9869	INFS
19	8	0.5468	0.2384	0.7853	1	0.9531	ECLE
20	13	0.241	0.5301	0.7711	1	0.6498	HEXA
21	6	0.0992	0.6476	0.7468	1	0.9904	IGS
22	10	0.8599	-0.1896	0.6703	1	0.9944	TCS
23	12	0.4479	0.1747	0.6226	1	0.964	WPRO
24	8	0.7434	-0.1372	0.6061	1	0.2558	RSI
25	12	0.0374	0.545	0.5825	1	0.9043	PFT
26	7	0.4723	0.0269	0.4992	1	0.9368	CAMB
27	9	-0.2292	0.6554	0.4261	1	0.3915	ONTR
28	12	-0.1332	0.457	0.3238	1	0.8649	CMC
29	7	0.5478	-0.2988	0.249	1	0.5225	PANO
30	11	0.2114	-0.1832	0.0283	1	0.2186	TATA
31	8	-0.1506	0.1615	0.0108	1	0.2742	ICRA

The Table 5 clearly reveals the heterogeneity of Indian multinationals, when one considers the great variability in the range of estimated marginal and scale elasticities. These confirm that the companies are heterogeneous with distinct production function coefficient estimates. The Cobb-Douglas SCE estimates range from 5.6319 for rank 1 Trigyn Tech denoted as 'TRIG' to 0.0108 for rank 31 'ICRA' in Table 5.

We can surmise that a more general non-homogenous production function will also suggest that different Indian multinationals are distinct from one another. We report estimates after including the cross-product term to incorporate nonlinearities arising from the input interactions in the next section.

4 Percent Compound Growth Rates Compared

Our data set contains several missing values, especially with stock market indicators. Our growth rate study in this section considers 31 companies having an adequate number of non-missing data. Accordingly, our data covers years representing (2004 to 2016). Let X denote the values for a particular company from the list of variables (Emp, Asst, VaR, RoaR, ShPr, MktK). We have already encountered the notation Emp for employees, Asst for assets, and VaR for value-added in Rupees. Newer variables are 'rate of return on assets in Rupees,' (RoaR), share price (ShPr), and market capitalization (MktK).

Let the available data range be $X(t_1)$ to $X(t_2)$. For example, VaR data for KPIT Tech is available from 2004 to 2016. Hence, X(2004), X(2016) will denote VaR values for those years. Now the overall percent compound growth rate r over the included period is given by solving the following equation for the rate

$$X(t_2) = X(t_1)(1 + r)^{\tau}, \quad \text{where} \quad \tau = (t_2 - t_1 + 1). \qquad (9)$$

The percent growth rate is $r=100[(X(t2)/X(t1))(1/\tau)-1]$ assuming

that the denominators τ and $X(t_1)$ are nonzero.

Table 6 reports growth rates of various companies included in the study

sorted by their asset growth rates ranging from −7.97% for Melstar Information

Tech (MIT) to 45.17% for Eclerx Services (ECLE). See Tables 14 to 16 in the Appendix for more detailed names of companies.

Table 6: Percent Growth Rates sorted by Asset growth

	Emp	Asst	VaR	RoaR	ShPr	MktK
MIT	0.69	-7.97	-3.50	-13.60	-4.48	-4.91
APTE	-3.27	-2.90	-6.00	-1.20	1.50	3.85
PFT	1.77	1.01	2.89	-2.18	0.57	0.91
TATA	6.23	1.32	0.01	-4.29	4.81	4.89
MAST	-2.58	1.91	1.27	-4.23	12.80	-0.88
CMC	12.80	6.20	3.55	2.39	11.95	18.64
XCS	-14.47	7.15	1.64	5.53	39.19	1.86
RSI	-5.07	7.30	13.61	31.28	-7.47	9.83
SONA	10.68	7.45	12.62	7.77	22.79	22.78
AKS	9.69	8.40	9.60	14.42	28.58	33.89
SCT	-5.20	8.68	5.71	7.27	-0.05	-4.11
GEO	1.79	9.69	7.94	1.25	-6.55	13.07
INTE	2.10	10.52	24.05	-23.62	8.69	1.21
HEXA	7.91	10.60	10.80	5.10	-1.84	12.19
TIMK	0.95	10.94	3.39	-3.10	19.50	15.63
SAKS	1.85	12.65	4.08	4.12	8.02	3.91
ICRA	14.52	13.37	7.69	-2.65	21.72	21.14
HCLT	18.62	14.29	14.87	3.91	9.58	21.82
ABMK	2.12	14.70	19.51	15.00	39.97	39.97
PANO	7.31	16.03	4.29	-10.57	-20.20	14.48
WPRO	9.44	16.32	11.72	-1.60	-6.55	12.07

MPHA	14.92	17.50	11.86	-6.74	10.40	13.76
CAMB	-9.07	18.74	4.88	-5.80	12.49	10.14
INFS	16.65	18.85	13.06	-2.74	-10.21	17.90
MINT	16.33	20.36	15.07	-0.26	-2.38	13.45
KPI	21.01	21.63	19.42	-1.60	-2.60	27.61
INTR	8.31	23.58	14.75	0.95	33.51	33.64
VAKR	13.79	26.12	33.67	20.62	3.81	61.22
INFE	13.98	33.13	15.07	-9.86	1.25	17.51
TCS	19.73	39.60	77.82	21.69	4.82	17.89
ECLE	20.12	45.17	34.74	-6.25	20.29	31.08

Scatterplots of various pairs of columns in Table 6 (omitted for brevity) show that the relations are not linear. Hence we report generalized correlation coefficients in Table 7 based on the R function gmcmtc0() in R package 'generalCorr.' The matrix entries are non-symmetric in that the entry at location [i, j] along row i and column j does not, in general, equal the across-diagonal entry at location [j, i].

Comparing across-diagonal entry pairs, the one with the larger magnitude

is identified by the superscript 'L' for larger. According to the theory described in Vinod (2019) this is Cr3 of three criteria (Cr1 to Cr3) for determination of causal paths. That is, the variable named in the column is 33% likely to be the cause, since the other two criteria based on residuals of flipped kernel regressions may well suggest the opposite causal path.

For example, consider Table 7 row 2 for Asst and column 1 for Emp has 0.8833^L, which implies that the generalized correlation between the two variables is 0.8833. Moreover, the superscript suggests that the column heading Emp for employee growth is at least 33% likely to be the 'cause' of the row heading Asst for growth in assets. The usual Pearson correlation coefficient between (Emp, Asst) 0.6015 is a bit smaller than 0.8833. Not surprisingly, Pearson correlations (assuming linear relations) are almost always smaller in magnitude than generalized correlation coefficients based on nonparametric, nonlinear kernel regressions.

Table 7: Generalized Correlations Between Percent Growth Rates, superscript L indicates larger absolute value where column name has the potential cause

	Emp	Asst	VaR	RoaR	ShPr	MktK
Emp	1	0.6279	0.7719^{L}	-0.1241^{L}	0.7776^{L}	0.5651
Asst	0.8833^{L}	1	0.7363	0.2393^{L}	-0.1584	0.5819
VaR	0.6011	0.9014^{L}	1	0.35^{L}	-0.0083	0.3996
RoaR	-0.079	0.2041	0.3303	1	0.1665	0.3609^{L}
ShPr	0.0427	-0.4346^{L}	-0.0603^{L}	0.6622^{L}	1	0.8033^{L}
MktK	0.6322^{L}	0.8818^{L}	0.4145^{L}	0.3265	0.4658	1

Table 7 reveals positive correlations between MktK growth and all other variables in the bottom row. However, growth in ShPr has a negative correlation with Asst and VaR. The negative correlation between RoaR and Emp suggests that increasing return on assets negatively impacts employee count growth.

Instead of focusing causal paths suggested by only one (Cr3) of the three criteria (superscript L) as in Table 7, it is better to consider comprehensive causal paths (based on unanimity strength index UI) between all pairs of growth rates reported in Table 8 with column headings described in Section 2.2. The Table 8 reports approximate causal paths based on a (UI) using all three criteria (Cr1 to Cr3) for all possible (=15) pairs of growth rates among the six variable.

Table 8: Causal paths between growth rates of variables

	cause	response	strength	corr.	p-value
1	Emp	Asst	100	0.5655	2e-05
2	Emp	VaR	4.724	0.5297	9e-05
3	RoaR	Emp	31.496	-0.0237	0.88945
4	ShPr	Emp	100	0.0041	0.97927
5	Emp	MktK	31.496	0.4425	0.00335
6	Asst	VaR	100	0.7044	0
7	RoaR	Asst	31.496	0.0436	0.78409
8	ShPr	Asst	37.008	-0.1616	0.27243
9	Asst	MktK	100	0.3367	0.02064
10	RoaR	VaR	100	0.3361	0.02955
11	ShPr	VaR	37.008	-0.0036	0.98066
12	VaR	MktK	50.394	0.3228	0.02687
13	RoaR	ShPr	100	0.1863	0.2697
14	RoaR	MktK	21.26	0.2779	0.09589
15	MktK	ShPr	31.496	0.3735	0.01149

First, we list the following plausible causal paths between growth rates:

Emp→ Asst, ShPr → Emp, Emp→ MktK, Asst→ VaR, RoaR → Asst,

Asst →MktK, RoaR → VaR, VaR→ MktK, RoaR → ShPr, RoaR→ MktK, and MktK → ShPr.

The following causal paths are based on negative correlations suggesting that growth in the 'cause' reduces the growth in the response variable. RoaR [Neg]→ Emp, ShPr [Neg] → Asst, and ShPr [Neg] → VaR. Their relatively low 'strength' values may explain why they are intuitively less plausible. We also find that the following path is most likely bi-directional: Emp↔ VaR, because the unanimity strength index is less than 5%.

5 Individual company non-homogenous production function estimates

This section reports estimates of the non-homogenous (or variable elasticity of substitution, VES) production function (4) having the cross-product term. Similar to Table 5, we report various elasticities evaluated at the data means in Tables 9 and 10 using the VES. Both tables have a column for EOS, except that the EOS is always unity in Table 9 for the Cobb-Douglas specification. Note that a large firm like TCS with the highest market capitalization (table 11) ranks low in terms of SCE (table 9), suggesting perhaps it is farther down the cost curve with fewer opportunities to exploit scale economies. On the other hand, TCS ranks among the top (table 10) in terms of EOS suggesting that the firm has greater flexibility to substitute capital for labor and vice versa.

Table 9 reports the top 31 companies ranked by their SCE, whereas Table 10 reports the top 31 companies ranked by their EOS. In addition to elasticities, we report the R^2 and a four-character abridged name for the company. The reader can know the corresponding long names of any company from alphabetic lists in Tables 14 to 16 in the Appendix.

Table 9: Marginal elasticities, scale and substitution elasticities with R^2 and n for non-missing observation count, sorted by SCE

rank	n	MEK	MEL	SCE	EOS	R^2	Nam
1	6	4.8462	0.4395	5.2858	0.5675	0.9924	TRIG
2	12	2.0759	0.6136	2.6895	-0.1578	0.9274	CSS
3	8	0.1728	2.0069	2.1797	0.5909	0.3848	FINT
4	10	-0.9057	2.8049	1.8993	0.5464	0.9488	MPHA
5	11	1.905	-0.0219	1.8831	-0.2973	0.4043	APTE
6	13	-0.0268	1.4836	1.4568	0.489	0.1271	TIMK
7	7	0.5812	0.8206	1.4018	-0.4972	0.9747	NITT
8	12	0.4735	0.9156	1.3891	0.6505	0.4434	MIT
9	9	0.9262	0.3106	1.2368	28.6707	0.9601	ALLS
10	13	0.2277	0.9819	1.2097	1.0603	0.907	ASMT
11	12	-0.6492	1.7555	1.1063	0.3374	0.9731	SONA
12	6	0.8585	0.2357	1.0942	0.5913	0.8906	MAST
13	7	0.2712	0.6708	0.942	1.1151	0.9365	OMNI
14	8	0.1662	0.767	0.9332	0.7955	0.9971	MINT
15	13	0.3881	0.5173	0.9055	1.1612	0.9273	HCLT
16	13	0.4149	0.4868	0.9017	0.5786	0.6641	HEXA
17	10	1.2212	-0.4075	0.8138	0.1052	0.6344	SAKS
18	13	-0.1525	0.9306	0.7781	1.5469	0.9776	KPI
19	8	1.6482	-0.8881	0.7601	-1.1136	0.9888	ECLE
20	6	0.2511	0.4764	0.7275	0.8599	0.9939	IGS
21	11	0.6198	0.1078	0.7275	2.3843	0.9943	INFS
22	10	1.1223	-0.4933	0.629	1.3125	0.997	TCS
23	12	0.1836	0.4445	0.6282	-2.5316	0.9113	PFT
24	12	0.4174	0.1321	0.5496	2.7816	0.9743	WPRO
25	10	-0.0453	0.5945	0.5492	-0.3335	0.9444	MIND
26	8	0.2419	0.2379	0.4798	-0.0485	0.402	RSI
27	7	0.439	0.0179	0.4569	2.3336	0.9402	CAMB
28	9	-0.2101	0.6299	0.4198	0.4706	0.3949	ONTR
29	7	-0.0774	0.3876	0.3101	-0.0836	0.7056	PANO
30	12	-0.2096	0.4891	0.2795	-0.7526	0.8833	CMC
31	8	0.5712	-0.4029	0.1683	-0.0565	0.8589	ICRA

Equation (6) assures us that SCE is an indicator of the productive efficiency of inputs. Since the last column of the table contains an abridged company name, referring to Tables 14 to 16, the reader can know the full names of relatively inefficient companies from the bottom parts of the table. The names of relatively efficient companies are found in the top part of the table where SCE values are positive and large.

Under assumptions of neoclassical production theory, equation (7) assures us that EOS measures the robustness of a company's input mix when the company is faced with input price shocks. Positive EOS values are known to be more desirable.

Table 10 has identified some Indian multinationals with negative EOS estimates, which appear to be too sensitive to input price shocks. Since the last column of the table contains an abridged company name, the reader can identify relatively non-robust input price shock companies from negative EOS values near the bottom of the table. Indian companies that are robust against input price shocks are named in the top part of Table 10 where the EOS values are relatively large.

Our marginal elasticity estimates assume that the VES functional form of the production function is valid. The coefficient estimates allow us to do thought experiments on what happens to output when input increases by one percent. One can imagine individual company situations where these thought experiments are inappropriate. Readers interested in productive efficiency are encouraged to supplement our production function-based comparisons with the traditional ratio comparisons discussed next.

5.1 Traditional stock market and productivity ratios

Stock market analysts consider 'rate of return on assets in Rupees' (RoaR), share price (ShPr), and market capitalization (MktK). Growth rates of these variables were already discussed in Section 4. Traditional productivity ratios are value-added output per unit of total assets (y/K) and value-added output per employee (y/L). We report in Table 11 the above values for selected 31 publicly traded Indian multinationals included in our data set. The 31 companies are chosen because they have relatively large-scale elasticity (SCE) values, as reported earlier in Table 9. The reader is referred to alphabetically listed long company names and their abbreviations Tables 14 to 16 in the Appendix.

The reported numbers are simple averages over the set of 13 years covered in our data set. In some years, some multinationals appear to have suffered net accounting losses resulting in negative rates of return (RoaR). Tables for the remaining companies are omitted for brevity.

Table 10: Marginal elasticities, scale and substitution elasticities with R^2 and n for non-missing observation count, sorted by EOS

rank	n	MEK	MEL	SCE	EOS	R^2	Nam
1	9	0.9262	0.3106	1.2368	28.6707	0.9601	ALLS
2	12	0.4174	0.1321	0.5496	2.7816	0.9743	WPRO
3	11	0.6198	0.1078	0.7275	2.3843	0.9943	INFS
4	7	0.439	0.0179	0.4569	2.3336	0.9402	CAMB
5	13	-0.1525	0.9306	0.7781	1.5469	0.9776	KPI
6	10	1.1223	-0.4933	0.629	1.3125	0.997	TCS
7	13	0.3881	0.5173	0.9055	1.1612	0.9273	HCLT
8	7	0.2712	0.6708	0.942	1.1151	0.9365	OMNI
9	13	0.2277	0.9819	1.2097	1.0603	0.907	ASMT
10	6	0.2511	0.4764	0.7275	0.8599	0.9939	IGS
11	8	0.1662	0.767	0.9332	0.7955	0.9971	MINT
12	12	0.4735	0.9156	1.3891	0.6505	0.4434	MIT
13	6	0.8585	0.2357	1.0942	0.5913	0.8906	MAST
14	8	0.1728	2.0069	2.1797	0.5909	0.3848	FINT
15	13	0.4149	0.4868	0.9017	0.5786	0.6641	HEXA
16	6	4.8462	0.4395	5.2858	0.5675	0.9924	TRIG
17	10	-0.9057	2.8049	1.8993	0.5464	0.9488	MPHA
18	13	-0.0268	1.4836	1.4568	0.489	0.1271	TIMK
19	9	-0.2101	0.6299	0.4198	0.4706	0.3949	ONTR
20	12	-0.6492	1.7555	1.1063	0.3374	0.9731	SONA
21	10	1.2212	-0.4075	0.8138	0.1052	0.6344	SAKS
22	10	-0.3789	0.288	-0.091	0.0212	0.7163	ACCL
23	8	0.2419	0.2379	0.4798	-0.0485	0.402	RSI
24	8	0.5712	-0.4029	0.1683	-0.0565	0.8589	ICRA
25	7	-0.0774	0.3876	0.3101	-0.0836	0.7056	PANO
26	12	2.0759	0.6136	2.6895	-0.1578	0.9274	CSS
27	11	1.905	-0.0219	1.8831	-0.2973	0.4043	APTE
28	11	0.2146	-0.1863	0.0283	-0.3029	0.2196	TATA
29	10	-0.0453	0.5945	0.5492	-0.3335	0.9444	MIND
30	7	0.5812	0.8206	1.4018	-0.4972	0.9747	NITT
31	12	-0.2096	0.4891	0.2795	-0.7526	0.8833	CMC

Table 11: Rate of return on assets, share price, market capitalization, Value added output per unit of asset, y/K and output per employee y/L sorted by SCE as in Table 9

rank	RoaR	ShPr	MktK	y/K	y/L	Name
1	0.0473	21	57	0.28308	0.52435	TRIG
2	0.0494	16	43	0.19487	0.42958	CSS
3	0.1308	930		0.21625	3.78306	FINT
4	0.1449	328	7148	0.41391	0.32088	MPHA
5	0.0209	101	516	0.16953	0.71148	APTE
6	0.1048	186	1358	0.24615	1.37531	TIMK
7	0.1479	259		0.51492	0.63205	NITT
8	-0.0236	8	12	0.45185	0.27545	MIT
9	-0.0111	84	120	0.48903	0.13289	ALLS
10	0.1068	59	29	0.67396	0.35541	ASMT

Table 11 (Continued)

rank	RoaR	ShPr	MktK	y/K	y/L	Name
11	0.1313	53	557	0.48907	0.61377	SONA
12	0.1188	303	589	0.79449	1.21776	MAST
13	0.0972	87	154	0.27178	1.69991	OMNI
14	0.164	706	4220	0.86683	0.90282	MINT
15	0.16	555	44953	0.40239	0.71241	HCLT
16	0.1461	198	2958	0.43583	0.4838	HEXA
17	0.0851	90	91	0.37515	0.47064	SAKS
18	0.1102	163	1409	0.45239	0.45108	KPI
19	0.4481	755	2310	0.86843	0.41254	ECLE
20	0.1052			0.73792	0.75912	IGS
21	0.2363	2561	141079	0.69068	1.5233	INFS
22	0.2874	1487	228926	0.82199	1.1119	TCS
23	0.1012	145	1435	0.88645	0.75961	PFT
24	0.1608	587	92470	0.53045	1.04123	WPRO
25	0.0336	32	67	0.26063	0.42662	MIND
26	0.0921	106	410	0.49784	0.4901	RSI
27	-0.0151	35	51	0.66482	0.36499	CAMB
28	0.0047		24	0.13555	0.2579	ONTR
29	0.0922	72	115	0.12996	2.89643	PANO
30	0.1122	1088	2360	0.3488	0.43895	CMC
31	0.1105	1671	1670	0.25241	2.78426	ICRA

6 Causal paths between SCE or EOS and stock market indicators

This section reports causal path estimates between RoaR, ShPr, and MktK separately paired with SCE in Table 12 and with EOS in Table 13. We use column headings described in Section 2.2.

Table 12: causal paths paired with SCE

	cause	response	strength	corr.	p-value
1	SCE	RoaR	31.496	-0.093	0.60666
2	SCE	ShPr	31.496	-0.2518	0.17945
3	SCE	MktK	100	-0.1264	0.50584

Table 12 reports causal paths between scale elasticity SCE and stock market evaluations, RoaR, ShPr and MktK. The table is similar to our earlier pooled data causality Table 4. We find that the scale of the firm measured by SCE drives the stock market evaluations.

Table 13 reports causal paths between elasticity of substitution EOS and stock market evaluations, RoaR, ShPr and MktK. The column headings are described in Section 2.2. We find that RoaR drives the EOS, suggesting that the flexibility to input price shocks does not much affect accounting rate of return. By contrast, independent variation in EOS does cause ShPr and MktK.

Table 13: causal paths paired with EOS

	cause	response	strength	corr.	p-value
1	RoaR	EOS	100	-0.219	0.22069
2	EOS	ShPr	31.496	-0.06	0.75284
3	EOS	MktK	100	0.025	0.89577

7 Final Remarks

Publicly traded Indian multinationals have clients around the world, mostly in advanced countries. They 'produce' mostly information and communication technology services (ICT). This paper studies certain publicly available data on them to look for patterns not only in data levels, but also in percent rates of growth. There is a significant number of missing data regarding the number of employees and value-added outputs.

There are two standard measures of productive efficiency called scale elasticity or SCE and sensitivity to price shocks by the elasticity of substitution (EOS) developed by Hicks and explained by Ferguson (1971). We estimate SCE and EOS values for a non-homogeneous VES production function with a cross-product term. The analysis using SCE assumes "thought experiments" to assess what might happen to the output when one or both inputs are increased by one percent. The EOS analysis considers even more sophisticated "thought experiments" to assess what might happen to marginal rates of transformation between the two inputs when relative prices of inputs are changed.

Despite heterogeneous firms and missing data, we find plausible estimates revealing overall patterns based on pooled data in Table 9 sorted by SCE reveals names of efficient firms along the top rows and inefficient firms along bottom rows. Similarly, Table 10 sorted by EOS identifies firms with poor flexibility against input price shocks in the ICT sector along the bottom rows, especially where EOS values are negative, whereas flexiable ones are named along top rows.

Our individual company estimation reveals great heterogeneity among the firms. The heterogeneity leads to a variety of marginal elasticities, scale elasticities (SCE), and elasticity of substitution (EOS) among these firms. Focusing on 31 companies with relatively complete data, we are able to rank and identify by name efficient and price-shock-robust companies in two separate tables.

A novel study of causal paths between SCE, the scale elasticity, and stock market valuations in terms of individual company rate of return, share price, and market capitalization (RoaR, ShPr, and MktK) shows that SCE does drive stock market values, supporting the Hicksian production theory and rational ranking of these companies by the Indian stock market. We also find that most causal paths between growth rates of data are plausible.

Among the limitations of our research, we must mention that efficiency and price-shock sensitivities can have many unmeasured aspects. Our naming of companies should be treated as indicating a need for a further focus on why certain companies have high (low) estimated values of SCE and EOS. Our estimates remain subject to sampling variation. We also report traditional output per employee and output per unit of capital. Thus we provide a wealth of information regarding the overall health of Indian multinationals, as well as detailed estimates for several individual companies for potential use by academics, investment analysts, and policy-makers.

8 Appendix

We report the long names of the ICT multinationals with their abbreviations in the Appendix. Since we have a great many missing data values, only a subset of these companies is included in the present study, which will be extended to include additional companies at a future date if and when more complete data become available.

Table 14: Alphabetic (A to H) table of abbreviated company names and their longer forms

Row	Short Name	Long Name
1	ABMK	A B M Knowledgeware
2	ACCL	Accel
3	AKS	Accelya Kale Solutions
4	ALLS	Allsec Tech
5	APTE	Aptech
6	ASMT	A S M Tech
7	BIR	Birlasoft
8	BRIS	Bristlecone India
9	CAMB	Cambridge Tech
10	CIGN	Cigniti Tech
11	CMC	C M C
12	CSS	Cybertech Systems and Software
13	DFIN	Datamatics Fin
14	DGS	Datamatics Global Services
15	DPLM	3D P L M Software
Solutions		
16	ECLE	Eclerx Services
17	FINT	Financial Tech
18	GEO	Geometric
19	HACK	Hackett
20	HCLT	H C L Tech
21	HEAL	Healthfore Tech
22	HEXA	Hexaware Tech
23	HIGH	Highbar Tech
24	HIND	Hinduja Global
25	HMIT	Helios and Matheson Info Tech
26	HOV	H O V

Table 15: Alphabetic (I to O) table of abbreviated company names and their longer forms

Row	Short Name	Long Name
27	IBPO	Infosys B P O
28	ICRA	I C R A
29	IGS	Igate Global Solutions
30	IINF	3I Infotech
31	INCO	Infinite Computer
32	INFE	Info Edge
33	INFS	Infosys
34	INTE	Intense Tech
35	INTR	Intrasoft Tech
36	ITCI	I T C Infotech
37	KPI	KPIT Tech
38	LTI	Larsen and Toubro Infotech
39	MAH	Mahindra Eng
40	MAST	Mastek
41	MIND	Mindteck
42	MINT	Mindtree
43	MIT	Melstar Information Tech
44	MPHA	Mphasis
45	NEIL	Neilsoft

46	NIIT	N I I T Smartserve
47	NITT	N I I T Tech
48	OBPO	Oracle B P O
49	OMNI	Omnitech
Infosolutions		
50	ONTR	Ontrack Systems
51	ONW	Onward Tech

Table 16: Alphabetic (P to Z) table of abbreviated company names and their longer forms

Row	Short Name	Long Name
52	PANO	Panoramic Universal
53	PFT	Polaris Fin Tech
54	REL	Reliance Mediaworks
55	RSI	R Systems International
56	RSS	R S Software
57	SAKS	Saksoft
58	SCT	Sasken Communication Tech
59	SONA	Sonata Software
60	STER	Steria
61	SUND	Sundaram Infotech
62	SYNT	Syntel
63	TATA	Tata Communications
64	TCS	TCS
65	TIMK	Timken India
66	TMAH	Tech Mahindra
67	TRIG	Trigyn Tech
68	USH	Unisys Softwares and Holding
69	VAKR	Vakrangee
70	WINF	Winfoware Tech
71	WINF	Cades Digitech Pvt
72	WPRO	Wipro
73	XCS	Xchanging Solutions
74	XRXI	Xerox India
75	ZEN	Zensar Tech

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AN EMPIRICAL ANALYSIS OF DIMENSIONAL TRUST IN ONLINE GROUP BUYING SITES

ABSTRACT

Building websites that generate adequate perception of ability, integrity, and benevolence dimensions of trust amongst even the first-time visitors is critically important for online group buying (OGB) sites; otherwise, visitors may be reluctant to transact. Current literature suggests that certain website features can induce overall trust perception (TP); however, their impact on specific trust dimensions has received little attention resulting in scholarly and managerial lacunae to precisely diagnose and remedy the problem with TP. To address this knowledge gap, this study first categorizes the trust-inducing features and then explores their impact on the trust dimensions of an OGB website in India. The results indicate differential impact of feature categories on the trust dimensions, thereby revealing new insights into the theory and practice of achieving targeted trust perception in online retail stores. The study describes limitations and offers meaningful scholarly and managerial implications.

Keywords: Trust dimensions, benevolence, integrity, ability, online group buying sites, website features classification, targeted trust.

INTRODUCTION

Whereas generating TP for online extensions of physical stores is relatively easy because of prior consumer familiarity (Gefen, 2000), it is far more difficult for firms that are created and operate only online (Jarvenpaa et al., 2000; Tan and Thoen, 2000). For such firms, lack of trust is the greatest barrier impeding first time consumers from conducting transactions (Urban et al., 2009) as shoppers remain skeptical. Earning consumer TP becomes even more important for the OGB sites because of the ephemeral availability of their offerings as well as perception of their impermanence due to lack of physical presence and frequent business closures, acquisitions, or mergers. Their deeply discounted deals on less known brands also raise suspicions about quality of the offerings. Despite these drawbacks, such sites have become popular among millennials seeking value at deep discounts, however, other online shoppers stay away because of lack of TP. Therefore, the primary focus of OGB websites is to create enough TP even amongst their non-millennial newest visitors, lessen their risk perception, and develop favorable shopping attitudes toward OGB (Heijdn et al., 2003).

Website trust encompasses three dimensions: integrity, ability, and benevolence (Schlosser et al., 2006). All three contribute toward overall TP; lack of TP on any dimension may undermine trust (Mayer et al., 1995). Current literature suggests that individually, certain website features can create overall TP (Basso et al., 2001; Fogg et al., 2003). What remains less explored, however, is the differential impact of these features on specific trust dimensions. In the absence of such knowledge, it is difficult for pure online stores such as OGB sites to adjust website features to modify consumer TP and for scholars to precisely diagnose the TP problem and offer managerially useful strategies to rectify the problem. This study fills this gap by first developing meaningful categories of disparate trust inducing features using Hunt's (1991) criteria and then exploring their impact on the trust dimensions. The main underlying logic is that classification schemata are the primary means not only for organizing a phenomenon into classes that are amenable to systematic empirical investigation but also in theory development. Therefore, the results of the study should substantively contribute to the theory and practice of OGB websites. At the theoretical front, the study builds a bridge between trust development in corporate retail websites and the OGB websites. The results of the study can provide opportunities to develop diagnostic tools to assess consumer TP of website trust dimensions and offer solutions to alleviate and/or enhance them. The results may also enable the website managers to modify specific feature categories to adjust the TP of the relevant dimension and also assist web-designers in customizing feature categories to achieve the targeted level of TP on specific dimensions for domestic and foreign buyers. This is important as online shopping is increasingly becoming more globally widespread (www.statista.com, 2017); there are more than three million e-commerce websites worldwide (www.shopify.com, 2017)

The remainder of the study proceeds as follows: the first section deals with the OGB sites in India and the need for building dimensional TP; the second provides a discussion on the website features, their categorization process, and the impact of feature categories on the respective trust dimensions. The third and fourth sections describe the research methodology, analysis and discussion of results. Lastly, we describe the contributions toward theory and practice of OGB and other online retail sites, limitations, and implications for future research.

INDIAN ONLINE GROUP BUYING WEBSITES

The literature review brings out about 20 OGB (*a.k.a. daily deal*) sites currently functional in India, showing a remarkable growth over the past decade from around ten pioneer sites appearing in 2008 after the arrival of Groupon in the US. According to Sharma and Balaram (2009), Koovs.com, Mydala.com, Snapdeal.com, Mobstreet.in, Dealsandyou.com, Taggle.com, Buzzintown.com, Govasool.com, Grabon.com and Sosata.com were some of the pioneer Indian OGB sites. Over time Sosata got acquired by Groupon (https://nextbigwhat.com/, 2011) and mobstreet by the Groffr group (https://track2realty.track2media.com/, 2011), and Taggle as well as Govasool closed their operations (https://economictimes.indiatimes.com, 2011). Despite the frequent closures or acquisition of some OGB sites, others such as koovs.com, snapdeal.com and mydala.com remained functional while new sites such as PaytmMall.com, Nearby.com, and Myntra.com keep coming up. Among the current OGB sites, SnapDeal.com, MyDala.com, Koovs.com, and Dealivore.com are rated as the top OGB sites (https://cluecommerce.com/, 2015). This vibrancy of the OGB market in India even after a decade of inception can be attribute to at least two key reasons. First, India has about 440 million millennials, the second largest number in the world (Caixa Bank Research, 2018), and they like to shop at OGB sites for variety and value (Dholakia and Kimes 2011; Klein and Sharma 2018). Second, the size of e-commerce market in India is on a growth trajectory to $67 billion by 2023 (https://www.statista.com/, 2017).

The Indian OGB sites are primarily Groupon-clones duly modified for local consumers such as in language, product portfolio, and payment practices. These sites encourage consumer participation through emails, text messages and by friends or families for specific deals and enable them to download deal-coupons for redeeming at the designated locations. Consumers get additional bonuses if they bring in new customers or make referrals. On their part, consumers can access these sites through a variety of social media such as Facebook, twitter, Google+, LinkedIn, and Instagram in case of deal-related or merchant-related problems or refund. On the procurement side, these sites incentivize merchants to supply them with products and services by promising them with increased potential sales, rapid inventory turnover, and increased brand awareness. Like their US counterparts, the Indian OGB sites act as online retail stores for scrambled portfolios of consumer necessities and aspirations products and services (Klein and Sharma 2018) exhibiting the following common characteristics. First, they offer a variety of product and service categories ranging from food, appliances, entertainment to electronics, but with limited choice within each category. Second, the discounts on daily deals usually range from 50% to 70% on mostly local or relatively lesser known brands. Third, the offered deals usually pertain to aspirational products and services that consumers want but higher prices keep postponing their consumption. These include, for example, laser hair removal, spa services, vacation, and popular branded electronic products. Summing up the description of the OGB sites in India, one can logically conjecture that the OGB phenomenon is well-entrenched and is likely to expand as online shopping is forecasted to grow. Furthermore, these OGB sites are catering to a large segment of millennials who are primarily working professionals having resources to purchase what these sites offer. However, frequent closures and re-appearance of OGB sites under different names raises consumer concerns about the longevity of their existence. Another source of consumer risk perception stems from the quality of local/lesser known brands. Though deep discounts on such products are enticing, they still raise consumer suspicions about their quality. Lastly, there is inherent high-risk perception about online transactions among shoppers (Schlosser et al. 2006). Taken together, such consumer concerns make it important for OGB firms to generate adequate TP about their integrity, ability, and benevolence toward consumers to make them feel comfortable in transacting with them. This would enable the OGB sites to increase their customer base as their industry is headed for growth in the foreseeable future.

