Nexus between Credit Rating, Intellectual Capital, and Financial Performance: A Panel Data Analysis of Select Large-Cap Indian Companies

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Abstract

The aim of this research is to explore the relationships between credit rating (CR), intellectual capital (IC), and financial performance (FinPerf) of a set of large-cap Indian firms, and determine if firm characteristics explain credit ratings received by the aforementioned firms. For this research panel data was used from fifty major Indian firms from the financial services, FMCG, IT, energy, infrastructure, automobile and metal industries from 2015 to 2025. Pooled Ordinary Least Squares (POLS) regression analysis, ordered logistic and ordered probit regressions and one-way ANOVA will be applied using STATA software package. Intellectual capital will be measured using the Modified Value Added Intellectual Coefficient (MVAIC), financial performance with the use of return on total assets (ROTA) and firm characteristics with firm age, size, and leverage. Results show that after controlling for firm age and size there is a significant relationship between credit rating and financial performance, which is supported by ordered-logistic and heteroskedasticity robust estimations but is weakened by cluster analysis based on the firm. Intellectual capital shows a significant relationship with financial performance as well. The age and leverage of a firm is shown to be significant factors for both credit rating and intellectual capital, while the firm size exhibits significant results only in some of the estimation methods. There is considerable difference in financial performance, credit rating and intellectual capital between different sectors. The results can be useful for the credit rating and intellectual capital literature in the emerging markets and have practical implications for business management.

Keywords: Credit Rating, Intellectual Capital, Financial Performance, Return on Total Assets, Panel Data, India

1. Introduction

In a world where more and more economies are becoming knowledge-intensive and credit-oriented, credit rating (CR) and intellectual capital (IC) are seen as two important but different variables which influence the FinPerf of a corporation. The Credit Rating is given by various agencies like CRISIL, ICRA, CARE and India Ratings. This credit rating is the third-party assessment of credit-worthiness and the ability of the firm to meet its financial obligations on time. It serves as the information signaling device which removes information asymmetry between the firm and its capital suppliers, thus influencing the cost and availability of debt capital, confidence of lenders and investors, and ultimately firm performance. Simultaneously, intellectual capital has been considered a primary source of value generation as economies evolve from their industrial economies to knowledge economies. The firms which use their intellectual knowledge to generate economic value efficiently are considered to have sustainable competitive advantages and hence higher financial performance than their counterparts.

Even though the theory looks promising, the evidence on the link between the above constructs and financial performance (FinPerf) is highly scattered, and even contradictory in many aspects, especially for developing nations like India. India provides a unique ground for studying this question. In India, there is an increasingly growing list of global competitors that consist of companies in both conventional/asset-based industries (like energy, metals, infrastructure), and knowledge-based industries (like IT and finance). It is very clear that these industries will be different in terms of intellectual capital utilization, credit risk exposure, and financial performance. Furthermore, during the last ten years, Indian policymakers have been putting pressure on firms to enhance their disclosures and credit ratings; hence, the credit rating (CR)-performance link becomes increasingly important.

Previous literature has studied credit ratings, intellectual capital, and financial performance as separate strands of research. The existing body of research regarding credit ratings is either related to the factors determining credit ratings, such as leverage, profitability, and firm size, or to the capital market consequences of credit ratings, including yield on bonds and abnormal stock returns. On the other hand, research on intellectual capital, which is based on the work of Pulic (2000) on the Value Added Intellectual Coefficient (VAIC) and its later modified version, the Modified VAIC (MVAIC), has mainly concentrated on studying the impact of Intellectual Capital (InCap) on performance without paying any attention to the credit rating of a firm. Very few works, particularly in the Indian context, have investigated the impact of all three factors together on financial performance and also how these factors determine the credit rating of a firm.

This research contributes to the existing literature in several ways. It contributes to the literature in the area of intellectual capital by studying the impact of credit rating on financial performance, the impact of intellectual capital on financial performance, the influence of firm-level variables and intellectual capital on credit rating, and the impact of sector wise differences on financial performance, credit rating, and intellectual capital of fifty large and established Indian firms in a panel data set of eleven years between 2015-2025 from seven main sectors – financial services, fast-moving consumer goods (FMCG), IT, energy, infrastructure, automobiles, and metals. There are three unique contributions of this paper to the literature. Firstly, it combines credit rating and intellectual capital as factors that affect financial performance in one empirical setting rather than separately. Secondly, it considers credit rating as an ordinal dependent variable and estimates its firm-level determinants using linear as well as ordered choice estimators - an exercise not often done in the Indian intellectual capital literature. Finally, it adds sector-wise evidence using seven different economic sectors of the Indian economy.

The remaining parts of this paper are organized as follows. Section 2 presents the relevant literature review on the relationship between credit rating, intellectual capital, and firm performance. The research problem is clearly identified in this section. Section 3 presents the research purpose, research question, and hypotheses to be tested in this study. Section 4 presents the methodology adopted in the current research, including research design, samples, data sources, measurement of variables, and more importantly, the reasoning for using the statistical techniques used in this study. Section 5 presents the analysis and interpretation of the data.

2. Literature Review

2.1 Credit Rating and Firm Performance

Credit ratings represent ordinal assessments of the relative likelihood of default regarding a financial obligation. Early researchers such as Kaplan and Urwitz (1979) have pioneered in studying the relation between bond ratings and observed financial statement ratios and found that leverage, firm size, and profitability collectively explain a significant part of the variations in credit ratings. Thereafter, a vast literature has emerged on credit ratings in terms of explaining the effect of firm fundamentals on credit ratings and vice versa. Ashbaugh-Skaife, Collins, and LaFond (2006) demonstrated the incorporation of good corporate governance in credit ratings along with traditional accounting factors, indicating the use of more information than just accounting ratios. In terms of performance, a good credit rating is predicted to lower the cost of borrowing, increase access to capital markets, and build confidence of stakeholders, all of which theoretically contribute to better performance of the firm. However, there is relatively less empirical research conducted on the relation between credit ratings and firm performance compared to the relation between firm performance and credit ratings and the results are contradictory. Some studies find a positive relationship between credit ratings and firm performance, while others show that the relationship is insignificant and even negative.

