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Effect of Intellectual Capital on Firms' Competitive Advantage Condition: An Empirical Investigation in India

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Abstract: This paper aims to model the effect of intellectual capital on firms' competitive advantage condition across selected Indian industries. Using a panel dataset consisting of 146 Indian companies listed in the Bombay Stock Exchange (BSE), spanning across 7 industries during 2003 to 2012. The study suggests that the firms' competitive advantage condition is relatively better explained by some of the individual intellectual capital components rather than by the Public's Composite Value Added Intellectual Capital Coefficient (VAIC) measure. Physical and financial capital efficiency (VACA) statistically determines the firms' competitive advantage condition irrespective of the industry segments. However, along with VACA, human capital efficiency (HCVA) is also observed to be a significant determinant of firms' competitive advantage conditions for automobiles, consumer goods, health and pharmaceuticals and information technology industries. The result extends the understanding of how VAIC and other associated components determine competitive advantage condition of firms' across industries in India. To the best of authors' knowledge, for the first time the firms' competitive advantage condition is modeled in a VAIC framework.

Keywords: Intellectual capital; Competitive advantage; Physical capital; Structural capital and human capital; Innovative capital and relational capital

JEL Classifications: L20, L21, L25

1. Introduction

A firm's competitive advantage condition has a bearing on its possession and utilization of intellectual capital (IC) which has been drawing the attention of strategic management scholars for a long time. Porter (1985) defines competitive advantage as the ability of the firm to earn return on investment consistently over the industry average. IC has a significant impact on a firm's performance and development (Hall; 1992), growth and competitive advantage (Pfeffer; 1994, Tovstiga and Tulugurova; 2007 and Marr; 2008), growth and survival, (Stewart; 1997), economic value (Maguire; 2008) and export competitiveness (Kavida and Sivakoumar; 2010). Stewart (1997), Allee (1999), Wright *et al.* (2001), Chen and Lin (2004), Wall *et al.* (2004), Goh (2005) and Kong and Prior (2008) advocate that IC is critical in creating a competitive advantage for an organization in the long run.

Studies on IC measurement and its effect on firms' competitive behaviour are scanty in emerging economies. Given the significance of emerging economies to the world, to date, little work has been done in the emerging economies to provide an understanding of measurement, management and effect of IC on firms performance and competitive advantage conditions. To the best of our knowledge, no such study is available that examines the effect of firms' IC on their competitive advantage condition in a fastest growing emerging economy like India and thus, authors at work have made an attempt to fill such a gap.

2. Literature Review and Hypotheses Development

IC is categorized as intangible asset (Stewart, 1991); corporate strategic asset (Barney, 1991); human and structural capital (Bontis; 1999); human capital, organizational capital and customer capital (Edvinsson and Malone; 1997); physical, human and structural capital (Pulic; 1998); innovation, human and organizational capital (Lev; 2001) and human, information, organization capital (Marr and Chatzkel, 2004), physical, structural, human, innovative and relational capital (Tripathy *et al*., 2015). Stahle *et al.* (2011) argues that IC is difficult to conceptualize and categorize. However, existing stock of literature do not extend solidarity upon the universal definition of IC. Campisi and Costa (2008) argue that IC as a source of competitive advantage needs to be measured with appropriate methods.

But the literature broadly claims that whatever may be the measurement methods, IC is considered as packaged useful knowledge (Stewart, 1997), practical translation of combined knowledge into brands, trademarks and processes (Roos *et al*., 1997), a moving force for business success (Pulic, 2000), knowledge that derives tangible profit (Sullivan, 2000), differentials of a firm's market and book value (Edvinsson and Malone, 1997), capable of generating superior financial performance (Nazari and Herremans, 2007; Campisi and Costa, 2008) and major and increasing driver of long term competitive advantage (Ordóñez de Pablos, and Edvinsson, 2014). Moreover, IC is interchangeably used by several authors as intangibles, intangible resources, intangible goods, knowledge assets and intellectual resources and knowledge capital (Lev, 2000).