WEBSITE TRUST

According to Jarvenpaa et al. (2000), trust in an internet store is the consumer willingness to rely on the seller even though this would leave them vulnerable to seller's opportunism. Corritore et al. (2003) define online trust as consumer attitude of confident expectations that the seller will not exploit his/her vulnerabilities. Such definitions are logical extensions of the offline trust--a multidimensional concept with three dimensions: integrity, ability, and benevolence that together produce the overall TP (Mayer et al., 1995). Gefen (2002) argued that these trust dimensions also apply to the online context. Subsequent studies have largely replicated such recommendations to the retail websites (Sirdeshmukh et al., 2002; Schlosser et al., 2006; Urban et al., 2009) while recognizing differences in consumer risk perception between the two store formats (Heijden and Verhagen, 2004; Wang and Emurian, 2005). In our view, such differences accentuate the importance of developing websites that can speedily generate TP even in their first-time visitors, a crucial element of their success (Lumsden, 2009), lacking which may become a major barrier to consumer purchasing (Urban et al., 2009). According to Alsudani and Casey (2009), consumers make first impression of trust in a website within a few seconds and this is critical as they may continue interacting with it or switch to another one. According to Fung and Lee (1999), visitors look for signals like appearance, design, and information quality to develop TP in a website. Schlosser et al. (2006) found that websites can earn consumer trust through signaling website investment. Sha (2009) observed that consumer perception of seals of approval and vendor-specific guarantees can generate trust intentions. McKnight et al. (2002) also found that perceived quality of a website strongly leads to trust formation. Pengnate and Sarathy (2017) noted that the visual appeal of a website produces greater impact on TP than its ease of use. In short, online firms can create TP by adding suitable features to their websites, which can convert visitors to consumers (Schlosser et al., 2006). However, which feature(s) affect specific trust dimensions remains scantily explored and, herein lies the *raison d'être* of this study.

As described earlier, the website trust comprises of integrity, ability, and benevolence dimensions. Based upon Mayer and Davis (1999), we provide a brief description of these dimensions in the context of an OGB website. The *Integrity* of an OGB site entails consumer perception that the site follows moral principles or acceptable professional standards in interaction with consumers. In short, the site follows acceptable ethical standards in customer dealings. The *Ability* of the OGB site lies in consumer perception that the website has the skills and resources to perform the promised tasks to be undertaken such as purchase transactions, delivery, or return of merchandise as promised. The *Benevolence* of an OGB website stems from consumer perception that the site has consumer interest at heart and does not solely focus on profitmaking, implying that the firm’s prices are reasonable and provide appropriate value for the monies paid. According to Mayer et al. (1995), each trust dimension provides a unique perspective to assessment of trust and all three contribute toward overall TP; absence or inadequacy of any of these dimensions may undermine trust. And, in case of no previous information about a website, the integrity dimension becomes most salient for the visitor and the perception of benevolence comes later. In analyzing consumer perception of dimensional trust in a U.S. retail website, Gefen (2002) found that the integrity and the benevolence dimensions significantly contribute toward the overall TP whereas the ability dimension does not, thereby partially supporting Mayer et al. (1995). The present study involving the impact of website features on perceptions of trust dimensions in an Indian OGB website not only supplements the findings of Gefen (2002) on trust dimensions in retail websites, but also opens opportunities specifically in creating and developing targeted level of TP in the OGB websites.

Trust Generating Website Features

The Cheskin Research study (1999) suggests that the website features that communicate trustworthiness are seals of approval, brand name, ease of navigation, information on order fulfilment process, high quality design, and professionalism. According to Basso et al. (2001), real time interactivity with a website increases perception of trustworthiness. In their classic study, Fogg et al. (2003) found that features such as design look, structure, company motive, information usefulness, accuracy of information, name recognition and reputation, advertising, and tone of writing induce website credibility. Eye catching graphics, ease of navigation, vendor advice, feedback mechanisms, and security-based seal of approval can create trust even among the first-time visitors to a website (Obal and Kunz, 2013; Tsygankov, 2004). Given the large number of disparate trust-inducing website features and suggestions, a few studies have categorized them for their specific objectives. For example, Hausman and Siekpe (2009) classified website features into computer factors that provide task relevant functionality and human factors that provide satisfaction. Karimov et al. (2011) classified website features into visual design, social cue design, and content design. They observed that visual dimensions, human-like cues, social media, assistive interface features such as recommendations, and e-assurances are important to initial trust formation. Lastly, Tan et al. (2009), classified features into 14 categories which are further reducible to four meta-categories: Content/information, Presentation, Website identity, and Accessibility from the view of a web-designer. Based upon these studies we generated a list of 21 trust-inducing features and following Hunt's (1991) criteria, we classified them into four categories from a first-time visitor's perspective to study their impact on individual dimensions of TP in an OGB website. The primary advantage of this perspective is that in addition to the first-time visitors, it also covers infrequent OGB shoppers.

Authenticity features (AF) are likely to give an impression of genuineness of the website even to a first-time visitor. The seven website features included in this category are *professional looks*, *attractiveness*, *multimedia features*, *high quality graphics*, *company name and logo in bold letters*, *well-organized*, and *security certificate/logo*. According to Fogg et al. (2003), individually, these features induce consumer perception of trustworthiness of a website. Robins and Holmes (2008) found that the visual design and the aesthetics of a website add to its credibility. Building upon this line of thinking, we suggest that, collectively, these features let a consumer know that the website is genuine for two primary reasons: the online firm has invested substantial effort in building the website and it can adequately undertake transaction-relevant tasks (Schlosser et al. 2006). Bilgihan and Bujisic (2015) observed that both the affective as well as the utilitarian features in a website affect trust. Taken together, these studies lead us to believe that the AF are likely to not only generate perception of the ability dimension, but also create perception about the integrity and benevolence dimensions of the website.

Company accessibility features (CAF) depict various ways consumers can access the firm behind the website. The six features comprising this category are *contact information* (such as email and phone number), *social networking links*, *ease of access*, *customer support*, *active links*, and *always up and available website*. These features collectively offer multiple channels of communication for website visitors so that they can psychologically experience close proximity to the firm. And, in case consumers have issues, they can resolve them. As a result, we think that the CAF category is likely to generate consumer perception of benevolence, integrity, and ability dimensions of website trustworthiness. Our thinking finds support in Othman et al. (2008), who suggest that inclusion of company phone number, e-mail address, and physical address in a website contributes to its trustworthiness. Likewise, Karimov et al. (2011) suggest that a high inclusion of company identity information can contribute toward initial trust formation. Taken together, a website passing the first two tests establishes its genuineness and perception of accessibility to consumers. Once a website passes the first two tests, the visitor is likely to assess the quality of website information by interacting with features relevant to a specific purchase.

Information quality features (IQF) portray the quality of website information provided to help consumer decision-making. The four features included in this category are *usefulness of contents*, *completeness of contents* (such as product and purchase relevant information), *currency of website*, and *accuracy of information*. These features create perception of information quality (Bovee 2004). According to Lumsden (2009), consumers utilize such interactive features to understand more about the information they contain. This category of features enables not only consumer prudence in decision-making, but also benefits the firm as the consumer is less likely to complain, spread negative WOM, or file lawsuit against the firm. The consumer may leave the website in case the information is outdated, irrelevant, or misleading. Like the first two feature categories, we also view that the IQF category is likely to influence consumer perception of all three dimensions of website trustworthiness. Our position finds support in Nicolaou and McKnight (2006) who observed that information quality positively affects trusting beliefs, reduces risk perception, and both in turn, increase consumer participation intentions. Most importantly, perceived accuracy of information influences the benevolence dimension of TP (Mayer and Davis, 1999).

Website usage-related features (WUF) cover four domains: *testimonials from previous buyers*, *clear statement of terms of use*, *clearly stated privacy policies*, and *elaborate FAQ*s. According to Litvin et al. (2008), new consumers regard testimonials from previous buyers as more trustworthy than the website information. Clear statements about using the website and product purchasing let consumers know about their responsibilities and those of the firm. Privacy policy statements show visitors the firm's intention to provide security and protect privacy. Finally, the elaborate FAQs provide visitors with helpful information about frequently asked questions. Such features enable consumers to interact with the website with little or no confusion. Like the previous three feature categories, we think that the usage-related feature category is also likely to impact consumer perception of all three dimensions of website trustworthiness.

In our view, these four categories of features would help a visitor to develop adequate TP of the ability, integrity, and benevolence dimensions in a website. Guided by the assumption that to varying degrees all four feature categories impact all three dimensions of trust, Figure 1 depicts the conceptual model.

Figure 1 about here

METHODOLOGY

Guided by the objectives of the study, we randomly selected a functional OGB site in India. The participants chosen were the graduate students of a large Indian university. We considered them relevant for the study because they are active in online shopping. The survey instrument was constructed using a five-point Likert scale with anchorage depicting 1=strongly agree, 2=agree, 3=neither agree nor disagree, 4=disagree, and 5=strongly disagree. The survey also included Schlosser et al.'s (2006) scale of trust dimensions and a demographic section seeking participants' information on gender and online shopping frequency. The participants were instructed to visit the selected website and record their perceptions on each item of the questionnaire and return it after completion within a week. In return, the participants earned extra class credit for submitting the completed task. A total of 194 completed responses were obtained. Using the SPSS tool for outlier detection, three responses were rejected thereby leaving 191 usable responses for the study.

We are cognizant that the study uses student data obtained from a convenient sample, however, such a type of data is considered appropriate for conducting exploratory analyses (Calder et al., 1982). Moreover, the results of the study are descriptive in nature and have no use for forecasting purposes. A second reason for the appropriateness of this type of data is that it comes from participants for whom online buying is a normal mode of shopping and such samples are commonly used in online shopping studies. The gender distribution of the sample showed 79 females (41.4%) and 112 males (58.6%). All respondents belonged to the 20 to 30 years old age group. In their response to the question about the frequency with which they visit online shopping sites each week, 56.5% had less than 10 visits, 35.1% had 10-20 times visits, 4.2% visited sites between 20-30 times, and the rest had visits more than 30 times.

The reliability analysis of Schlosser et al. (2006) scale for trust dimensions didn't result in removal of any item from the original scale. On the other hand, to check for internal consistency of items comprising the four scales (one for each website features category), we removed four items due to low item-total correlations within respective scales resulting in seventeen items. Table 1 depicts the mean and standard deviation of each remaining item comprising the specific scales. For each scale, the table also shows the composite mean, standard deviations and Cronbach's alpha. According to Hair et al. (2009), the generally agreed lower limit acceptable for Cronbach's alpha is 0.70 for scale to be reliable. As is clear from Table 1, all scales have alpha values above 0.7 except for the information quality (alpha =0.68) and website-related usage (alpha=0.67) scales. Since these two values are almost equal to 0.7, we considered them reliable for the study.

Next, we performed factor analysis using the principle component analysis with varimax rotation. The study identified 7 underlying factors with Eigen values greater than one. The KMO measure of sampling adequacy for the features was 0.893 and for the TP dimensions was 0.836 and both were statistically significant (p=0.000). Table 1 also shows factor loadings for each scale. To minimize the possibility of multi collinearity, the factor scores for the independent and the dependent variables were saved for regression analyses. The VIF value was found to be 1.0. The normality plot also showed good fit of the data with no significant deviation from normality. Next, the data was subjected to multiple regression analysis using the IBM SPSS Statistics 24.

Table 1 about here

This study uses four website feature categories to assess their impact on each of the three website trust dimensions deploying the general multiple regression analysis equation:

$$Y_{\text{trust dimension}} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \epsilon$$

The dependent variable $Y_{\text{trust dimension}}$ is the specific trust dimension for each model. It is the Website Ability for model 1, Website Integrity for model 2, and Website Benevolence for model 3. The four independent factors for all three models are X_1 =Authenticity features (AF), X_2 = Company Accessibility features (CAF), X_3 = Information Quality features (IQF), and X_4 = Website Usage-related Features (WUF). Whereas β_0 is the constant, β_1, β_2, β_3 and β_4 are the regression coefficients of the independent factors for all models resulting in three seemingly unrelated regression models, and ϵ = an error term with zero mean. The resulting regression equations for the three models are:

Model 1: $\text{Website Ability} = \beta_0 + \beta_1 AF + \beta_2\, CAF + \beta_3\, IQF + \beta_4\, WUF + \epsilon$

Model 2: $\text{Website Integrity} = \beta_0 + \beta_1 AF + \beta_2\, CAF + \beta_3\, IQF + \beta_4\, WUF + \epsilon$

Model 3: $\text{Website Benevolence} = \beta_0 + \beta_1 AF + \beta_2\, CAF + \beta_3\, IQF + \beta_4\, WUF + \epsilon$

We are aware that running several independent multiple regressions in a model may increase the possibility of Type I error (Hair et al., 2009). However, according to Menon et al. (1999), such a method is appropriate for testing the impact of a set of independent variables on each dimension of a multidimensional dependent variable if the potential of increasing the Type I error is minimum. To check this possibility, they conducted an omnibus test using canonical correlation analysis with all independent and dependent variables and found that the canonical correlation was significant, which justified the use of 10 multiple regression models in their study. Following their recommendation, we also conducted a canonical correlation analysis using all the independent and dependent factors and found the results of the omnibus test to be significant (Wilks' lambda =0.376, F= 81.18, p <0.0001), thereby indicating that the potential for Type I error is minimal. Therefore, in line with Menon et al. (1999), we think that the use of three multiple regression models to analyze the impact of four feature categories on three trust dimensions is justified. Mayer and Davis's (1999) seminal work on trust management used a similar methodology in which they conducted multiple independent regressions for the same set of independent variables on each trust dimension, which further supports our line of analysis.

RESULTS AND DISCUSSION

To check for the goodness of fit for each regression model, we examined the values of multiple correlation coefficient (R), coefficient of determination (R^2), and F-ratios. Table 2 shows the regression results for each model.

Table 2 about here

For models 1, 2 and 3, the multiple correlation coefficient values of R= 0.748, 0.575, and 0.526 respectively indicate the respondents' perception of strong relationship between the four independent factors and the respective dependent factors. Taken together, the R^2 values indicate that the four categories of website features provide highest explained variation for the ability dimension (0.559), followed by the integrity (0.331). and the benevolence dimension (0.277) of trust suggesting that the perception of the benevolence dimension of trust may increase with visitors' experience with the website. This result finds corroboration in Mayer et al. (1995) suggestions that in case of no prior information about a trustee, the integrity dimension becomes most salient for the trustor and the perception of benevolence comes later.

Except for the WUF category, all other three categories of features exhibit significant impact on consumer perception of the ability, integrity, and the benevolence dimensions of trust of the OGB site. However, for model 3, all four categories of features exhibit significant impact on consumer perception of the benevolence dimension of website trust. In other words, the usage-related website features contribute significantly toward the benevolence dimension of website trust only, thereby partially corroborating the study's assumption that to varying degrees all four categories of features affect all three dimensions of trust of the OGB site.

Impact of Individual Feature Categories on Trust dimensions

For all three models, the regression coefficients indicate that the AF have the strongest impact on consumer perception of the ability (β=0.456, p=0.000), followed by integrity (β=0.358, p=0.000), and benevolence (β=0.279, p=0.000) of the OGB website. This suggests that the AF category of features impacts differentially on all three dimensions of the OGB website. Likewise, the regression coefficients for the CAF category of features indicate the strongest impact on perception of the ability (β=0.545, p=0.000), followed by integrity (β=0.375, p=0.000), and benevolence (β=0.321, p=0.000) dimensions of the OGB site. Once again, the implication is that an OGB website having a good company accessibility features affects all three dimensions of TP of the website differentially. However, the results provide a further insight that the CAF features lend greater credence to the integrity of the OGB site than the AF features suggesting that accessibility of the firm behind the OGB website enhances consumer trust in the integrity of site. The third category of the website features, the IQF also significantly influences the ability, integrity, and benevolence dimensions of the OGB website TP. The regression coefficients for benevolence (β=0.248, p=0.000), integrity (β=0.241, p=0.000), and ability (β=0.231, p=0.000) though smaller than the AF and CAF feature categories, suggest that these features have almost similar impact on perception of all three dimensions of TP of the site. That is, an OGB website providing high quality information garners high TPs from its visitors on all three dimensions. Once again, our results find support in Nicolaou and McKnight (2006) and Mayer and Davis 1999. Lastly, the WUF features exhibit a significant impact only on the benevolence dimension of TP of the OGB site, which suggests that the features such as customer testimonials and elaborate FAQs on the OGB site only enhance the perception of benevolence dimension of the website trust.

In sum, the results of the study suggest that the four website feature categories exhibit differential impacts on the first-time visitors' perceptions of the OGB website's ability, integrity, and benevolence dimensions of trust. Though exploratory, these results provide significant insights about diagnosing the OGB website TP problems, isolating them, and developing precise solutions. Since OGB sites are also a version of online retail stores, these results can also provide diagnostics for online corporate retail stores.

CONCLUSION

As described earlier, several studies have demonstrated the relationship between certain individual website features and website trustworthiness. However, what remained insufficiently answered was a key question: what are the differential impacts of website features on the OGB website trust dimensions? We designed the study to answer this specific question. In this context, the study first categorized the website features into four categories from the perspective of a first-time visitor to an OGB website. The guiding principle used was how a first-time website visitor would approach assessing dimensional TP of an OGB website. The results indicate that the website feature categories exhibit differential impact on the three trust dimensions, and they are very much in line with Gefen (20002). Furthermore, the results also provide an indirect validation of the classification of website features, which reinforces the widely held notion about theoretical rigor of Hunt's classification schema.

The results of the study provide substantive contributions toward the theory and practice of development and maintenance of targeted website dimensional TP. The first contribution this study makes toward the theoretical front is the establishment of a bridge between 'trust development in corporate retail websites and the OGB websites,' thereby opening research opportunities for scholars to conduct analysis on the similarities or differences pertaining to consumer patronage development for these two online retail formats. Second, the study creates research opportunities in categorization of website features as well as the development of diagnostic tools for website dimensional trust problems. Finally, the third contribution points toward potential research opportunities in the development of specific categories of website features to increase consumer loyalty for all pure online retail websites. The results of this study can also open avenues for web-designers about customization of website trust for OGB or other online retail firms for extension of their operations to specific foreign markets. This would require web-designers to include cultural-specific trust inducing website features for local consumers as culture moderates the relationship between the website design factors and TP (Ganguly et el. 2010). The OGB site managers can also adjust the dimensional TP of their website by adding or removing features depending upon their consumer research. For example, OGB firms interested in enhancing perception of integrity and ability trust dimensions of their websites should strengthen the authenticity and accessibility features.

The study uses student data from a convenient sample to analyze the impact of different website trust-inducing feature categories on the dimensions of website trust. Given the objective of the study, this type of data is appropriate (Calder et al.); however, such data also limits the generalizability of the results to a larger universe of OGB or other retail websites. Limitations aside, this study furnishes opportunities for future studies to use random samples of online shoppers to enhance generalizability of their results to a larger universe of websites. In conclusion, this study makes substantive contributions to the scholarship, design, and management of dimensional TP in the OGB websites in domestic and foreign markets lacking which leads to consumer reluctance to follow website advice and share personal information with the site (McKnight et al. 2002) and hence shop at the site (Hsiao et al. 2010).

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Website Features Categories and Trust Dimensions

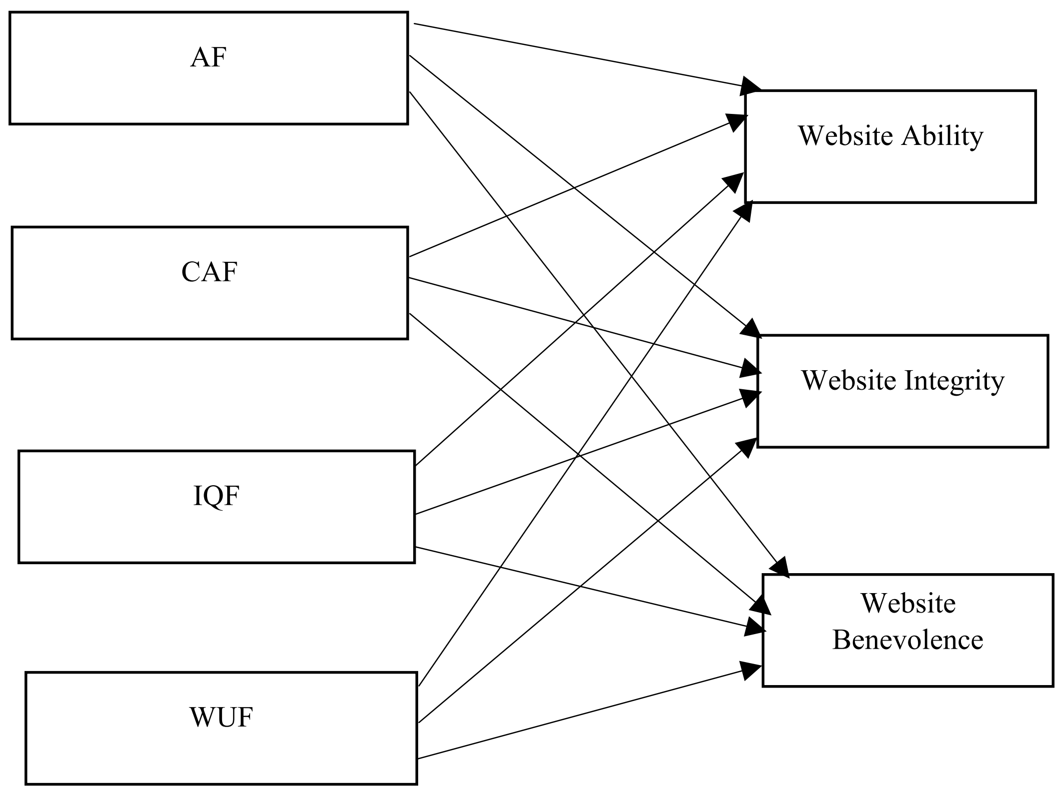

Figure 1

Table 1

Properties of Dependent and Independent Variables

Variables	Mean (SD)	Cronbach Alpha	Factor Loading
<u>Dependent Variable</u>			
Website Ability	**2.086 (0.890)**	**0.903**	
Capability of performing online transactions	1.95 (0.899)		0.909
Successful at the things the web site tries to do	2.05(0.875)		0.915
Knowledgeable to fulfill Online Transactions	2.01(0.843)		0.882
Confidence in Website's Online Skills	2.34(0.943)		0.819
Website Benevolence	**2.601 (0.870)**	**0.749**	
Concern about Consumer Welfare	2.71 (0.911)		0.627
Importance of consumer needs and desires to the website	2.49 (0.894)		0.771
Website Knowingly Wouldn't do anything to Hurt Consumers	2.30 (0.860)		0.660
Helpful Nature of the Website	2.73 (0.870)		0.739
Website Cares for what is Important to Consumers	2.78 (0.817)		0.725
Website Integrity	**2.467 (0.848)**	**0.739**	
Strong Sense of Justice of the Website	2.63 (0.809)		0.772
Fairness in Dealings of the Website	2.19 (0.906)		0.769
Website Values	2.43 (0.873)		0.769
Soundness of Principles Guiding Website Behavior	2.61 (0.800)		0.677
<u>Independent Variable</u>			
Authentic Features (AF)	**2.10 (0.735)**	**0.861**	
Professional looking Website	2.03 (1.107)		0.752
Company Name/Logo	1.95 (0.986)		0.636
Attractiveness of Website	2.21 (0.978)		0.800
Well-organized Website	2.08 (1.017)		0.767
Multimedia features	2.16 (0.898)		0.652
Security certificate/Logo	2.17 (0.977)		0.438
High quality Graphics	2.16 (1.000)		0.683
Company Accessibility Features (CAF)	**2.00 (0.722)**	**0.862**	
Contact Information	1.85 (0.923)		0.813
Social Networking Logos	1.89 (0.953)		0.818
Ease of Access	1.89 (0.931)		0.644
Always up and Available	2.17 90.937)		0.665
Customer Support	2.22 (0.920)		0.718
Active Hyperlinks	1.99 (0.971)		0.560
Information Quality Features (IQF)	**2.41 (0.831)**	**0.68**	
Currency of Website	2.49 (1.110)		0.882
Accuracy of Website	2.35 (0.818)		0.693
Website Usage-related Features (WUF)	**2.45 (0.920)**	**0.67**	
Testimonials	2.42 (1.100)		0.851
FAQs	2.48 (1.210)		0.667

Table 2

Results of Website Feature Categories on Trust Dimensions

Model	Goodness of Fit		Beta Value	Significance
Model 1: Dependent variable : Website Ability				
Multiple R = 0.748; R square= 0.559; F = 59.008				0.000
Independent Variables		AF	0.456	0.000
		CAF	0.545	0.000
		IQF	0.231	0.000
		WUF	0.031	0.531
Model 2: Dependent variable : Website Integrity				
Multiple R= 0.575; R square= 0.331; F = 22.991				0.000
Independent Variables		AF	0.358	0.000
		CAF	0.375	0.000
		IQF	0.241	0.000
		WUF	0.066	0.273
Model 3: Dependent variable : Website Benevolence				
Multiple R = 0.526; R square = 0.277; F = 17.778				0.000
Independent Variables		AF	0.279	0.000
		CAF	0.321	0.000
		IQF	0.248	0.000
		WUF	0.062	0.003

Credit Risk Modelling for Assessing Creditworthiness for Homeowners Who Can Avail Solar on Finance at Peacock Solar, Gurugram

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ABSTRACT

Peacock Solar is a household solar installation company based in Gurugram, Haryana. It provides hassle free installation of solar power. In an era of rising demand for renewable energy, solar power is seen as a future of energy. The markets are becoming more competitive as better technologies increase the efficiency and lower the cost of solar power. In India, solar power is in its nascent stage of development and being price sensitive markets, cost remains the bottom line of competition.

The present study is an attempt to showcase the strategy adopted by Peacock solar to enhance its sales by making solar available on finance." The objective of this research paper is come up with a model that anticipates the probability associated with default for homeowner who avails solar on finance. The next objective is to develop a scorecard that represents this probability of default in form of credit score for enhanced understanding and decision making.

By making solar available on finance, the company aims to overcome its price related hindrances. The methodology used for development of credit risk model is Logistic Regression as it is one of the best techniques for predicting a binary outcome (will default or will not default). This is followed by a technique for scorecard development. It can then be concluded that credit risk can be reduced to a considerable extent if correct analytical methodologies are put in place which will bring down the default rates on credit.

Keywords: Credit risk modelling, creditworthiness and solar power

Credit Risk Modelling for Assessing Creditworthiness for Homeowners Who Can Avail Solar on Finance at Peacock Solar, Gurugram

INTRODUCTION

1.1 Company Profile

Peacock Solar specialises in solar services. It provides hassle free installation of solar power. Since, its inception in 2017, it has successfully completed 40+ projects and has thus saved 24 metric tonnes of carbon dioxide emission. In terms of power, it has till date installed project of 200KW. Presently operating in Kota (Rajasthan), the company is all set to mark its presence in pan India.

With the advent of 21st century, the energy demands have skyrocketed all over the world. Lack of technological development in the energy sector has put pressure of non-renewable sources to match up the demand for energy. This has caused rise in the level of carbon dioxide and other poisonous gases to increase at an alarming rate.

As solar remains a tough market to compete in Indian environment, Peacock solar has maintained its edge by deploying cutting edge technology and financial innovation to increase its reach and reduce the cost of solar installation. Peacock solar strives for cleaner environment by providing solar as an energy alternative. With technological advancement in last decade, cost of solar panels has reduced significantly.

1.2 Introduction to credit risk modelling

Credit risk is the chance of a borrower defaulting on a debt by failing to make the required payments. Risk is an inherent part of the lending paradigm for financial institutions and other lenders. Pinpointing the amount of risk that comes with each loan is a difficult task. Credit risk modelling has multiple aspects to it, not only we need to calculate the probability for measuring the chances for default, we also need to assess what is the extent to which the company will suffer a loss in case of default.

Historical data of consumers is collected to study the behaviour of consumers based on selected parameters from the data. Then data is refined and worked to bring out a model that will help in anticipating the associated probabilities of default. This helps companies to create a cover that will enable them to prepare for such uncertainties.

1.3 How peacock solar aims to use credit risk modelling

Peacock solar operates under two business model:

- CAPEX
- OPEX

Under CAPEX (Capital Expenditure) business model, the homeowners pay upfront for solar power installation at their place. In this way entire burden of the cost is borne by the homeowners.

Under OPEX (Operational Expenditure) business model, the company on its own expenditure installs the plant at homeowner's premise and the homeowners are expected to pay for their monthly usage unit wise. Here arises the risk of default on the part of homeowner. If homeowner defaults then entire cost is borne by the company. So, to reduce this risk the company want to develop a credit risk model to assess the probability of default of the homeowner before the installation is made.

2. LITERATURE REVIEW

Credit risk can be assessed using accounting measures (Altman, 1968 and Ohlson, 1980). They made accounting variables as a basis for assessing the risk for corporate bankruptcy. Applying statistics to accounting variable help to get a score. They developed a Z score that would show the chances for business to enter bankruptcy. The higher the score greater will be the chances of company facing bankruptcy. The limitation of this study was that is predictability is based on financial statements which are prepared on the principal of going concern and thus it is assumed that the firm will not default.

The concept of value at risk is a better measure for assessing the credit risk (Jorion, 2006). This approach is used by J.P. Morgan and chase and is based on the idea that the model used to manage credit risk has to be applicable to all types of financial instruments subjected to substantial credit risk and valuation methods have to correspond with actual market prices. Credit Metrics is therefore used for valuation of bond prices. Credit Metrics offers a different approach to credit risk measuring than structural models. It uses completely different variables than structural approaches. Credit Metrics offers so called empirical Value at Risk approach to measuring credit risk, which should reflect current market prices, and addresses the question "how much funding will be lost" in the worst case. As it more of a hybrid model and contains structural model characteristic. Then the stock price consideration will again act as a drawback because market prices do not reflect true market sentiments and does not have all information contained in them.

"Risk neutrals", which is a way in which we compute no risk probabilities of upcoming cash flows and the calculating their present value at T-bill rate (Jarrow and Turnbull,1992). They divided the problem of credit risk modelling in two part, firstly assessing the chances of default and the assessing the loss that can be suffered due to default.

2.1 Consolidated Research gaps

- Analytical approach to assessing credit risk remains a research gaps in all of the articles that were reviewed. A proper analytical tool or methodology could be a better way for assessing the credit risk.
- Representation of credit risk in form of probability associated with default is another research gap identified. There should be a lucid way to represent probability of default that would enhance the interpretability for results.

2.2 Research objective

Based on research gaps explored above in the literature review and based on the recommendations of the company, Peacock Solar, the following are the objectives of research report

- To develop a model for estimating probability of default associated to an applicant homeowner who wants solar on finance.
- To develop a scorecard to effectively represent probability of default for enhanced understanding.

3. RESEARCH METHODOLOGY

As research objectives have been formulated above based on the gaps identified in the literature review. This part of report describes the research methodology in a logical sequence which can be adopted to achieve these objectives.

3.1 Methodology for objective 1

3.1.1 Sample size

The dataset that is used for model development is an American dataset that has 466284 observations.

3.1.2 Modelling technique

Logistic regression has been used to develop the model for anticipating the probability associated with default.

3.1.3 Modelling steps

3.1.3.1 General pre-processing of data

As this model development was done on python, the first step was to get each and every variable into a correct datatype as supported in python.