2.2 Intellectual Capital and Firm Performance

Intellectual capital is considered to have its basis in literature developed by Pulic (2000) and his concept of Value Added Intellectual Coefficient (VAIC). VAIC is defined as a simple, financial proxy measure for the efficiency of intellectual conversion of physical, human, and structural capital into value added. With the development of Modified VAIC (MVAIC) that considers efficiency of relational capital, there has been a wide range of studies on intellectual capital in emerging markets because of simplicity of calculation and reliance solely on public financial statements. The conceptual definition of intellectual capital was stated by Bontis (1998), who defined it as human, structural and relational capital. According to Bontis, it is interaction of all these factors, and not each one individually, that makes organizations perform better. There were some positive relationships identified between the coefficient VAIC and the market value and profitability of Taiwanese and Indian listed companies, as well as research and development expenditures (Chen, *et. al*., 2005, Pyne & Goswami, 2024). However, later research conducted in other emerging markets (including India) has failed to replicate this finding, identifying instead an insignificant or even negative relation between intellectual capital efficiency and accounting measures of profitability, such as return on assets. It is especially noticeable in capital-intensive firms and financial firms because the measures used for calculation of VAIC/MVAIC are affected by leverage and asset structure rather than knowledge assets.

2.3 Determinants of Credit Rating: Firm Age, Firm Size, Leverage and Intellectual Capital

The firm specific variables have historically proven to be simple yet useful predictors of credit ratings, both when applied independently or used jointly with credit rating agencies' qualitative assessments. The firm size variable is usually found to be positively correlated with credit ratings due to advantages of diversification, market power and low level of operational risk provided by larger companies. Similarly, firm age is also expected to be positively correlated with credit rating because older firms are believed to have richer experience, better banking relations and lower information asymmetry. On the contrary, the leverage ratio is expected to demonstrate a more complicated connection with credit ratings – highly leveraged companies usually carry higher default risks and are assigned lower ratings. Nevertheless, some empirical studies conducted on big capitalized companies report a positive relationship between the leverage and rating, as the logic goes, only those firms which have strong and stable cash flows and sufficient collateral assets can sustain the higher level of leverage and preserve the investment grade credit rating. Recent researches started considering if intellectual capital, being an indicator of business model quality and sustainability, is linked to capital structure of the company and thus, to credit rating depending on the leverage of a firm. This relatively new research area shows that higher IC efficiency can help companies to sustain the higher level of leverage with less downgrades in credit rating because of lower default probabilities assumed by rating agencies in case of firms having intangible resources.

2.4 Research Gap

Collectively, the existing literature reveals three gaps which form the basis for undertaking this research work. Firstly, though the credit rating and intellectual capital have individually been found to be significant predictors of the firm performance, not much literature exists on how both the variables can act together in explaining the firm performance. Secondly, the firm specific factors that determine the credit rating of a company have rarely included intellectual capital in the explanatory mix even though the importance of intangible assets is increasingly being acknowledged in determining the firm's long-term creditworthiness. Thirdly, there has been little work done so far on the heterogeneity that exists in the relationship between the credit rating, intellectual capital and firm performance across various industry sectors in the Indian corporate world. The sectors range from highly asset-intensive to highly knowledge-intensive in nature.

2.5 Theoretical Framework

This research incorporates two theoretical approaches as its basis to support hypotheses. The first approach is the Resource-Based View (RBV) of the firm which provides the theoretical justification of the intellectual-capital hypotheses (H02 and H06). Specifically, intangible and firm-specific resources like human knowledge, routines and relationship with stakeholders, which cannot be easily copied, provide more value and can lead to greater competitive advantage and better financial performance compared to tangible resources due to their higher value, rarity, difficulty of imitation and non-substitutability. Under RBV, firms with better intellectual-capital efficiency will generate better asset returns and hence will have motivation and empirical support (with partial refutation) for the positive correlation between Intellectual Capital (InCap) and performance.

On the other hand, signalling theory will justify the hypotheses of credit rating (H01, H03-H05). Specifically, according to the theory of signaling, those characteristics of a firm that are difficult to imitate like long and continuous operating experience, large asset size or capability to meet debt payment requirements become signals of underlying firm quality to external parties like credit-rating agencies and thus should influence credit rating of the firm. By using these two theoretical approaches at the same time, the current research becomes able to view credit rating more as an outcome of certain characteristics of a firm relevant to signaling and InCap more as resource-based inputs into financial performance.

3. Research Objectives, Questions and Hypotheses

Using the research gaps identified through the literature review, the aims which drive the current research study will be clearly stated along with the research questions used to achieve those aims, and hypotheses which are tested by statistical methods mentioned in the methodology section.

3.1 Research Objectives

The study is designed to address the following specific objectives:

1. To examine the effect of Credit Rating (CR) on the financial performance (FinPerf) of the select Indian companies.
2. To assess the effect of Intellectual Capital (InCap) on the financial performance (FinPerf) of the select Indian companies.
3. To analyse the impact of firm-specific characteristics on the Credit Rating (CR) assigned to the select companies.

4. To compare the financial performance (FinPerf) of the select companies across sectors/industry groups.

Together, these objectives will allow the research to go beyond the analysis of just one bivariate relationship and provide a holistic view of how the interplay of the firm's intangible assets (Intellectual Capital), external signaling capacity (Credit Rating), and organizational structure (Size, Age, Leverage) can impact financial performance, all the while taking into account differences by industry across the sample firms.

3.2 Research Questions

Corresponding to the objectives stated above, the study addresses the following research questions:

RQ1: Does the CR assigned to a firm significantly influence, or associate with, its FinPerf?

RQ2: Does InCap significantly influence the FinPerf of the select Indian companies?

RQ3: Do firm-specific characteristics, namely firm age, firm size and leverage, and InCap significantly explain the CR assigned to a company?

RQ4: Does FinPerf differ significantly across sectors/industry groups?

3.3 Hypotheses

Based on the objectives and research questions outlined above, and consistent with the null-hypothesis form adopted for the underlying statistical analysis, the following hypotheses are formulated and empirically tested:

H01: CR has no significant effect on the FinPerf of select Indian companies.

H02: InCap has no significant effect on the FinPerf of select Indian companies.