IC is mostly intangible in nature and considered as a corporate strategic asset which can generate competitive advantage for the firm (Barney, 1991; Stewart, 1991). A wide array of the literature considers the influential role of IC on firm performance (Barney, 1991; Pulic, 2000; Marr *et al*., 2003; Nazari and Herremans, 2007; Kamath, 2008; Campisi and Costa, 2008; Choudhury, 2010). It is a strategic tool against competitors (Naquiyuddin and Heong, 1992), meaningful factor of production that is superior to the physical and financial capital (Drucker, 1993). IC is the driver for firm productivity (Shiu, 2006), firm valuation (Tseng and James Goo, 2005; Wang and Chang, 2005; Tripathy *et al*., 2014, Tripathy *et al.* 2015), firm value creation (Cabrita and Landeiro Vaz, 2006), firm growth (Al-Twaijry, 2009) firm competitive advantage (Stewart, 1997; Johnson, 1999; Allee, 1999; Marr *et al*., 2003; Chen and Lin, 2004; Chen *et al*., 2005; and Kong and Prior, 2008). IC assets are necessary, but not sufficient to derive competitive advantage for firms Suciu (2006).

The varied theoretical viewpoints and empirical studies provide ample evidence that IC and matters for growth, performance, value, competitive advantage condition of the firms in the industry. Despite the significant amount of work on IC and firm's competitive advantage conditions across the world wide industries, there is still exist some missing links especially in the emerging countries. Thus, very little attention has been paid to the influence of IC on Indian firms' competitive advantage conditions in their respective industries. Against this backdrop, we hypothesise that:

H1-1a: Firms having a higher level of VAIC tend to have a competitive advantage in the industry.

The literature also suggests that changes in individual IC components also impact the competitive advantage condition of the firms. Pfeffer (1994) and Tovstiga and Tulugurova (2007) confirm that firms sustain fast growth and competitive advantage through their human capital. Hall (1992), Stewart (1997), Maguire (2008) and Marr (2008) posit that IC with its human, organizational and relational components significantly impact firm's performance, development, growth, survival efficiency, effectiveness and competitive advantages for the firm. Structural capital comprises firms' information systems, organizational structure and policies, strategies and databases and development such a capital would reduce costs and enhance profitability (Mondal and Ghosh, 2012). Bernadette (2000) claimed that structural capital includes all assets and values that would remain in the firm if all the employees left the firm. Thus it is very important as they are the only assets that are truly owned by the firms. In addition, Bontis (1998) also stated that structural capital supports employees in their effort to achieve maximum intellectual performance. Therefore, both human capital and structural capital support each other in the process of developing value for the firms. Hitt *et al.* (2001) suggest that the firm's competitive advantage rests on its IC and physical capital, while the role of intangible capital finds a dominant place over and above the tangible capital in this context.

Drawing on the findings of the previous studies it is somewhat understood that IC associated components may be considered as important determinants of the firm's competitive advantage. Against this backdrop, we hypothesize that:

H2-1a: Firms having higher level of VACA tend to have a competitive advantage condition in the industry.

H2-2a: Firms having higher level of HCVA tend to have a competitive advantage condition in the industry.

H2-3a: Firms having higher level of SCVA tend to have a competitive advantage condition in the industry.

The literature also suggests that changes in individual intellectual components like relational capital and innovative capital also impact the competitive advantage condition of the firms in the industry. Sullivan (1998) posits that the innovative capital is the core of IC providing the base for gaining competitive advantage. Roos *et al*. (2005) relational capital includes all the firms' relationships with customers, suppliers, intermediaries, representatives, partners, owners and lenders. Hence the relational capital would be able to create competitive advantages for the firm through the establishment of a distinctive core competency in the form of relationships embedded into organization controlled networks (Subramaniam and Youndt, 2005). Cabrita and Vaz (2006), reveal that social capital and relational capital have a direct effect and human capital has an indirect effect on competitive advantage of the banks. Kong and Prior (2008) affirm that relational capital enables the links between diverse groups and organizations, while also providing a rationale for continued inter and intra organizational relationships with a variety of stakeholders. On the basis of above arguments, we hypothesize that:

H3-1a: In the presence of high level of VAIC, firms having a higher level of relational capital tend to have a competitive advantage in the industry.