Identifying data types of each variable

Figure 1

Import Data ¶

```
loan_data_backup = pd.read_csv(r'C:\Users\Aditya\Desktop\excel files\loan data.csv')
```

```
C:\Users\Aditya\anaconda3\lib\site-packages\IPython\core\interactiveshell.py:3063: DtypeWarning: Columns (19) have mixed types.
Specify dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

```
In [20]: # to view datatype of each variable in the dataset
         loan_data.info()
         # term and employment_length should be numeric but they are strings(object data type)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 466285 entries, 0 to 466284
Data columns (total 74 columns):
 #   Column                        Non-Null Count   Dtype
---  ------                        --------------   -----
 0   id                            466285 non-null  int64
 1   member_id                     466285 non-null  int64
 2   loan_amnt                     466285 non-null  int64
 3   funded_amnt                   466285 non-null  int64
 4   funded_amnt_inv               466285 non-null  float64
 5   term                          466285 non-null  object
 6   int_rate                      466285 non-null  float64
 7   installment                   466285 non-null  float64
 8   grade                         466285 non-null  object
 9   sub_grade                     466285 non-null  object
 10  emp_title                     438697 non-null  object
 11  emp_length                    445277 non-null  object
 12  home_ownership                466285 non-null  object
 13  annual_inc                    466281 non-null  float64
 14  verification_status           466285 non-null  object
```

Pre-processing continuous variables

Identifying all different values that a continuous variable is taking using unique () python function.

Figure 2

```
In [21]: # what are the different values that variable is taking. This ideally should be a numeric variable but is string variable(Object
         ## To convert it into numeric we will have to remove strings from it and then convert it. Strings contained are "years", "year",'
         loan_data['emp_length'].unique()

Out[21]: array(['10+ years', '< 1 year', '1 year', '3 years', '8 years', '9 years',
                '4 years', '5 years', '6 years', '2 years', '7 years', nan],
               dtype=object)
```

Removing strings from the continuous variable to convert them to numeric datatype.

Figure 3

```
In [22]: # lets define a new variable and that put all changed values into it. str.replace function asks for two arguments(1. string to be
         loan_data['emp_length_int'] = loan_data['emp_length'].str.replace('\+ years','')
         loan_data['emp_length_int'] = loan_data['emp_length_int'].str.replace('< 1 year',str(0))
         loan_data['emp_length_int'] = loan_data['emp_length_int'].str.replace('n/a',str(0))
         loan_data['emp_length_int'] = loan_data['emp_length_int'].str.replace('years','')
         loan_data['emp_length_int'] = loan_data['emp_length_int'].str.replace('year','')
```

Now finally converting to numeric datatype.

Figure 4

```
In [24]: # pandas function to_numeric convert string datatype to numeric datatype
         loan_data['emp_length_int'] = pd.to_numeric(loan_data['emp_length_int'])

In [25]: # again check to see if data type is changed or not. Yes now its changed to numeric. So we have successfully processed first con
         type(loan_data['emp_length_int'][0])
```

This example above shows how a single continuous variable in the dataset was converted to its correct form for operations in python. In a similar way all other continuous variables were also processed to make them ready for further analysis in python.

Pre-processing of discrete variables

An example of one of the discrete variables ‘Grades’ is taken to show how all discrete variables in the data set were processed to their correct datatype in python.

Firstly, dummy variables were created for each of the categories of discrete or categorical variable.

Figure 5

```
In [43]: ## Discrete variables that will be taken into consideration.( Grade, sub_grade,homeownership,Verification status,loan_status,purp
         # we need to create dummy variables for discrete variables.Lets go ahead with grade variable.Dummy variables are binary variables
         ## to create dummy variable pandas has dedicated method called get.dummies. It creates as many dummy variabkes as there are categ
         pd.get_dummies(loan_data['grade'])
         ## Lets create a new data frame where we will store all new dummy variable and then concatenate this data frame to loan data data
```

Figure 6

```
In [44]: # Also note that the new created dummy variables have the same name as that of the original categories. If we are about to appen
         # categories of dummy variable have same name as that of original category for the variable. Therefore lets change that.
         pd.get_dummies(loan_data['grade'], prefix = 'grade',prefix_sep = ':')
```

Out[44]:

	grade:A	grade:B	grade:C	grade:D	grade:E	grade:F	grade:G
0	0	1	0	0	0	0	0
1	0	0	1	0	0	0	0
2	0	0	1	0	0	0	0
3	0	0	1	0	0	0	0
4	0	1	0	0	0	0	0
...	...	...	...	...	...	...	...
466280	0	0	1	0	0	0	0
466281	0	0	0	1	0	0	0
466282	0	0	0	1	0	0	0
466283	1	0	0	0	0	0	0
466284	0	0	0	1	0	0	0

In this way every observation in the dataset will have value of 1 at the grade category to which it belongs and rest all will be zero.

In a similar way dummy variable were created for all discrete variables for better representations.

Figure 7

```
In [45]: ## We will assign all of the resulting dummy variables as a list to a new variables called loan_data_dummies.
         # for every record you will only find 1 at that grade to which it originally belongs to for rest all 0
         ## In a similar way we can create dummy variable for each discrete variable and let's also cretae a new variable that will contai
         loan_data_dummies = [pd.get_dummies(loan_data['grade'], prefix = 'grade', prefix_sep =':'),
                              pd.get_dummies(loan_data['sub_grade'], prefix = 'sub_grade', prefix_sep =':'),
                              pd.get_dummies(loan_data['home_ownership'], prefix = 'home_ownership',prefix_sep =':'),
                              pd.get_dummies(loan_data['verification_status'], prefix ='verification_status', prefix_sep = ':'),
                              pd.get_dummies(loan_data['loan_status'], prefix = 'loan_status', prefix_sep = ':'),
                              pd.get_dummies(loan_data['purpose'], prefix = 'purpose', prefix_sep = ':'),
                              pd.get_dummies(loan_data['addr_state'], prefix = 'addr_state', prefix_sep = ':'),
                              pd.get_dummies(loan_data['initial_list_status'], prefix = 'initial_list_status', prefix_sep = ':')]
```

Pre-processing for missing values

Identify missing values in each column using is null function of python.

Figure 8

```
In [50]: # Now lets go ahead and complete general processing by fixxing the missing value issue at many observations all across the data
         ## Pandas has a dedicated function called isnull() that locates all missing values in the data set. True represents missing value
         loan_data.isnull()
```

Out[50]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownership
0	False	False	False	False	False	False	False	False	False	False	True	False	False
1	False	False	False	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	True	False	False
3	False	False	False	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...	...	...	...
466280	False	False	False	False	False	False	False	False	False	False	False	False	False
466281	False	False	False	False	False	False	False	False	False	False	False	False	False
466282	False	False	False	False	False	False	False	False	False	False	False	False	False
466283	False	False	False	False	False	False	False	False	False	False	False	False	False
466284	False	False	False	False	False	False	False	False	False	False	True	False	False

Replacing missing values of interest variables with zero.

Figure 9

```
In [57]: loan_data['mths_since_earliest_cr_line'].fillna(0, inplace=True)
         loan_data['acc_now_delinq'].fillna(0, inplace=True)
         loan_data['total_acc'].fillna(0, inplace=True)
         loan_data['pub_rec'].fillna(0, inplace=True)
         loan_data['open_acc'].fillna(0, inplace=True)
         loan_data['inq_last_6mths'].fillna(0, inplace=True)
         loan_data['delinq_2yrs'].fillna(0, inplace=True)
         loan_data['emp_length_int'].fillna(0, inplace=True)  # lets fill missing values for all columns for appropiate values
         # We fill the missing values with zeroes.
```

3.1.3.2 *PD model: Data preparation*

The first step is setting up of dependent variable or the what is to be predicted. The variable of interest in the dataset is ‘loan status’, as it clearly sets out the status of an individual on his loan obligation. Therefore, to be able to distinguish between good and bad loans, it will need to define what default is. More specifically, it needs a default definition. This definition comprises rules stating when a borrower is considered to have defaulted on a loan.

A common definition is that a borrower has defaulted if they are more than 90 days past due on the loan. But this is not the only definition to be used though. The default definition results in the loan being classified as a not defaulted or good or defaulted or bad. Usually, a new variable in the data set of a Boolean or binary type is created. Zero will stand for defaulted loan and 1 for good loan.

Figure 10

The established statistical methodology to model probability of default is a logistic regression where the dependent variable is precisely whether a customer defaulted or not. The logistic regression estimates relationship between two things, the logarithm of odds of an outcome of interest or dependent variable and a linear combination of predictors. In our case the outcome of interest is the non-default or default event.

Figure 11

$$\ln\left(\frac{\text{Non-defaults}}{\text{Defaults}}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_m X_m$$

When it comes to PD model, interpretability is of prime importance as required by regulator for Basel 2. The model should be very easy to understand and apply. Even people who have never heard of statistical analysis should be able to work with it. This is why it is an established practice for all independent variables in PD model to be dummy variables that is binary categorical variables or indicator variable.

In other words, independent variables will be included in the model as dummy variable. Dummy variables were already created earlier. But, while it has many discrete variables such as external rating etc, it also has many continuous variables. The convention is to convert continuous variable to dummy variable. Once that is achieved the PD model will be a logistic regression model with the binary indicator for good or bad or non-default or default.

Figure 12

Processing Dependent variable

Identifying all unique values that dependent variable is taking.

Figure 13

```
In [59]: # Lets see what unique values loan status which is our dependent variable is taking. Evidently accounts that are fully paid or cu
         loan_data['loan_status'].unique()

Out[59]: array(['Fully Paid', 'Charged Off', 'Current', 'Default',
                'Late (31-120 days)', 'In Grace Period', 'Late (16-30 days)',
                'Does not meet the credit policy. Status:Fully Paid',
                'Does not meet the credit policy. Status:Charged Off'],
               dtype=object)
```

Using value count to see how many accounts belongs to each of categories of dependent variables.

Figure 14

```
In [60]: # now lets see how many accounts are there under each of the category. We use value counts method to see how many accounts are th
         loan_data['loan_status'].value_counts()

Out[60]: Current                                                224226
         Fully Paid                                             184739
         Charged Off                                             42475
         Late (31-120 days)                                       6900
         In Grace Period                                          3146
         Does not meet the credit policy. Status:Fully Paid       1988
         Late (16-30 days)                                        1218
         Default                                                   832
         Does not meet the credit policy. Status:Charged Off       761
         Name: loan_status, dtype: int64
```

The loan status of charged off, default, does not meet credit policy status: charged off, late (31-120 days) are all to be counted under defaulted loan rest all in not defaulted. Going ahead with a code that would segregate all loans under default column as 0 and all other as 1. It will then be stored in a new variable called good bad variable that will act as dependent variable.

Figure 15

```
In [62]: ## Now lets define a more precise default definition. We will store our good or bad flag in a new varaible called good_bad.
         ## pandas has a function called np.where, it is most likely like if function of Excel(its a numpy function). isin method checks i
         loan_data['good_bad'] = np.where(loan_data['loan_status'].isin(['Charged Off', 'Default', 'Does not meet the credit policy. Statu

In [63]: loan_data['good_bad']
Out[63]: 0         1
         1         0
         2         1
         3         1
         4         1
                  ..
         466280    1
         466281    0
         466282    1
         466283    1
         466284    1
         Name: good_bad, Length: 466285, dtype: int32
```

Processing Independent continuous variable to categorical dummy variables.

Continuous variables are required to be converted to categorical dummy variable so going ahead with PD model. This can be achieved using technique of Fine classing, weight of Evidence, Coarse classing, Information value.

Below is an example to explain this work.

Example: If we select a variable to range from zero to 100 such as the debt-to-income ratio, it could split it into 50 categories with 2% width each. 0-2, 2-4, 4-6 and so on. These initial categories rarely matter as it will later bundle them up nonetheless.

Figure 16

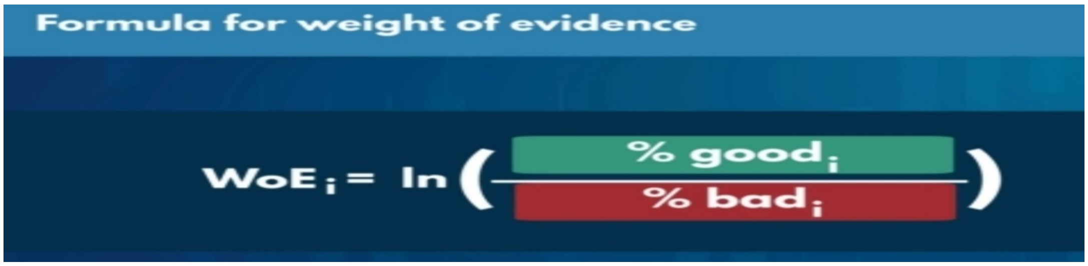
So conceptually with fine classing both discreet and continuous variable can be represented in the form of categories. But the question that still remains is how to actually run these arbitrary categories into good usable dummies. Since it will be having categories in both cases i.e. discrete and continuous, the approach of creating dummies for continuous variable will remain same.

It starts by getting some rough initial assessment of the ability of each category in continuous variable to predict the dependent variable. Using the technique called Weight of Evidence we can differentiate in a better way between good and bad loans. More specifically, WoE shows the extent to which each of the different categories of an independent variable explains the dependent variable. It is calculated using the formula.

The formula of the weight of evidence is the natural logarithm of the ratio of the proportion of observations of the first type of outcome of the dependent variable that fall in each of the category of the explanatory variable and the proportion of the observation of the second type of outcome of the dependent variable that fall into the each of the categories of the explanatory variable.

So, this formula in our case will be like this. The two type of outcome are not defaulted and defaulted or bad. So, the weight of evidence would be the natural logarithm of the ration of the proportion of goods from the total number of good loans that fall into the category to the proportions of bads to total number of bads that fall into a category.

Figure 17



The course classing is a process of merging initial categories based on similar WoE and creating broader categories. It has many continuous variables that will have initially 5 or 6 or may even have 50 categories initially. But, based on weight of evidence it will combine them into bigger categories. Usually, it has preferred those categories that have similar weight of evidence to be bundled up together. In this way it lowers the number of dummies and improve our PD model.

For information value understanding, let us assume that an original independent variable has been split into categories. It may have been categorical originally or categories might have been determined through fine classing. Suppose there are k categories of this variable, then it can calculate weight of evidence for each of the k categories. From there it can weight these weights of evidence of each category. It can weight each by the difference of the proportion of goods from the total number of good that fell into the respective category and the proportion of bads from the total number of bads that fall into the respective category. Then it simply sums them to reach a weighted average of the weight of evidence of the k categories. The result is called Information value of the original explanatory variable with respect to the outcome variable.

Information value shows the extent to which original explanatory variable explains the outcome variable. Therefore, information value can be used for preselection of variable.

Figure 18

$$\sum_{i=1}^{k}\left[\left(\%\,good - \%\,bad\right) \times \ln\left(\frac{\%\,good}{\%\,bad}\right)\right]$$

The value of information value ranges between zero and one. The father away the value is from zero, the better the independent variable is explaining the dependent variable.

Calculating weight of evidences for discrete variables

Weight of evidences calculated for each of the discrete variables. Below is an example showing how this was carried out for ‘Grade’ variable.

First all those accounts that are identified that belonged to each of the grade.

Figure 19

```
In [182]: # Now we can create a new DATAFRAME called df1 where we will store only the independent variable grade from the df inputs pre prc
          ## and the dependent variable good bad from the df targets pre processing data frame.
          df1 = pd.concat([df_inputs_prepr['grade'], df_targets_prepr], axis = 1)
          df1.head()
Out[182]:
```

	grade	good_bad
362514	C	1
288564	E	1
213591	C	1
263083	C	1
165001	A	1

The values of the grade variable are letters from A to G. They represent external grades, with A showing the highest credit worthiness and G showing the lowest. In order to find the weight of evidence of grade, it must first find the proportion of good and bad borrowers by grade. Thus, it first calculates number of borrowers in each grade. To do that it need to count the rows that contain each of the grades.

Figure 20

```
In [184]: ## Let's start by knowing how many borrowers are there for each grade.
          # To do that we can count the rows that contain each of the grades. We do this with t
          ## In our case we want to split by grade.So we type DFA one dot group by and in brack
          # We know that it is the first column in our data frame. Recall that counting in Pyth
          ## If we group like this the grouped values become indexes in the result we get havir
          ## We are actually interested in the number of rows or the count the rows in each grc
          # Since we want the total count of rows.We'll apply the count method.
          df1.groupby(df1.columns.values[0], as_index = False)[df1.columns.values[1]].count()
```

Out[184]:

	grade	good_bad
0	A	15108
1	B	27199
2	C	25048
3	D	15390
4	E	7145
5	F	2699
6	G	668

Another piece of information that will be need is the proportion of good and bad borrowers are within each group. This can be summarised either by the proportion of good borrowers or by the proportion of bad borrowers. It does not matter which one. Since the proportion of good borrowers equal to 1 minus proportion of bad borrowers. Let's calculate proportion of good borrowers here. The good bad variable has a value equal to 1 when the borrower is good and 0 when borrower is bad. Hence, it would get proportion of good borrower simply by calculating the average of good or bad.

Figure 21

```
In [185]: # Now we have total number of borrower for each grade. Now we need to find proportion of good or proportion of bad borrower.
          ## Remember that the good bad variable has a value of 1 when the borrower is good and the value of 0 when the borrower's bad henc
          ## We can apply the same statement as above except that at the end we apply the mean method instead of the count method.
          df1.groupby(df1.columns.values[0], as_index = False)[df1.columns.values[1]].mean()
```

Out[185]:

	grade	good_bad
0	A	0.962338
1	B	0.923085
2	C	0.882905
3	D	0.844314
4	E	0.805178
5	F	0.775472
6	G	0.697605

Now the two previous tables are concatenated.

Figure 22

	grade	n_obs	prop_good
0	A	15108	0.962338
1	B	27199	0.923085
2	C	25048	0.882905
3	D	15390	0.844314
4	E	7145	0.805178
5	F	2699	0.775472
6	G	668	0.697605

Now calculate proportion of observation that falls into each grade. It is the number of observations in each row divided by the sum of the number of observations in each in each row.

Figure 23

```
In [190]: # Let's calculate the proportion of observations that falls into each grade. It is the number of observations in each row divi
          df1['prop_n_obs'] = df1['n_obs'] / df1['n_obs'].sum()

In [191]: df1
Out[191]:
```

	grade	n_obs	prop_good	prop_n_obs
0	A	15108	0.962338	0.162004
1	B	27199	0.923085	0.291656
2	C	25048	0.882905	0.268591
3	D	15390	0.844314	0.165028
4	E	7145	0.805178	0.076616
5	F	2699	0.775472	0.028942
6	G	668	0.697605	0.007163

Now calculate number of good and bad borrower by grade. It will store the number of good borrowers in a variable called good.

Figure 24

In [192]:
```
# lets also calculate number of good and bad borrower
df1['n_good'] = df1['prop_good'] * df1['n_obs']
df1['n_bad'] = ( 1 - df1['prop_good']) * df1['n_obs']
df1
```

Out[192]:

	grade	n_obs	prop_good	prop_n_obs	n_good	n_bad
0	A	15108	0.962338	0.162004	14539.0	569.0
1	B	27199	0.923085	0.291656	25107.0	2092.0
2	C	25048	0.882905	0.268591	22115.0	2933.0
3	D	15390	0.844314	0.165028	12994.0	2396.0
4	E	7145	0.805178	0.076616	5753.0	1392.0
5	F	2699	0.775472	0.028942	2093.0	606.0
6	G	668	0.697605	0.007163	466.0	202.0

Now calculate the proportion of good borrowers and bad borrowers for each grade.

Figure 25

In [193]:
```
# lets now calculate proportion of good and bad borrower FOR EACH OF THE GRADE. T
df1['prop_n_good'] = df1['n_good'] / df1['n_good'].sum()
df1['prop_n_bad']   =  df1['n_bad'] / df1['n_bad'].sum()
df1
```

Out[193]:

	grade	n_obs	prop_good	prop_n_obs	n_good	n_bad	prop_n_good	prop_n_bad
0	A	15108	0.962338	0.162004	14539.0	569.0	0.175027	0.055839
1	B	27199	0.923085	0.291656	25107.0	2092.0	0.302250	0.205299
2	C	25048	0.882905	0.268591	22115.0	2933.0	0.266231	0.287831
3	D	15390	0.844314	0.165028	12994.0	2396.0	0.156428	0.235132
4	E	7145	0.805178	0.076616	5753.0	1392.0	0.069257	0.136605
5	F	2699	0.775472	0.028942	2093.0	606.0	0.025197	0.059470
6	G	668	0.697605	0.007163	466.0	202.0	0.005610	0.019823

In this way there is everything it need to calculate weight of evidence for the categories of grade variable.

Figure 26

In [194]:
```
# now let's calculate the WoE for this variable.
df1['WoE'] = np.log(df1['prop_n_good'] / df1['prop_n_bad'])
df1
```

Out[194]:

	grade	n_obs	prop_good	prop_n_obs	n_good	n_bad	prop_n_good	prop_n_bad	WoE
0	A	15108	0.962338	0.162004	14539.0	569.0	0.175027	0.055839	1.142469
1	B	27199	0.923085	0.291656	25107.0	2092.0	0.302250	0.205299	0.386785
2	C	25048	0.882905	0.268591	22115.0	2933.0	0.266231	0.287831	-0.078010
3	D	15390	0.844314	0.165028	12994.0	2396.0	0.156428	0.235132	-0.407554
4	E	7145	0.805178	0.076616	5753.0	1392.0	0.069257	0.136605	-0.679261
5	F	2699	0.775472	0.028942	2093.0	606.0	0.025197	0.059470	-0.858767
6	G	668	0.697605	0.007163	466.0	202.0	0.005610	0.019823	-1.262323

Arranging it in ascending order.

Figure 27

In [195]:
```
# lets sort this WoE and arrange it to ascending order
df1 = df1.sort_values(['WoE'])
df1 = df1.reset_index(drop = True)
df1
```

Out[195]:

	grade	n_obs	prop_good	prop_n_obs	n_good	n_bad	prop_n_good	prop_n_bad	WoE
0	G	668	0.697605	0.007163	466.0	202.0	0.005610	0.019823	-1.262323
1	F	2699	0.775472	0.028942	2093.0	606.0	0.025197	0.059470	-0.858767
2	E	7145	0.805178	0.076616	5753.0	1392.0	0.069257	0.136605	-0.679261
3	D	15390	0.844314	0.165028	12994.0	2396.0	0.156428	0.235132	-0.407554
4	C	25048	0.882905	0.268591	22115.0	2933.0	0.266231	0.287831	-0.078010
5	B	27199	0.923085	0.291656	25107.0	2092.0	0.302250	0.205299	0.386785
6	A	15108	0.962338	0.162004	14539.0	569.0	0.175027	0.055839	1.142469

Also calculate differences in the proportion of good loans between two subsequent categories and the difference of weight of evidence between two subsequent categories.

Figure28

```
df1['diff_prop_good'] = df1['prop_good'].diff().abs()
df1['diff_WoE'] = df1 ['WoE'].diff().abs()
df1
```

Out[196]:

	grade	n_obs	prop_good	prop_n_obs	n_good	n_bad	prop_n_good	prop_n_bad	WoE	diff_prop_good	diff_WoE
0	G	668	0.697605	0.007163	466.0	202.0	0.005610	0.019823	-1.262323	NaN	NaN
1	F	2699	0.775472	0.028942	2093.0	606.0	0.025197	0.059470	-0.858767	0.077868	0.403556
2	E	7145	0.805178	0.076616	5753.0	1392.0	0.069257	0.136605	-0.679261	0.029706	0.179506
3	D	15390	0.844314	0.165028	12994.0	2396.0	0.156428	0.235132	-0.407554	0.039136	0.271707
4	C	25048	0.882905	0.268591	22115.0	2933.0	0.266231	0.287831	-0.078010	0.038590	0.329543
5	B	27199	0.923085	0.291656	25107.0	2092.0	0.302250	0.205299	0.386785	0.040181	0.464796
6	A	15108	0.962338	0.162004	14539.0	569.0	0.175027	0.055839	1.142469	0.039252	0.755683

Lastly calculating information value for this variable.

Figure 29

In [197]:
```
#Finally we can calculate information value.
df1['IV'] = (df1['prop_n_good'] - df1['prop_n_bad']) * df1['WoE']
df1['IV'] = df1['IV'].sum()
df1
```

Out[197]:

	grade	n_obs	prop_good	prop_n_obs	n_good	n_bad	prop_n_good	prop_n_bad	WoE	diff_prop_good	diff_WoE	IV
0	G	668	0.697605	0.007163	466.0	202.0	0.005610	0.019823	-1.262323	NaN	NaN	0.300551
1	F	2699	0.775472	0.028942	2093.0	606.0	0.025197	0.059470	-0.858767	0.077868	0.403556	0.300551
2	E	7145	0.805178	0.076616	5753.0	1392.0	0.069257	0.136605	-0.679261	0.029706	0.179506	0.300551
3	D	15390	0.844314	0.165028	12994.0	2396.0	0.156428	0.235132	-0.407554	0.039136	0.271707	0.300551
4	C	25048	0.882905	0.268591	22115.0	2933.0	0.266231	0.287831	-0.078010	0.038590	0.329543	0.300551
5	B	27199	0.923085	0.291656	25107.0	2092.0	0.302250	0.205299	0.386785	0.040181	0.464796	0.300551
6	A	15108	0.962338	0.162004	14539.0	569.0	0.175027	0.055839	1.142469	0.039252	0.755683	0.300551

This same task is required to be done for all discrete variable therefore instead of repeating it, here is a code that will automate this process for all discrete variable.

Figure 30

```
def woe_discrete(df,discrete_variable_name, good_bad_variable_df):
    df = pd.concat([df[discrete_variable_name],good_bad_variable_df], axis = 1)
    df = pd.concat([df.groupby(df.columns.values[0], as_index = False)[df.columns.values[1]].count(),
                    df.groupby(df.columns.values[0], as_index = False)[df.columns.values[1]].mean()], axis = 1)

    df = df.iloc[: , [0,1,3]]
    df.columns = [df.columns.values[0], 'n_obs', 'prop_good']
    df['prop_n_obs'] = df1['n_obs'] / df['n_obs'].sum()
    df['n_good'] = df['prop_good'] * df['n_obs']
    df['n_bad'] = ( 1 - df['prop_good']) * df['n_obs']
    df['prop_n_good'] = df['n_good'] / df['n_good'].sum()
    df['prop_n_bad']  =  df['n_bad'] / df['n_bad'].sum()
    df['WoE'] = np.log(df['prop_n_good'] / df['prop_n_bad'])
    df = df.sort_values(['WoE'])
    df = df.reset_index(drop = True)
    df['diff_prop_good'] = df['prop_good'].diff().abs()
    df['diff_WoE'] = df['WoE'].diff().abs()
    df['IV'] = (df['prop_n_good'] - df['prop_n_bad']) * df['WoE']
    df['IV'] = df['IV'].sum()
    return df
```

Once the process is automated for obtaining WoE, it can now go ahead with the process of coarse classing. For this a plot of WoE for all the categories of original independent variable and then see which of the categories can be combined together. Those categories which have similar WoE mean that they differentiate between good and bad borrower equally (dependable variable) so they can then be combined together to form a new category. This reduces number of dummy variables in the model.

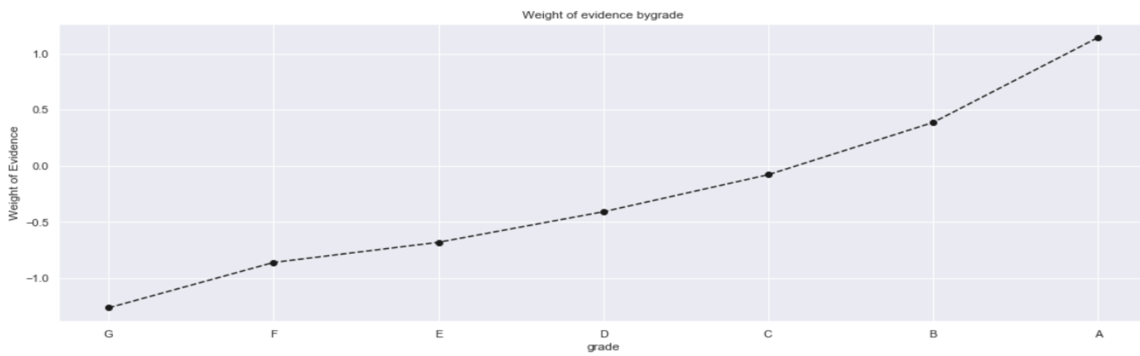
So, python library matplotlib was imported and created a function under variable name df_temp that would every time automatically plot WoE of any variable.

Figure 31

```
def plot_by_woe(df_WoE, rotation_of_x_axis_labels = 0):
  x = np.array(df_WoE.iloc[: , 0].apply(str))
  y = df_WoE['WoE']
  plt.figure(figsize = (18,6)) # First let's specify the dimensions
  plt.plot(x ,y , marker = 'o', linestyle = '--', color = 'k') # Nex
  plt.xlabel(df_WoE.columns[0]) # Now let's put some titles on the a
  plt.ylabel('Weight of Evidence') # similarly penalty y label will
  plt.title(str('Weight of evidence by' + df_WoE.columns[0])) # We c
  plt.xticks(rotation = rotation_of_x_axis_labels) # Finally let's m
```

So, let us now go ahead and plot WoE for grade variable.

Figure 32



From the plot, it can be noted that none of the grade category seem to have similar weight of evidence, and this is correct. That is because grades are issues by external credit rating agencies and they make sure that each grade by them carry different weightage. The greater the weight, the greater is the weight. Thus, it would be wise to keep all the original seven categories of grade variable for PD model. All the final dummy categories were stored in an excel file "List of dummies". When these categories will be used for regression, it should keep one category out as 'Reference Category'. It is the category against which the impact of all others will be assessed. So, it has established that it will keep that category as reference category which will have worst credit risk i.e., the category with lowest Weight of evidence.

Figure 33

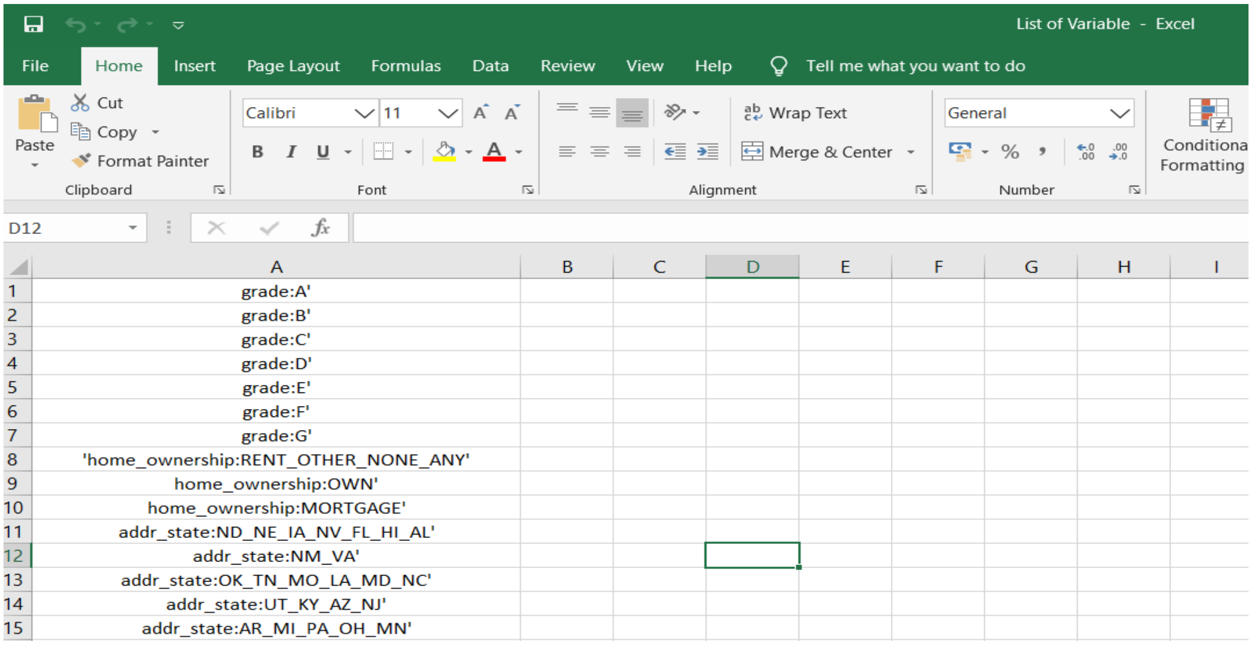
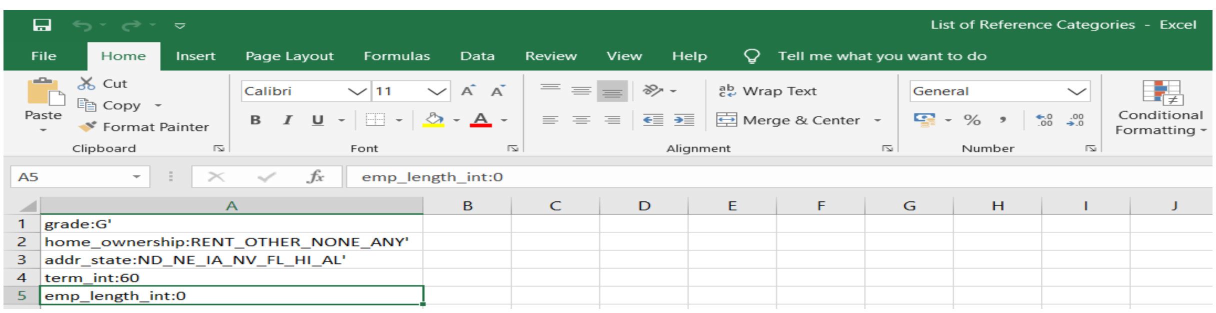


Figure 34



Coarse Classing

Below is an example showing coarse classing is done for all the discreet and continuous variables to obtain final categories for regression.

First, weight of evidence was obtained for variable 'home ownership'.

Figure 35

In [203]:
```
#  based on weight of evidence,We must decide how to organize the original categories of the discrete variables into dummy variat
## We can apply the w o e underscore discrete function to the Home Ownership variable to calculate weight of evidence directly.We

df_temp = woe_discrete(df_inputs_prepr, 'home_ownership', df_targets_prepr)
df_temp
```

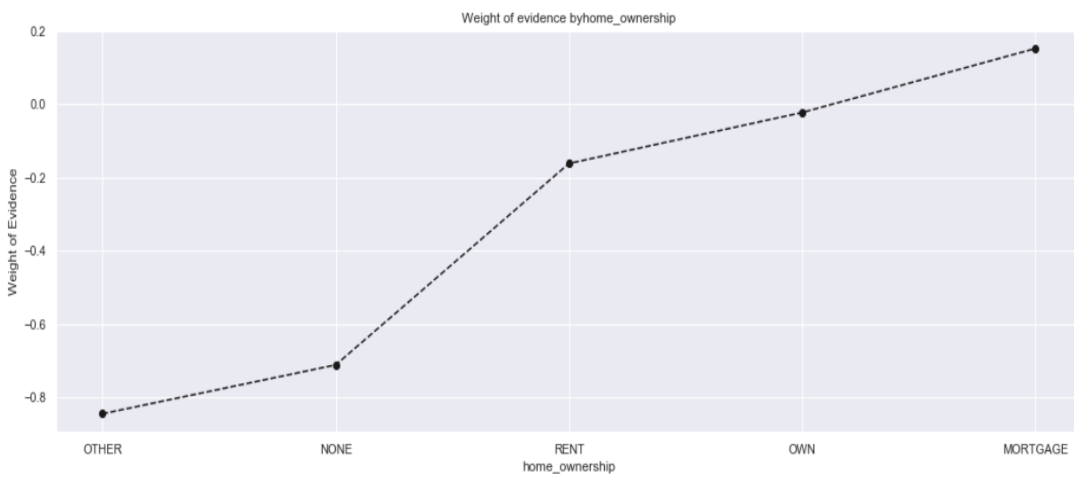
Out[203]:

	home_ownership	n_obs	prop_good	prop_n_obs	n_good	n_bad	prop_n_good	prop_n_bad	WoE	diff_prop_good	diff_WoE	IV
0	OTHER	45	0.777778	0.076616	35.0	10.0	0.000421	0.000981	-0.845478	NaN	NaN	0.022938
1	NONE	10	0.800000	0.028942	8.0	2.0	0.000096	0.000196	-0.711946	0.022222	0.133531	0.022938
2	RENT	37874	0.874003	0.268591	33102.0	4772.0	0.398498	0.468302	-0.161412	0.074003	0.550534	0.022938
3	OWN	8409	0.888572	0.165028	7472.0	937.0	0.089951	0.091953	-0.022006	0.014568	0.139406	0.022938
4	MORTGAGE	46919	0.904751	0.007163	42450.0	4469.0	0.511033	0.438567	0.152922	0.016179	0.174928	0.022938

Next a plot of WoE for all its categories and see if any of them can be merged.

Figure 36

In [204]:
```
plot_by_woe(df_temp)
```



Deciding which categories to merge together.

- Clearly the categories “OTHERS” and “NONE” are associated with the highest probability of default.
- It is still worth looking into their proportion in the table above the graph for the total number of observations.
- From n_obs it can be seen that very few loans are associated with these categories, so it doesn’t really make sense to have dummy variable for these categories. So, “other”,” none” can be combined with the next riskiest category “Rent”.

Figure 37