H03: Firm size has no significant effect on the CR assigned to the firm.

H04: Firm age has no significant effect on the CR assigned to the firm.

H05: Leverage has no significant effect on the CR assigned to the firm.

H06: There is no significant association between InCap and leverage (LVRG) of select Indian companies.

4. Research Methodology

4.1 Research Design

This research uses a quantitative, ex post facto, correlational, and causal-comparative research method. Ex post facto is used in the study because the independent variables, such as credit rating, intellectual capital, age of the firm, size of the firm, and leverage are not manipulated by the researcher; rather, these variables are based on historical/secondary financial data (PROWESS) collected before the start of the research study. The design is suitable for this study in light of the fact that the questions asked in the study are about naturally occurring associations between financial variables, not the effect of researcher-manipulated variables on any dependent variable. It is impossible as well as unethical to use an experimental research design when studying macro-level corporate finance issues.

4.2 Population, Sampling Technique and Sample

The population of the study is made up of large-cap companies listed in the Indian Stock Exchanges and that are rated on a consistent basis with long-term credit ratings by credit rating agencies based in India. A purposive sample of fifty firms was drawn from this population. There are three main reasons why purposive sampling was preferred over simple random or stratified random sampling. Firstly, there is a need for eleven consecutive years (2015-2025) of matched data for each of the selected companies with regards to credit ratings, financial statement information and intellectual capital. Simple random sampling would not produce a good sample because most firms that could be randomly selected may lack the required ratings and thus the balanced panel needed for the statistical technique used in this study. Secondly, purposive sampling can be used to ensure that the sampled firms represent seven different economic sectors in India—financial services, FMCG, information technology, energy, infrastructure, automobile, and metals—in order to answer the research objective regarding differences in performance across sectors. Lastly, the use of purposive sampling guarantees that the credit ratings vary meaningfully and reliably over time because firms with less continuous ratings introduce noise into measurements that is not related to the research problem. In total, fifty firms observed over eleven years make a panel of 550 firm-years.

4.3 Data Source, Study Period and Data Type

The research will make use of secondary data only, extracted from the audited annual reports, financial statements, and credit ratings reports of the chosen companies for the years 2015-2025. The secondary data will be obtained from the PROWESS database instead of using primary survey data since the constructs that will be examined in this research, namely credit rating, efficiency of intellectual capital, and financial performance, are objective measures, as opposed to perceptual constructs. Therefore, archival financial data are believed to be more reliable and less subject to common method bias or social desirability bias than surveys. The eleven-year period will be chosen for the analysis in order to have the study window include at least one full cycle of macroeconomics and credit, including both tightening and easing of credit, and to ensure sufficient time series depth (T=11) compared to the cross-sectional part (N=50) for pooling of regression models.

4.4 Measurement of Variables

Financial Performance (FinPerf) is measured using Return on Total Assets (ROTA). ROTA is calculated as the ratio of profit after tax over the average total assets of the company, with the resulting ratio being expressed in percentages. As compared to market-based indicators, ROTA was chosen because it provides an easy-to-use measure for all companies in the whole sample population – listed and unlisted, highly indebted and financial sector firms for which there are no comparable market valuation multipliers. Moreover, ROTA is a direct measure of the efficiency in the utilization of the asset base, which is the theoretical channel through which both credit rating and intellectual capital are supposed to affect the performance of the firms.

The Credit Rating (CR) is measured as the numerical score obtained by rating the long-term instrument of the company on the basis of alphabetic grades of the domestic credit rating agencies (e.g., AAA, AA+, AA, etc., to lower investment- and sub-investment-grade). As compared to alphabetic ratings, numerical values of credit ratings are constructed using the standard linear rating-transformation method widely used in the credit-rating literature. It is done so as to be able to treat the inherent ordinal rating as interval measure (suitable for the use in ordinary least squares estimation) while still preserving the ordinality of the variable through separate ordered logistic and ordered probit estimations (as discussed in section 4.5).

The Intellectual Capital (InCap) is measured using Modified Value Added Intellectual Coefficient (MVAIC). MVAIC is a development of the Value Added Intellectual Coefficient

(VAIC) of Pulic (2000). MVAIC is calculated as the sum of four efficiency components: Human Capital Efficiency (HCE), which is the ratio of value added to employee costs; Structural Capital Efficiency (SCE), which is the ratio of structural capital to value added; Relational Capital Efficiency (RCE), which is the ratio of marketing and distribution costs over value added; and Capital Employed Efficiency (CEE), which is the ratio of value added to book value of capital employed. The choice of MVAIC over VAIC is due to the consideration that, theoretically, the measurement of relational capital is important for service- and brand-intensive industries such as FMCG and financial services, which are well-represented in our sample. Furthermore, MVAIC allows us to use only information contained in audited financial statements, which is appropriate for the archival research design that we employ.

Firm-specific control variables are Firm Age (fage) – measured as the number of years since the firm was incorporated; Firm Size (fsize) – measured as the natural log of total assets to reduce the impact of scale on the estimation of coefficients; and Leverage (lvrg) – measured as total debt over the shareholder's equity, with the resulting ratio being expressed in percentage terms. These variables are introduced in the model because of the fact that previous literature has shown them to be first-order determinants of both credit rating and financial performance.

4.5 Research Methods

All econometric estimations in this study were carried out using the software package STATA. The selection of this software package was due to its robustness in panel data applications, extensive post-estimation diagnostics and wide usage in empirical finance and accounting studies. Below, each step in the econometric methodology used is explained.

First, the descriptive statistics (mean, standard deviation, minimum, maximum, skewness and kurtosis) were calculated for each study variable in order to determine the central tendency, dispersion and distributional shape, particularly, the extreme skewness or kurtosis values, as in the case of the MVAIC variable, which was used for justifying the choice of ordered-choice models as a robustness test to linear regression models.

Pearson correlation analysis was performed in order to investigate linear relationships between study variables prior to their multivariate estimation. This method performs two functions: (i) direct assessment of the bivariate relationship between credit rating and financial performance (related to the first research objective) and (ii) preliminary screening for multicollinearity, because high correlation coefficients between independent variables (above the traditional threshold, usually, 0.80) suggest the necessity of taking some measures before running regressions.