H3-2a: In the presence of high level of VAIC, firms having a higher level of innovative capital tend to have a competitive advantage in the industry.

H3-3a: After controlling SCVA, firms with higher relational capital efficiency (SDBV) tend to have a competitive advantage in the industry.

H3-4a: After controlling SCVA, firms with higher innovation capital efficiency (RDBV) tend to have a competitive advantage in the industry.

It is expected that the firms will build up their IC base in order to face up to intense competition. Competition in the market space will direct the managers to secure the best available human, physical and structural resources. These resources will affect a firm's competitive advantage position in the industry space; the firms who spend more on these resources are expected to have a greater competitive advantage in the market space. Against this backdrop, aforesaid hypotheses are examined to seek a better understanding of the effect of IC on firms' competitive advantage conditions in India. The outcome of the study provides additional evidence as to the usefulness of IC by examining the explanatory and predictive power of IC in predicting a firm's competitive advantage conditions in an emerging market context.

The rest of the paper is organized as follows: The section 3 deals with the research design, in which the conceptual framework, the data and the sample selection, along with the variables and the construction methodologies and the econometric models employed in the paper, are discussed. The empirical findings are presented in the section 4. The last section delineates the conclusions that arise from the study.

3. Research Design

3.1 Conceptual framework

A conceptual model is presented following the wide arrays in the literature that show the expected effect of the IC composite measure and its different dimensions including innovative capital and relational capital on a firm's competitive advantage and disadvantage conditions.

3.2 Data and sample selection

The study is based on the secondary data, which are obtained either from the Center for Monitoring Indian Economy (CMIE) Prowess database or from annual reports of the individual companies. In selecting the sample firms for the study, all listed and permitted companies in BSE, during the study period are brought under the sampling frame. An extensive search is carried out in the Prowess database to gather the required data for the empirical analysis. There is a large number of Indian companies, which are no doubt in the stock market, however such companies are excluded from the present study due to two important reasons i.e. information bias in financial reporting and inaccessibility of detailed information desired to construct our variables.

A three stage filtering technique is used in selecting final sample firms for the study. At the first stage, we omitted those companies which do not have data at least for one of the parameters employed in the research. At the second stage, we omitted those companies which do not have at least 7 data points for all the parameters across the stated period. At the third stage, individual company's annual reports are consulted to fill the remaining missing cells and if this resulted impossible we dropped those companies except the ones missing data points across the parameters in the study period. Finally using nearest mean interpolation methods for the corresponding companies, at best one missing cell is filled in to arrive at the list of sample companies.