```
In [205]: # # Now let's decide how to organize the categories of the home ownership variable for the final model. the categories other and
          ## In these cases we combine such underrepresented categories that are similar to them.We will be mainly examining weights of evi
          ## thus for the Home Ownership variable will have one dummy variable for categories rent other none and any a separate dummy vari
          ## The only thing we have left is to combine the dummy variables for rent.Other none and any let's name it.Home ownership colon r
          df_inputs_prepr['home_ownership:RENT_OTHER_NONE'] = sum([df_inputs_prepr['home_ownership:RENT'], df_inputs_prepr['home_ownership:
```

So, now this independent variable 'home_ownership' has 3 categories only for PD model. First is 'rent_other_none', 'own", 'mortgage'. The reference category is 'rent_other_none'.

Similar pre-processing is done for all the independent variable (discrete or continuous). All the resulting final categories are collected in a separate excel file. These will later be used as independent variable for logistic regression.

3.1.3.3 PD Model estimation

Importing logistic regression model from sklearn (library for python) and applying appropriate functions to get coefficients and p-values for independent variable.

Figure 38

```
In [12]: # we employ sklearn for model estimation and let us import logistic regression from sklearn linear model.

         from sklearn.linear_model import LogisticRegression
         from sklearn import metrics

In [13]: # let reg be an instance of logistic regression class
         reg = LogisticRegression()

In [14]: # since we will have a lot of output lets make sure all rows are printed.
         pd.options.display.max_rows = None

In [15]: # we estimate our model by fitting the inputs and the targets. We can do that by applying fot method on the reg object and supply
         reg.fit(inputs_train, loan_data_targets_train)  # inputs_train contain dummy variable for all the independent variable and the lo
         # This command alone will estimate our model and will store the result in the reg object.
```

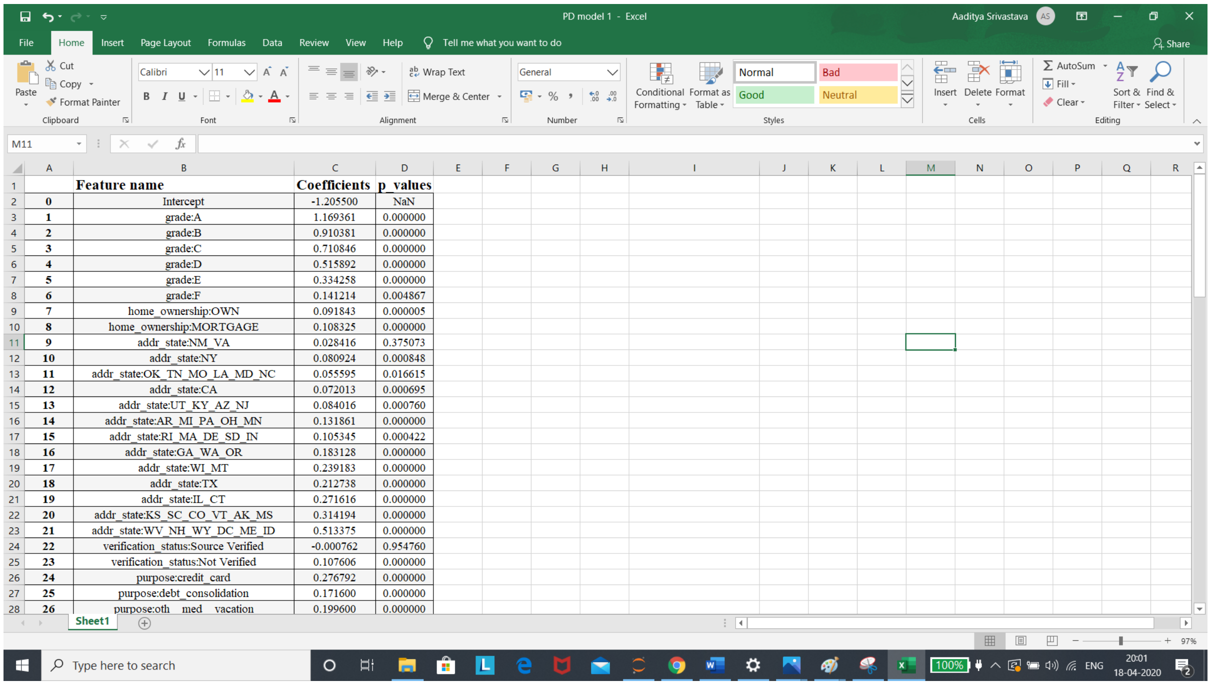
The result for above command is (this only shows 22 coefficients, however actually there were 95 in total coefficients) shown mellow.

Figure 39

	Feature name	Coefficients	p_values
0	Intercept	-1.205500	NaN
1	grade:A	1.169361	4.493461e-38
2	grade:B	0.910381	3.476704e-50
3	grade:C	0.710846	4.238955e-36
4	grade:D	0.515892	9.043260e-22
5	grade:E	0.334258	3.725820e-12
6	grade:F	0.141214	4.867169e-03
7	home_ownership:OWN	0.091843	5.322101e-06
8	home_ownership:MORTGAGE	0.108325	1.399228e-17
9	addr_state:NM_VA	0.028416	3.750734e-01
10	addr_state:NY	0.080924	8.479656e-04
11	addr_state:OK_TN_MO_LA_MD_NC	0.055595	1.661469e-02
12	addr_state:CA	0.072013	6.948737e-04
13	addr_state:UT_KY_AZ_NJ	0.084016	7.599898e-04
14	addr_state:AR_MI_PA_OH_MN	0.131861	5.235381e-09
15	addr_state:RI_MA_DE_SD_IN	0.105345	4.216553e-04
16	addr_state:GA_WA_OR	0.183128	7.143258e-12
17	addr_state:WI_MT	0.239183	4.971770e-07
18	addr_state:TX	0.212738	2.916894e-16
19	addr_state:IL_CT	0.271616	1.614996e-20
20	addr_state:KS_SC_CO_VT_AK_MS	0.314194	2.512285e-24
21	addr_state:WV_NH_WY_DC_ME_ID	0.513375	5.165606e-22
22	verification_status:Source Verified	-0.000762	9.547595e-01

The next task is to identify which of these coefficients are statistically significant (alpha = 0.5). This was done separately in a excel sheet.

Figure 40



	Feature name	Coefficients	p_values
0	Intercept	-1.205500	NaN
1	grade:A	1.169361	0.000000
2	grade:B	0.910381	0.000000
3	grade:C	0.710846	0.000000
4	grade:D	0.515892	0.000000
5	grade:E	0.334258	0.000000
6	grade:F	0.141214	0.004867
7	home_ownership:OWN	0.091843	0.000005
8	home_ownership:MORTGAGE	0.108325	0.000000
9	addr_state:NM_VA	0.028416	0.375073
10	addr_state:NY	0.080924	0.000848
11	addr_state:OK_TN_MO_LA_MD_NC	0.055595	0.016615
12	addr_state:CA	0.072013	0.000695
13	addr_state:UT_KY_AZ_NJ	0.084016	0.000760
14	addr_state:AR_MI_PA_OH_MN	0.131861	0.000000
15	addr_state:RI_MA_DE_SD_IN	0.105345	0.000422
16	addr_state:GA_WA_OR	0.183128	0.000000
17	addr_state:WI_MT	0.239183	0.000000
18	addr_state:TX	0.212738	0.000000
19	addr_state:IL_CT	0.271616	0.000000
20	addr_state:KS_SC_CO_VT_AK_MS	0.314194	0.000000
21	addr_state:WV_NH_WY_DC_ME_ID	0.513375	0.000000
22	verification_status:Source Verified	-0.000762	0.954760
23	verification_status:Not Verified	0.107606	0.000000
24	purpose:credit_card	0.276792	0.000000
25	purpose:debt_consolidation	0.171600	0.000000
26	purpose:oth__med__vacation	0.199600	0.000000

The criteria followed to select the significant variable was that if any category of original independent proved to be significant then that entire variable was taken along with all of its categories. Even if other categories would be insignificant. So, in this way there are all significant variables along with their coefficients.

3.3.3.4. Calculating probability of default

First, multiply the values of a borrower on the independent dummy variables by the respective model coefficients. So, when an exponent is raised on this result, it equals the odds for being good versus bad. From there it can easily estimate probability of being good. Now each observation from all the dummy categories of the original independent variable can only have a value of 1 for one of the dummy variables, the rest are always zero. So, calculating the power on which the exponents should be raised to obtain the odds boil down to the following to summing the regression coefficients for all dummy variables to which an observation belongs.

Below is how it's done using a practical example in python. Taking the first observation from this dataset. Its index is 362514.

Figure 41

In [78]:
```
# we already leaned how to interpret the PD model and how to estimate the probability of default and respectively the probability
pd.options.display.max_columns = None
# Sets the pandas dataframe options to display all columns/ rows.
```

In [79]:
```
inputs_test_with_ref_cat.head()
```

Out[79]:

	grade:A	grade:B	grade:C	grade:D	grade:E	grade:F	grade:G	home_ownership:RENT_OTHER_NONE_ANY	home_ownership:OWN	home_ownership:M
362514	0	0	1	0	0	0	0	0	0	
288564	0	0	0	0	1	0	0	0	0	
213591	0	0	1	0	0	0	0	0	0	
263083	0	0	1	0	0	0	0	0	0	
165001	1	0	0	0	0	0	0	0	0	

	Feature name	Coefficients	p_values
0	Intercept	-1.183466	NaN
1	grade:A	1.151895	6.137378e-37
2	grade:B	0.903520	7.517394e-50
3	grade:C	0.705951	4.232927e-36
4	grade:D	0.513173	5.412867e-22
5	grade:E	0.332815	1.441472e-12
6	grade:F	0.142842	3.415817e-03
7	home_ownership:OWN	0.090532	6.935442e-06
8	home_ownership:MORTGAGE	0.107185	2.591450e-17
9	addr_state:NM_VA	0.034580	2.800890e-01
10	addr_state:NY	0.078688	1.129390e-03
11	addr_state:OK_TN_MO_LA_MD_NC	0.058511	1.143435e-02

First, taking the intercept = -1.183466; then the external grade of this observation is 'C' as for this observation it is taken dummy = 1 at grade C. Adding its respective coefficient to intercept. And similarly, coefficients of all dummies will be added that have observation of 1. So, the final summation that it gets = -1.183466 + 0.705951+ 0.107185+ 0.074778+0.001095+ 0.259357+ 0.054842+ 0.076765+ 0.095389 = 0.191896.

This value of 0.191896 are log odds. Ln((1-PD)/PD) = 0.191896.

Getting rid of the logarithm by raising the exponents to a power.

(1 – PD) / PD = exp (0.191896) = 1.211544

Therefore, the estimated probability of being good borrower is equal to 1.211544 / (1+1.211544) = .547827.

Therefore, the probability that this person will not default is 54.78 %.

3.2. Methodology for objective 2

As mentioned previously, that PD model must be easy to understand and interpret. Even people having no understanding of statistical analysis should be able to understand it. Thus, keeping that in mind it has converted the PD model into a scorecard that can easily be understood by anyone.

A scorecard tool produces individual credit worthiness assessment that directly corresponds to a specific probability of default. As these credit worthiness assessments are named after the scorecard. They are thus called Credit scores. Thus, it will create a scorecard based on our PD model. Summary table contains all the coefficients of the PD model arranged as a data frame

Assigning minimum and maximum values for scorecard is required. In this project it has taken minimum score = 300 and maximum score = 850. It then went ahead to store these values in two different variables.

Figure 42

```
In [88]: # in order to create a scorecr we nee
         min_score = 300
         max_score = 850
```

Next is to rescale these credit worthiness assessments is terms of probabilities to the credit score range. To achieve that, apart from the range of scorecard it also needs highest and lowest of the credit worthiness that PD model can estimate.

Theoretically, the lowest credit worthiness calculation it can get from the PD model would be in the case if borrower fall into all those categories of original independent variable with the lowest model coefficients. Similarly, the maximum credit worthiness assessment it can get from the PD model would be in the case where a borrower falls into a category of original independent variables with highest model coefficients. So, let us first find this minimum and maximum.

Figure 43

```
In [89]: # we must rescale the credit worthiness assessment produces by our model to
         ## lets find this minimum and maximum. We have the names of the original inc
         df_scorecard.groupby('Original feature name')['Coefficients'].min()
         # Groups the data by the values of the 'Original feature name' column.
         # Aggregates the data in the 'Coefficients' column, calculating their minimu
```

Figure 44

```
min_sum_coef = df_scorecard.groupby('Original feature name')['Coefficients'].min().sum()
# Up to the 'min()' method everything is the same as in te line above.
# Then, we aggregate further and sum all the minimum values.
min_sum_coef
```

```
)]: -1.4380390435978003
```

Figure 45

```
In [91]: df_scorecard.groupby('Original feature name')['Coefficients'].max()
         # Groups the data by the values of the 'Original feature name' column.
         # Aggregates the data in the 'Coefficients' column, calculating their maxim
```

Figure 46

```
: max_sum_coef = df_scorecard.groupby('Original feature name')['Coefficients'].max().sum()
  # Up to the 'min()' method everything is the same as in te line above.
  # Then, we aggregate further and sum all the maximum values.
  max_sum_coef
```

```
: 5.524043629713964
```

Now the question is how do it rescale coefficients to score? For converting each dummy variable coefficient to a score, it has to multiply each coefficient by ratio of the difference between the maximum score and minimum desired score to the difference between the maximum sum of coefficients and the minimum sum of coefficients.

Figure 47

$$variable\_score = variable\_coef \frac{(\max\_score - \min\_score)}{(\max\_sum\_coef - \min\_sum\_coef)}$$

Let's do this for all regression coefficients and store the result in score-calculation variable.

Figure 48

Out[93]:

	index	Feature name	Coefficients	p_values	Original feature name	Score - Calculation
0	0	Intercept	-1.183466	NaN	Intercept	-93.493078
1	1	grade:A	1.151895	6.137378e-37	grade	90.998953
2	2	grade:B	0.903520	7.517394e-50	grade	71.377494
3	3	grade:C	0.705951	4.232927e-36	grade	55.769666
4	4	grade:D	0.513173	5.412867e-22	grade	40.540299
5	5	grade:E	0.332815	1.441472e-12	grade	26.292204
6	6	grade:F	0.142842	3.415817e-03	grade	11.284456
7	7	home_ownership:OWN	0.090532	6.935442e-06	home_ownership	7.151996
8	8	home_ownership:MORTGAGE	0.107185	2.591450e-17	home_ownership	8.467530
9	9	addr_state:NM_VA	0.034580	2.800890e-01	addr_state	2.731758
10	10	addr_state:NY	0.078688	1.129390e-03	addr_state	6.216295
11	11	addr_state:OK_TN_MO_LA_MD_NC	0.058511	1.143435e-02	addr_state	4.622340

Intercept seems to have an unusual value. This is because the intercept is not a dummy variable, it is an integral part for calculation of credit worthiness assessment. In fact, the score reflecting the intercept is very close to the lowest score an observation would get in worst credit rating wise.

So, it wishes to replace the current score of intercepts with the minimum desired score which is 300.

Figure 49

$$intercept\_score = \frac{(intercept\_coef - \min\_score)}{(\max\_sum\_coef - \min\_sum\_coef)}(\max\_score - \min\_score) + \min\_score$$

Figure 50

	index	Feature name	Coefficients	p_values	Original feature name	Score - Calculation
0	0	Intercept	-1.183466	NaN	Intercept	320.111070
1	1	grade:A	1.151895	6.137378e-37	grade	90.998953
2	2	grade:B	0.903520	7.517394e-50	grade	71.377494
3	3	grade:C	0.705951	4.232927e-36	grade	55.769666
4	4	grade:D	0.513173	5.412867e-22	grade	40.540299
5	5	grade:E	0.332815	1.441472e-12	grade	26.292204
6	6	grade:F	0.142842	3.415817e-03	grade	11.284456

So, the only thing left is to round off the scores to the nearest figure.

Figure 51