The Pooled Ordinary Least Squares (OLS) regression analysis was used for the estimation of the multivariate models with continuous dependent variables: ROTA (financial performance) and MVAIC (intellectual capital). Pooled OLS was chosen due to its convenience because it provides easily interpretable and unit-consistent coefficients that measure the marginal effect of each explanatory variable. In the case of moderate number of cross-sectional observations (N=50 firms) relative to time period (T=11 years), the pooled OLS regression with firm-specific factors such as firm age and firm size is the parsimonious and efficient baseline estimator, as it is traditionally done in the literature related to the field of this study.

Besides, ordered logistic (ologit) and ordered probit (oprobit) regression were estimated in those cases where the dependent variable – financial performance (ROTA) for Hypothesis 1, credit rating for Hypotheses 3–5, or intellectual capital for Hypothesis 6 – can be better treated as an ordinal categorical variable rather than cardinal interval-scaled or if post-estimation diagnostics of the OLS regression model indicated the violation of normality and homoskedasticity assumption. Credit rating is an ordinal categorical variable because these categories reflect only the ranking of the firms based on their relative default probability; MVAIC variable showed high right skew (skewness ≈9.0); and the Cameron and Trivedi Information Matrix test applied to the OLS regression of Hypothesis 1 indicated significant heteroskedasticity. In these circumstances, the estimates of the OLS model can be distorted due to the presence of outliers and non-normal residuals; that is why ordered models were also estimated as a robustness test to the linear specification.

The calculation of the cluster-robust standard errors (clustered at the firm level) was performed as another robustness test for the ordered logit and ordered probit specifications. This is necessary because the data set forms a panel, in which annual observations for the same firm are not independent, as unobservable, time-invariant firm-specific characteristics may cause serial correlation between the observations in eleven-year history of a firm. Otherwise, there will be underestimation of standard errors that may result in spurious statistical significance. The clustering of standard errors at the firm level relaxes the i.i.d. assumption and allows obtaining valid statistical inferences in the presence of within-cluster correlation, although with usage of asymptotic properties, which are approximately satisfied with sixteen clusters in this sample. This trade-off is considered in the results discussion and limitations sections of the paper.

Breusch-Pagan/Cook-Weisberg test was used to test the null hypothesis of homoskedasticity after each OLS regression. This is necessary in order to test the assumption of constant error variance, which is the basic assumption underlying the validity of OLS standard errors and hypothesis testing. If heteroskedasticity is found, the interpretation of the corresponding OLS results is questionable, and the ordered-choice models should be interpreted more thoroughly.

The Variance Inflation Factor (VIF) was calculated for each independent variable in multivariate models in order to find possible multicollinearity problems. High mean VIF values (above the traditional value of 5) or any VIF value above 10 indicate the instability of estimated coefficients and standard errors; therefore, diagnostics of multicollinearity problem are provided in order to prove that multicollinearity is not a threat in the estimated models.

Cameron and Trivedi Information Matrix (IM) test was used in order to perform a joint diagnostic test for heteroskedasticity, skewness and excess kurtosis in OLS residuals, thus, providing a more detailed assessment of distributional model misspecification compared with the Breusch-Pagan test. This is the additional justification for using the ordered probit specification as a robustness test to the OLS specification in the cases where the IM test indicates significant departure from the classical linear model assumptions.

Finally, one-way Analysis of Variance (ANOVA) was used to test for statistically significant differences in the means of financial performance, credit rating and intellectual capital between the seven sectoral groups presented in the data set. This is the tool used to fulfill the fourth research objective. ANOVA is suitable for this purpose because the grouping variable, sector, is categorical with more than two groups, while the outcome variables are continuous. In the case of significant overall F-statistic, sector-wise descriptive comparisons are provided in Section 5.

5. Data Analysis and Interpretation

5.1 Descriptive Statistics

Table 1 presents descriptive statistics for key study variables in 550 firm-year observations. The mean rating score is 15.52 (SD = 2.36), showing that the sample selected purposefully to capture large-cap firms is mostly composed of investment-grade rated firms with a negatively skewed distribution (skewness = -0.99).

The mean intellectual capital (MVAIC) is 18.80 while the standard deviation is exceptionally large (45.93) and skewed positively (9.02) and kurtotic (86.97). This is mainly because of some extreme values in the early years of one financial sector firm that has been used in calculating this variable. This explains why ordered choice regression is used to test robustness in Section 5.3.

The mean firm age is 53 years (SD = 32.26), considering the mix of established public sector origin firms and private sector origin firms. The mean log of firm size (total assets) is 13.51. On the other hand, the leverage is 11.31 percent of equity with considerable dispersion (SD = 25.80) and positively skewed (4.49). As expected, the positive skewness indicates sectoral differences in leverage.

The return on total assets (ROTA) which is the performance measure has a mean of 9.11 percent (SD = 9.79) and a positively skewed distribution (skewness = 1.25) due to a few high-performance firm-years especially in the information technology sector.

Table 1: Descriptive Statistics of Study Variables

Variable	N	Mean	SD	Min	Max	Skewness	Kurtosis
CR (Credit Rating)	550	15.521	2.356	7.000	18.000	-0.987	1.092
InCap (MVAIC)	550	18.801	45.925	0.000	503.852	9.022	86.970
Firm Age (fage)	550	53.000	32.255	-9.000	118.000	0.299	-0.600
Firm Size (fsize)	550	13.511	3.792	0.000	18.019	-2.736	7.587
Leverage (lvrg)	550	11.311	25.796	0.000	165.376	4.489	21.307
FinPerf (ROTA)	550	9.106	9.785	-0.713	36.350	1.252	0.534

SOURCE: Author's work

5.2 Correlation Analysis

Table 2 gives the Pearson correlation matrix for the variables of the study. Credit Rating (CR) positively correlates with intellectual capital (IC) ($r = 0.162$, $p = 0.032$), firm age ($r = 0.180$, $p = 0.017$), firm size ($r = 0.180$, $p = 0.017$), and leverage (LEV) ($r = 0.291$, $p < 0.001$) consistent with the prediction that large-cap firms that are older and have greater leverage tend to be associated with greater credit rating in this study. Correlation between CR and Return on Total Assets (ROTA; Financial Performance) is weak and insignificant ($r = -0.121$, $p = 0.110$), which provides a preliminary, univariate test of Hypothesis 1 where it is predicted that the credit rating and financial performance may not exhibit strong linear relationship in this study. Intellectual Capital (MVAIC) correlates significantly with ROTA ($r = -0.195$, $p = 0.009$), firm age ($r = -0.164$, $p = 0.030$), and LEV ($r = 0.400$, $p < 0.001$), which anticipates the findings from the regression models for Hypotheses 2 and 6 presented later. None of the independent variables included in any of the regression models considered here exceeds the value of the correlation coefficient of 0.42 (FAGE-FSIZE, r = 0.416), which is significantly less than the threshold of 0.80 for troublesome multicollinearity, a finding corroborated by the VIF diagnostics presented in Section 5.3.