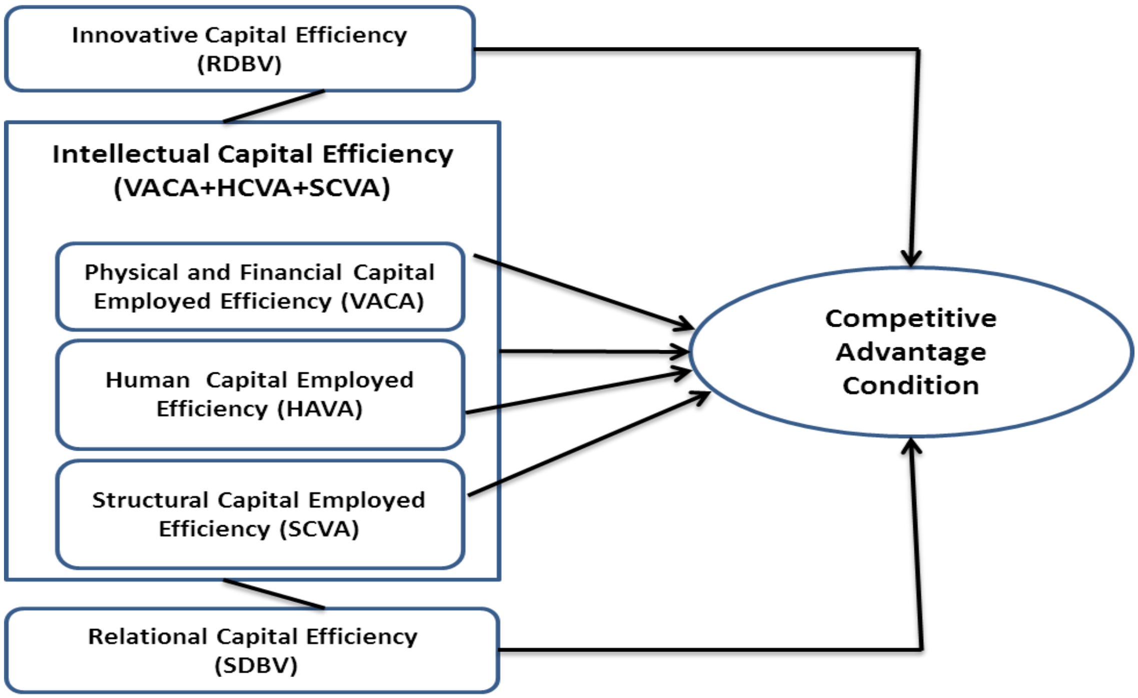

Figure 1. Conceptual framework

Finally, 146 firms qualified for the empirical investigation, where data is gathered in a panel set consisting of firms across 7 industry segments such as automobiles and accessories, consumer goods, healthcare and pharmaceuticals, information technology, infrastructure, and metal and mining industry for a decade (2003-2012). The detail distributions of the companies and a process flow chart of sample selection, data collection and analysis are presented in Table 1.

Table 1. Distribution of sample firms

Sector	No. of firms	Firms (%)
Automobiles & Auto Parts	19	13.01
Consumer Goods	19	13.01
Finance	24	16.44
Healthcare & Pharma	19	13.01
Information Technology	19	13.01
Infrastructure	24	16.44
Metal & Mining	22	15.07
Total	146	100.00

3.3 Constructs and variables

The first part in this sub-section delineates the proxies used for measuring the dependant variable (competitive condition) in the panel model framework. The second part discusses the construction and proxy selection methodologies for the interest and control variables. The study uses two broad segments of interest variables such as measuring IC at composite level and individual component levels.

3.3.1 Competitive advantage condition

The firm's competitive advantage in an industry at time t is computed using the comparative position of the firm's Return on Asset (ROA) and industry ROA. A firm's ROA is estimated by the firm's market capitalization divided by sum of market capitalization of all the firms in that industry for the given year. An industry's ROA is estimated by summing up all firms' ROA in that industry for the given year divided by the total number of firms in the said industry. Finally a firm's competitive advantage or disadvantage conditions are decided by comparing a firm's ROA with that of the industry ROA of a given year. If the firm's ROA is greater than the industry ROA for a specific year then the firm is considered to have the condition of competitive advantage. In the empirical investigation, a dummy variable is used where 1 represents the condition of a firm having competitive advantage and 0 is used to capture the condition of a firm having competitive disadvantage in the industry.

3.3.2 Intellectual capital efficiency measurement

The composition and measurement of IC remains a challenge for researchers and practitioners. Ramanauskaitė and Rudžionienė (2013) report that the academic literature engages more than sixty different methods of valuating intellectual of enterprises. Bontis (2002) posits that the evolutions of different methodologies are due to the complexity of IC measurement and valuation. We have adopted Pulic (1998) VAICTM method for intellectual capital measurement. It is an indirect measure of efficiency of the value added by corporate IC. This method provides information about the efficiency of tangible and intangible assets that can be used to generate value for a firm. The VAIC is composed of three major dimensions, these being Physical and Financial Capital employed efficiency (VACA), Human Capital efficiency (HCVA) and Structural Capital efficiency (SCVA). The rationale of choosing this method even with the inherent deficiencies emanates from two facts that some of our sample companies hail from the public sector and in such cases we find the extensive use of this method in the intellectual capital valuation literature.