```
n [95]: # the only thing that is left to do to get a simple interpreatble and user friendly credit score is to roundoff credit
        df_scorecard['Score - Preliminary'] = df_scorecard['Score - Calculation'].round()
        # We round the values of the 'Score - Calculation' column.
        df_scorecard
```

Figure 52

	index	Feature name	Coefficients	p_values	Original feature name	Score - Calculation	Score - Preliminary
0	0	Intercept	-1.183466	NaN	Intercept	320.111070	320.0
1	1	grade:A	1.151895	6.137378e-37	grade	90.998953	91.0
2	2	grade:B	0.903520	7.517394e-50	grade	71.377494	71.0
3	3	grade:C	0.705951	4.232927e-36	grade	55.769666	56.0
4	4	grade:D	0.513173	5.412867e-22	grade	40.540299	41.0
5	5	grade:E	0.332815	1.441472e-12	grade	26.292204	26.0
6	6	grade:F	0.142842	3.415817e-03	grade	11.284456	11.0
7	7	home_ownership:OWN	0.090532	6.935442e-06	home_ownership	7.151996	7.0
8	8	home_ownership:MORTGAGE	0.107185	2.591450e-17	home_ownership	8.467530	8.0
9	9	addr_state:NM_VA	0.034580	2.800890e-01	addr_state	2.731758	3.0
10	10	addr_state:NY	0.078688	1.129390e-03	addr_state	6.216295	6.0
11	11	addr_state:OK_TN_MO_LA_MD_NC	0.058511	1.143435e-02	addr_state	4.622340	5.0

4. FINDINGS

Objective 1

- An analytical approach using logistic regression model that helps in estimating the probability of default associated with any borrower.

Objective 2

- Successfully converted the probability of default model for first objective into a scorecard. This would enable easier interpretability of the probability of default model.

5. CONCLUSION

- Models based on analytical techniques such as logistic regression prove to be a viable alternative all the theories discussed in literature review. It provides more precise and realistic approach for estimating probability of default. Building a scorecard has indeed provided with better representation of this probability.
- This model will now enable Peacock solar to thoroughly examine the applicant homeowner who want solar on finance and then take a decision if he should be given solar on credit based on his credit score.

6. LIMITATION

The data used for creating the model was a banking industry data, there was no historical data available for solar industry. Therefore, banking industry data was used a proxy for solar industry data.

The dataset that has been used is American dataset. Ideally as this project is for Indian company for business in India, Indian data set should have been used. But, as no previous data was available for India, it used American dataset.

7. MANAGERIAL IMPLICATIONS

Probability of default model will help managers to make better decisions before deciding to give out credit. This will enhance decision making and will certainly bring down number of defaults, thereby helping them to enhance the profitability of the company

A wider analysis of the relevant factors helps boost confidence in managers while they make efficient decisions for the company. A scorecard helps them to increase the interpretability of the model thereby contributing to easy decision making.

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A STUDY ON SUSTAINABILITY OF PAYMENT BANKS IN INDIA USING TECHNOLOGY ACCEPTANCE MODEL

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ABSTRACT

Payment banks are new era banks that provide limited services but with simple access. The Reserve Bank of India established it with an aim to offer remittance services to migrant labor workforce, low-income households, small businesses, and other unorganized sector entities. Awareness plays a major role in the mindset of the people towards the digitalized mode of the payment system. Payment banks are currently facing many challenges as they are not allowed to lend money. Their major source of income comes only from the interest of the government securities in which they can invest. Despite all these, payment banks are struggling with huge losses and their existence is in a dubious situation. Six out of eleven payment banks are assessing the option of converting themselves into a small finance bank. In this context, the study focusses to analyze the key factors contributing to sustainability of the of payment banks. A measure of the trust and its role was used to test the relationship along with perceived usefulness and perceived ease of use. Actual usage was observed as a perception of usefulness and ease of use among the respondents. Payment banks offer a paradigm shift in making India a digital economy.

Keywords: Payment banks, Digital banking, e-wallets, Technology acceptance model

JEL Classification: E42, J33

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INTRODUCTION

Financial inclusion signifies including financially excluded sections within the frontier of the formal financial system. Nevertheless, its growth was a major hurdle for a long period as residents in financially excluded sectors were outside the limits of the formal financial system. This prompted the introduction of a payment bank system by the Reserve Bank of India in the year 2014.

The world of digitalization permits people to conveniently perform online banking transactions, paying bills, and so on. But many of them still preferred the traditional banking system because of various challenges like security, privacy, internet usage illiteracy, and so on. But because of the recent pandemic of the coronavirus or COVID 19, RBI and the government recommended the banks to promote digital payments to avoid social contact. Contactless payments like digital wallets can efficiently diminish human connections. Banks have come up with a new strategy of providing mobile ATMs to avoid the risk of traveling. The RBI reports that there has been a surge of 50% in the usage of mobile banking systems since the beginning of 2020.

Payment banks were initiated with a difficult business model where they neither could offer credit nor accept higher deposits. They could operate in remittance, payment transfer, utility payment and so on which were also offered by Wallets and Fin Techs also. Hence some of them like Cholamandalam, Tech Mahindra and Sun Pharma surrendered their license even before starting the business.

The future of payment banks is vague and require regulatory and government support to accomplish their goals. Some payment banks like India Post payment bank, Paytm, Fino are planning to transform the business model and get improved into a small finance bank that will permit them to lend to their customers and render other financial services. It is also planning to join hands with the Common Service Centre to offer various services together with banking, remittance, insurance, and so on. With this, it is understood that they are planning to go in for backward integration.

Payment banks went through a lot of difficulties when the government abolished Merchant Discount Rate recently which was one of the ways of earning for them. Now they have requested RBI to increase the deposit limit from one lakh to five lakhs to approach the small merchants and traders. Payment banks need to add more customers and merchants to sustain and manage costs. The intent of additions in terms of higher users can be materialized by the providing usefulness in the application and establishing trust among the end-users. The current study attempts to answer a. What role does trust play in the usage of the payment application? and b. how perceived usefulness leads to the actual usage of an application?

REVIEW OF LITERATURE

In this dynamic atmosphere, banking systems hunt for novel strategies that assist in online sharing of information and transactions. Connecting the banking systems to the customers through mobile phones or internet is one of the unique strategies that make providing of services easier [Gebba, 2013]. Information technology is the major driver for the transformation taking place around the world in the field of banking. Mobile banking is the latest and innovative strategy used by the banks [Rahmath Safeena H. D., 2012].

With the advancement of mobile technology, not only the customers but banks are also beneficial as they can easily provide convenient services and virtually connect with their customers for rendering various services far and wide. This also brings efficiency to the banking system. Banks should gain the trust of the customers to gain return on the investment made on the technology [Asnakew, 2020].

With extensive usage of mobile phones and the rising internet access, there are many chances for the growth of financial inclusion with the help of technology. The growth of financial inclusion in India was very sluggish during the period of 2010-2015 because of various reasons like lack of bank branches, maintaining of minimum balance and so on. Understanding the factors for adoption of technology based financial services would help to perk up rates of adoption and, also helps in the growth of financial inclusion. This was one of the reasons for initiating the introduction of payment bank system in India by Reserve Bank of India [Mishra, 2017].

Innovation plays an important role in providing opportunities in terms of digitalization of banks. One such innovation that came into existence in the field of banking was introduction of payment banks. But payment banks came into existence with certain restrictions. [J.C.Pande, 2015]. Payment bank system was accepted by many for various reasons like cashless mode, offers, easy access and the interest rates offered. But there were reasons for its unawareness like ignorance, financial illiteracy, lack of publicity and lack of trust.

Trust is very essential for the survival of the financial system. Financial crisis may lead to serious frauds and eventually a reduction in the trust. Trust has a key role in the development of financial system. One way to restore trust is transferring of power from financial intermediaries to investors [Guiso, Luigi, 2010]. Personal financial crisis experienced by the customers' leads to not only decrease in trust but also have a negative effect of generalized trust [Carin Van, Jakob, and David, 2016].

There is a need for a framework with a view to adopt online financial services on a continuous basis. It was observed that trust is a very influential factor for adoption. Various other factors that affected adoption included security, company awareness, previous internet experience, personalization, and navigation functionality [Shih-Ming Pi, 2012]. Demographic factors like age, ethnicity, marital status, and gross annual income also have an impact on trust. These factors help in understanding the needs and wants of the consumers. It was observed that people belonging to the age group of 35 and above trust more; divorced people also have more trust than others; trust level rises with increase in the income and people with South Asian background trust more [S M A Moin, 2017].

One of the important components for maintaining long term relationship between the customer and vendor is trust. It is a crucial element for both traditional as well as electronic commercial activities. Quality of support is the key in creating an impact on developing online trust. Perceived security also plays an important role. Loyalty is crucial for building online trust [Lova Rajaobelina, 2014].

Corporate image is also a significant tool in managing the trust of the consumers particularly in internet banking. Concept of synergy plays a key role because rather than managing it as whole, different elements it is composed of should be given a thought. Decision makers should understand the role played by each of the elements. Length of relationship also affects trust. This can be achieved by providing favorable experiences with the system. This in turn boosts the initial trust [Carlos Flavián, 2005].

A website characteristic is considered as one of the main aspects that influence customer perception regarding the ease of use of internet banking system. This contains factors like simplicity of navigation, customization, and usability. Perceived risk is another factor that negatively influences the customer adoption to internet banking. Therefore, security and privacy are real barriers in the adoption of internet banking [Esawai, 2017].

The internet banking sites should provide handy and constructive features to persuade and patronage the customers to use their services. They should also highlight and stress on convenience and security levels in performing internet banking transactions [Lallmahamood, 2007].

Development in E-banking has led to a new way of managing the matters of banks known as online banking system. This system was speedily accepted in many parts of the world. This was observed with the help of Technology Acceptance Model (TAM). It was observed that perceived ease of use has less effect when compared to perceived usefulness. This information helps the managers in the process of planning [Tero Pikkarainen, 2004].

The most prominent factors that help in understanding the use of online banking system includes perceived ease of use, perceived usefulness, attitude, subjective norm, and perceived behavioral control. Hence the banks must stress on benefits, ease of use, security to perk up the trust of the banking customers [Rahmath Safeena H. D., 2013].

Though many people have accepted internet banking, not everyone has accepted. Hence it became necessary to understand the factors that influence acceptance among the consumers. Previous experience plays a very important role about attitude towards usage. Bankers should educate the potential consumers about the usefulness. Perceived usefulness is a positive factor with respect to acceptance [Chuleeporn Changchit, 2017].

An attempt was made to understand the relationship between Technology Readiness Index [TRI] and Technology Acceptance Model [TAM]. It was observed that TRI dimensions had an essential influence on perceived usefulness and perceived ease of use of M-payments. Perceived ease of use did not have an influence on the intention to use m-payments [Miriam Martens, 2017].

To maintain good relationships with the customers and ensure their loyalty trust is the vital key apart from expertise and ethics. Ethics of the salesperson do not have much effect on the satisfaction of the customers, but the financial knowledge does affect the satisfaction factor [David Bejou, 1998].

Customer satisfaction is a significant key for adoption of online banking system which depends on factors like trust, reliability, compatibility, connectivity, cost effectiveness, ease of use, perceived usefulness, and system quality. Another factor is customer perception which depends on factors like security concerns, competitive advantage and relative advantage, perceived risk, structure assurance and service quality [Palaniappan, 2019].

Trustworthiness is another major aspect in building the trust among consumers. Trust operates with the help of main drivers like expertise, competence, communication, concern, shared values, integrity, and consistency that are intervened by trustworthiness. Trustworthiness influences both the dimensions of trust i.e., cognitive, and affective. Hence customers should be treated reasonably and there should be no sign of partiality to gain the trust and improve customer relationships [Harjit Sekhon, 2014].

The focal point of cognitive portion is on rendering of timely and consistent internet banking services while the focal point of affective aspect is on sharing the common goals with the users of services which helps in building trustworthiness among the customers. Trust act as a mediator between trustworthiness and internet banking usage relationship. When banks fail to communicate the value, they lose a prospect in building customer trust. [Khong, 2015].

Trust is also a key factor in the process of adopting a technology-based distribution channels like ATMs, internet, and mobile banking. It is also important in adopting new technologies like e-banking and e-commerce as it mitigates social complexity for the e-consumers. Affective trust is a significant forecaster in case of mobile and internet channels and cognitive trust in case of ATMs. Affective is more important than cognitive which can be built through transparency, fairness, keeping promises. [Sergios Dimitriadis, 2008].

Belief and behavior also influence using of mobile banking technology. Favorable attitude leads to intention to use. Attitude will imitate favorable or unfavorable thoughts towards behavior and hence attitude is developed based on the experience. Banking systems should also work on customizing the mobile apps based on the requirements of the customers to develop the adoption rates [F. Mu˜noz-Leivaa, 2016].

Thought there were many barriers in using online banking services like reluctance to change and adopt new technology, insecurity etc., the need for using mobile banking system became more evident during the period of demonetization. Hence there was increase in the average time spent in using the digital payment systems [Sivathanu, 2018].

Mobile money is a very vital technological innovation developed in mobile communication technology. It can be considered as an effective and an efficient way to achieve financial inclusion objectives. Mobile money act as a link between cash and digital economies and help those people who cannot get access to banks to load cash in a mobile wallet and do transactions digitally [Komlan Gbongli, 2019].

Financial technology has been assisting in managing of investments with the help of artificial intelligence called robo-advisors. Therefore, banks and other financial institutions have an edge over their competitors as it acts as a source of competitive advantage. Attitude is a major predictor of behavioral intention in using these robo-advisory services and then comes the subjective norms [Daniel Belanche, 2019].

The development of superior technology has aided the people in exchanging information at the fingertips and eradicates the requirement for human support and artificial intelligence play a very important role in this regard. With the purpose of learning and communicating like humans and to reply to ad-hoc queries in real time, AI has been driving the financial services industry. Chatbot services provide usefulness and ease of use with respect to speed and accuracy [Kanchan Patil, 2019]. Chatbot helps banks to render 24/7 services and can be accessed from anywhere. It can deliver speedy responses to the queries of the customers thereby improving the experiences and efficiency [Richad Richad, 2019].

Payment banks and the mobile commerce have grown phenomenally in the recent years with demonetization and the Covid-19 events. Technology and mobile penetration can be a thrust to the payment banks provided they are able to demonstrate the perceived usage. The various literature substantiates the role of trust in banking, the advances in technology with respect to banking and usage of internet banking services. The mobile commerce and the acceptance of technology through mobiles as applications is least explored. And the current study aims at the ease of use, perceived usefulness among users and trust in the acceptance of payments banks by users.

RESEARCH METHODOLOGY

Descriptive research using primary data was used to collect the information with the help of questionnaire from 227 respondents. The data collected was grouped and coded in excel. Percentages and frequency were used to describe the nature of data. The type of sampling design used is non-probability sampling. Under non-probability sampling, convenience sampling was used. Information was collected from the people who are currently using the services of payment banks. ANOVA was used to test the hypothesis. Correlation and regression were used to analyze the degree of association and the impact of variance.

STATEMENT OF PROBLEM

The licensee for payment banks was given in the year 2014 to 11 players of which only 4 players continue to operate and be into existence. The players in the industry do not have a revenue generation model due to which they continue to burn on cash funding. The RBI mandates the payment banks to continue for a minimum period of 5 years post which they can convert into a small finance bank. Given the circumstance, it is essential that the players continue to attract new customers to build the base and at the same time retain existing customers in the business of e-transactions. The current context of payment banks and their sustainability is a cause for concern in the absence of a viable revenue generation. The role of payment banks to instill the usefulness of the application and demonstrate its ease of use and there by gain trust until the small bank license is crucial.

OBJECTIVES

1. To measure the trust levels of payment banks customers.
2. To analyze the relationship between perceived usefulness and attitude towards usage.
3. To analyze the relationship between perceived ease of use on attitude towards usage.
4. To measure the impact of trust on actual usage of payment banks application.

ANALYSIS & INTERPRETATION

The responses were coded and tabulated using Microsoft excel. The demographic profile is provided in Table 1 and Table 2.

Table 1: Demographic profile of respondents.

		N	%
Gender	Male	108	47.6
	Female	119	52.4
Marital Status	Single	198	87.2
	Married	29	12.8

Table 2: Age profile and Income classification

Usage	Urban	192	Rural	35
Age Group	18-25	26-38	39-53	Above 54
	180	38	8	1
	79.3	16.7	3.5	0.4
Income	LT 20000	20k - 1L	1L-5L	MT 5L
	99	22	21	85
	43.6	9.7	9.3	37.4

The gender classification among the respondents was observed almost equal with 48% Male respondents and 52% Female. Majority of the respondents were married [87%]. The Usage was largely in Urban area as compared to the rural counterparts. The usage among the younger cohorts was observed dominant. The income category was largely observed with higher percentage of use among the lowest income category and the largest income category.

Table 3: Usage of payment banks by name

Applications	No. of respondents	Percentage
PAYTM	134	25%
GOOGLEPAY	186	35%
MOBIKWIK	9	2%
PHONEPE	134	25%
BHIM APP	56	11%
OTHERS	12	2%
TOTAL	531	100%

The usage of the payment application was obtained by multiple choice among the respondents. Multiple applications provided the spectrum of applications used for mobile transactions. A single user could have installed multiple application for transfer of money and table 3 presents the usage statistics. The most popular among the apps is GOOGLE PAY. PAYTM and PHONE PE were observed to rank second with equal preference (Table 3) of choice among the users.

The least used application was MOBIWIK. BHIM, the Unified Payment Interface [UPI] application was observed third in the ranking.

TABLE 4: Perceived Usefulness of Mobile App

PERCEIVED USEFULNESS	SA	A	N	DA	SDA
Using mobile service improves my working and living performance	74	121	25	6	1
It is less time consuming than doing transactions at bank sites.	138	82	6	1	0
I think mobile banking allows me to manage my banking activities more efficiently	94	107	21	4	1
would find mobile banking useful in getting information such as bank statements	88	113	21	1	4

The questions forming the construct of Perceived usefulness was obtained from the Technology Acceptance Model [TAM], modified, and used for mobile application. The utility of using the service is fund transfers. The use of such an application is observed to benefit the speed of transaction, efficiency, and record verification.

TABLE 5: Perceived Ease of Use of Mobile Commerce

PERCEIVED EASE OF USE	SA	A	N	D	SDA
Learning to use this mobile service is easy for me	113	104	8	1	1
I find it easy to get mobile banking to do what I want it to do for my banking purposes	83	119	22	1	2
It is very easy to do transactions through mobile banking	104	108	12	1	2
Using mobile banking does not require a lot of mental effort	84	122	15	5	1

The Ease of use was obtained as a measure using the Likert scale. The measure was obtained by 4 items and unless an application is perceived to be user friendly and easy to navigate, it will not be easy to appeal to the customer to even make the initial trial for the actual usage. It was observed that the perceived use of the mobile application was inclined to agree and strongly agree. It was observed that a higher proportion of respondents have strongly agrees for learning to use the application.

TABLE 6: Intention to Use a mobile application.

INTENTION TO USE	SA	A	N	DA	SDA
I intend to continue using this mobile service	93	108	22	3	1
My intentions are to use this payment bank service than use any alternative means [online services]	66	119	36	6	0

If I could, I would like to discontinue my use of this payment bank service	23	49	70	63	22

The initial use was observed using the perceived usage attributes in the TAM model, but once an application is installed by the user, the continuation of the usage is measured by the intention of usage and the above items from the TAM model were modified for the payment service of the bank. It was observed that for continued service the application provided should reinstate advertisements, point of contacts with the vendor tie-ups and incentivize users to compete and be competitive in the market.

TABLE 7: Attitude of a payment bank usage

ATTITUDE	SA	A	N	DA	SDA
I feel satisfied with using this payment bank service	82	120	23	1	1
I feel pleased with using this payment bank service	55	122	40	9	1
I feel comfortable transacting via payment banks	85	110	26	5	1
I prefer to do payment banking transaction than other forms of banking	74	117	28	7	1

The attitude of usage was measured using the Likert scale and it was observed that the respondents were comfortable in using the application and were satisfied of the usage. The measure can be used by the providers to advertise at vendor points along with the customers response.

TABLE 8: Actual Usage of a mobile payment application

ACTUAL USAGE	SA	A	N	D	SDA
I conduct my banking transactions using payment banks	64	112	43	8	0
I use payment bank services more than traditional banking services	73	128	21	2	3
I use payment banks as it is more convenient, efficient, and effective than internet banking	70	115	35	6	1
I use payment banks as it saves my time in performing banking transactions	91	110	24	0	2

The actual usage by the respondents highlighted the fact that users are shifting or preferring the mobile transactions as compared to the conventional banking. The traditional banking services also must be upgraded with the shift towards a mobile platform to protect a loss of existing customers. A mobile application is preferred to the internet transaction and this instinct provide the thrust to the paradigm shift of usage among the respondents.

TABLE 9: Measures of trust among Payment bank users

TRUST MEASURES	SA	A	N	DA	SDA
I trust my payment bank to do what it says it will do	62	108	44	9	4
My payment bank is very reliable	54	128	40	3	2
I trust my payment bank to have best interests	53	124	45	5	0
My payment bank is always honest with me	53	121	45	7	1
My payment bank makes every effort to address my needs	57	122	43	3	2
My payment bank has a reputation for being dependable	50	125	49	2	1

Trust plays an important role in monetary transactions and banking system. The respondents were observed with higher levels of trust in using the application. It is evident that the application provider needs to reinstate the trust in the usage of the service.

TABLE 10: Trust Drivers in a mobile application usage

TRUST DRIVERS	SA	A	N	DA	SDA
Does whatever it takes to make me happy	50	100	71	4	2
Keeps its word	46	128	51	1	1
Shows high integrity	57	108	54	7	1
Conducts transactions fairly	71	118	31	7	0
Competently handles my needs	55	112	52	6	2
Is responsive when contacted	52	113	38	16	8
Informs me immediately of new developments	70	121	31	4	1

The drivers of trust were also measured along with the trust of actual trust in a mobile application for transaction or money transfer purpose. Fair transactions in transfers and Integrity were the prominent drivers and responsiveness among the application providers was observed low compared to the other items used for the measure.

Relationship between perceived usefulness and attitude towards usage:

Table 11: Regression estimates of Perceived Usefulness and attitude

	Coefficients	T Stat	P-value
Intercept	2.93	8.85	2.67E-16
PERCEIVED USEFULNESS	0.32	3.61	0.00038
R Square	0.05	F	13.01

Dependent Variable: Attitude towards Usage

The estimates were observed significant at 1% with a positive co-efficient [Beta od 0.32]. The predictive power was only 5% as observed from the R-Square value. Hence it can be inferred that the attitude to use is depended upon the perceived usefulness of the application.

Relationship between perceived ease of use on attitude towards usage:

Table 12: Regression estimates of Perceived ease of use and attitude.

	Coefficients	T Stat	P-value
Intercept	2.29	8.22	1.57E-14
PERCEIVED EASE OF USE	0.34	5.35	2.15E-07
R Square	0.11	F	28.63
Dependent Variable: Attitude towards Usage			

The perceived ease of use among the users' needs to be demonstrated by the application provider and the regression was tested for checking the relationship between the constructs. The R-square value was 11% with a positive co-efficient of 0.34 [Beta]. The model was significant and hence it can be inferred that the Ease of use that the end users perceive is important to develop the attitude toward usage.

Impact of trust on actual usage of payment banks application:

Table 13: Regression estimates of Trust and actual usage.

	Coefficients	T Stat	P-value
Intercept	2	8.7	6.15E-16
TRUST	0.5	9.2	3.37E-17
R Square	0.27	F	83.8
Dependent Variable: Actual Usage			

Trust in use of a payment application is crucial as the application integrates with the bank account and transactions involve transfer of money. It was evident from the regression estimates with a R-square value of 27% and the positive coefficient of 0.5 proves that a higher demonstration of trust would translate to higher actual usage. The overall model was observed significant.

FINDINGS & INTERPRETATION:

The variables were tested and analyzed using regression for the cause-and-effect relationship. The key variables were perceived usefulness, perceived ease of use, intention to use, attitude towards the usage of payment banks, actual usage, and trust.

86% of the respondents agreed that payment bank services enhance their living and working performances. 97% of them feel that it is less time consuming and they get faster services. 88% of them feel that they can manage their accounts efficiently using payment bank services. 89% of them are satisfied with the information provided by payment banks.

94% of the respondents agree that it is easy to learn to use the payment bank services. 89% of them agree that it is easy to get all banking needs using payment banks. 93% of them agree that it is easy to do transactions using payment banks. 91% of them agree that it does not require much of mental efforts. Majority of the respondents fell that it is easy to learn and understand.

89% of the respondents agree that they intend to continue using payment bank services. 81% of them agree that they will not use any other alternative options available. Majority of them i.e. 38% of them disagree that that they want to discontinue the using of payment bank services. The respondents want to continue using payment banks services.

89% of the respondents agree that they are satisfied with payment bank services. 86% of them are very comfortable using payment bank services. 84% of them agree that they prefer payment bank apps to perform any transactions. Hence majority of the respondents are convinced and are at ease in using payment bank services.

78% of them agree that they conduct all transactions using payment banks. 88% of them agree that they use payment banks more than any traditional bank services. 82% of them agree that payment banks are more efficient, effective, and convenient. 88% of them agree that payment bank services are used by them as it saves a lot of time. Hence majority of them use payment banks more than traditional bank services as it is more proficient and handier.

75% of them agree that they trust payment banks. 80% of them agree that it is reliable. 78% of them agree that they work with best interests. 77% of them agree that they are honest with the customers. 79% of them agree that it makes every effort to meet the needs of the customers. 77% of them agree that it is dependable. Hence majority of them have a lot of trust on the payment banks.

66% of the respondents agree that payment banks do anything to keep the customers happy. 77% of them agree that it keeps its words. 73% of them agree that it shows high integrity. 83% of them agree that it conducts transactions fairly. 74% of them agree that it handles the needs proficiently. 73% of them agree it is very responsive. 84% of them agree that it informs the details on new developments quickly. Hence majority of the respondent's trust payment banks because of these drivers of trust.

RECOMMENDATIONS & IMPLICATIONS:

Based on the above findings concerning payment bank services, some recommendations are offered for possible consideration.

It was observed that some payment banks are performing much better with a greater market share among the sample size. Hence other payment bank companies can focus in increasing their market share by offering better services to the customers.

It was observed that 78% of them conduct transactions using payment banks but others still have an opinion that it is not efficient and effective in conducting transactions. Hence payment banks can take measures to improve its efficiency and convenience factor to make to provide the payments service completely digitalized.

It was observed that approximately 75% of them have trust in payment banks but remaining respondents are still under the umbrella of fear and do not trust them easily. Hence payment banks can take measures to enhance the trust among the customers by putting more efforts in meeting their needs, showing integrity, being fair in conducting transactions, keeping its promises and so on.

SCOPE FOR FURTHER RESEARCH:

The green shoots of banking are visible with digital banking, and the two major events that transformed the way of digital economy, namely the demonetization and the Covid-19. Conventional banking still caters the requirements of the current elderly population and with mobile penetration and easy applications, payment banks can distort the current conventional banking. Further with new technologies emerging, the role of blockchain in the finance industry can be looked like an opportunity to seal the black economy. The pros and the cons of offering a small bank license to the payment banks can be studied as a revenue generation possibility. The current system of GOOGLEPAY as an app or a mobile wallet like a PAYTM can be explored for the safety of the user's credentials and cash in the account. Cyber security is another area to be looked upon in the current scenario of cyber frauds and loss of money from digital wallets.

CONCLUSION:

The main idea of the research was to understand the role of trust in determining the sustainability of payment banks. The data was collected through questionnaires from 227 respondents and it was analyzed using ANOVA and regression. The earlier literature highlighted that customers are likely to accept mobile banking services provided by payment banks if the process or operation is easy to use and improve their work performance. From the data collected it was evident that majority of the respondents can learn the process of using payment bank services easily and without much of mental efforts. There was a positive impact of trust on usage, which indicates that when customers have more trust on payment banks then they automatically continue to use their services and do not shift to alternative options. They continue to be more loyal towards the payment banks. It was also concluded that there is a positive relationship between perceived usefulness and attitude towards use. It indicated that when the customers identify the uses then their attitude towards usage will change. The previous literature also indicated the same and the results of the studies matched prior studies. It was concluded that there is a positive relationship between perceived ease of use and intention to use. It indicated that when the process is easy to use people will intend to an actual use. Prior studies indicated that there is no relation between the two. But it was observed that there is an impact of perceived ease of use on the intention to use in case of payment bank apps. Trust is influential in helping the payment banks to digitalize the world of payment system and to disrupt the field of conventional banking if offered a small bank license.

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Title of the paper:

Significance of Psychological Contract in Education – A Study with Special Reference to Response of Students to Online Classes at the Time of Lockdown Due to Covid 19.

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Abstract:

Psychological contracts are being studied by many researchers in the present days. This paper attempts to establish the importance of psychological contract during formal education stage, by considering the response of UG and PG students to online classes at the time of lockdown due to Covid 19.

With the limited literature research it was found that many have tried to understand the benefits and pitfalls of online teaching. But the researches that establish a relationship between online education and psychological contract were found to be less explored, which is exactly what this paper attempts to do.

The objectives of the study is to find out the challenges faced by the students and the faculty members during the online classes and to understand the reasons behind the decreased student attendance.

A pilot tested questionnaire was used to collect the data from 246 students and 112 Faculty members from various streams including Engineering, Commerce and Management. The collected data were analysed using Chi Square test.

The results showed that weaker psychological contract plays a major role in the decrease in student attendance during the online classes. Other factors include lack of face to face interaction, internet connectivity issues etc.

Key Words:

Psychological Contract (PC), Covid 19, online classes, ICT, education, attendance

JEL Classification Code: I20, I21, O33

Introduction:

The world has witnessed many challenging situations in the year 2020, Covid 19 being one of them. The effects of this pandemic are calamitous. Apart from the number of victims affected and deceased, the news-paper articles and TV channels have also highlighted about loss of jobs, vulnerable firms, pay cuts etc. Some businesses took major hit and suffered from losses, some had to shut down their firms. The challenges posed by this pandemic have hinted some huge changes of the future the world is going to face. One of these changes is humongous increase in the use of Information and Communications Technology (ICT) in education.

***Information and Communication Technology and Education*:** ICT is the integration of telephone networks with computer system (Wikipedia) combined to achieve various purposes such as communication, transfer of information in mostly digital form. It is widely used in many industries for their business operations.

Education sector being one of the prominent among them. ICT plays a vital role in enhancing quality of teaching and ability of learning [Richard Pankomera, Darelle Van Greunen 2017]. It helps the students to understand and visualize a concept better rather than just teaching orally. It helps the teachers to gain credibility as they can provide valid proofs and hands on experience to the students.