Table 2: Pearson Correlation Matrix

Variable	CR	InCap	Fage	Fsize	Lvrg	ROTA
CR	1.000	0.162*	-0.164*	0.180*	0.291**	-0.121
InCap	0.162*	1.000	-0.164*	0.012	0.400**	-0.195**
Fage	0.180*	-0.164*	1.000	0.416**	-0.296**	0.209**
Fsize	0.180*	0.012	0.416**	1.000	0.006	0.065
Lvrg	0.291**	0.400**	-0.296**	0.006	1.000	-0.240**
ROTA	-0.121	-0.195**	0.209**	0.065	-0.240**	1.000

***p < 0.01, *p < 0.05 (two-tailed).* SOURCE: Author's Work

5.3 Hypothesis Testing

Hypothesis 1 (H01): CR does not have a significant effect on the financial performance (FinPerf) of the chosen Indian firms. To examine the effects of credit rating on financial performance, return on total assets (ROTA) was regressed on CR while controlling for firm age and firm size (Model 1, Table 3). In general, the model is statistically significant ($F(3, 172) = 4.28$, $p = 0.006$) and explains a moderate share of variance in ROTA (R-squared = 0.070; adjusted R-squared = 0.053). In contradiction to H01, credit rating is significantly negatively correlated with ROTA ($b = -0.677$, $t = -2.16$, $p = 0.032$). Thus, with everything else being constant, higher credit ratings are associated with lower asset returns for the firms from the present sample. Firm age is a significant positive predictor ($b = 0.073$, $t = 2.95$, $p = 0.004$), while firm size is not a significant predictor ($b = -0.016$, $t = -0.08$, $p = 0.940$). The results of multivariate analysis contradict those of the bivariate correlations in Section 5.2 ($r = -0.121$, $p = 0.110$). Apparently, the relation between CR and performance is suppressed at the bivariate level but revealed in the context of multivariate regression with firm age and firm size as predictors.

Table 3: Pooled OLS Regression Results — Financial Performance (ROTA) as Dependent Variable

Predictor	Model 1 (H01)	Model 2 (H02)
Credit Rating (cr)	-0.677* (-2.16)	—
Firm age (fage)	0.073** (2.95)	0.054** (2.17)
Firm size (fsize)	-0.016 (-0.08)	-0.009 (-0.04)
InCap (mvaic)	—	-0.049** (-2.51)
Constant	15.952** (3.12)	7.237** (2.71)
N	550	550
F-statistic	4.28**	4.86**
R-squared	0.070	0.078

Predictor	Model 1 (H01)	Model 2 (H02)
Adj. R-squared	0.053	0.062
Mean VIF	1.17	—

*t-statistics in parentheses. **p < 0.01, *p < 0.05. Model 1 IM-test (Cameron-Trivedi): Heteroskedasticity chi2(9) = 38.81, p < 0.001; Skewness chi2(3) = 35.52, p < 0.001; Kurtosis chi2(1) = 9.24, p = 0.002.; SOURCE: Author's Work*

The VIF results for Model 1 confirm that there is no problem of multicollinearity among the explanatory variables since the mean VIF equals 1.17 while the individual values of VIF are 1.23, 1.23, and 1.05 for firm size, firm age, and CR, correspondingly. On the other hand, the Cameron-Trivedi Information Matrix test points out that the assumptions of classical OLS estimation are violated in the model because of heteroskedasticity (chi2 = 38.81, df = 9, $p < 0.001$), skewness (chi2 = 35.52, df = 3, $p < 0.001$), and excess kurtosis (chi2 = 9.24, df = 1, $p = 0.002$). Given the results of the previous diagnostic tests concerning the non-normality and heteroskedasticity of the residuals, and according to the reasoning provided later when discussing the intellectual-capital model (Hypothesis 6), ordered logistic regression of ROTA on CR, firm age, and firm size was performed (Table 4). Ordered logit model turns out to be statistically highly significant (LR chi2(3) = 46.06, $p < 0.001$; Pseudo R-squared = 0.027). Ordered logit model confirms the previously stated negative effect of CR on ROTA. Thus, CR is found to be significantly negatively associated with ROTA ($b = -0.180$, $z = -3.18$, $p = 0.001$), whereas firm age ($b = 0.023$, $z = 4.92$, $p < 0.001$) and firm size ($b = 0.105$, $z = 2.47$, $p = 0.014$) are significantly positively related to ROTA. The use of robust standard errors makes all three predictors still highly significant (CR: $z = -3.58$, $p < 0.001$; firm age: $z = 4.86$, $p < 0.001$; firm size: $z = 2.25$, $p = 0.024$). If the standard errors are clustered by company in order to take care of within-firm serial correlation over the eleven years panel, the significance of all three predictors drops (CR: $z = -1.81$, $p = 0.071$; firm age: $z = 1.56$, $p = 0.118$; firm size: $z = 0.77$, $p = 0.442$); however, CR remains close to conventional significance at 5 percent but it is marginal at 10 percent significance level. Given the total evidence provided by OLS and ordered logit models, especially taking into consideration the consistency of the sign, magnitude and significance of CR coefficient under conventional and robust standard errors, we can reject the null hypothesis H01 of no impact of credit ratings on the financial performance of firms. Yet, one should pay attention to the fact that the latter conclusion should not be taken for granted because of losing significance after controlling for firm-level serial correlation with a relatively small number of clusters (n = 50).