Our choice of explanatory variables reflects both the theory of determinants of competitive advantage in connection with the intellectual capital and the data availability. We have used six explanatory variables such as VAIC, VACA, HCVA, SCVA, RDBV and SDBV, which are part of the VAIC measurement methodology (see Chin *et al*., 2005). To capture the combined effect of intellectual capital on firm's competitive advantage in the industry, VAIC is used as one of the composite explanatory variable. Individual components of VAIC are used as explanatory variables to capture the individual effect of intellectual capital on firm's competitive advantage condition in the industry. Further, RDBV and SDBV are used as separate explanatory variables, which emanates from few empirical investigations that show that VAIC calculation does not capture mostly the innovative capital and relational capital components of the firm. We thus, deploy hereunder the detailed method of measuring each of the components of VAIC.

Value Added (VA): The value added (VA) of a firm is defined as the difference between incomes from goods and services sold and material expense and services which have been bought. The VA computation methods for finance and non finance firms are different and we have followed Riahi-Belkaoui (2003) to such computation. The net earnings retained are computed as:

$$R = S - B - DP - W - I - D - T$$

where, R = retained earnings for the period, S = net sales revenue obtained for the period, B = cost of goods sold plus all operational and other expenses in the period apart from labour, taxation, interest, dividend and depreciation, DP = depreciation charged during the period, W = wages and salaries paid to the employees for the period, I = interest expenses paid during the period, D = dividends paid to the shareholders for the period, and T = taxes for the period. Rearranging terms, we get

$$S - B = DP + W + I + D + T + R.$$

The chart below shows the definitions and calculation of the terms used later.

Term	Definition	Calculation
VA (Value Added) of Non-Finance Firms	Value Added of Non-Finance Firms	Net Sales Revenue - Cost of Goods Sold
VA (Value Added) of Finance Firms	Value Added of Finance Firms	DP + W + I + D + R + T
VACA	The Physical and financial capital efficiency	VA made by employing physical and visible assets/employed capital
HCVA	The human capital efficiency	HCVA = VA generated by employees /Total Compensation to employees
SCVA	The structural capital efficiency (SC = VA – HC)	SCVA = SC/VA
VAIC	Value added Intellectual Capital Efficiency	VAIC = VACA+HCVA + SCVA
RDBV	The innovative capital efficiency	RDBV= Research and Development Expenses (RD)/ the Book Value (BV)
SDBV	The relational capital efficiency	SDBV= Sales & Distribution Expenses (SD)/ the Book Value (BV)

3.4 Econometric models

The probability of a firm being competitively advantaged or disadvantaged is modeled using a set of multivariate logistic regressions. In each period the firm is experiencing the condition of having either a competitive advantage or disadvantage in the industry. Accordingly our dependant variable, firm competitive advantage dummy takes the value 1, if the firm enjoys competitive advantage and takes the value 0 otherwise. The probability that a firm will enjoy competitive advantage in a particular year in a particular industry is hypothesized to be a function of a vector of n predictors ($X_{i,t}$). Let $P_{(i,t)}$ denote a dummy variable that takes the value 1 when the firm enjoys competitive advantage in industry i at time t and a value of 0 otherwise. α is a vector of n unknown coefficients and $F(\alpha' X_{(i,t)})$ is the cumulative probability density function evaluated at $\alpha' X_{(i,t)}$. In order to fit a logistic regression model to a given set of data the n unknown parameters, α_1, α_2, α_3, …, α_n have first to be estimated. These parameters are estimated using maximum log likelihood. The log likelihood function of the multivariate logistic regression is:

$$LnL = \sum_{i=1}^{7} \sum_{t=1}^{10} P(i,t) \ln\left[F\left(\alpha' X(i,t)\right)\right] + \left[1 - P(i,t)\right] \ln\left[1 - F\left(\alpha' X(i,t)\right)\right]$$

The logistic functional form is used in modelling multiple logistic probability distributions. The interpretation of the estimated coefficients that emerged from this functional form is quite different from the estimated coefficients in multiple regression. In this case a coefficient indicates the effect of change in predictor variable on $\ln[P(i,t)/(1-P(i,t)]$. Thus, the change in the probability value of whether the firm is to be competitively advantaged or otherwise depends on the initial values of all the predictors and their coefficients. The strength of association between explained and an explanatory variable is examined by the slope of the cumulative probability distribution function at ($\alpha' X(_{i,t})$) and the direction is examined by the sign of the coefficients.