Though the use of ICT has a history of approximately 290 years as ICT and online classes are associated with many historical threads such as computers, telecommunication, distance learning etc. [Favid Ferrer 2019], it started to gain tremendous importance during the pandemic in the year 2020. This was the moment the world had to witness a greatest challenge they had even thought of. It also taught the education sector that online teaching is going to be the future of education.

However, many institutions also reported that the attendance in the online classes during Covid 19 lock down were considerable during the initial days but turned out to be significantly less and kept decreasing drastically during later days. Some of the institutions may have already witnessed this problem, but the reason it gained importance during covid 19, is because of the increase in usage. Almost all the educational institutions of the world used online modes for teaching more than ever.

The answers given by the respondents in the interviews conducted during this research also does not specify the concrete reason for the reduced numbers. Some of the responses such as internet connectivity issues, does not clearly explain the good number of attendance during initial days of lock down.

Psychological Contract (PC) in Education: The above mentioned occurrences were the major inspiration to do this current research. Many previous researches and studies have highlighted about the need for interest to learn. In this study too, many respondents mentioned about student's interest to learn (learnability) and teacher's commitment to teach, which becomes vital for a teaching and learning activity to be successful.

In other words, there is an immense need for mutually accepted mental agreement between teacher and the learner. This undocumented mental agreement between two parties is called as a Psychological Contract [Schein 1978; Conway & Briner 2005; Kelly Windle & Kathrynvon Treuer 2014, Argyris 1960; Rousseau 1989].

JEL Classification Code: I20, I21, O33

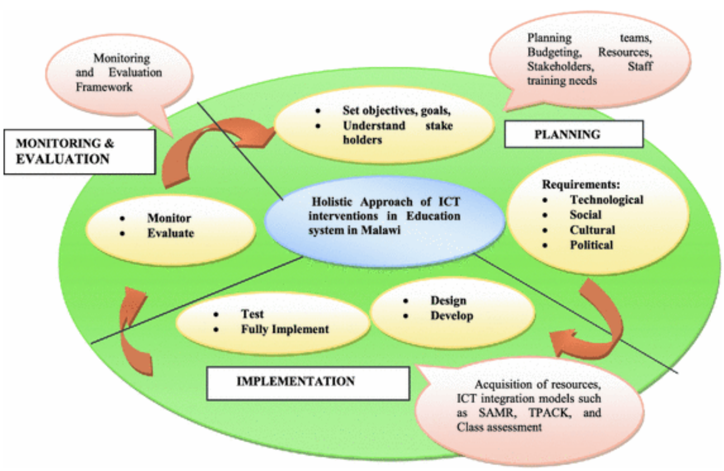
It exists between the people irrespective of industry, say for instance, between an employer and an employee, or between a coach and trainee, a teacher and a student etc.

The importance of psychological contract between a teacher and a learner is absolutely necessary during regular class room sessions, but becomes more essential during online classes. Some of the obvious reasons for this are absence of usual face to face communication, stability of internet, whether or not other ICT techniques were used to make the class interesting, interest in the subject, teacher's mastery in the subject and articulation, capability to adapt to online teaching etc.

This paper aims to establish the importance of psychological contract in education, especially during the online classes.

Literature review:

ICT in education: Richard Pankomera, Darelle Van Greunen [2017], who proposed a model for intervention of ICT in education system at Malawi (shown in Figure 1), say that in the developed countries ICT would be incorporated at all the levels of education system, but for developing countries there would be resource constraints that might make implementation of ICT at all the levels challenging. They also suggest that ICT incorporation in education would be meaningful and enhance effectiveness by engaging all the stakeholders such as Government, community, decision makers, policy makers, private sectors etc.



Source: link.springer.com

Figure 1: ICT Model to enhance Teaching and Learning

Syed Noor-Ul-Amin, from University of Kashmir, reviewed various articles to bring together different perspectives about ICT as a change agent in education. Referring to hundreds of literatures, the author considers few major areas, which includes enhancing learning environment, making the process of teaching and learning better, making education quality oriented and more accessible, enhancing the passion and motivation to learn, enhancing scholastic performance etc. and argues that ICT has positive impact in each one of these aspects. According to Victoria L. Tinio, ICT which earlier included radio and television, in the recent days also includes many digital technologies such as computer, internet etc. and if used appropriately these are powerful tools to change and reform education.

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But this alone may not assure the reformation and guarantee successful learning. It also depends on factor such as readiness of the educational institution, funds available for long term, competencies of teachers, academic curriculum and its objectives etc.

Ting Seng Eng [2005], from National institute of Singapore analyses the trends of ICT in education and reviews number of literatures identify how ICT has benefitted the education over period of time. The findings of this author suggests that ICT can reduce the time taken to learn a concept. It has other advantages such as enhancing motivation towards learning. According to the author's studies, subjects like Mathematics, languages etc. are easier to learn using computer based learning.

Psychological contract: Several researchers have attempted to study the concept of PC since quite a long time. The concept of psychological contract was explained initially by Argyris [1960] and developed later by Schien [1965] and Rousseau [1989]. Their study also implies that the concept of PC was very closely related to Blau's social exchange theory [1964]. According to Levinson [1962] who is known as the father of the concept has defined psychological contract as unwritten contract, the sum of the mutual expectations between the two parties. It could be employer and employee, teacher and student, mentor and mentee etc.

The definition given by Rousseau [1990] highlights employees perception of the existence of mutual obligations deposited with the employer. Herriot and Pemberton [1995] defined it as "The perceptions of both parties to the employment relationship, organization and individual, of the obligations implied in the relationship".

McLean Parks, Kidder and Gallagher [1998] have provided a conceptual overview considering the perspectives of employer and employee. According to their argument utilizing the dimensions of psychological contracts are extremely helpful in understanding the differences that arise between an employer and an employee and thus helps to create a flexible working environment. Jacqueline A-M et al [2008] from London school of economics and political science specifies in SAGE handbook of organization behaviour that the basic foundation to formation of psychological contract begins from the society in large. Schools, family, peer groups, social interactions have a greater role in formation of PC. The author attempts to explain the concept of PC by reviewing hundreds of literatures. They specify that number of assumptions are made by a person before and during their first employment regarding their job, salary, work environment, recognitions etc. These assumptions give rise to a psychological promise made by the employee. In other words, this is the anticipatory stage of PC.

Denise M Rousseau et al, [2013], elucidates in their study about conceptual framework of psychological contract. They explain not just formation and importance of PC and its formation, but also about breach of the contract and its impact on contemporary organizations. According to them, reaction to psychological contract breach is theorized to be stronger than unfulfilled expectations, although expectations during pre-employment might positively impact on formation of PC. P. Matthijs Bal and Tim Vantilborgh [2018], in their article titled "Life span perspectives on psychological contract" discusses various phases of PC, including development, growth and maturity. They also specify how the contract might change by considering age as one of the major factor. They argue that, it is very important for the company to understand how relationships and expectations changes over time with young, middle-aged and older workers, in order to keep their employees motivated and satisfied. Based on socio-emotional selectivity theory, it can be predicted that younger workers have greater interest in development compared to older workers.

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And this highlights the importance of anticipatory stage of PC for effective recruitments. Maria Pepur, Zoran Mihanović and Sandra Pepur [2013], start by continuing the work of Kingshott and Pecotich [2007] and by extending his conceptual model. They say that the arguments of psychological contracts arise from social exchange theory. Their study and analysis considered partners in financial markets. The number of questionnaires analysed were about 356. The study confirms that psychological contract has positive influence on relationship quality between partners in the financial markets as well.

Ade I. Anggraeni et al [2017] in their study which aims at finding out the impact of psychological contract on employee commitment and organizational citizenship behaviour with reference to 150 young Indonesian entrepreneurs, reveal that the intangible elements such as the sense of belongingness, organizational commitment, responsibility etc. has a greater impact on psychological contract.

PC in education: Suqun Liao [2013] attempted to study the psychological contract between teachers and students in Shauguan University with reference to a network course of psychology. The findings of this study specifies that the students' behaviour and learning efficiency was dependent on the teacher's commitment. The learning enthusiasm and efficiency was damaged when the desired behaviour of the teacher was not met. Hong Fan from Jilin Sport University [2014], in an article that aims at studying the relationship between performance and psychological contract. The results say that the sports teachers whose strength of psychological contract was low, showed reduced performance in their colleges, thus indicating that decrease in psychological contract also decreases motivation to work, thereby reducing the performance.

Need for the study and research gap:

With the limited literature review, it was found that, many researches are conducted in the area of psychological contract, but mostly considering the perspectives of employers and employees. But very limited research was conducted, which tries to establish the need for psychological contract in education, between a teacher and a student, especially during online classes. Hence this paper focuses mainly on the significance of psychological contract between teachers and students during online classes.

Objectives of the study:

To identify the challenges faced by both students and teachers during the online classes.

To evaluate the strength of psychological contract between teachers and students during the online classes.

To establish the significance of psychological contract during online classes.

Research Methodology:

The data required for this descriptive study were collected through both primary and secondary sources. Primary data was collected in two stages. In the first stage, information related to challenges faced by teachers and students during online classes was collected, using an online survey.

In the second stage, pilot tested questionnaires were circulated to 384 samples, out of which 112 Teachers (who mostly taught UG and PG courses), and 246 students (who were also from UG and PG courses) responded, resulting in total sample size of 358.

These respondents were selected mostly using non – probability sampling techniques. The questionnaire was tested for reliability using Chronbach's alpha which was 0.806 for the responses of Teachers and 0.67 for that of students. The questionnaire was developed by adapting a research instrument which was originally designed by A.G (Linda) Schieven [2009] which had reliability measure of 0.81.

Secondary data were mostly collected through Journals, Newspaper articles and websites.

Analysis and Interpretation of findings:

The study began with few questions such as, what are the challenges faced by students as well as teachers while teaching online? Is the psychological contract which in other words, the mental agreement and commitment between students (to understand their subjects) and teachers (to make those subjects understandable) strong enough? What significance does psychological contract have in this trending online education system?

The data collected from 358 samples (112 Teachers and 246 Students), were analysed using Chi Square tests on SPSS, to find out relationships between dependent and independent variables from the perspective of both teachers and students, and thus tries to establish a significance of psychological contract between them for successful teaching and learning. Demographic information such as age group, income level, gender, experience, designation, type of institution etc. were taken as independent variables and Chi Square tests were conducted to find out if these variables have any impact on psychological contract. Here psychological contract is expressed in terms of elements such as passion to teaching/learning, flexibility, motivation, commitment, accountability which are some of its influencing variables [Ade I. Anggraeni et al 2017; Festing and Schäfer 2014; Feldman and Butts 2014].

Though there are many variables that influence psychological contract the present paper is limited to analysis of only few variables, due to time constraints.

To test if the independent variables have any association with psychological contract, hypothesis was tested separately for both Teachers and Students.

Hypothesis testing – Teachers: The psychological contract of teachers were analysed in terms of Passion for teaching, motivation, flexibility and monetary expectation.

Hypothesis 1:

H0: Age group does not have any significant impact on psychological contract

H1: Age group has significant impact on psychological contract.

Hypothesis 2:

H0: Income level does not have any significant impact on psychological contract

H1: Income level has significant impact on psychological contract.

Hypothesis 3:

H0: Qualification does not have any significant impact on psychological contract

H1: Qualification has significant impact on psychological contract.

Hypothesis 4:

H0: Experience does not have any significant impact on psychological contract

H1: Experience has significant impact on psychological contract.

The value of Chi Square analysed for the above variables is as shown in table 1.

Table 1: Chi Square Tests – Teachers

Pearson Chi Square analysis for	Values	Number of valid cases	Df	Asymptotic Significance (2-sided)	H0 accepted or rejected
Age group Vs Passion towards teaching	17.131[a]	112	15	0.311	H0 Accepted
Age group Vs Flexibility towards job	3.355[a]	112	10	0.972	H0 Accepted
Age group Vs Motivation to contribute to the Institution	10.138[a]	112	15	0.811	H0 Accepted
Age group Vs Monetary expectation for additional contribution made	14.741[a]	112	20	0.791	H0 Accepted
Income Vs Passion towards teaching	14.724[a]	112	12	0.257	H0 Accepted
Income Vs Flexibility towards job	2.483[a]	112	8	0.963	H0 Accepted
Income Vs Motivation to contribute to the Institution	20.738[a]	112	12	0.05	H0 Rejected
Income Vs Monetary expectation for additional contribution made	26.260[a]	112	16	0.05	H0 Rejected
Qualification Vs Passion towards teaching	4.582[a]	112	9	0.869	H0 Accepted
Qualification Vs Flexibility towards job	5.496[a]	112	6	0.482	H0 Accepted
Qualification Vs Motivation to contribute to the Institution	9.123[a]	112	9	0.426	H0 Accepted
Qualification Vs Monetary expectation for additional contribution made	10.552[a]	112	12	0.568	H0 Accepted
Experience Vs Passion towards teaching	11.734[a]	112	9	0.229	H0 Accepted
Experience Vs Flexibility towards job	1.818[a]	112	6	0.936	H0 Accepted
Experience Vs Motivation to contribute to the Institution	7.240[a]	112	9	0.612	H0 Accepted
Experience Vs Monetary expectation for additional contribution made	6.716[a]	112	12	0.876	H0 Accepted

(Source: SPSS Software) **JEL Classification Code: I20, I21, O33**

The following observations were made from the analysis shown in Table 1:

The variables Age group, Qualification and Experience did not have any impact on psychological contract of teachers. Out of 112 teachers 22 belonged to the age group between 25 to 30 years, 32 belonged to age group of 30 to 35 years, 34 belonged to 35 to 40 years, 13 belonged to 34 to 45 years, 5 belonged to 45 to 50 years and remaining 6 belonged to age group above 50 years.

Similarly, there were respondents who had their academic qualifications from diverse areas such as Engineering, Science, Arts, Commerce and Management and many other streams.

Some of the respondents taught UG, some taught PG and some taught both. Also, these respondents had their work experience ranging from minimum of less than a year till maximum of above 15 years.

In spite of all these differences, their passion for teaching, flexibility, motivation and monetary expectation for extra work remained unaffected by the age group they belonged to. This is clearly indicated by the Chi Square table, in which the asymptotic significance is above the significance level 0.05. Hence we fail to reject the null hypothesis in all these three cases.

The analysis is different in case of income level. Through the income level does not impact flexibility largely, it somewhat has an effect on passion. In other words, though asymptotic significance is more than 0.05, the value is not too large enough to be highly insignificant. Hence there could be a possibility that the income level of a teacher may to a minor extent have an impact on their passion for teaching.

But, the table clearly indicates that the values of motivation and monetary expectation for extra work done are significant. This means, motivation to contribute to the institution and monetary expectation for extra work done, are significantly impacted by income level. For instance, a person who has high income level may not expect extra income for additional work performed, which is opposite in case of a person with lesser income. Similarly, the motivational level of a teacher also significantly depends on his/her income level, which means a higher income level person might have a higher motivation to teach and contribute to the institution than that of a person having lower income.

Hypothesis testing – Students: The PC of students were analysed in terms of Passion to learning, motivation, flexibility, commitment and accountability.

Hypothesis 1:

H0: Age group does not have any significant impact on psychological contract

H1: Age group has significant impact on psychological contract.

Hypothesis 2:

H0: Gender does not have any significant impact on psychological contract

H1: Gender has significant impact on psychological contract.

Hypothesis 3:

JEL Classification Code: I20, I21, O33

H0: Type of course does not have any significant impact on psychological contract

H1: Type of course has significant impact on psychological contract.

The value of Chi Square analysed for the above variables is as shown in table 2.

Table 2: Chi Square Tests – Students

Pearson Chi Square analysis for	Values	Number of valid cases	Df	Asymptotic Significance (2-sided)	H0 accepted or rejected
Age group Vs Passion towards learning	16.506[a]	246	12	0.169	H0 Accepted
Age group Vs Commitment	12.440[a]	246	12	0.411	H0 Accepted
Age group Vs Motivation	5.053[a]	246	12	0.956	H0 Accepted
Age group Vs Flexibility	13.566[a]	246	12	0.329	H0 Accepted
Age group Vs Accountability	22.014[a]	246	12	0.037	H0 Rejected
Gender Vs Passion towards learning	3.339[a]	246	4	0.503	H0 Accepted
Gender Vs Commitment	2.025[a]	246	4	0.731	H0 Accepted
Gender Vs Motivation	5.811[a]	246	4	0.214	H0 Accepted
Gender Vs Flexibility	5.516[a]	246	4	0.238	H0 Accepted
Gender Vs Accountability	1.690[a]	246	4	0.792	H0 Accepted
Course studying Vs Passion towards learning	12.682[a]	246	4	0.013	H0 Rejected
Course studying Vs Commitment	15.116[a]	246	4	0.004	H0 Rejected
Course studying Vs Motivation	5.970[a]	246	4	0.201	H0 Accepted
Course studying Vs Flexibility	9.094[a]	246	4	0.05	H0 Rejected
Course studying Vs Accountability	49.146[a]	246	4	0	H0 Rejected

(Source: SPSS Software)

The following observations were made from analysis shown in table 2:

According to the data collected in the first stage, internet connectivity issues, lack of face to face communication, adaptability to change from traditional classroom to online classroom were some of the important challenges faced by the students. But that did not explain the reason for fall in the numbers, which were significantly higher during the initial days of the classes.

The analysis from the table 2 clearly indicates that, in case of age group and gender the Chi Square values are more than 0.05, which is why we fail to reject the null hypothesis, which means there is no significant effect of age group and gender on psychological contract.

JEL Classification Code: I20, I21, O33

But the analysis showed that type of course had a higher impact on psychological contract of students. Even if in case of motivation, the value is more than 0.05, it is not large enough to be highly insignificant. In all other cases the asymptotic significance values are lower than 0.05, which indicates that type of course might affect the psychological contract of students. Out of 246 respondents, 208 students studied post-graduation courses and remaining 38 were from under-graduation courses. It seems that issues like internet connectivity and lack of face to face communication seem to have affected very less, as the maturity and intelligence level the PG students usually possess is known to be higher than that of UG students, which is why technical ability to adapt to the changes should have been higher compared to UG students. It could also be a reason that PG students are seldom dependent on teachers, which might have reduced the strength of psychological contract with students. Hence this has to be studied further, by developing suitable interventions.

Findings of the study:

The paper aimed at two primary objectives. Firstly, to identify the challenges faced by the students and teachers during online classes. Internet connectivity, lack of face to face communication, lack of ability to adapt to new technology were found to be the major issues faced by the students and teachers. But in spite of the challenges, the commitment from the teachers' side did not decrease much. But it was opposite in case of the students. One of the reason for this also could be unpreparedness of students, especially in tier 2 and tier 3 Institutions of India, to shift from traditional classroom setup to completely virtual set up for almost an entire semester due to Covid 19, which was highly unpredictable.

To understand the reason behind massive decrease in the attendance during online classes, the study further aimed at evaluating the strength psychological contract between teachers and students, which could understand the problem in depth and from both perspectives effectively. The results of the study showed that the psychological contract with teachers were stronger than that of students. The study also indicates that enhanced accountability, passion, commitment, motivation and a little flexibility from both student and teachers could fix the issues that occur at the time of online classes. In other words, there is a need for stronger psychological contract between teachers and students might reduce the issues that occur while handling online classes.

Conclusion and scope for further studies:

The pandemic crisis has hinted at an unpredictable world which is demanding for changes in the way people work. These changes are becoming inevitable in education sector too. Thus it is high time to adapt to the new era of digital education, for success of which, stronger psychological contract between teacher and student is essential. To enhance the teaching effectiveness especially during online classes, the teachers must look for innovative techniques such as use of creative ICT tools to retain the interest levels of students rather than focussing just on syllabus completion, while the students must reflect to the teachers' efforts with better accountability, commitment and passion for learning.

However, the strength of psychological contract between the teachers and students can be understood more accurately and effectively by considering the respondents from same institution, since the students and the teachers would be known to each other well, which would enhance the clarity of the mutual expectations.

JEL Classification Code: I20, I21, O33

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JEL Classification Code: I20, I21, O33

Web links:

https://www.tsijournals.com/articles/study-on-the-relationship-between-psychological-contract-effect-and-job-performance-in-the-construction-of-regular-colle.pdf

https://elearning.tsu.ge/pluginfile.php/183/mod_resource/content/0/ict_docs/ICT_in_education.pdf

https://doi.org/10.1016/S0360-1315(01)00045-8

https://thebestschools.org/magazine/online-education-history/

https://en.wikipedia.org/wiki/Information_and_communications_technology#:~:text=Information%20and%20communications%20technology%20(ICT,software%2C%20middleware%2C%20storage%2C%20and

JEL Classification Code: I20, I21, O33

Sl. No.	Part A - 1. Please select the age group you belong to:	2. Please specify your Gender:	3. Please select the course you have taught online during Covid 19:	4. Please specify your income level:	5. Please select your highest education level:	6. How many years of experience do you have in teaching?	7. Please select the type of your institution:	8. Please specify your designation.	9. Please specify the State of India you are located in:
1	30 to 35 Years	Female	PG	Greater than 50K per month	Post-Graduation	Above 15 Years	Private	Assistant professor	Karnataka
2	30 to 35 Years	Female	Both	Less than 20K per month	Post-Graduation	5 to 10 Years	Government	Assistant professor	Andhrapradesh
3	25 to 30 Years	Male	Both	20K to 30K per month	Mcom, Net, Kset B.ed	1 to 5 Years	Private	Assistant professor	Karnataka
4	35 to 40 Years	Male	Both	30K to 40K per month	PhD	10 to 15 Years	Private	Assistant Professor	Tamilnadu
5	40 to 45 Years	Male	PG	40K to 50K per month	Post-Graduation	5 to 10 Years	Private	Assistant Professor	KARNATAKA
6	30 to 35 Years	Male	UG	30K to 40K per month	Post-Graduation	10 to 15 Years	Private	Lecturer	Karnataka
7	35 to 40 Years	Male	PG	30K to 40K per month	Post-Graduation	10 to 15 Years	Private	Asst Professor	Karnataka
8	30 to 35 Years	Male	PG	20K to 30K per month	Post-Graduation	10 to 15 Years	Private	ASSISTANT PROFESSOR	UTTARPRADESH
9	35 to 40 Years	Male	Both	20K to 30K per month	Post-Graduation	Above 15 Years	Private	Visiting Faculty	Maharashtra
10	25 to 30 Years	Male	UG	30K to 40K per month	Post-Graduation	5 to 10 Years	Private	Asst professor	Main branch in Bangalore
11	30 to 35 Years	Male	PG	30K to 40K per month	PhD	5 to 10 Years	Private	Assistant Professor	Karnataka
12	25 to 30 Years	Female	Both	Less than 20K per month	Post-Graduation	10 to 15 Years	Private	ASSISTANT PROFESSOR	Yes
13	25 to 30 Years	Male	UG	Greater than 50K per month	Post-Graduation	1 to 5 Years	Government	Assistant Professor	Karnataka
14	40 to 45 Years	Female	Both	Greater than 50K per month	PhD	5 to 10 Years	Government	Assistant professor	Tamil Nadu
15	30 to 35 Years	Female	UG	40K to 50K per month	PhD	1 to 5 Years	Private	Assistant Professor	Karnataka
16	35 to 40 Years	Male	UG	Less than 20K per month	Post-Graduation	1 to 5 Years	Private	LECTURER	INDIA
17	Above 50 years	Female	UG	40K to 50K per month	PhD	Above 15 Years	Private	Associate Professor of English	Andhrapradesh
18	25 to 30 Years	Male	UG	20K to 30K per month	Post-Graduation	5 to 10 Years	Private	Assistant Professor	Karnataka
19	35 to 40 Years	Female	UG	20K to 30K per month	PhD	10 to 15 Years	Private	Assistant Professor	Tamilnadu
20	30 to 35 Years	Female	UG	Less than 20K per month	PhD	5 to 10 Years	Private	Assistant professor	Tamil Nadu
21	30 to 35 Years	Male	PG	20K to 30K per month	PhD	5 to 10 Years	Private	00	Very good sir
22	30 to 35 Years	Female	PG	40K to 50K per month	Post-Graduation	10 to 15 Years	Private	Associate Professor	Karnataka
23	40 to 45 Years	Male	Both	Less than 20K per month	PhD	10 to 15 Years	Private	Associat professor and Head of statistics	Tamilnadu
24	30 to 35 Years	Female	Both	Greater than 50K per month	PhD	5 to 10 Years	Private	Assistant professor Sr	Andhra Pradesh
25	30 to 35 Years	Female	PG	Less than 20K per month	Post-Graduation	1 to 5 Years	Private	lecturer	AndhraPradesh
26	35 to 40 Years	Male	Both	30K to 40K per month	PhD	5 to 10 Years	Government	Assistant Professor	Madhya Pradesh
27	35 to 40 Years	Male	Both	Less than 20K per month	PhD	1 to 5 Years	Private	Assistant professor	Tamilnadu
28	25 to 30 Years	Male	PG	Less than 20K per month	Post-Graduation	5 to 10 Years	Private	Special Education	Uttar Pradesh India
29	40 to 45 Years	Male	Both	Less than 20K per month	PhD	Above 15 Years	Private	Professor	Up
30	45 to 50 Years	Male	UG	20K to 30K per month	PhD	Above 15 Years	Private	Professor	A P
31	35 to 40 Years	Male	Both	30K to 40K per month	PhD	10 to 15 Years	Private	Asst. Prof.	T N , COIMBATORE
32	45 to 50 Years	Female	PG	Greater than 50K per month	PhD	Above 15 Years	Private	AP	Kerala
33	35 to 40 Years	Female	PG	20K to 30K per month	PhD	10 to 15 Years	Private	Assistant professor	Andhra Pradesh
34	30 to 35 Years	Male	PG	30K to 40K per month	Post-Graduation	5 to 10 Years	Private	ASST.PROFESSOR	VIJAYAWADA
35	40 to 45 Years	Female	Both	Less than 20K per month	PhD	Above 15 Years	Private	Assistant Professor	Tamil Nadu
36	30 to 35 Years	Male	PG	30K to 40K per month	PhD	10 to 15 Years	Government	Asst prof	Guj
37	30 to 35 Years	Male	Both	Greater than 50K per month	Post-Graduation	10 to 15 Years	Private	Assistant Professor	Karnataka
38	45 to 50 Years	Male	UG	Greater than 50K per month	Post-Graduation	Above 15 Years	Private	Assoc Prof	Karnataka
39	30 to 35 Years	Female	UG	20K to 30K per month	Net qualified	5 to 10 Years	Private	Assistant Professor	Uttar Pradesh
40	30 to 35 Years	Male	Both	30K to 40K per month	Post-Graduation	10 to 15 Years	Private	Associate prof	Karnataka
41	30 to 35 Years	Female	PG	30K to 40K per month	Post-Graduation	10 to 15 Years	Private	Assistant professor	Karnataka
42	25 to 30 Years	Female	UG	20K to 30K per month	Post-Graduation	1 to 5 Years	Private	Assistant Professor	Karnataka
43	30 to 35 Years	Male	UG, PG	40K to 50K per month	Post-Graduation	10 to 15 Years	Private	Assistant Professor	Karnataka
44	30 to 35 Years	Male	UG	40K to 50K per month	Post-Graduation	5 to 10 Years	Private	Assistant Professor	Karnataka
45	25 to 30 Years	Female	UG	20K to 30K per month	Post-Graduation	5 to 10 Years	Private	Assistant professor	Karnataka
46	25 to 30 Years	Male	UG	20K to 30K per month	Post-Graduation	1 to 5 Years	Government	Lecturer in political science	Telangana
47	25 to 30 Years	Female	Both	Less than 20K per month	M.ed	5 to 10 Years	Private	ASSISTANT PROFESSOR	Jbl
48	35 to 40 Years	Male	UG	30K to 40K per month	PhD	10 to 15 Years	Private	ASSISTANT PROFESSOR	Telangana
49	40 to 45 Years	Male	Both	Less than 20K per month	PhD	Above 15 Years	Private	Professor	Up
50	25 to 30 Years	Female	UG	20K to 30K per month	Post-Graduation	1 to 5 Years	Private	Assistant professor	Maharashtra
51	30 to 35 Years	Female	UG	40K to 50K per month	Post-Graduation	5 to 10 Years	Private	Assistant Professor	Karnataka
52	35 to 40 Years	Female	UG	40K to 50K per month	Post-Graduation	10 to 15 Years	Private	Asst. Professor	Karnataka
53	Above 50 years	Male	Both	Greater than 50K per month	Post-Graduation	Above 15 Years	Private	Proffesor	Karnataka
54	30 to 35 Years	Female	UG	20K to 30K per month	Post-Graduation	5 to 10 Years	Private	Assistant professor	Karnataka
55	25 to 30 Years	Female	UG	20K to 30K per month	Post-Graduation	1 to 5 Years	Private	Assistant professor	Karnataka
56	30 to 35 Years	Male	PG	30K to 40K per month	Post-Graduation	1 to 5 Years	Private	Assistant professor	Karnataka
57	35 to 40 Years	Female	UG	20K to 30K per month	Post-Graduation	10 to 15 Years	Private	Assistant professor	Karnataka
58	25 to 30 Years	Female	UG	20K to 30K per month	Post-Graduation	5 to 10 Years	Private	ASSISTANT PROFESSOR	BANGALORE
59	35 to 40 Years	Male	PG	20K to 30K per month	PhD	Above 15 Years	Private	Assistant Professor	Tamilnadu
60	35 to 40 Years	Male	PG	Less than 20K per month	Post-Graduation	10 to 15 Years	Private	Assistant Professor	HYDERABAD AND India
61	35 to 40 Years	Male	UG	20K to 30K per month	Post-Graduation	10 to 15 Years	Private	Assistant professor	Tamilnadu,coimbatore
62	35 to 40 Years	Male	Both	20K to 30K per month	Post-Graduation	10 to 15 Years	Private	HOD	Tamil Nadu
63	30 to 35 Years	Male	UG	20K to 30K per month	Post-Graduation	5 to 10 Years	Private	Asst prof	Andhra Pradesh
64	35 to 40 Years	Female	UG	30K to 40K per month	Graduation	Above 15 Years	Government	Teacher	BHADOHI
65	25 to 30 Years	Male	Both	Less than 20K per month	Post-Graduation	5 to 10 Years	Private	Special Education Uttar Pradesh India	Uttar Pradesh
66	35 to 40 Years	Male	UG	Greater than 50K per month	Post-Graduation	5 to 10 Years	Government	ASSISTANT PROFESSOR OF ENGLISH	KARNATAKA INDIA
67	25 to 30 Years	Male	Both	Less than 20K per month	Post-Graduation	5 to 10 Years	Private	Head of the Department	Tamilnadu
68	45 to 50 Years	Female	UG	20K to 30K per month	Post-Graduation	5 to 10 Years	Private	Asst professor	Karnataka
69	40 to 45 Years	Female	UG	40K to 50K per month	PhD	Above 15 Years	Private	Professor	Andhra pradesh
70	40 to 45 Years	Female	Both	Less than 20K per month	PhD	5 to 10 Years	Government	Assistant professor	Tamil nadu
71	40 to 45 Years	Female	Both	Less than 20K per month	PhD	10 to 15 Years	Private	Head Department of Education	M.p.
72	30 to 35 Years	Male	Both	30K to 40K per month	Post-Graduation	5 to 10 Years	Private	Assistant Professor	WG
73	25 to 30 Years	Female	Both	Less than 20K per month	Post-Graduation	1 to 5 Years	Private	Research Scholar	Tamilnadu
74	25 to 30 Years	Male	Both	Less than 20K per month	PhD	1 to 5 Years	Private	Assistant professor	Tamilnadu

Part B: Please select the best option possible. [I Teach because it is my passion]	Part B: Please select the best option possible. [I am ready to spend extra time to teach the students if need arises]	Part B: Please select the best option possible. [My primary goal is to complete the syllabus on time]	Part B: Please select the best option possible. [I am motivated to contribute 100% to the institution I am working for.]	Part B: Please select the best option possible. [I expect the institution to pay for extra classes and subjects I handle.]	Part B: Please select the best option possible. [I use ICT because it is mandatory]	Part B: Please select the best option possible. [I would love to learn new technology if it benefits my teaching.]	Part B: Please select the best option possible. [Students always find my ICT based teaching interesting.]	Part B: Please select the best option possible. [I always develop my own contents for the subjects I handle.]	Part B: Please select the best option possible. [I believe that ICT enabled classes has potential to gain interest of even most naughty students of my class.]
Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree
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Neutral	Agree	Agree	Agree	Neutral	Neutral	Strongly agree	Neutral	Agree	Neutral

Sl. No.	Part A - 1. Please select the age group you belong to:	2. Please specify your Gender:	3. Please select the course you have taught online during Covid 19:	4. Please specify your income level:	5. Please select your highest education level:	6. How many years of experience do you have in teaching?	7. Please select the type of your institution:	8. Please specify your designation.	9. Please specify the State of India you are located in:
75	35 to 40 Years	Female	PG	20K to 30K per month	PhD	1 to 5 Years	Private	Assistant Professor	Tamil Nadu
76	25 to 30 Years	Male	UG	Less than 20K per month	PhD	1 to 5 Years	Private	Assistant Professor of Commerce (CA)	Tamilnadu
77	40 to 45 Years	Female	UG	Less than 20K per month	Graduation	Above 15 Years	Government	Teacher	Uttar Pradesh
78	35 to 40 Years	Male	PG	20K to 30K per month	PhD	10 to 15 Years	Private	Associate professor	India
79	35 to 40 Years	Male	Both	Greater than 50K per month	Post-Graduation	10 to 15 Years	Private	Assistant Professor	Karnataka
80	Above 50 years	Female	PG	Greater than 50K per month	Post-Graduation	10 to 15 Years	Private	Assistant professor	Karnataka
81	35 to 40 Years	Female	PG	Greater than 50K per month	M.phil	10 to 15 Years	Private	Asst professor	Karnataka
82	40 to 45 Years	Female	Both	30K to 40K per month	PhD	Above 15 Years	Private	Associate Professor	Delhi
83	35 to 40 Years	Female	Both	Less than 20K per month	PhD	10 to 15 Years	Government	Govt. Model College Jhabua	M.P.
84	35 to 40 Years	Male	PG	20K to 30K per month	Post-Graduation	5 to 10 Years	Private	Assistant professor	Karnataka
85	35 to 40 Years	Male	UG	Greater than 50K per month	PhD	Above 15 Years	Government	Asst. Professor	Karnataka
86	40 to 45 Years	Female	Both	Less than 20K per month	PhD	Above 15 Years	Government	ASSISTANT PROFESSOR	TAMILNADU
87	30 to 35 Years	Male	Both	Greater than 50K per month	PhD	10 to 15 Years	Government	Karnataka State Akkamahadevi women's University	Karnataka
88	40 to 45 Years	Male	Both	Less than 20K per month	PhD	10 to 15 Years	Private	Assistant Professor	Tamil Nadu
89	30 to 35 Years	Male	Both	Less than 20K per month	Post-Graduation	5 to 10 Years	Private	Associate professor	Karnataka
90	Above 50 years	Male	Both	Greater than 50K per month	PhD	Above 15 Years	Private	Professor	Karnataka
91	Above 50 years	Male	UG	Greater than 50K per month	Graduation	Above 15 Years	Private	Administration	Maharashtra
92	30 to 35 Years	Female	Both	Greater than 50K per month	Post-Graduation	5 to 10 Years	Government	ASSISTANT PROFESSOR	Karnataka
93	25 to 30 Years	Female	Both	Less than 20K per month	PhD	1 to 5 Years	Private	Research Scholar	Tamilnadu
94	35 to 40 Years	Male	Both	40K to 50K per month	Post-Graduation	Above 15 Years	Private	Associate Professor	Telangana
95	35 to 40 Years	Female	UG	Less than 20K per month	PhD	5 to 10 Years	Private	Assistant Professor	Tamil Nadu
96	35 to 40 Years	Female	PG	40K to 50K per month	Post-Graduation	5 to 10 Years	Private	Assistant Professor	Karnataka
97	30 to 35 Years	Female	Both	Greater than 50K per month	PhD	10 to 15 Years	Private	Associate Professor	Uttar Pradesh
98	35 to 40 Years	Male	UG	Greater than 50K per month	PhD	10 to 15 Years	Private	Professor	Andhra Pradesh
99	45 to 50 Years	Female	PG	30K to 40K per month	Post-Graduation	10 to 15 Years	Private	Assistant professor	Karnataka
100	30 to 35 Years	Male	PG	Less than 20K per month	Post-Graduation	10 to 15 Years	Government	Guest Teacher	West Bengal
101	30 to 35 Years	Female	UG	30K to 40K per month	Post-Graduation	10 to 15 Years	Private	Assistant professor	Karnataka
102	30 to 35 Years	Female	UG	Less than 20K per month	PhD	5 to 10 Years	Private	Assistant professor	Tamil Nadu
103	35 to 40 Years	Male	PG	20K to 30K per month	PhD	10 to 15 Years	Private	Associate professor	Andhra pradesh
104	25 to 30 Years	Female	Both	Less than 20K per month	Post-Graduation	1 to 5 Years	Private	Assistant professor	Sultanpur
105	Above 50 years	Male	Both	20K to 30K per month	PhD	Above 15 Years	Government	M.Com., M.Phil, Ph.D UGC-NET/SLET	Karnataka
106	35 to 40 Years	Female	Both	20K to 30K per month	Post-Graduation	5 to 10 Years	Private	assistant professor	karnataka
107	30 to 35 Years	Female	UG	30K to 40K per month	Post-Graduation	5 to 10 Years	Private	Assistant professor	Uttar Pradesh
108	25 to 30 Years	Female	UG	Less than 20K per month	Post-Graduation	1 to 5 Years	Government	Research Scholar	Uttar Pradesh