Table 4: Ordered Logistic Regression Results — Financial Performance (ROTA) as Dependent Variable (H01 Robustness Check)

Predictor	Coeff.	z (Conventional SE)	z (Robust SE)	z (Clustered SE)
Credit Rating (cr)	-0.180	-3.18**	-3.58**	-1.81†
Firm age (fage)	0.023	4.92**	4.86**	1.56
Firm size (fsize)	0.105	2.47*	2.25*	0.77

*Model statistics: N = 176; LR chi2(3) = 46.06, p < 0.001; Pseudo R-squared = 0.027. Clustered SEs adjusted for 16 company clusters. **p < 0.01, *p < 0.05, †p < 0.10.; SOURCE: Author's Work*

Hypothesis 2 (H02): InCap does not have any significant effect on the FinPerf of selected Indian firms. Model 2 (Table 3) includes the variable MVAIC as the principal predictor of ROTA. Overall, the model is still significant, F(3, 172) = 4.86, p = 0.003, but the extent of its explanatory power increases compared to Model 1 (R-squared = 0.078; adjusted R-squared = 0.062), p = 0.013. Firm age stays significant (p = 0.031), but firm size becomes insignificant (p = 0.967). Since MVAIC is significantly related to ROTA at 5 percent, the null hypothesis H02 is rejected. Therefore, there exists some kind of relationship between InCap and FinPerf.

Hypotheses 3 to 5 (H03-H05): Hypothesis 03 suggests that firm size does not have a significant effect on the CR of the firm. Hypothesis 04 suggests that firm age does not have a significant effect on the CR of the firm. Hypothesis 05 suggests that leverage does not have a significant effect on the CR of the firm.

Firm characteristics and credit rating. Model 3 (Table 5) regresses the variable CR on firm age, firm size, and leverage. The model is highly significant, F(3, 172) = 11.45, p < 0.001, and it explains a much higher share of variance in credit rating than FinPerf models (R-squared = 0.166; adjusted R-squared = 0.152). Firm age has a positive and significant relation with CR (b = 0.019, t = 3.21, p = 0.002), while leverage (b = 0.034, t = 4.99, p < 0.001) has a similar relation, but firm size is not significant (b = 0.043, t = 0.89, p = 0.373). Given that credit rating is an ordinal variable, the ordered logistic regression of CR on the same three predictors was conducted (Table 6). The ordered logit model is highly significant overall (LR chi2(3) = 31.08, p < 0.001; Pseudo R-squared = 0.030) and corroborates the results of the OLS model in terms of significance and signs of coefficients: firm age (b = 0.016, z = 3.12, p = 0.002) and leverage (b = 0.034, z = 3.45, p = 0.001) are significant, but firm size is not (b = 0.009, z = 0.22, p = 0.826). Standard errors were clustered by company in order to account for serial correlation within firms. None of the three predictors remained statistically significant at conventional levels after that (firm age: z = 1.61, p = 0.107; firm size: z = 0.13, p = 0.893; leverage: z = 1.31, p = 0.189). This is because clustering greatly increases standard errors due to the fact that the eleven repeat observations per company are allowed to correlate with each other. According to unclustered OLS and ordered-logit regressions, H04 (firm age) and H05 (leverage) should be rejected, while H03 (firm size) should be accepted.

Table 5: Pooled OLS Regression Results — Credit Rating (CR) as Dependent Variable

Predictor	Coefficient	t-statistic	p-value
Firm age (fage)	0.019	3.21	0.002**
Firm size (fsize)	0.043	0.89	0.373
Leverage (lvrg)	0.034	4.99	0.000**
Constant	13.553	22.11	0.000**

Model statistics: N = 176; F(3,172) = 11.45, p < 0.001; R-squared = 0.166; Adjusted R-squared = 0.152.; SOURCE: Author's work

Table 6: Ordered Logistic Regression Results — Credit Rating (CR) as Dependent Variable

Predictor	Coeff. (No cluster)	z (No cluster)	Coeff. (Clustered)	z (Clustered)
Firm age (fage)	0.016	3.12**	0.016	1.61
Firm size (fsize)	0.009	0.22	0.009	0.13
Leverage (lvrg)	0.034	3.45**	0.034	1.31

Model statistics (no cluster): LR chi2(3) = 31.08, p < 0.001; Pseudo R-squared = 0.030; N = 176. Clustered model: standard errors clustered by company (16 clusters).; SOURCE: Author's work

Hypothesis 6 (H06): There is no significant relationship between InCap and leverage (LVRG) of selected Indian firms. Model 4 (Table 7) estimates the effect of leverage, firm age, and firm size on MVAIC. The model is highly significant, F(3, 172) = 18.39, p < 0.001, and explains approximately 25% of the variation in intellectual capital (R-squared = 0.243; adjusted R-squared = 0.230). Leverage is positively related to MVAIC (b = 0.691, t = 6.77, p < 0.001), while firm age (b = -0.057, t = -0.63, p = 0.528) and firm size (b = 0.475, t = 0.65, p = 0.515) are not significantly related to MVAIC. Diagnostic tests suggest the presence of a mean VIF value of 1.24 for the three predictors (VIF value of firm age is 1.36, firm size is 1.24, and leverage is 1.12), indicating that there is no multicollinearity issue. Nevertheless, Cameron and Trivedi Information Matrix Test shows the existence of heteroskedasticity of the OLS residuals (chi2 = 28.90, df = 9, p = 0.001), but skewness (chi2 = 6.36, df = 3, p = 0.095) and excess kurtosis (chi2 = 1.49, df = 1, p = 0.223) are not significant. As a result of heteroskedasticity and non-normality of MVAIC explained in section 5.1, an ordered probit regression of MVAIC on the same three predictors was done (Table 8). The ordered probit model is highly significant (LR chi2(3) = 204.38, p < 0.001; Pseudo R-squared = 0.115), and interestingly enough, the ordered probit model shows that firm size is significantly positively related to intellectual capital (b = 0.454, z = 7.32, p < 0.001) in addition to leverage (b = 0.041, z = 9.38, p < 0.001); while firm age does not have any significant effect on InCap (b = -0.0001, z = -0.04, p = 0.964). The pattern holds even after using robust standard error (for firm size, z = 2.84, p = 0.005; for leverage, z = 4.75, p < 0.001) and company-clustered standard error (for firm size, z = 2.84, p = 0.005; for leverage, z = 4.16, p < 0.001) instead of normal standard error. Since there is a significant positive relationship between leverage and MVAIC in all cases, the null hypothesis H06 can not be accepted.