To investigate whether intellectual capital and other associated components of it affect the firms' competitive advantage condition, five panel logit models out of which two are composite and three are segmented, are estimated. The choice of the panel model whether fixed or random effect is decided based on the result of the Hausman test. The specifications are defined as follows:

$$CA_{i,t} = \alpha_i + \beta_1 \mathrm{VAIC}_{\mathrm{i,t\text{-}j}} + \varepsilon_{i,t} \tag{1}$$

$$CA_{i,t} = \alpha_i + \beta_4 \mathrm{VAIC}_{\mathrm{i,t}} + \beta_5 \ \mathrm{RDBV}_{\mathrm{i,t}} + \beta_6 SDBV_{\mathrm{i,t\text{-}j}} + \varepsilon_{\mathrm{i,t\text{-}j}} \tag{2}$$

$$CA_{i,t} = \alpha_i + \beta_1 \mathrm{VACA}_{\mathrm{i,t\text{-}j}} + \beta_2 \mathrm{HCVA}_{\mathrm{i,t\text{-}j}} + \beta_3 \mathrm{SCVA}_{\mathrm{i,t\text{-}j}} + \varepsilon_{\mathrm{i,t\text{-}j}} \tag{3}$$

$$CA_{i,t} = \alpha_i + \beta_1 \mathrm{VACA}_{\mathrm{i,t\text{-}j}} + \beta_2 \mathrm{HCVA}_{\mathrm{i,t\text{-}j}} + \beta_3 \mathrm{SCVA}_{\mathrm{i,t\text{-}j}} + \beta_5 \ \mathrm{RDBV}_{\mathrm{i,t\text{-}j}} + \beta_6 SDBV_{\mathrm{i,t\text{-}j}} + \varepsilon_{\mathrm{i,t\text{-}j}} \tag{4}$$

$$CA_{i,t} = \alpha_i + \beta_1 \mathrm{VACA}_{\mathrm{i,t\text{-}j}} + \beta_2 \mathrm{HCVA}_{\mathrm{i,t\text{-}j}} + \beta_5 \ \mathrm{RDBV}_{\mathrm{i,t\text{-}j}} + \beta_6 SDBV_{\mathrm{i,t\text{-}j}} + \varepsilon_{\mathrm{i,t\text{-}j}} \tag{5}$$

where *i* stands for the individual firm varies from 1to 146; *t* stands for the year varies from 2003 to 2012; and *j* is a numerical value varies in between 0 and 1 so as to capture the contemporaneous and lag effect. $CA_{i,t}$ is a binary response variable, where 1 indicates a firm which enjoys competitive advantage in industry *i* , in a year *t*. Where, all the explanatory variables are metric in nature.

4. Results and Discussions

This section is organized under three sub-sections. Under the first one of these, the findings of the contemporaneous model are captured. Under the second and third sub-sections the results obtained from the lagged effect model and the before and after financial crisis effects are captured. While examining the soundness of a logistic regression model, there is a need to examine the (i) overall model evaluation, (ii) statistical tests of individual predictors, (iii) goodness-of-fit statistics, and (iv) validations of predicted probabilities. These evaluations are illustrated below for all 5 of the contemporaneous models, 5 lagged models and 5 before and after financial crisis effect models.

4.1 Findings from the contemporaneous model

Overall model evaluation: A logistic regression model is said to provide a better fit to the data, if the model outcome demonstrates an improvement over null model (model with intercept-only). An intercept-only model serves as a good baseline because it contains no predictors. Consequently, according to this model, all observations would be predicted to belong in the largest outcome category. An improvement over this baseline is examined by using the three inferential statistical tests: the likelihood ratio, score, and Wald tests. All three tests yield similar conclusions for all five models (Table 2). Thus it is inferred that, all five logistic models are observed to be more effective than their corresponding null models.