109	35 to 40 Years	Female	Both	20K to 30K per month	Post-Graduation	10 to 15 Years	Private	Teacher	Maharashtra
110	35 to 40 Years	Male	Both	30K to 40K per month	Post-Graduation	5 to 10 Years	Government	Assistant professor	MAHARASHTRA
111	35 to 40 Years	Male	Both	20K to 30K per month	Post-Graduation	10 to 15 Years	Private	Assistant Professor	Karnataka
112	25 to 30 Years	Male	UG, PG, Both	40K to 50K per month	PhD	1 to 5 Years	Private	Salem	Tamil Nadu

Part B: Please select the best option possible. [I Teach because it is my passion]	Part B: Please select the best option possible. [I am ready to spend extra time to teach the students if need arises]	Part B: Please select the best option possible. [My primary goal is to complete the syllabus on time]	Part B: Please select the best option possible. [I am motivated to contribute 100% to the institution I am working for.]	Part B: Please select the best option possible. [I expect the institution to pay for extra classes and subjects I handle.]	Part B: Please select the best option possible. [I use ICT because it is mandatory]	Part B: Please select the best option possible. [I would love to learn new technology if it benefits my teaching.]	Part B: Please select the best option possible. [Students always find my ICT based teaching interesting.]	Part B: Please select the best option possible. [I always develop my own contents for the subjects I handle.]	Part B: Please select the best option possible. [I believe that ICT enabled classes has potential to gain interest of even most naughty students of my class.]
Strongly agree	Strongly agree	Strongly agree	Strongly agree	Neutral	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Agree
Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Neutral
Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Strongly agree	Strongly agree	Agree	Strongly agree	Neutral	Neutral	Strongly agree	Agree	Strongly agree	Agree
Agree	Strongly agree	Agree	Strongly agree	Neutral	Agree	Strongly agree	Strongly agree	Strongly agree	Agree
Strongly agree	Strongly agree	Neutral	Agree	Agree	Disagree	Strongly agree	Agree	Strongly agree	Agree
Strongly agree	Strongly agree	Strongly agree	Strongly agree	Neutral	Strongly agree	Strongly agree	Agree	Strongly agree	Strongly agree
Strongly agree	Agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Agree	Strongly agree	Strongly agree
Agree	Agree	Agree	Agree	Neutral	Agree	Agree	Agree	Agree	Agree
Strongly agree	Agree	Neutral	Agree	Strongly disagree	Agree	Strongly agree	Strongly agree	Agree	Agree
Strongly agree	Strongly agree	Strongly agree	Agree	Strongly agree	Neutral	Agree	Neutral	Strongly agree	Neutral
Strongly agree	Strongly agree	Agree	Strongly agree	Neutral	Disagree	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Neutral	Strongly agree	Strongly agree	Strongly agree	Disagree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Neutral
Neutral	Neutral	Neutral	Neutral	Neutral	Neutral	Neutral	Neutral	Neutral	Neutral
Strongly agree	Strongly agree	Strongly agree	Strongly agree	Neutral	Neutral	Agree	Agree	Agree	Agree
Strongly agree	Agree	Agree	Agree	Agree	Agree	Strongly agree	Agree	Agree	Agree
Strongly agree	Strongly agree	Agree	Strongly agree	Strongly disagree	Agree	Agree	Neutral	Neutral	Neutral
Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Agree	Agree
Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly disagree	Agree	Strongly agree	Agree	Strongly agree	Neutral
Agree	Strongly agree	Agree	Agree	Neutral	Strongly disagree	Agree	Agree	Agree	Agree
Strongly agree	Strongly agree	Disagree	Strongly agree	Strongly agree	Disagree	Strongly agree	Neutral	Strongly agree	Neutral
Strongly agree	Agree	Agree	Strongly agree	Agree	Agree	Strongly agree	Agree	Agree	Agree
Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Strongly agree	Strongly agree	Agree	Strongly agree	Agree	Neutral	Agree	Neutral	Agree	Agree
Strongly agree	Strongly agree	Neutral	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Agree	Strongly agree	Strongly agree
Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Strongly agree	Strongly agree	Neutral	Strongly agree	Agree	Agree	Agree	Agree	Agree	Agree
Strongly agree	Strongly agree	Strongly agree	Strongly agree	Disagree	Neutral	Strongly agree	Agree	Strongly agree	Strongly agree
Agree	Strongly agree	Neutral	Strongly agree	Agree	Neutral	Strongly agree	Agree	Strongly agree	Neutral
Agree	Agree	Agree	Agree	Agree	Agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Agree	Agree	Strongly agree	Strongly agree	Strongly agree	Agree	Strongly agree	Strongly agree	Strongly agree	Agree
Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Strongly agree	Strongly agree	Strongly agree	Strongly agree	Agree	Strongly agree	Agree	Agree	Agree	Strongly agree
Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Neutral	Neutral	Agree	Neutral	Strongly disagree	Strongly disagree	Disagree	Strongly disagree	Strongly disagree	Strongly disagree

Sl. No	Part A: 1. Please select the age group you belong to:	2. Please specify your Gender:	3. Please select the course you are studying in:	4. Please select the type of the college you are studying in:	Part B: Please select the best option possible. [I learn a subject to gain knowledge rather than just to gain marks.]	Part B: Please select the best option possible. [I listen to all my teachers with same interest.]	Part B: Please select the best option possible. [I am 100 % motivated to learn new things every day]	Part B: Please select the best option possible. [I am ready to attend any number of extra classes if needed.
1	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Strongly agree	Agree
2	20 to 25 Years	Male	PG	Private	Neutral	Agree	Strongly agree	Agree
3	20 to 25 Years	Male	PG	Private	Agree	Neutral	Agree	Agree
4	20 to 25 Years	Female	PG	Private	Neutral	Disagree	Agree	Agree
5	20 to 25 Years	Female	PG	Government	Neutral	Strongly agree	Agree	Strongly agree
6	20 to 25 Years	Male	PG	Private	Strongly agree	Neutral	Agree	Neutral
7	20 to 25 Years	Female	PG	Private	Strongly agree	Neutral	Strongly agree	Strongly agree
8	20 to 25 Years	Female	PG	Private	Strongly agree	Strongly agree	Strongly agree	Agree
9	20 to 25 Years	Female	PG	Private	Agree	Neutral	Disagree	Agree
10	20 to 25 Years	Female	PG	Private	Strongly agree	Neutral	Strongly agree	Strongly disagree
11	20 to 25 Years	Male	PG	Private	Disagree	Strongly agree	Strongly agree	Strongly agree
12	20 to 25 Years	Female	PG	Government	Agree	Neutral	Agree	Agree
13	20 to 25 Years	Female	PG	Government	Agree	Neutral	Neutral	Disagree
14	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Agree	Agree
15	25 to 30 Years	Male	PG	Private	Neutral	Agree	Strongly agree	Neutral
16	20 to 25 Years	Female	PG	Private	Agree	Disagree	Agree	Agree
17	20 to 25 Years	Female	PG	Private	Strongly agree	Disagree	Strongly agree	Neutral
18	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Neutral	Disagree
19	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Neutral	Strongly disagree
20	20 to 25 Years	Male	UG	Private	Strongly agree	Disagree	Neutral	Disagree
21	Less than 20 Years	Male	UG	Private	Neutral	Neutral	Agree	Strongly disagree
22	20 to 25 Years	Male	PG	Private	Strongly agree	Strongly agree	Strongly agree	Strongly agree
23	20 to 25 Years	Female	PG	Private	Strongly agree	Strongly agree	Agree	Agree
24	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Neutral	Strongly agree
25	20 to 25 Years	Male	PG	Private	Strongly agree	Strongly agree	Strongly agree	Agree
26	20 to 25 Years	Male	PG	Private	Agree	Disagree	Neutral	Strongly disagree
27	20 to 25 Years	Male	PG	Government	Agree	Strongly agree	Strongly agree	Agree
28	25 to 30 Years	Male	PG	Private	Strongly agree	Strongly agree	Strongly agree	Agree
29	20 to 25 Years	Male	PG	Private	Strongly disagree	Neutral	Neutral	Disagree
30	20 to 25 Years	Female	PG	Private	Strongly agree	Neutral	Agree	Agree
31	20 to 25 Years	Female	PG	Private	Strongly agree	Disagree	Neutral	Disagree
32	20 to 25 Years	Female	PG	Government	Neutral	Agree	Strongly agree	Agree
33	20 to 25 Years	Female	PG	Private	Strongly agree	Strongly agree	Strongly agree	Agree
34	20 to 25 Years	Female	PG	Private	Agree	Agree	Agree	Neutral
35	20 to 25 Years	Female	PG	Private	Agree	Disagree	Strongly agree	Agree
36	20 to 25 Years	Female	PG	Private	Agree	Neutral	Agree	Agree
37	20 to 25 Years	Male	PG	Private	Strongly agree	Strongly agree	Strongly agree	Agree
38	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Strongly agree	Agree
39	20 to 25 Years	Male	UG	Private	Agree	Disagree	Neutral	Disagree
40	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Strongly agree	Neutral
41	Less than 20 Years	Male	UG	Private	Neutral	Neutral	Agree	Disagree
42	20 to 25 Years	Male	PG	Private	Strongly agree	Neutral	Strongly agree	Neutral
43	20 to 25 Years	Male	PG	Private	Agree	Disagree	Agree	Neutral
44	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Strongly agree	Agree
45	20 to 25 Years	Male	PG	Private	Strongly agree	Strongly agree	Strongly agree	Neutral
46	20 to 25 Years	Male	PG	Private	Agree	Neutral	Neutral	Agree
47	20 to 25 Years	Female	PG	Private	Strongly agree	Neutral	Agree	Neutral
48	20 to 25 Years	Male	PG	Private	Strongly agree	Neutral	Agree	Agree
49	20 to 25 Years	Male	UG	Private	Agree	Agree	Agree	Neutral
50	20 to 25 Years	Male	PG	Private	Agree	Neutral	Disagree	Disagree
51	20 to 25 Years	Male	PG	Private	Agree	Neutral	Disagree	Disagree
52	20 to 25 Years	Female	PG	Private	Agree	Agree	Neutral	Disagree
53	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Strongly agree	Strongly agree
54	20 to 25 Years	Male	PG	Private	Strongly agree	Strongly disagree	Neutral	Strongly disagree
55	20 to 25 Years	Female	PG	Private	Agree	Neutral	Agree	Agree

Part B: Please selec the best option possible. [I do not blame my teachers i I score less in my exam even if they have not taught me well.]	Part B: Please select the best option possible. [Online classes are more interesting compared to offline classes.]	Part B: Please select the best option possible. [I pay complete attention during classes even if my teacher cannot see me.]	Part B: Please select the best option possible. [I have never created any disturbance during the online classes.]	Part B: Please select the best option possible. [Using technology in teaching enhances my interest to learn.]	Part B: Please select the best option possible. [I can clear any subject even if the teacher is average or below average.]
Strongly agree	Neutral	Strongly agree	Agree	Agree	Strongly agree
Agree	Neutral	Agree	Strongly agree	Agree	Strongly agree
Neutral	Disagree	Agree	Agree	Agree	Agree
Strongly disagree	Strongly disagree	Disagree	Neutral	Neutral	Strongly disagree
Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Agree	Disagree	Neutral	Strongly agree	Neutral	Agree
Strongly agree	Neutral	Agree	Strongly agree	Strongly agree	Neutral
Strongly agree	Neutral	Neutral	Strongly agree	Agree	Strongly agree
Agree	Disagree	Agree	Strongly agree	Agree	Neutral
Neutral	Strongly disagree	Strongly disagree	Strongly disagree	Strongly agree	Strongly agree
Agree	Agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Agree	Strongly agree	Disagree	Agree	Agree	Neutral
Agree	Neutral	Agree	Agree	Agree	Agree
Strongly disagree	Strongly disagree	Neutral	Strongly agree	Neutral	Neutral
Neutral	Disagree	Neutral	Neutral	Neutral	Agree
Strongly disagree	Strongly disagree	Neutral	Strongly agree	Neutral	Neutral
Agree	Strongly agree	Agree	Strongly agree	Agree	Strongly agree
Strongly agree	Strongly disagree	Strongly disagree	Strongly agree	Neutral	Strongly disagree
Agree	Disagree	Neutral	Strongly agree	Neutral	Agree
Disagree	Neutral	Agree	Strongly agree	Strongly agree	Strongly agree
Disagree	Strongly disagree	Strongly disagree	Agree	Neutral	Strongly disagree
Strongly disagree	Strongly disagree	Agree	Strongly agree	Disagree	Strongly disagree
Neutral	Neutral	Agree	Disagree	Neutral	Agree
Agree	Agree	Neutral	Neutral	Agree	Strongly agree
Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Neutral	Strongly disagree	Strongly disagree	Agree	Strongly disagree	Strongly agree
Neutral	Strongly disagree	Agree	Strongly agree	Agree	Agree
Agree	Neutral	Agree	Agree	Strongly agree	Agree
Neutral	Strongly disagree	Disagree	Disagree	Disagree	Disagree
Agree	Strongly disagree	Neutral	Strongly agree	Neutral	Neutral
Agree	Strongly disagree	Neutral	Strongly agree	Strongly agree	Agree
Agree	Disagree	Agree	Neutral	Agree	Agree
Agree	Neutral	Strongly agree	Strongly agree	Strongly agree	Agree
Strongly agree	Neutral	Neutral	Strongly agree	Agree	Neutral
Agree	Strongly disagree	Neutral	Agree	Agree	Agree
Agree	Neutral	Agree	Strongly agree	Neutral	Agree
Strongly agree	Disagree	Agree	Strongly agree	Agree	Strongly agree
Agree	Agree	Agree	Agree	Neutral	Agree
Disagree	Disagree	Agree	Agree	Neutral	Disagree
Strongly agree	Neutral	Agree	Strongly agree	Neutral	Agree
Neutral	Strongly disagree	Agree	Neutral	Strongly agree	Neutral
Strongly agree	Disagree	Agree	Strongly agree	Agree	Agree
Neutral	Strongly disagree	Strongly disagree	Neutral	Strongly disagree	Strongly disagree
Agree	Strongly disagree	Disagree	Neutral	Agree	Agree
Neutral	Strongly disagree	Strongly disagree	Strongly agree	Neutral	Neutral
Agree	Strongly disagree	Neutral	Agree	Neutral	Strongly agree
Neutral	Disagree	Disagree	Disagree	Neutral	Neutral
Strongly agree	Neutral	Agree	Strongly agree	Agree	Strongly agree
Agree	Strongly disagree	Strongly disagree	Agree	Agree	Disagree
Disagree	Strongly disagree	Disagree	Neutral	Disagree	Neutral
Disagree	Strongly disagree	Disagree	Neutral	Disagree	Neutral
Agree	Strongly disagree	Neutral	Strongly agree	Agree	Disagree
Strongly agree	Strongly disagree	Agree	Agree	Agree	Agree
Strongly agree	Strongly disagree	Neutral	Strongly agree	Strongly agree	Agree
Strongly agree	Strongly disagree	Agree	Agree	Disagree	Neutral

Sl. No	Part A: 1. Please select the age group you belong to:	2. Please specify your Gender:	3. Please select the course you are studying in:	4. Please select the type of the college you are studying in:	Part B: Please select the best option possible. [I learn a subject to gain knowledge rather than just to gain marks.]	Part B: Please select the best option possible. [I listen to all my teachers with same interest.]	Part B: Please select the best option possible. [I am 100 % motivated to learn new things every day]	Part B: Please select the best option possible. [I am ready to attend any number of extra classes if needed.
56	20 to 25 Years	Male	PG	Private	Strongly agree	Neutral	Agree	Agree
57	20 to 25 Years	Female	PG	Private	Strongly agree	Neutral	Agree	Agree
58	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Agree	Neutral
59	20 to 25 Years	Male	PG	Government	Strongly agree	Strongly agree	Strongly agree	Neutral
60	20 to 25 Years	Male	PG	Private	Strongly agree	Disagree	Agree	Strongly disagree
61	20 to 25 Years	Male	PG	Private	Agree	Disagree	Agree	Agree
62	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Agree	Neutral
63	Above 30 years	Female	PG	Private	Strongly agree	Agree	Strongly agree	Neutral
64	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Agree	Neutral
65	20 to 25 Years	Female	PG	Private	Agree	Strongly agree	Strongly agree	Strongly agree
66	20 to 25 Years	Male	PG	Private	Neutral	Agree	Strongly agree	Neutral
67	20 to 25 Years	Male	PG	Private	Agree	Neutral	Agree	Strongly agree
68	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Strongly agree	Strongly agree
69	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Strongly agree	Agree
70	20 to 25 Years	Male	PG	Private	Strongly agree	Strongly agree	Strongly agree	Strongly agree
71	20 to 25 Years	Male	PG	Private	Strongly agree	Neutral	Agree	Neutral
72	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Strongly agree	Neutral
73	20 to 25 Years	Male	PG	Private	Strongly agree	Strongly agree	Strongly agree	Strongly agree
74	20 to 25 Years	Female	PG	Private	Agree	Agree	Agree	Agree
75	20 to 25 Years	Female	PG	Private	Neutral	Neutral	Agree	Strongly disagree
76	20 to 25 Years	Male	PG	Private	Agree	Agree	Strongly agree	Disagree
77	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Strongly agree	Agree
78	20 to 25 Years	Female	PG	Government	Neutral	Agree	Strongly agree	Agree
79	20 to 25 Years	Female	PG	Private	Agree	Neutral	Agree	Disagree
80	25 to 30 Years	Male	PG	Private	Strongly agree	Strongly agree	Strongly agree	Strongly agree
81	25 to 30 Years	Male	PG	Private	Strongly agree	Neutral	Agree	Neutral
82	25 to 30 Years	Female	UG	Private	Neutral	Agree	Agree	Neutral
83	20 to 25 Years	Female	PG	Private	Neutral	Neutral	Neutral	Neutral
84	20 to 25 Years	Female	PG	Private	Strongly agree	Neutral	Agree	Neutral
85	25 to 30 Years	Male	PG	Private	Strongly agree	Strongly agree	Strongly agree	Strongly agree
86	25 to 30 Years	Male	PG	Private	Strongly agree	Strongly agree	Strongly agree	Strongly agree
87	25 to 30 Years	Male	PG	Private	Strongly agree	Strongly agree	Strongly agree	Strongly agree
88	20 to 25 Years	Male	PG	Private	Agree	Strongly agree	Agree	Strongly agree
89	20 to 25 Years	Male	PG	Private	Agree	Agree	Strongly agree	Neutral
90	20 to 25 Years	Male	UG	Private	Strongly disagree	Disagree	Strongly agree	Strongly disagree
91	20 to 25 Years	Female	PG	Private	Agree	Neutral	Agree	Agree
92	20 to 25 Years	Female	PG	Private	Strongly agree	Neutral	Strongly agree	Disagree
93	20 to 25 Years	Male	PG	Private	Strongly agree	Neutral	Strongly agree	Agree
94	20 to 25 Years	Female	PG	Private	Strongly agree	Strongly agree	Strongly agree	Strongly agree
95	20 to 25 Years	Female	PG	Government	Neutral	Agree	Strongly agree	Agree
96	20 to 25 Years	Female	PG	Private	Agree	Agree	Agree	Agree
97	20 to 25 Years	Female	PG	Private	Agree	Neutral	Agree	Neutral
98	20 to 25 Years	Female	PG	Private	Strongly agree	Neutral	Strongly agree	Agree
99	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Agree	Strongly agree
100	20 to 25 Years	Female	PG	Private	Agree	Neutral	Strongly agree	Disagree
101	20 to 25 Years	Female	PG	Private	Agree	Agree	Agree	Disagree
102	20 to 25 Years	Male	PG	Private	Agree	Neutral	Strongly agree	Agree
103	20 to 25 Years	Female	PG	Government	Agree	Agree	Strongly agree	Agree
104	20 to 25 Years	Female	PG	Private	Agree	Neutral	Neutral	Agree
105	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Strongly agree	Neutral
106	20 to 25 Years	Female	PG	Private	Agree	Agree	Strongly agree	Agree
107	20 to 25 Years	Male	PG	Private	Agree	Agree	Agree	Agree
108	20 to 25 Years	Female	PG	Private	Strongly agree	Strongly disagree	Agree	Strongly disagree
109	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Strongly agree	Agree
110	20 to 25 Years	Female	PG	Private	Disagree	Agree	Agree	Neutral

Part B: Please selec the best option possible. [I do not blame my teachers i I score less in my exam even if they have not taught me well.]	Part B: Please select the best option possible. [Online classes are more interesting compared to offline classes.]	Part B: Please select the best option possible. [I pay complete attention during classes even if my teacher cannot see me.]	Part B: Please select the best option possible. [I have never created any disturbance during the online classes.]	Part B: Please select the best option possible. [Using technology in teaching enhances my interest to learn.]	Part B: Please select the best option possible. [I can clear any subject even if the teacher is average or below average.]
Neutral	Strongly disagree	Neutral	Neutral	Neutral	Agree
Agree	Disagree	Neutral	Agree	Agree	Agree
Agree	Disagree	Neutral	Strongly agree	Neutral	Disagree
Agree	Strongly disagree	Agree	Strongly agree	Agree	Agree
Neutral	Strongly disagree	Disagree	Strongly disagree	Neutral	Neutral
Agree	Disagree	Disagree	Agree	Agree	Agree
Neutral	Disagree	Neutral	Agree	Strongly agree	Neutral
Agree	Neutral	Agree	Strongly agree	Agree	Strongly agree
Strongly agree	Neutral	Agree	Strongly agree	Agree	Strongly agree
Neutral	Strongly disagree	Agree	Strongly agree	Agree	Neutral
Agree	Strongly disagree	Neutral	Agree	Agree	Agree
Agree	Neutral	Agree	Agree	Agree	Agree
Neutral	Strongly disagree	Agree	Strongly agree	Agree	Neutral
Agree	Disagree	Agree	Strongly agree	Neutral	Agree
Strongly agree	Disagree	Agree	Agree	Agree	Agree
Agree	Strongly disagree	Agree	Strongly agree	Agree	Agree
Agree	Strongly disagree	Neutral	Agree	Disagree	Neutral
Agree	Strongly disagree	Strongly agree	Strongly agree	Strongly disagree	Strongly disagree
Agree	Neutral	Agree	Agree	Agree	Agree
Strongly agree	Strongly disagree	Strongly disagree	Strongly disagree	Neutral	Neutral
Agree	Strongly disagree	Neutral	Agree	Agree	Agree
Agree	Disagree	Neutral	Strongly agree	Neutral	Agree
Agree	Disagree	Agree	Neutral	Agree	Agree
Disagree	Disagree	Neutral	Disagree	Disagree	Neutral
Strongly agree	Neutral	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Neutral	Strongly disagree	Disagree	Strongly agree	Strongly agree	Agree
Strongly agree	Neutral	Agree	Strongly agree	Agree	Neutral
Neutral	Neutral	Neutral	Neutral	Neutral	Neutral
Neutral	Disagree	Disagree	Disagree	Neutral	Neutral
Agree	Neutral	Strongly agree	Agree	Strongly agree	Agree
Agree	Neutral	Strongly agree	Agree	Strongly agree	Agree
Agree	Neutral	Strongly agree	Agree	Strongly agree	Agree
Agree	Agree	Agree	Strongly agree	Agree	Neutral
Strongly agree	Neutral	Strongly agree	Agree	Agree	Agree
Strongly disagree	Disagree	Neutral	Neutral	Agree	Strongly agree
Neutral	Agree	Neutral	Strongly agree	Agree	Neutral
Strongly agree	Disagree	Neutral	Strongly agree	Strongly agree	Strongly agree
Strongly agree	Neutral	Strongly agree	Neutral	Strongly agree	Strongly agree
Strongly agree	Disagree	Agree	Strongly agree	Strongly agree	Neutral
Agree	Disagree	Agree	Neutral	Agree	Agree
Agree	Disagree	Neutral	Strongly agree	Neutral	Neutral
Strongly agree	Disagree	Neutral	Strongly agree	Neutral	Agree
Agree	Strongly disagree	Neutral	Strongly agree	Agree	Strongly agree
Agree	Disagree	Agree	Strongly agree	Agree	Strongly agree
Neutral	Strongly disagree	Agree	Strongly agree	Neutral	Strongly agree
Neutral	Agree	Agree	Disagree	Agree	Strongly disagree
Disagree	Agree	Agree	Neutral	Strongly agree	Strongly agree
Strongly disagree	Strongly disagree	Agree	Strongly agree	Neutral	Neutral
Disagree	Neutral	Agree	Strongly agree	Agree	Agree
Neutral	Neutral	Neutral	Strongly agree	Agree	Neutral
Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Agree	Neutral	Agree	Strongly agree	Agree	Agree
Strongly disagree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Strongly agree	Neutral	Agree	Agree	Agree	Neutral
Agree	Agree	Neutral	Agree	Agree	Disagree

Sl. No	Part A: 1. Please select the age group you belong to:	2. Please specify your Gender:	3. Please select the course you are studying in:	4. Please select the type of the college you are studying in:	Part B: Please select the best option possible. [I learn a subject to gain knowledge rather than just to gain marks.]	Part B: Please select the best option possible. [I listen to all my teachers with same interest.]	Part B: Please select the best option possible. [I am 100 % motivated to learn new things every day]	Part B: Please select the best option possible. [I am ready to attend any number of extra classes if needed.
111	20 to 25 Years	Female	PG		Strongly agree	Strongly agree	Strongly agree	Neutral
112	20 to 25 Years	Male	PG	Private	Strongly agree	Neutral	Agree	Neutral
113	20 to 25 Years	Male	PG		Agree	Agree	Agree	Neutral
114	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Strongly agree	Agree
115	20 to 25 Years	Female	PG	Private	Strongly agree	Neutral	Agree	Neutral
116	20 to 25 Years	Female	PG	Private	Agree	Strongly agree	Neutral	Neutral
117	20 to 25 Years	Male	PG	Private	Agree	Strongly agree	Strongly agree	Agree
118	20 to 25 Years	Male	PG	Private	Strongly agree	Disagree	Agree	Neutral
119	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Strongly agree	Agree
120	20 to 25 Years	Male	PG	Private	Agree	Neutral	Agree	Neutral
121	20 to 25 Years	Male	PG	Private	Agree	Neutral	Strongly agree	Neutral
122	20 to 25 Years	Male	PG	Private	Agree	Neutral	Agree	Disagree
123	20 to 25 Years	Male	PG	Private	Agree	Neutral	Strongly agree	Neutral
124	20 to 25 Years	Female	PG	Private	Agree	Neutral	Agree	Neutral
125	20 to 25 Years	Female	PG	Private	Agree	Neutral	Agree	Neutral
126	20 to 25 Years	Female	PG	Private	Strongly agree	Strongly agree	Strongly agree	Agree
127	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Strongly agree	Agree
128	20 to 25 Years	Male	PG	Private	Strongly agree	Strongly agree	Strongly agree	Neutral
129	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Agree	Agree
130	20 to 25 Years	Female	PG	Private	Strongly agree	Strongly agree	Strongly agree	Strongly agree
131	20 to 25 Years	Female	PG	Private	Agree	Agree	Agree	Agree
132	20 to 25 Years	Female	PG	Private	Agree	Agree	Agree	Agree
133	20 to 25 Years	Female	PG	Government	Agree	Strongly disagree	Strongly agree	Strongly disagree
134	20 to 25 Years	Female	PG	Private	Agree	Agree	Agree	Strongly agree
135	20 to 25 Years	Female	PG	Private	Agree	Agree	Agree	Agree
136	20 to 25 Years	Male	PG	Private	Neutral	Agree	Agree	Agree
137	20 to 25 Years	Female	PG	Private	Strongly agree	Strongly agree	Strongly agree	Strongly agree
138	20 to 25 Years	Female	PG	Private	Agree	Agree	Agree	Agree
139	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Strongly agree	Agree
140	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Strongly agree	Agree
141	20 to 25 Years	Male	UG	Private	Neutral	Disagree	Strongly agree	Neutral
142	20 to 25 Years	Female	PG	Government	Strongly agree	Agree	Strongly agree	Strongly agree
143	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Agree	Agree
144	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Strongly agree	Strongly agree
145	20 to 25 Years	Female	PG	Private	Strongly agree	Strongly agree	Strongly agree	Strongly agree
146	20 to 25 Years	Male	PG	Private	Strongly agree	Strongly agree	Strongly agree	Strongly agree
147	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Agree	Agree
148	20 to 25 Years	Female	PG	Private	Strongly agree	Strongly agree	Agree	Strongly agree
149	20 to 25 Years	Male	PG	Private	Neutral	Agree	Agree	Disagree
150	20 to 25 Years	Male	PG	Private	Agree	Neutral	Neutral	Strongly agree
151	20 to 25 Years	Male	PG	Private	Agree	Agree	Agree	Agree
152	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Strongly agree	Strongly agree
153	25 to 30 Years	Male	PG	Private	Strongly agree	Agree	Strongly agree	Agree
154	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Strongly agree	Agree
155	20 to 25 Years	Female	PG	Private	Strongly agree	Neutral	Agree	Disagree
156	20 to 25 Years	Male	PG	Private	Agree	Neutral	Neutral	Neutral
157	20 to 25 Years	Female	PG	Private	Agree	Agree	Agree	Agree
158	20 to 25 Years	Female	PG	Private	Strongly agree	Neutral	Agree	Neutral
159	20 to 25 Years	Female	PG	Private	Strongly agree	Strongly agree	Strongly agree	Strongly agree
160	20 to 25 Years	Female	PG	Private	Strongly agree	Strongly agree	Strongly agree	Strongly agree
161	20 to 25 Years	Male	PG	Private	Agree	Agree	Strongly agree	Strongly agree
162	20 to 25 Years	Female	PG	Private	Agree	Agree	Agree	Neutral
163	20 to 25 Years	Female	PG	Private	Agree	Neutral	Neutral	Disagree
164	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Strongly agree	Agree
165	20 to 25 Years	Male	PG	Private	Strongly agree	Strongly agree	Strongly agree	Agree

Part B: Please selec the best option possible. [I do not blame my teachers i I score less in my exam even if they have not taught me well.]	Part B: Please select the best option possible. [Online classes are more interesting compared to offline classes.]	Part B: Please select the best option possible. [I pay complete attention during classes even if my teacher cannot see me.]	Part B: Please select the best option possible. [I have never created any disturbance during the online classes.]	Part B: Please select the best option possible. [Using technology in teaching enhances my interest to learn.]	Part B: Please select the best option possible. [I can clear any subject even if the teacher is average or below average.]
Neutral	Strongly disagree	Neutral	Strongly agree	Neutral	Neutral
Agree	Neutral	Agree	Agree	Neutral	Agree
Neutral	Disagree	Neutral	Neutral	Disagree	Disagree
Agree	Disagree	Agree	Strongly agree	Agree	Agree
Disagree	Disagree	Neutral	Strongly agree	Neutral	Strongly agree
Agree	Strongly disagree	Strongly agree	Strongly agree	Neutral	Agree
Agree	Strongly disagree	Strongly agree	Strongly agree	Neutral	Agree
Neutral	Strongly disagree	Neutral	Agree	Neutral	Agree
Strongly agree	Disagree	Strongly agree	Strongly agree	Agree	Agree
Agree	Strongly disagree	Neutral	Neutral	Agree	Agree
Neutral	Strongly disagree	Neutral	Strongly agree	Strongly disagree	Neutral
Neutral	Disagree	Neutral	Neutral	Agree	Neutral
Strongly agree	Strongly disagree	Neutral	Strongly agree	Strongly agree	Neutral
Strongly agree	Strongly agree	Strongly agree	Agree	Strongly agree	Agree
Neutral	Disagree	Neutral	Agree	Neutral	Agree
Strongly agree	Neutral	Agree	Strongly agree	Agree	Agree
Neutral	Disagree	Neutral	Agree	Neutral	Neutral
Agree	Agree	Agree	Strongly agree	Strongly agree	Strongly agree
Agree	Disagree	Agree	Strongly agree	Strongly agree	Neutral
Strongly agree	Neutral	Agree	Neutral	Agree	Neutral
Agree	Neutral	Agree	Agree	Neutral	Agree
Agree	Neutral	Agree	Agree	Agree	Agree
Neutral	Strongly agree	Disagree	Agree	Neutral	Strongly disagree
Agree	Strongly disagree	Neutral	Strongly agree	Disagree	Strongly agree
Agree	Agree	Agree	Agree	Agree	Agree
Neutral	Strongly disagree	Disagree	Agree	Neutral	Neutral
Strongly agree	Strongly disagree	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Agree	Disagree	Agree	Strongly agree	Agree	Agree
Neutral	Disagree	Agree	Strongly agree	Agree	Agree
Neutral	Disagree	Agree	Strongly agree	Agree	Agree
Disagree	Agree	Disagree	Strongly agree	Neutral	Neutral
Neutral	Agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Agree	Strongly disagree	Neutral	Agree	Agree	Agree
Agree	Neutral	Neutral	Neutral	Neutral	Agree
Strongly agree	Agree	Agree	Agree	Agree	Agree
Strongly agree	Neutral	Agree	Strongly agree	Agree	Agree
Agree	Disagree	Neutral	Strongly agree	Neutral	Agree
Agree	Disagree	Agree	Strongly agree	Strongly agree	Strongly agree
Neutral	Neutral	Disagree	Agree	Disagree	Agree
Agree	Neutral	Agree	Strongly agree	Neutral	Agree
Strongly agree	Disagree	Neutral	Neutral	Disagree	Neutral
Strongly agree	Neutral	Strongly agree	Strongly agree	Agree	Agree
Strongly agree	Disagree	Neutral	Strongly agree	Neutral	Neutral
Agree	Neutral	Agree	Strongly agree	Agree	Agree
Strongly agree	Strongly disagree	Neutral	Strongly agree	Neutral	Strongly agree
Neutral	Disagree	Neutral	Agree	Neutral	Neutral
Neutral	Neutral	Neutral	Strongly agree	Neutral	Strongly agree
Strongly agree	Neutral	Agree	Neutral	Agree	Strongly agree
Disagree	Neutral	Agree	Strongly agree	Agree	Neutral
Strongly agree	Disagree	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Strongly agree	Strongly disagree	Agree	Strongly agree	Strongly agree	Strongly agree
Disagree	Disagree	Agree	Strongly agree	Neutral	Agree
Neutral	Disagree	Neutral	Agree	Neutral	Disagree
Agree	Disagree	Agree	Strongly agree	Agree	Agree
Neutral	Disagree	Strongly agree	Strongly agree	Agree	Strongly agree

Sl. No	Part A: 1. Please select the age group you belong to:	2. Please specify your Gender:	3. Please select the course you are studying in:	4. Please select the type of the college you are studying in:	Part B: Please select the best option possible. [I learn a subject to gain knowledge rather than just to gain marks.]	Part B: Please select the best option possible. [I listen to all my teachers with same interest.]	Part B: Please select the best option possible. [I am 100 % motivated to learn new things every day]	Part B: Please select the best option possible. [I am ready to attend any number of extra classes if needed.
166	20 to 25 Years	Male	PG	Private	Strongly agree	Strongly agree	Strongly agree	Agree
167	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Neutral	Strongly agree
168	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Strongly agree	Strongly agree
169	20 to 25 Years	Female	PG	Private	Agree	Agree	Agree	Strongly agree
170	20 to 25 Years	Female	PG	Private	Agree	Agree	Strongly agree	Neutral
171	20 to 25 Years	Female	PG	Private	Agree	Neutral	Neutral	Agree
172	20 to 25 Years	Female	PG	Private	Agree	Agree	Agree	Agree
173	20 to 25 Years	Female	PG	Private	Strongly agree	Strongly agree	Strongly agree	Agree
174	20 to 25 Years	Female	PG	Private	Agree	Neutral	Agree	Neutral
175	20 to 25 Years	Male	PG	Private	Agree	Agree	Strongly agree	Strongly agree
176	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Agree	Strongly agree
177	20 to 25 Years	Male	PG	Private	Agree	Neutral	Agree	Disagree
178	20 to 25 Years	Female	PG	Private	Strongly agree	Strongly agree	Agree	Agree
179	20 to 25 Years	Female	PG	Private	Strongly agree	Strongly agree	Strongly agree	Strongly agree
180	20 to 25 Years	Male	PG	Private	Strongly agree	Neutral	Neutral	Neutral
181	20 to 25 Years	Male	PG	Private	Agree	Agree	Agree	Agree
182	20 to 25 Years	Female	PG	Private	Agree	Agree	Agree	Agree
183	20 to 25 Years	Female	PG	Private	Strongly agree	Disagree	Agree	Disagree
184	20 to 25 Years	Female	PG		Neutral	Agree	Strongly agree	Neutral
185	20 to 25 Years	Female	PG	Private	Strongly agree	Strongly agree	Neutral	Agree
186	20 to 25 Years	Female	PG	Private	Strongly agree	Disagree	Neutral	Neutral
187	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Strongly agree	Strongly agree
188	20 to 25 Years	Male	PG	Private	Agree	Agree	Strongly agree	Neutral
189	20 to 25 Years	Female	PG	Private	Strongly agree	Strongly agree	Strongly agree	Strongly agree
190	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Agree	Agree
191	20 to 25 Years	Male	PG	Private	Agree	Neutral	Agree	Neutral
192	20 to 25 Years	Female	PG	Private	Agree	Strongly agree	Strongly agree	Strongly agree
193	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Strongly agree	Agree
194	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Strongly agree	Agree
195	20 to 25 Years	Female	PG	Private	Agree	Neutral	Strongly agree	Agree
196	20 to 25 Years	Female	PG	Private	Strongly agree	Neutral	Agree	Disagree
197	20 to 25 Years	Male	PG	Private	Disagree	Strongly agree	Strongly agree	Disagree
198	20 to 25 Years	Female	PG	Private	Strongly agree	Strongly agree	Strongly agree	Strongly agree
199	20 to 25 Years	Male	PG	Private	Agree	Neutral	Disagree	Disagree
200	20 to 25 Years	Female	PG	Private	Strongly agree	Strongly agree	Strongly agree	Strongly agree
201	25 to 30 Years	Male	PG	Private	Agree	Strongly disagree	Neutral	Agree
202	20 to 25 Years	Male	PG	Private	Agree	Neutral	Agree	Disagree
203	20 to 25 Years	Female	PG	Private	Strongly agree	Strongly agree	Strongly agree	Agree
204	20 to 25 Years	Female	PG	Private	Agree	Agree	Strongly agree	Agree
205	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Agree	Neutral
206	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Strongly agree	Agree
207	20 to 25 Years	Male	PG	Private	Agree	Agree	Strongly agree	Strongly agree
208	20 to 25 Years	Male	PG	Private	Strongly agree	Neutral	Strongly agree	Neutral
209	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Strongly agree	Strongly agree
210	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Agree	Strongly agree
211	20 to 25 Years	Male	PG	Private	Strongly agree	Agree	Strongly agree	Strongly agree
212	20 to 25 Years	Male	PG	Private	Agree	Neutral	Neutral	Neutral
213	20 to 25 Years	Female	PG	Private	Strongly agree	Agree	Agree	Neutral
214	20 to 25 Years	Male	PG	Private	Agree	Strongly agree	Strongly agree	Agree
215	20 to 25 Years	Female	PG	Private	Agree	Agree	Neutral	Disagree
216	20 to 25 Years	Female	PG	Private	Strongly agree	Neutral	Agree	Neutral
217	20 to 25 Years	Male	UG	Private	Agree	Neutral	Agree	Strongly disagree
218	Less than 20 Years	Female	UG	Private	Agree	Agree	Strongly agree	Neutral
219	20 to 25 Years	Female	UG	Private	Agree	Disagree	Strongly agree	Agree
220	20 to 25 Years	Male	UG	Private	Strongly agree	Strongly agree	Strongly agree	Agree

Part B: Please selec the best option possible. [I do not blame my teachers i I score less in my exam even if they have not taught me well.]	Part B: Please select the best option possible. [Online classes are more interesting compared to offline classes.]	Part B: Please select the best option possible. [I pay complete attention during classes even if my teacher cannot see me.]	Part B: Please select the best option possible. [I have never created any disturbance during the online classes.]	Part B: Please select the best option possible. [Using technology in teaching enhances my interest to learn.]	Part B: Please select the best option possible. [I can clear any subject even if the teacher is average or below average.]
Agree	Disagree	Disagree	Disagree	Agree	Agree
Strongly agree	Disagree	Neutral	Strongly agree	Strongly agree	Strongly agree
Strongly agree	Disagree	Neutral	Agree	Disagree	Neutral
Strongly agree	Neutral	Strongly agree	Disagree	Agree	Agree
Neutral	Strongly disagree	Neutral	Strongly agree	Agree	Agree
Strongly agree	Neutral	Agree	Neutral	Neutral	Strongly agree
Agree	Neutral	Agree	Agree	Agree	Agree
Strongly agree	Disagree	Agree	Strongly agree	Agree	Strongly agree
Neutral	Neutral	Neutral	Strongly agree	Neutral	Neutral
Strongly agree	Disagree	Disagree	Agree	Disagree	Disagree
Agree	Strongly disagree	Agree	Strongly agree	Agree	Strongly agree
Agree	Disagree	Disagree	Agree	Neutral	Neutral
Agree	Agree	Agree	Strongly agree	Agree	Agree
Agree	Neutral	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Neutral	Neutral	Neutral	Neutral	Strongly disagree	Strongly disagree
Strongly agree	Disagree	Neutral	Neutral	Disagree	Neutral
Agree	Disagree	Neutral	Strongly agree	Agree	Agree
Agree	Disagree	Agree	Strongly agree	Agree	Agree
Agree	Neutral	Neutral	Agree	Neutral	Neutral
Neutral	Neutral	Strongly agree	Strongly agree	Agree	Agree
Agree	Disagree	Neutral	Neutral	Agree	Agree
Strongly agree	Neutral	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Agree	Disagree	Agree	Agree	Disagree	Agree
Neutral	Agree	Strongly agree	Strongly agree	Agree	Neutral
Strongly agree	Neutral	Disagree	Strongly agree	Strongly agree	Disagree
Disagree	Disagree	Neutral	Neutral	Neutral	Disagree
Agree	Disagree	Agree	Strongly agree	Agree	Agree
Strongly agree	Strongly disagree	Agree	Strongly agree	Strongly agree	Agree
Strongly agree	Neutral	Neutral	Agree	Neutral	Strongly agree
Disagree	Disagree	Neutral	Neutral	Neutral	Agree
Strongly disagree	Strongly disagree	Strongly disagree	Neutral	Disagree	Strongly disagree
Strongly agree	Disagree	Strongly agree	Disagree	Disagree	Strongly agree
Agree	Disagree	Agree	Strongly agree	Agree	Agree
Agree	Neutral	Neutral	Strongly agree	Neutral	Neutral
Strongly agree	Strongly agree	Strongly agree	Strongly agree	Strongly agree	Agree
Strongly disagree	Strongly disagree	Strongly disagree	Agree	Strongly disagree	Strongly disagree
Strongly disagree	Strongly disagree	Agree	Neutral	Agree	Strongly disagree
Agree	Agree	Agree	Agree	Agree	Strongly agree
Agree	Neutral	Agree	Strongly agree	Agree	Agree
Agree	Neutral	Agree	Strongly agree	Neutral	Neutral
Disagree	Strongly disagree	Agree	Agree	Agree	Agree
Strongly agree	Disagree	Disagree	Agree	Disagree	Disagree
Agree	Strongly disagree	Disagree	Strongly agree	Agree	Agree
Neutral	Neutral	Agree	Strongly agree	Agree	Neutral
Strongly agree	Agree	Agree	Agree	Agree	Agree
Agree	Agree	Agree	Neutral	Neutral	Agree
Neutral	Strongly disagree	Strongly disagree	Neutral	Disagree	Strongly disagree
Agree	Neutral	Agree	Strongly agree	Agree	Agree
Agree	Agree	Agree	Agree	Agree	Agree
Strongly agree	Disagree	Strongly disagree	Strongly agree	Disagree	Agree
Neutral	Disagree	Disagree	Disagree	Neutral	Neutral
Strongly disagree	Strongly disagree	Strongly disagree	Strongly agree	Neutral	Strongly disagree
Neutral	Disagree	Agree	Agree	Agree	Neutral
Disagree	Agree	Disagree	Agree	Agree	Strongly agree
Strongly agree	Strongly disagree	Agree	Strongly agree	Agree	Strongly agree

Sl. No	Part A: 1. Please select the age group you belong to:	2. Please specify your Gender:	3. Please select the course you are studying in:	4. Please select the type of the college you are studying in:	Part B: Please select the best option possible. [I learn a subject to gain knowledge rather than just to gain marks.]	Part B: Please select the best option possible. [I listen to all my teachers with same interest.]	Part B: Please select the best option possible. [I am 100 % motivated to learn new things every day]	Part B: Please select the best option possible. [I am ready to attend any number of extra classes if needed.