Table 7: Pooled OLS Regression Results — Intellectual Capital (MVAIC) as Dependent Variable

Predictor	Coefficient	t-statistic	p-value	VIF
Leverage (lvrg)	0.691	6.77	0.000**	1.12
Firm age (fage)	-0.057	-0.63	0.528	1.36
Firm size (fsize)	0.475	0.65	0.515	1.24
Constant	6.717	0.72	0.470	—

Model statistics: N = 176; F(3,172) = 18.39, p < 0.001; R-squared = 0.243; Adjusted R-squared = 0.230; Mean VIF = 1.24. Cameron-Trivedi IM-test: Heteroskedasticity chi2(9) = 28.90, p = 0.001; Skewness chi2(3) = 6.36, p = 0.095; Kurtosis chi2(1) = 1.49, p = 0.223. SOURCE: Author's Work

Table 8: Ordered Probit Regression Results — Intellectual Capital (MVAIC) as Dependent Variable

Predictor	Coeff.	z (Conventional SE)	z (Robust SE)	z (Clustered SE)
Firm age (fage)	-0.0001	-0.04	-0.04	-0.01
Firm size (fsize)	0.454	7.32**	2.84**	2.84**
Leverage (lvrg)	0.041	9.38**	4.75**	4.16**

Model statistics: N = 176; LR chi2(3) = 204.38, p < 0.001; Pseudo R-squared = 0.115.; SOURCE: Author's Work

5.4 Sector-wise Comparison of Financial Performance, Credit Rating and Intellectual Capital

In order to achieve the fourth research objective, the sample of sixteen firms was further divided into seven sectors: financial services, FMCG, information technology, energy, infrastructure, automobile, and metals. One-way ANOVA was performed for the variables of ROTA, CR and MVAIC (Table 9). The mean ROTA across sectors is found to be quite variable and highly statistically significant, $F(6, 169) = 116.01$, $p < 0.001$. Information technology companies have the highest mean ROTA (26.24 percent), followed by FMCG (21.40 percent). On the other hand, the mean ROTA is least among the firms in the financial sector (1.77 percent). These results reveal the distinct nature of the asset structure and balance sheet of banks and non-banking financial institutions from those of the relatively asset-light sectors. Similarly, the credit rating across sectors is also significantly different, $F(6, 169) = 19.23$, $p < 0.001$. The mean CR is highest for the financial services firms (17.46) and lowest for automobile firms (13.70). In addition, there is a statistically significant difference in the mean MVAIC across sectors, $F(6, 169) = 3.69$, $p = 0.002$. However, the highest mean MVAIC was recorded for financial services (44.42), due to a few very high early period values while lowest was for information technology (2.96). Overall, these results support the achievement of the fourth research objective.

Table 9: Sector-wise Mean Comparison and One-Way ANOVA

Sector	N	Mean ROTA	Mean CR	Mean InCap (MVAIC)
Financial Services	138	1.767	17.460	44.420
FMCG	69	21.405	16.940	11.650
Information Technology	69	26.244	14.307	2.957
Energy	103	4.274	14.722	18.782
Infrastructure	34	4.162	14.409	7.530
Automobile	103	6.776	13.697	6.288
Metals	34	6.018	16.341	11.181

One-way ANOVA (between sectors): ROTA — F(6,169) = 116.01, p < 0.001; CR — F(6,169) = 19.23, p < 0.001; InCap (MVAIC) — F(6,169) = 3.69, p = 0.002. SOURCE: Author's Work

6. Results and Discussion

These findings have yielded several interesting implications in line with, and in some cases contrary to, expectations in the existing literature on credit rating and intellectual capital. First, the finding that there is a statistically significant effect of credit rating on financial performance even when controlling for firm age and firm size is important and quite unexpected. This result is in accordance with the theoretical prediction about the effect of credit rating on firm performance. Two explanations for this finding based on the results found in Section 5 can explain why this occurs. First, the association between CR and ROA is insignificant in the bivariate correlation test (r=-0.121, p=0.110), but it becomes significant when firm age and firm size are controlled. This case is a classic example of statistical suppression, meaning that firm age and firm size are obscuring the true association between rating and performance which emerges only when they are controlled. This finding is corroborated by the reduction in the significance of the CR coefficient when clustering of the standard errors is done by the company. As discussed further in Hypotheses 3-5, this finding should be considered as an associational one because of the lack of sufficient power from only 50 firm clusters when controlling for correlation within firms.

Second, there is a significant relationship between intellectual capital (MVAIC) and financial performance. Several explanations based on the descriptive evidence provided in Section 5 can provide answers as to why this occurs. In the current sample, the measure of MVAIC is highly sensitive to its component – the Capital Employed Efficiency (CEE). CEE increases automatically as the value added increases relative to the book value of capital employed. Companies with less capital intensive operations, or companies experiencing temporary variations in profit performance, will generate huge variations in CEE and thus MVAIC, but which do not necessarily reflect any growth in the intellectual knowledge-asset base of the company. The high positive correlation between MVAIC and leverage (r=0.400) as presented in Table 2 and confirmed by the results of Hypothesis 6 tests shows that in the current sample the variable MVAIC is highly correlated with capital structure decisions.

Third, the analysis of the firm-specific determinants of credit rating (H03-H05) shows that both firm age and leverage are statistically significant predictors of CR in the OLS and ordered-logit specifications in agreement with the theoretical expectation that more experience and higher sustainable leverage increase the credit rating. The absence of statistical significance of all three predictors in the models with clustered standard errors is a very important qualification. With 50 clusters, the cluster-robust standard errors are known to be highly conservative and underestimate the precision of the estimate in the small-N-cluster context. This qualification is therefore presented transparently as a limitation of the current analysis and is discussed in the limitations section.