The quality of the model specification is examined here by the Akaike's information criterion (AIC). The realized AIC values across the contemporaneous models reveal that the regressions including intercepts and covariates seem to perform better compared to the regressions with intercepts only. However the fourth regression model appears to be the best model based on AIC. Further to check the over fitting of the data and model we have segregated and presented the overall model fitness test results classifying the dataset into two broad categories i,e, before 2008 and after 2008 models (Table 2). The results obtained from such segmented models corroborate our main findings in terms of specification and overall fitting of the data.

Table 2. Overall model evaluation test results for Firms' Competitive Advantage

Statistic	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Panel A: Contemporaneous effect					
Likelihood Ratio	137.7086***	144.6643***	208.167***	218.9686***	205.3768***
Score	71.6376***	84.0145***	141.6279***	146.2612***	133.7705***
Wald	67.8788***	75.4306***	129.2762***	138.8382***	122.353***
AIC (intercept only)	1997.952	1997.952	1997.952	1997.952	1997.952
AIC(intercept & covariates)	1862.243	1859.288	1795.785	1788.983	1800.575
Panel B: Lag effect					
Likelihood Ratio	127.6039***	134.0385***	194.0756***	203.3981***	190.7383***
Score	67.5974***	79.903***	131.2865***	134.8096***	125.0703***
Wald	63.1066***	70.4403***	121.7519***	129.2685***	114.1378***
AIC (intercept only)	1795.435	1795.435	1795.435	1795.435	1795.435
AIC(intercept & covariates)	1669.831	1667.397	1607.36	1602.037	1612.697

Note: ***, ** and * indicate 1% , 5% and 10% level of statistical significance, respectively.

Statistical tests of individual predictors: The impact of changes in the independent variables on the probability of whether the firm enjoying competitive advantage at time t in the industry 'i' is estimated by assuming a logistic distribution for all five models. Therefore, the coefficients attached with all the models βi indicate the impact of a change in the corresponding independent variable on the natural log of odds of a firm's competitive advantage. We are interested in the sign and magnitude of the coefficients attached to the predictors in the respective models.

If $\beta_i > 0$; then the odds of firms' competitive advantage gets positively influenced by the corresponding predictors and if $\beta_i < 0$, then the reverse would be true. The sign of the estimated coefficients in the model would indicate complementarily or substitutability between them in creating a condition for odds of firms' competitive advantage. Keeping all these treatments in mind we present below the results of the logistic regression:

While examining Model 1 and Model 2, it is observed if that the coefficient attached to the VAIC is greater than zero ($\beta > 0$), then the odds of a firm's competitive advantage are positive and significant at the 1% level of significance. This is also inferred from the coefficients of the relational capital in Model 2 which show the complementarities with the VAIC and positively influence the odds of firms' competitive advantage position. While examining the sign of the VACA, HCVA and SCVA in Models 3, 4 and 5 respectively, it is revealed that all three individual components of intellectual capital are positive and statistically significant at the 1% level. The results here suggest that the deployment of VACA, HCVA and SCVA are creating a condition for odds of firms' competitive advantage in the Indian industry space. The sign of the innovative capital and the level of significance confirms a negative and somewhat weak association with firms' competitive advantage, which means the investment on research and development in Indian firms in general fails to create a condition for odds of firms' competitive advantage. However, comparing the sign and coefficients of the relational capital in the composite VAIC models (Models 1 and 2) and component based models (Models 3, 4 and 5), the signs is do not conform (Table 3).