221	20 to 25 Years	Female	UG	Private	Strongly agree	Agree	Strongly agree	Agree
222	20 to 25 Years	Male	UG	Private	Agree	Disagree	Agree	Neutral
223	20 to 25 Years	Male	UG	Private	Agree	Agree	Strongly agree	Agree
224	20 to 25 Years	Male	UG	Private	Strongly agree	Disagree	Strongly agree	Agree
225	20 to 25 Years	Male	UG	Private	Neutral	Agree	Agree	Agree
226	20 to 25 Years	Male	UG	Private	Strongly agree	Agree	Strongly agree	Agree
227	20 to 25 Years	Female	UG	Private	Agree	Agree	Strongly agree	Neutral
228	20 to 25 Years	Male	UG	Private	Disagree	Disagree	Strongly agree	Neutral
229	20 to 25 Years	Male	UG	Private	Neutral	Strongly disagree	Disagree	Disagree
230	20 to 25 Years	Male	UG	Private	Neutral	Agree	Neutral	Agree
231	20 to 25 Years	Female	UG	Private	Strongly agree	Strongly agree	Strongly agree	Strongly agree
232	20 to 25 Years	Female	UG	Private	Strongly agree	Agree	Agree	Agree
233	Less than 20 Years	Female	UG	Private	Agree	Agree	Strongly agree	Agree
234	20 to 25 Years	Female	UG	Private	Agree	Neutral	Agree	Agree
235	Less than 20 Years	Female	UG	Private	Agree	Agree	Agree	Disagree
236	20 to 25 Years	Female	UG	Private	Agree	Agree	Agree	Agree
237	20 to 25 Years	Female	UG	Private	Agree	Neutral	Agree	Agree
238	20 to 25 Years	Female	UG	Private	Strongly agree	Neutral	Strongly agree	Neutral
239	20 to 25 Years	Male	UG	Private	Strongly agree	Agree	Agree	Neutral
240	20 to 25 Years	Male	UG	Private	Strongly agree	Agree	Strongly agree	Neutral
241	20 to 25 Years	Female	UG	Private	Strongly agree	Agree	Strongly agree	Strongly agree
242	20 to 25 Years	Female	UG	Private	Disagree	Neutral	Strongly disagree	Strongly disagree
243	20 to 25 Years	Male	UG	Private	Agree	Agree	Strongly agree	Disagree
244	20 to 25 Years	Female	UG	Private	Agree	Agree	Agree	Neutral
245	20 to 25 Years	Male	UG	Private	Strongly agree	Agree	Strongly agree	Neutral
246	20 to 25 Years	Female	UG	Private	Strongly agree	Neutral	Agree	Neutral

Part B: Please select the best option possible. [I do not blame my teachers if I score less in my exam even if they have not taught me well.]	Part B: Please select the best option possible. [Online classes are more interesting compared to offline classes.]	Part B: Please select the best option possible. [I pay complete attention during classes even if my teacher cannot see me.]	Part B: Please select the best option possible. [I have never created any disturbance during the online classes.]	Part B: Please select the best option possible. [Using technology in teaching enhances my interest to learn.]	Part B: Please select the best option possible. [I can clear any subject even if the teacher is average or below average.]
Neutral	Neutral	Agree	Agree	Agree	Agree
Strongly disagree	Strongly disagree	Disagree	Agree	Agree	Strongly disagree
Neutral	Strongly disagree	Agree	Agree	Agree	Agree
Agree	Strongly disagree	Disagree	Strongly disagree	Strongly agree	Disagree
Strongly disagree	Strongly disagree	Disagree	Strongly disagree	Neutral	Strongly disagree
Strongly disagree	Strongly disagree	Agree	Strongly agree	Agree	Strongly disagree
Disagree	Strongly disagree	Agree	Agree	Disagree	Neutral
Agree	Disagree	Agree	Agree	Neutral	Neutral
Neutral	Strongly disagree	Disagree	Agree	Disagree	Strongly agree
Disagree	Disagree	Agree	Agree	Agree	Agree
Agree	Neutral	Strongly disagree	Strongly agree	Neutral	Agree
Strongly disagree	Neutral	Agree	Strongly agree	Agree	Strongly agree
Disagree	Disagree	Agree	Agree	Agree	Agree
Disagree	Disagree	Neutral	Agree	Agree	Agree
Disagree	Strongly disagree	Agree	Agree	Agree	Agree
Disagree	Disagree	Agree	Disagree	Agree	Agree
Disagree	Disagree	Agree	Agree	Disagree	Agree
Neutral	Disagree	Neutral	Strongly agree	Neutral	Strongly agree
Neutral	Disagree	Strongly agree	Strongly agree	Agree	Agree
Neutral	Neutral	Neutral	Neutral	Agree	Neutral
Agree	Neutral	Strongly agree	Strongly agree	Strongly agree	Strongly agree
Strongly disagree	Strongly disagree	Strongly disagree	Strongly disagree	Neutral	Neutral
Strongly agree	Disagree	Agree	Strongly agree	Neutral	Agree
Neutral	Neutral	Agree	Agree	Agree	Agree
Neutral	Strongly agree	Agree	Strongly agree	Strongly agree	Agree
Disagree	Agree	Neutral	Strongly agree	Strongly agree	Strongly agree

Pearson Chi Square analysis for	Values	Number of valid cases	Df	Asymptotic Significance (2-sided)	H0 accepted or rejected
Age group Vs Passion towards learning	16.506[a]	246	12	0.169	H0 Accepted
Age group Vs Commitment	12.440[a]	246	12	0.411	H0 Accepted
Age group Vs Motivation	5.053[a]	246	12	0.956	H0 Accepted
Age group Vs Flexibility	13.566[a]	246	12	0.329	H0 Accepted
Age group Vs Accountability	22.014[a]	246	12	0.037	H0 Rejected
Gender Vs Passion towards learning	3.339[a]	246	4	0.503	H0 Accepted
Gender Vs Commitment	2.025[a]	246	4	0.731	H0 Accepted
Gender Vs Motivation	5.811[a]	246	4	0.214	H0 Accepted
Gender Vs Flexibility	5.516[a]	246	4	0.238	H0 Accepted
Gender Vs Accountability	1.690[a]	246	4	0.792	H0 Accepted
Course studying Vs Passion towards learning	12.682[a]	246	4	0.013	H0 Rejected
Course studying Vs Commitment	15.116[a]	246	4	0.004	H0 Rejected
Course studying Vs Motivation	5.970[a]	246	4	0.201	H0 Accepted
Course studying Vs Flexibility	9.094[a]	246	4	0.05	H0 Rejected
Course studying Vs Accountability	49.146[a]	246	4	0	H0 Rejected

Pearson Chi Square analysis for	Values	Number of valid cases	Df	Asymptotic Significance (2-sided)	H0 accepted or rejected
Age group Vs Passion towards teaching	17.131[a]	112	15	0.311	H0 Accepted
Age group Vs Flexibility towards job	3.355[a]	112	10	0.972	H0 Accepted
Age group Vs Motivation to contribute to the Institution	10.138[a]	112	15	0.811	H0 Accepted
Age group Vs Monetary expectation for additional contribution made	14.741[a]	112	20	0.791	H0 Accepted
Gender Vs Passion towards teaching	2.387[a]	112	3	0.496	H0 Accepted
Gender Vs Flexibility towards job	1.538[a]	112	2	0.464	H0 Accepted
Gender Vs Motivation to contribute to the Institution	5.803[a]	112	3	0.122	H0 Accepted
Gender Vs Monetary expectation for additional contribution made	1.793[a]	112	4	0.774	H0 Accepted
Income Vs Passion towards teaching	14.724[a]	112	12	0.257	H0 Accepted
Income Vs Flexibility towards job	2.483[a]	112	8	0.963	H0 Accepted
Income Vs Motivation to contribute to the Institution	20.738[a]	112	12	0.05	H0 Rejected
Income Vs Monetary expectation for additional contribution made	26.260[a]	112	16	0.05	H0 Rejected
Qualification Vs Passion towards teaching	4.582[a]	112	9	0.869	H0 Accepted
Qualification Vs Flexibility towards job	5.496[a]	112	6	0.482	H0 Accepted
Qualification Vs Motivation to contribute to the Institution	9.123[a]	112	9	0.426	H0 Accepted
Qualification Vs Monetary expectation for additional contribution made	10.552[a]	112	12	0.568	H0 Accepted
Experience Vs Passion towards teaching	11.734[a]	112	9	0.229	H0 Accepted
Experience Vs Flexibility towards job	1.818[a]	112	6	0.936	H0 Accepted
Experience Vs Motivation to contribute to the Institution	7.240[a]	112	9	0.612	H0 Accepted
Experience Vs Monetary expectation for additional contribution made	6.716[a]	112	12	0.876	H0 Accepted

Impact of COVID-19 on Stock Markets: An Investigation and Way Forward

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Impact of COVID-19 on Stock Markets: An Investigation and Way Forward

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ABSTRACT

This study analyzes the impact of the COVID-19 pandemic on stock markets in different regions of the world. Impact of COVID-19 on the stock market is like a black swan event. To analyze the impact of COVID-19 on the stock market, study includes different indices, ratios, strategies and past events to compare. Study is focused on the stock market of countries such as the United States and India to see effects on developed and developing countries. The trends were found similar worldwide. The United States, which has been a bull market for a long time, is also experiencing a plummeting stock market. In the Dow Jones Index's first quarter history, this year's first quarter has marked the worst performance ever. In the year 2020, Indian stock market from 1st January to 23rd March SENSEX has plunged 37.1% and from 1st January to 18th May SENSEX has plunged 27.2%. The study tries to touch upon the past crises and its impact on various stock markets.Sentiments of an investor play a major role in the stock market. A good strategy if used in this type of stock market can help generate profits and remain stable in the volatile situation as well.

Keywords:
Stock market, COVID-19, The Global Business Environment, Stock market of India & USA, Financial Crisis

INTRODUCTION

It all began in Wuhan, China. When a patient with pneumonia was found with an unknown cause. This first case was reported to WHO on 31st December, 2019. On 30th January, 2020 outbreak was declared. Finally, on 11th February, 2020 "COVID-19" name was given to the disease caused by novel coronavirus (WHO, 2020). There are different types of coronaviruses. Generally, human coronavirus is of alpha type or beta type. Humans have been infected by coronavirus in the past as well, namely Severe Acute Respiratory Syndrome (SARS) and Middle East Respiratory Syndrome (MERS) (CDC, 2020).

Any changes in the world and in the business environment directly or indirectly affects the stock market. These changes can be a pandemic, a war, a boom in an economy, an election or anything

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else. To see the change in dynamics of the stock market, indices are used in this study. Indices reflect the situation of the stock market. It is very important to know and understand the dynamics of the stock market. If an individual is good at understanding and following the dynamics of the stock market then he/she can nail it or else he/she can even experience the worst days of life.

RESEARCH OBJECTIVES, IDEATION AND METHODOLOGY

Impact of COVID-19 on the stock market is like a black swan event. Hence, study of this is very important. Therefore, researchers have identified three broad objectives of the study. Firstly, it analyzes the impact of the COVID-19 pandemic on stock markets in different regions of the world. Secondly, it tries to touch upon the past crisis such as financial crisis and Spanish flu and how stock market has reacted in those crises. Lastly, it includes analysis of factors that an individual should take into consideration while investing or trading. After going through the study an individual can decide where to invest and for how long to hold investment.

In this study secondary data is used. Data used is till 20th May, 2020.This study uses data that was originally produced in the form of an interview, research paper, review article and news article from different and reliable journals and websites. Graphs are used for easy understanding and comparison of the trend of one or more stock markets. Moreover, graphs provide continuous data. Data is included to establish a relationship between trends of the major and active stock market such as that of the United States, India, China, London, Toronto, European Union and Tokyo. Major focus was given to the stock market of India and the United States to generalize the trends of the stock market in developing and developed countries. Also, the impact caused by COVID-19 pandemic on the stock market is compared with that caused by other crises in the past. Most of the graphs were generated using data from the website TradingView (TradingView, 2020). This method allows easy and better understanding of the effects of the current, COVID-19 pandemic on the stock market and how the stock market has reacted in the past during similar crises, which may help us predict the stock market.

EFFECS OF COVID-19 ON STOCK MARKETS

Many, developing as well as developed countries were showing a decline in GDP growth rate before the COVID-19 pandemic started. Even in this period when the global economy was declining but the COVID-19 pandemic was not started, stock markets performed pretty good, which was not so obvious. But, this pandemic has brought stock markets down, breaking the illusion (Mohammad, 2020).

Pandemic duration is classified into 3 periods. 3 periods are incubation, outbreak and fever. Incubation period is from 2nd January to 17th January, 2020. Outbreak period is from 20th January to 21st February, 2020. Fever period is from 24th February to at least 6th March, 2020. Initiation of outbreak and fever period has remarkably brought investors' attention (Ramelli & Wagner, 2020).

For investors to make profit from this down falling market, shorting stocks of specific industry is a good choice. These industries must be selected such that they are immediately affected by the pandemic. So that one can buy back those stocks once the price of those stocks has dropped and reached bell bottom. Few of these industries include travel and travel related, technology, entertainment and gold. These industries have been chosen for certain reasons. Transport of any sort can easily spread the virus, especially international and intranational flights and cruise, thus travel was banned. This will affect the travel industry especially because in the vacation season most of the people will try to avoid travelling till the cure of COVID-19 is found. This would affect online travel agencies, hotel companies, and companies providing transportations such as airlines and cruise where there are no quick escape routes provided. Study classifies technology companies into hardware and software companies. In this pandemic, both hardware and software companies are affected but in different sense. Software companies got an opportunity to perform well. But hardware companies are expected to witness a drop and hence one should short hardware companies. With all the theme parks, malls, cinemas being closed down, the entertainment industry is also expected to hit hard. However, these industries will boom once flattening of the curve of the number of cases is attained and permissions are given to loosen up by the government. When the economy is hit hard, people tend to replace currency and stocks with gold to safeguard from fluctuating currency values and the stock market. Also, investors regard gold as a "safe-haven investment", especially at the time of outbreak. Similar trend was experienced, that is, price of gold and S&P was anti-correlated during SARS and the Great Recession (Yan, Stuart, Tu, & Zhang, 2020).

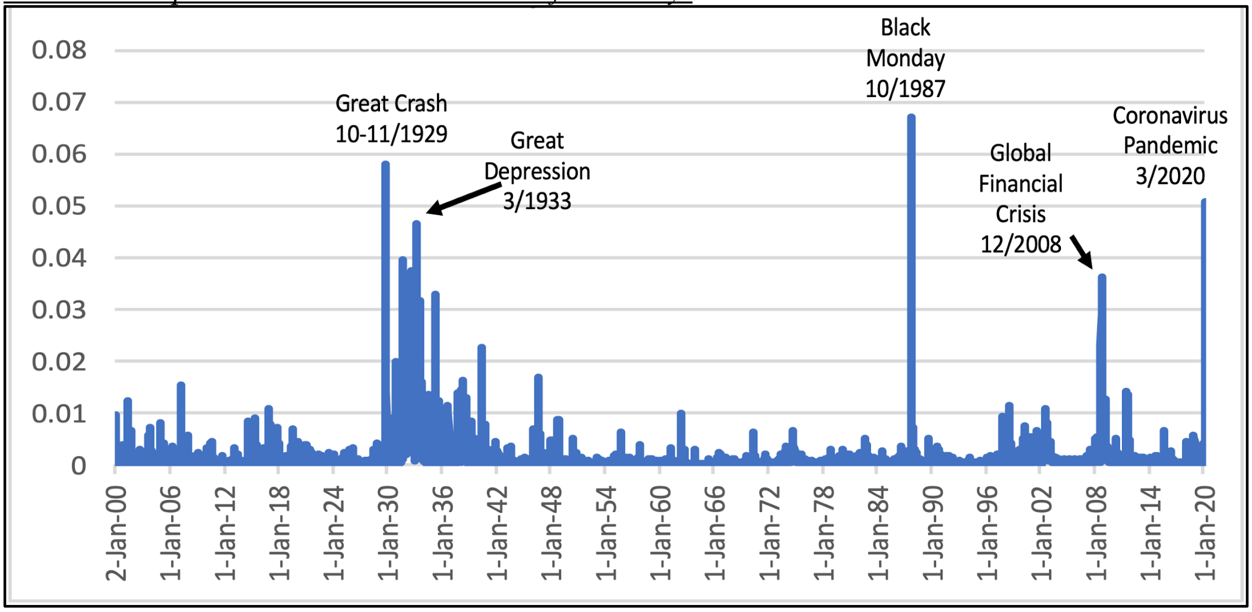
It is difficult to assess how fast the stock markets will recover. But, it depends on the investor's sentiment and how fast all the businesses start functioning by adapting to the new normal. Since, some visionaries say that COVID-19 has come to stay here for a long time, it is best for companies to adapt to the new normal and make the maximum profits possible, considering there is no going back to normal but just adapting to the new normal.

STOCK MARKET OF THE UNITED STATES

This pandemic has brought down the United States' long-lasting bull market. Moreover, in the Dow Jones Index's first quarter history, this year's first quarter has marked the worst performance ever. 170 of the total 195 countries are expected to observe a decline in their per capita income growth in 2020, as per the International Monetary Fund (IMF) (Oberoi, 2020).

During this pandemic in the United States' stock market, volatility is high and equities are plunging. Trend of VIX (Volatility Index) of the stock market of the United States is similar to that of the INDIA VIX (Graph 6 shows INDIA VIX). On comparing the recent (COVID-19) volatility to the volatility of past events (Graph 1), it is clear that recent volatility is higher than that of the Global financial crisis and Great depression (Baker, et al., 2020).

Graph 1: Volatility graph of U.S. Stock market (Baker, et al., 2020). X-axis represents timeline and Y-axis represents standard deviation of volatility.



Market-wide circuit-breakers are used to prevent panic trading by taking a pause of 15 minutes in trading. Its creation was mandated by the U.S. Security and Exchange Commission to prevent the scenario of the 19th October, 1987 market crash (commonly known as Black Monday), when the Dow Jones Industrial Average plunged by 22.6%. After its creation, it was triggered once in 1997. Surprisingly, market-wide circuit-breakers are triggered four times in March only, on 9th, 12th, 16th and 18th March, 2020. Trading halts on both the Dow and the Nasdaq when a circuit-breaker is triggered on the S&P 500. There are 3 levels of trading halts. In the level-1, trading halts for 15 minutes if market experiences a drop of 7%, similarly in level-2, trading halts for 15 minutes if market experiences a drop of 13% and finally in level-3, trading halts until next day if the market experiences drop of 20% (Funakoshi & Hartman, 2020).

Another thing that influences investors and traders to cause such large movements in the stock market of the United States are newspapers. A strategy is used to determine the number of jumps. Here, for everyday when the stock market of the United States moves by more than 2.5%, this fluctuation can be both upwards or downwards, study analyzes next day's newspaper to find the explanation of that fluctuation. From 1900 to 24th February 2020 approximately 1110 jumps were recorded but of which none of them were attributed to infectious disease outbreak. This duration of 120 years includes the era of Spanish flu, which killed approximately 2% of the world's population. Strangely, 18 jumps were recorded from 24th February 2020 to 24th March 2020. This duration includes 22 trading days only. In explanation of these 18 jumps, that of 15 to 16 jumps was attributed to COVID-19 (Baker, et al., 2020).

The Edge has selected a few firms, stocks of these are expected to soar by at least 50% once the pandemic is over. They are likely to outperform the S&P 500 Index after this crisis overcomes. These firms have good management, less debt, and strong cash flow but their stock prices are affected for no good reason (Osman, Jim, 2020). Few leading investment banks felt that market has bottomed itself, however; few equity strategists were not convinced (Oberoi, 2020). It can be concluded that the stock market of the United States was badly affected and investors reacted to the situation quickly, hence, resulting in high volatility and large dips.

STOCK MARKET OF INDIA

It can be said that the characteristics of the impact of COVID-19 on the stock market is very much similar to that of a black swan event. Investors in India have a low and short termed sentiment (Sharma, 2020). Indian stock market is one of the most affected stock markets by the COVID-19 pandemic. Although, India has relatively fewer registered cases of COVID-19 as compared to other countries during initial times. On the contrary, China, origin of COVID-19, has been least affected. Other active and large stock markets such as that of the United States, Tokyo, London, European Union and Toronto are in between India and China (Graph 2).

In the graph 2, SSE composite (000001) is an index used for China. TSX is an index (TSX composite) used for Toronto. NI225 is an index (Nikkei 225) used for Tokyo. DJI is an index (Dow Jones Industrial Average) used for the United States. UKX is an index (FTSE 100) used for London. N100 is an index (EURONEXT 100) used by the European Union. SENSEX is an index (S&P BSE SENSEX) used for India. On 1st January, 2020, SSE composite was at 3085, TSX composite was at 17099, Nikkei 225 was at 23204, Dow Jones Industrial Average was at 28868, FTSE 100 was at 7604, EURONEXT 100 was at 1158, S&P BSE SENSEX was at 41306. Graph shows the percentage change (y-axis) in the value of indices with respect to that on 1st January, 2020 and not the absolute value itself. Absolute value of index on 20th May, 2020 and percentage change in value of index from 1st January, 2020 to 20th May, 2020 is also mentioned in the graph.

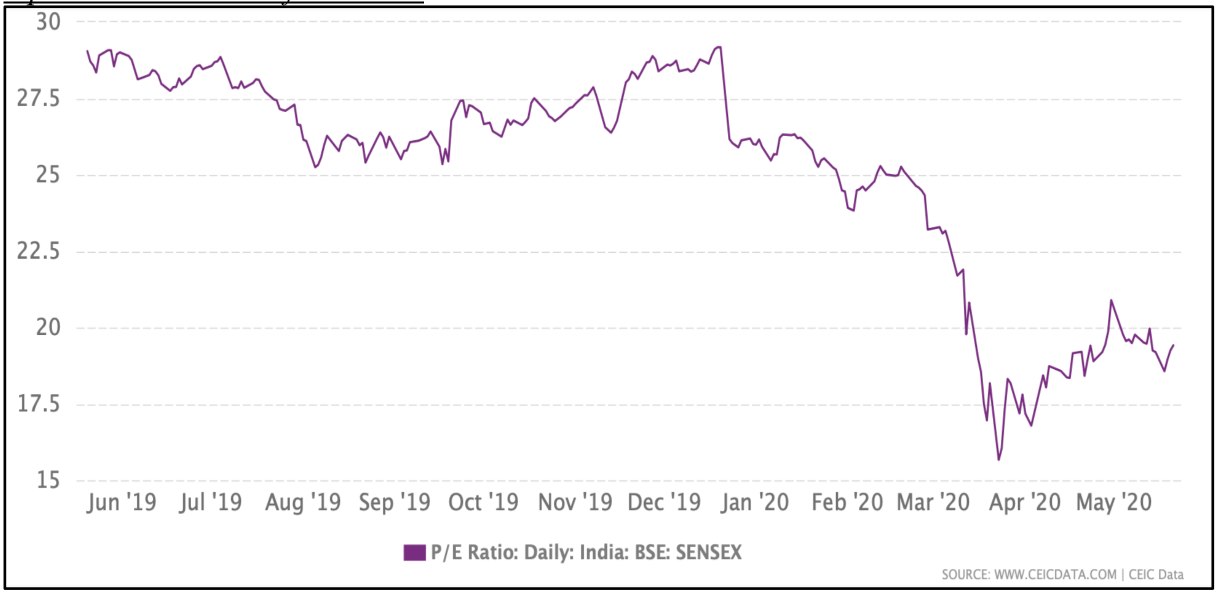
Graph 2: Percentage change of different indices on 20th May,2020 with respect to their prices on 1st January, 2020. X-axis represents timeline and Y-axis represents percentage change.

Source: Data collected and graph generated using www.tradingview.com (TradingView, 2020) by researchers

The Government of India and Reserve Bank of India (RBI) have come up with a few reforms to increase liquidity in the cycle. But, the impact of pandemic is dominating (Ravi, 2020). Yet, there are a few stocks in the NIFTY 50 index which are traded with single digit valuation (Sarkar, 2020). Foreign Portfolio Investors (FPI) have also contributed a bit towards the dip experienced by the Indian stock market. Because, FPIs are escaping emerging markets and are settling for safer dollar backed assets (Raja, 2020).

To understand whether the market or a particular stock is undervalued or overvalued, price to earnings ratio (P/E) ratio is used. P/E is important and the most widely used ratio for analysis. The P/E ratio is the ratio of market price to earnings. Low P/E ratio implies that a company or index is undervalued and therefore, it is preferred to buy. High P/E ratio implies investor's confidence in the company or index due to its strength or good future prospects, holding these stocks is not a bad idea. Too high P/E ratio implies that a company or index is overvalued and is not able to perform as per the expectation of investors, buying these stocks is not preferred.

Graph 3: Price to earnings (P/E) ratio of SENSEX. X-axis represents timeline and Y-axis represents P/E ratio of SENSEX.



Source: Data collected and graph generated using www.ceicdata.com

P/E of SENSEX was 18.57 on 18th May 2020, which is relatively low when compared to the P/E of the last 1 year (Graph 3). Hence, investing in companies with strong finance can be a good option in the long run.

It is important to understand whether the impact of COVID-19 on the stock market is biased towards companies or indices of different capitals. When comparing large capital, medium capital and small capital companies, graph 4 uses the SENSEX large cap index, SENSEX medium cap index and SENSEX small cap index. From 1st January to 20th May, a similar trend is seen in all the three indices, which is a large dip in late February and early March, which then starts to rise again till end of April. In the beginning of May, the curve experiences a small decline. No assurance can be given that the rise was just a rebound and the index will fall again or it has started to recover and no large drops are expected. It can be seen that the drop in large cap is more than that in mid cap and small cap, with respect to their prices on 1st January, 2020 (Graph 4). This is quite strange because large capital companies are expected to have stronger finances and hence more stable than medium and small capital companies.

Graph 4: Compares small, medium and large capital indices. X-axis represents timeline and Y-axis represents percentage change.

Source: Data collected and graph generated using www.tradingview.com (TradingView, 2020)

In graph 4, SMCAP is an index for small capital companies. MIDCAP is an index for medium capital companies. LRGCAP is an index for large capital companies. On 1st January, 2020 small capital index was valued at 13786, medium capital index was valued at 14998 and large capital index was valued at 4677. Absolute value of index on 20th May, 2020 and percentage change from 1st January, 2020 to 20th May, 2020 is also mentioned in the graph.

It is not necessary that all sectors are performing in same manner. But rather, in most cases, if one sector is performing well then there would be another sector which is experiencing a decline. Therefore, it is important to decide that in which sector an individual should invest in based on how a particular sector will react in future. Focusing on different sectors, graph 5 uses different sector indices of SENSEX to compare. Health care, Fast Moving Consumer Goods (FMCG), IT, energy, industrial and financial sectors are compared from 1st January, 2020 to 20th May, 2020. Financial sector has witnessed a large dip followed by the industrial sector but experienced small fluctuations close to their bottom. Whereas, IT and FMCG sectors have dropped, but relatively less than financial and industrial sectors. In fact, IT and FMCG sectors have recovered and reached close to values that were seen on 1st January, 2020. This is due to easy access to IT even during nationwide lockdowns. Even with difficulty to maintain a proper supply chain, FMCG being essential, was permitted by the government early on, thus able to recover fast. FMCG is a sector which is never much affected by recession, as it includes essential products. Hence, in most of the cases it is safe to invest in the FMCG sector when compared to other sectors. Health care sector is the only sector which has seen a large boom after a small dip due to its high demand. COVID-19 spreads easily and due to this more people are getting infected, hence, healthcare is increasing. Moreover, the Research and development of the healthcare sector is working a lot more to find a vaccine of COVID-19(Graph 5). Investing in the healthcare sector for the long term, till the vaccine for COVID-19 is out in the market, is not a bad option. Introduction of vaccines will further push the healthcare sector upwards due to increase in demands.

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Graph 5: Compares different sectors of the Indian stock market. X-axis represents timeline and Y-axis represents percentage change.

Source: Data collected and graph generated using www.tradingview.com (TradingView, 2020)

In graph 5, HC is the health care sector. FMCG is the fast-moving consumer goods sector. IT is the information technology sector. ENERGY is the energy sector. INDSTR is the industrial sector. FIN is the financial sector.

Most important deciding factor whether an individual can make profitable trade or investment is time – both entry time and exit time. Right time will have right prices of stocks. With increase in volatility on stock market, to trade or invest at right time and price becomes difficult. Volatility index (VIX) commonly known as fear index as well. It forecasts the volatility of the stock market. It does not represent actual volatility. Higher VIX i.e. more than 20, implies higher risk. VIX lower than 20 implies that the stock market is safe, hence low risk (Williams, 2013). As per the graph 6, until the end of February,2020, Indian stock market was safe (VIX below 20). From February end, 2020 to 24th March, 2020 VIX kept on increasing. India VIX was at 84 on 24th March, 2020 and then it started to decline. 84 is tremendously large number for VIX. (Graph 6). With reference to graph 6 and graph 7, it appears that on 23rd and 24th March, 2020, when the dip was large, the volatility index was also high. Although, in high volatility it looks easy to make money but, it is easier to lose money if an individual is not skilled enough.

Graph 6: Shows volatility of Indian stock market. X-axis represents timeline and Y-axis represents value of India VIX.

Source: Data collected and graph generated using www.tradingview.com (TradingView, 2020)

Graph 7: S&P BSE SENSEX. X-axis represents timeline and Y-axis represents the value of S&P BSE SENSEX.

Source: Data collected and graph generated using www.tradingview.com (TradingView, 2020)

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Stock market has an interesting history. It has faced terrific crashes and has recovered as well. Let us see the history of SENSEX. In 2020 (COVID-19), From 1st January to 23rd March SENSEX has plunged 37.1% and from 1st January to 18th May SENSEX has plunged 27.2% (Graph 7). In 2008(Financial crisis), SENSEX plunged 61% in 1 year but recovered 157% in 1.5 years. In 2000 (Tech Bubble), SENSEX plunged 56% in 1.5 years but recovered 138% in 2.5 years. In 1996 (Asian Crisis), SENSEX plunged 40% in 4 years but recovered 115% in 1 year. In 1992 (Harshad Mehta Scam), SENSEX plunged 53% in 1 year but recovered 127% in 1.5 years (Raja, 2020). Hence, recovery from this COVID-19 pandemic crash can be expected.

The crash and recovery cycle keeps on going. It is difficult to be sure whether SENSEX has reached bottom and started to recover or is it just a rebound and SENSEX is yet to fall again. But it is not healthy to enter the market to catch the falling knife, at least when an individual does not have enough experience or knowledge.

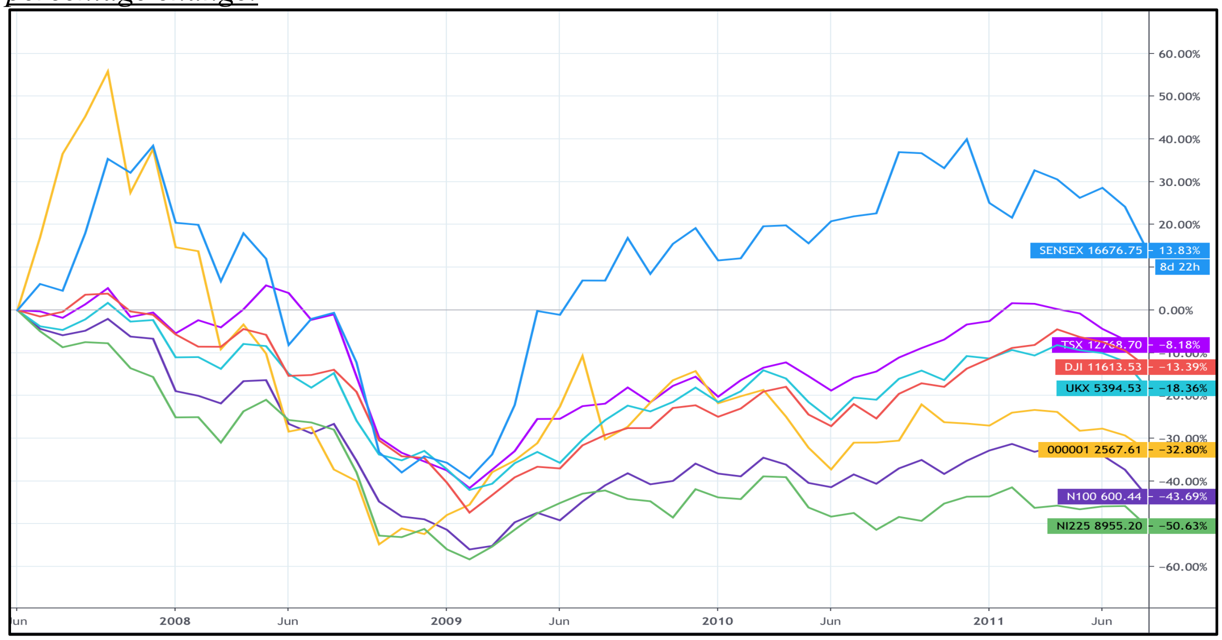
PAST CRISES

To compare current crisis with past crises. Study uses a recent crisis, i.e. financial crisis 2008, and a crisis of the same domain as that of the COVID-19 pandemic, i.e. Spanish Flu 1918. One of the major causes of the financial crisis was the subprime mortgage crisis. It boomed the housing market. Subprime mortgages were mortgages that were granted to low credit score (often below 600s) holders. Lower the credit score, higher the risk for the lender. This led to the formation of a bubble. Bubbles are supposed to burst someday. Subprime mortgage crisis had two major effects: it collapsed the housing market and it created the mistrust between banks (Sraders, 2019). It took long time to recover from the subprime crisis and before the global economy would have settled COVID-19 came with a bang. The stock market was at its peak in 2007. The financial crisis affected the United States' stock market badly. The Dow Jones Industrial Average started declining. But, the Dow Jones Industrial Average lost more than half of its value due to the untenable stock market costing a large number of investors. Decline of 57.8% in the S&P 500 was observed from 2007 to 2009. To save the dropping economy the government introduced the Economic Stimulus Act. (Sraders, 2019).

Along with the United States' stock market other large and active stock markets have experienced a dip in late 2008 and early 2009. But a good recovery was also witnessed (Graph 8). For some countries like India experienced a fast recovery and for other countries like Tokyo and European Union, recovery took more time but it eventually did take place. The stock market of China has seen the highest drop, approximately from +55% to -55% (from the graph 8). This tells that investors who invested in the stock market of China could have less reacted to the volatility of the stock market. China has learnt a lesson from the financial crisis of 2008. Therefore, in the COVID-19 pandemic the stock market of China is the one least affected. Even the stock market of India was also highly volatile. It dropped from +40% to -40% (approximately) and again reached +40% in the span of 3 years, quite volatile.

Major difference between the financial crisis and the COVID-19 pandemic is that, in the financial crisis, few great financial institutions declared themselves bankrupt. Only a few sectors and a selected population in a specific geographical region were directly affected. One sector got affected due to another, then the cycle continued. Whereas, in the case of the COVID-19, all the sectors are affected directly, because safety issues require social distancing, limiting the work environment. To overcome that problem, alternatives are needed that require the use of technology. Therefore, the technology and healthcare sector are performing good while others face tough consequences.

Graph 8: Compares percentage change of different stock market with respect to their prices on 1st June, 2007, beginning of financial crisis. X-axis represents timeline and Y-axis represents percentage change.



Source: Data collected and graph generated using www.tradingview.com (TradingView, 2020)

In graph 8, SSE composite is an index (000001) used for China. TSX is an index (TSX composite) used for Toronto. NI225 is an index (Nikkei 225) used for Tokyo. DJI is an index (Dow Jones Industrial Average) used for the United States. UKX is an index (FTSE 100) used for London. N100 is an index (EURONEXT 100) used by the European Union. SENSEX is an index (S&P BSE SENSEX) used for India. As per the graph 8, on June 2007 SSE composite was valued at 3820, TSX composite was valued at 13906, Nikkei 225 was valued at 18138, Dow Jones Industrial Average was valued at 13408, FTSE 100 was valued at 6607, EURONEXT 100 was valued at 1066 and S&P BSE SENSEX was valued at 14650.

The 'Spanish Flu' is one of the pandemics experienced by the world from 1918 to 1919. It occurred in three waves. March 1918 is marked as the beginning of the first wave. The second wave (most lethal) started in October 1918. The third wave started in February 1919 (Baltussen & Vliet, 2020).

In a study on the effect of World War I and the Spanish flu on the United States' stock market was done. It was found that the United States' stock market dropped by about 20%. This 20% includes the effect of both the Spanish flu and World War I. All the stocks followed a similar trend, it was all about which stocks did less worse, i.e. correlation was higher. The stocks which were less volatile and the stocks which were offered high dividends were safer. Small capital stocks were more volatile, hence, they showed relatively larger drop and better recovery. The stock market took time but recovered by the end of February 1919 (Baltussen & Vliet, 2020).

The COVID-19 pandemic is new for everyone. This makes it even more difficult to accurately predict the stock market based on past crisis. Various graphs, finding and analysis suggest that the effect of COVID-19 on the stock market is deeper and painful in comparison to the past crisis.

DISCUSSION AND MANGERIAL IMPLICATIONS

From the findings of the study it is clearly indicated that the COVID-19 pandemic has affected various stock markets globally. Surprisingly, China is relatively least affected, tough the origin of COVID-19 was from China. Recent volatility of the stock market is higher than that of the Global financial crisis and Great depression crisis. However, recovery is expected in due course of time due to the reopening of businesses and invention of vaccine. Few sectors such as FMCG, IT and Healthcare are protecting investors' interest and it is expected that these sectors will show positive results in coming days. Finding also suggest that the COVID-19 pandemic has worse impact than that by other past crises such as financial crisis (2008) and Spanish flu (1918-1919).

With the dip in the stock markets, it may appear to be safe to invest in most stocks right now, but it is not entirely true. Where to and how much to invest varies from investor to investor. Proper, in depth, analysis is required to dive into the stock market specially, at the time of crisis, when the stock market is highly volatile.

Investors or traders must choose the sector and stock with a high level of understanding, not only of the stocks but also of the reaction of stocks at the time of crisis. There are chances that many companies go bankrupt. So, investors and traders should be smart enough to filter the companies which are expected to boom in near future from the ones which are expected to go bankrupt. One of the most important factors that cannot be neglected is the investor's sentiment. One must take into consideration what other investors are thinking and how they are reacting to the changes in the stock market, which will ultimately determine the stock prices.

COVID-19 has affected the global business environment badly and recovery will take its own time. In any tough situation, the role of the government, regulatory body and financial institutions are significant. Across the globe, the government has cut down the taxes on various commodities and services to take care of the economy in the short run. Social expenditure by the government also increased and various policy rate cuts by the central bank indeed supplemented the efforts of the government in most of the economy. Such responsible efforts of the government, central bank and financial institutions has certainly improved the sentiments of investors and that could be a reason that stock market has started showing some meaningful recovery in the recent past though it is inconsistent.

The recovery of the stock market is bound to take place. But still a second dip is expected. No one can be so sure to say that when will recovery happen. To stay alive in the stock market, one has to take calculated risk. Nothing comes without a risk.

CONCLUSION

This study can conclude that the COVID-19 pandemic has affected stock market badly. It was not a coincidence. All the active stock markets across the world have experienced similar trend. Stock market of some countries like China are less affected while that of other countries like

India have been hit hard. Most of the other active stock markets lie in between that of India and China.

Understanding of similar events from past can help to overcome current crisis. Many stock market crises took place in past but the crisis due to the COVID-19 pandemic is totally different. Hence, predictions based on the analysis of the past crisis may not be accurate. This is the first ever infectious disease outbreak which has caused such a large dip in the stock market. Stock markets have seen a huge dip in mid-March, 2020 and followed by gradual gain in April, 2020. Stock markets can become stable for some time or rise a little bit but a second dip is expected in the near future. Recovery is assured but how long will it take is difficult to assess. It depends on the investor's sentiment. To narrow it down, now, investor's sentiment depends majorly on two factors - the speed at which all the businesses start functioning by adapting to the new normal and the invention of vaccine or some drug to cure the COVID-19 patient.

In highly volatile market it looks like money can be made quickly but, at the same time it can be lost at the same pace. To avoid loss of money an individual should have enough understanding, knowledge and experience of dynamics of the stock market. What matters most is the stock in which you invest. So, investor or trader should select a stock of a company which belongs to a sector which is performing well or will perform well in future. That company should have strong finance. Moreover, a company with continuous cash flow is preferred. Investors can also short stocks of the industries which are going to observe a decline in their prices. Investors should be very clear about what strategy they are following and in what way the repercussions can affect them.

ORIGINALITY

This study helps to answer the interesting questions which are unique in nature. How has the different country's stock market reacted to the COVID-19 pandemic? How closely does this event replicate previous crises such as the financial crisis, the Spanish flu? What all things an individual should take into consideration before investing or trading in such a highly volatile stock market? The attempts were made by researchers to provide logical explanations to all such interesting questions with unique analysis and approach is indeed the uniqueness of the paper.

LIMITATIONS AND FUTURE SCOPE

The COVID-19 pandemic is an ongoing scenario. Although the data available was fresh, it was limited. Moreover, in almost all of the past crises the volatility of the stock market was not as much as that observed in COVID-19 pandemic. So, it becomes difficult to make accurate predictions. Effect of COVID-19 on the stock market even after opening of businesses can be done, once no restrictions are there to run businesses. Researchers feel that a similar kind of study can be done having data of many more months/years to make it more meaningful.

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