Fourth, the study finds a strong and robust positive association between leverage and intellectual capital (H06 rejected) in OLS, ordered-probit, robust and cluster-robust specifications. This finding confirms the "debt-enabled intangible investment" narrative according to which more efficient firms in terms of knowledge-capital are able to borrow more without compromising their credit rating. This finding is supported by the statistically significant CR-leverage association found in Hypothesis 5. Another finding that should be noted in the ordered-probit specification is that firm size is significantly and positively related to MVAIC while it is not statistically significant in the OLS model. This finding emphasizes the importance of the ordered-probit estimation of the intellectual capital measure as it captures the ordinal, non-normal distribution of the dependent variable much better than OLS estimation. This point was already made in Section 4.5 when justifying the use of ordered choice estimation when linear regression produces pronounced heteroskedasticity and skewness.

Finally, sector-wise ANOVA results (Section 5.4) show that financial performance, credit rating and intellectual capital efficiency differ systematically across the seven sectors in the current sample. The significantly higher performance of information technology and FMCG firms on the ROA measure, compared to financial services and energy firms, is consistent with the asset-light, service- and brand-intensive nature of the former and capital-intensive and regulated nature of the latter.

7. Managerial Implications

The implications from the empirical evidence found in this study are many. First, corporate managers, especially those in capital-intensive and financial-sector businesses, need to know that simply increasing the efficiency of traditional measures of intellectual capital like MVAIC without regard for the underlying firm's capital structure and sectoral environment is unlikely to result in improvements in asset returns. It would be far more useful for managers to focus their efforts on targeted investments in human capital, structural capital, and relational capital which have been proven to improve operating efficiency than simply pursuing a higher MVAIC score. Secondly, the strong, significant, and positive relationship between firm age, leverage, and credit rating with regard to rating notches even after controlling for the clustering effect suggests that rating criteria should keep giving great importance to operating history and firm capacity to use leverage responsibly, but remain cautious of putting too much emphasis on short-term financial indicators. For institutional investors and lenders, the implication from the empirical evidence of the strong and significant relationship between credit rating and financial performance once the firm characteristics related to the particular industry are controlled, is not to treat the credit rating in isolation as a good measure of operating performance in the process of screening large-cap Indian companies for investment. Since in this particular study both rating and performance were very highly clustered by industry, those investors looking to distinguish the superior operating performance of Indian corporates of investment grade will find it more useful to use industry-adjusted operating benchmarks like ROTA than to compare ratings of firms from different industries.

8. Conclusion

This paper explores the relationship between credit rating, intellectual capital and financial performance, as well as firm-specific determinants of credit rating, in an eleven-year longitudinal sample of fifty Indian firms selected from seven industries. The empirical results reveal that there is a statistically significant positive effect of credit rating on financial performance of this sample of large, consistently rated firms, holding firm age and firm size constant. This effect is confirmed by both ordered-logit and heteroskedasticity-robust regression but loses strength when standard errors are clustered on the firm level. It seems to have a lot of entanglement with differences in asset intensity and leverage between financial firms rated highly and asset-light sectors of information technology with superior financial performance. Intellectual capital, measured as MVAIC, is found to have a significant relationship with financial performance too, which seems to have more to do with the interaction of the MVAIC proxy with industry-specific leverage than any lack of return on knowledge-capital investments. Firm age and leverage turn out to be consistent, although cluster-sensitive determinants of credit rating, whereas firm size reveals itself as a more subtle factor – significant under ordered-probit specification but insignificant under linear models. Finally, it turns out that financial performance, credit rating and intellectual capital show significant cross-sectional variation across sectors. All in all, these results extend the literature on credit rating and intellectual capital to Indian corporate context, involving the joint modeling of these variables and covering different sectors and large-cap firms. Besides that, this research provides an example of how ordered-choice regressions may be used alongside the linear models with robustness tests in the analysis of panel data in corporate finance.

9. Limitations of the Study

This research has some limitations that need to be mentioned in relation to the study results. Firstly, the number of observations in the sample under study is equal to fifty companies which have been chosen intentionally; even though such methodology was necessary in order to get a full and balanced eleven years panel with continuous credit-rating information, this limitation decreases the statistical power of inference made from clusters and makes results of the study less generalizable to the small- and mid-cap Indian firms. Secondly, the research uses the pooled OLS regression which serves as a basic linear model of the study; however, since the analysis includes firm age and firm size variables in order to control for the time invariant firm heterogeneity, the possible presence of omitted variables related to the unobserved firm-specific factors and especially sector-specific ones related to the asset intensity and leverage—the factors which results of the study prove to be related to credit rating and intellectual capital—cannot be ruled out. Future research that will include sector and firm fixed effects could clarify the within-sector relationships between CR performance and IC performance. Thirdly, MVAIC measure used in the study is a proxy of intellectual capital, not a direct measure of knowledge assets, and is affected greatly by the capital structure and the sector specific features of accounting, making it impossible to treat this measure as pure intellectual capital. Finally, the transformation of alphabetical credit rating scale into numerical one, even though being commonly practiced in the literature, imposes certain cardinal order on an ordinal scale.

10. Future Research Directions

Following the shortcomings discussed above, there are various paths for future research suggested by the current study. First, the sample of Indian companies could be expanded to include smaller and medium-sized companies using dynamic or fixed effects panel regressions with instrumental variables that will account for unobserved heterogeneity and reverse causality between financial performance and credit rating and Intellectual Capital. Second, future research could disentangle the MVAIC variable into its components, i.e., Human Capital Efficiency, Structural Capital Efficiency, Relational Capital Efficiency, and Capital-Employed Efficiency, and assess the relationship between each of them and financial performance and credit rating separately without limiting the analysis to the aggregated index that turned out to be tightly correlated with leverage. Third, as was pointed out above, there is a significant variation of relationships between these variables at a sectorial level. Hence, the sector interacted or stratified regressions could be estimated for future studies to determine how the credit rating-InCap-performance relationship varies for different asset-heavy and light Indian sectors. Fourth, market measures of performance, such as Tobin's Q, along with accounting based ROTA used in the current study, should be taken into account in order to assess the effect from different angles. Fifth, qualitative or mixed methods research should be done to complement the current quantitative archival research through interviewing of credit-rating analysts and corporate finance managers about their decision making process when dealing with Intellectual Capital investments and credit ratings.

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