Table 3. Logistic regression parameters estimation for the firms' competitive advantage obtained from the contemporaneous model

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-1.008*** (-10.33)	-0.952*** (-9.55)	-1.865*** (-11.59)	-1.894*** (-11.41)	-1.592*** (-11.50)
VACA			1.502*** (7.94)	1.653*** (7.91)	1.614*** (7.86)
HCVA			0.095*** (6.37)	0.084*** (5.65)	0.112*** (7-99)
SCVA			0.501*** (2.57)	0.705*** (3.25)	
RDBV		-5.497** (-2.43)		-3.961* (-1.81)	-2.826 (-1.20)
SDBV		0.279* (1.83)		-0.562* (-1.89)	-0.397 (-1.41)
VAIC	0.112*** (8.24)	0.105*** (7.71)			
Number of obs	1460	1460	1460	1460	1460
Chi Square	137.71***	144.66***	208.17***	218.97***	205.38***
Pseudo R^2	0.069	0.0725	0.104	0.110	0.103
Log likelihood	-927.122	-925.644	-893.892	-888.492	-895.288

Note: ***, ** and * indicate 1% , 5% and 10% level of statistical significance, respectively.

The odds ratios are usually the important parameters in a logistic regression. However, the estimated odds ratios tend to have skewed distribution with possible values ranging between 'zero' and 'infinite' with the null value equating 1. Hence keeping this theoretical issue in mind, along with the point estimates, 95% confidence intervals for the odds ratios were obtained by first calculating the end points of the confidence intervals for the coefficients and then exponentiating them.

The confidence interval estimates of the odds ratio for the VAIC suggest that the probability of the odds of a firm being in the situation of competitive advantage is 1.119 [=exp(0.112); Table 3] times greater than the odds for a firm being at a competitive disadvantage in the industry 'i' at time 't' at the 95% level of confidence in Model 1. If VAIC increases by 10 points, the odds increase from 1.0 to 1.119 [= exp10*(1.119)]. Similarly the examination of the odds ratios of the VACA, HCVA and SCVA showed that the probability of the odds of a firm being in the situation of competitive advantage is relatively greater than the odds for a firm being at a competitive disadvantage in the industry 'i' at time 't' at the 95% level. However, the odd ratios of the innovative capital shows that the probability of the odds of a firm being in the situation of competitive advantage is relatively lesser than the odds for a firm being at a competitive disadvantage (Table 4).

Goodness-of-fit statistic: The inferential test results are presented in Table 3. The Pseudo R Square values and their corresponding Chi Square statistics for Models 1 to 5 suggest that the models fit well to the data. In other words, the null hypothesis of a good model fit to data is tenable for all the contemporaneous models. However, of all the models, Model 4 is observed to be the best fitting model as its Pseudo R Square value is 0.110, which is the highest across all the models. Thus, Model 4 would seem to be the most appropriate according to the goodness of fit.

Table 4. Estimated odds ratios for the contemporaneous effect and lag effect models for the firms' competitive advantage

Indexes / Model	Explanatory Variables	Contemporaneous effect			Lag Effect		
		Odd Ratio	95% confidence limit		Odd Ratio	95% confidence limit	
Model 1	VAIC	1.119	1.089	1.149	1.121	1.09	1.153
Model 2	VAIC	1.111	1.081	1.141	1.113	1.082	1.145
	RDBV	0.004	<0.001	0.343	0.002	<0.001	0.33
	SDBV	1.322	0.98	1.784	1.345	0.965	1.874
Model 3	VACA	4.49	3.1	6.503	4.483	3.046	6.599
	HCVA	1.099	1.068	1.132	1.097	1.062	1.133
	SCVA	1.65	1.127	2.416	1.942	1.167	3.232
Model 4	VACA	5.223	3.468	7.865	5.315	3.472	8.136
	HCVA	1.088	1.057	1.12	1.089	1.055	1.124
	SCVA	2.024	1.324	3.095	2.256	1.32	3.856
	RDBV	0.019	<0.001	1.399	0.035	<0.001	6.343
	SDBV	0.57	0.318	1.022	0.542	0.29	1.012
Model 5	VACA	5.025	3.359	7.517	5.066	3.335	7.695
	HCVA	1.119	1.089	1.15	1.123	1.09	1.156
	RDBV	0.059	<0.001	5.96	0.03	<0.001	5.221
	SDBV	0.672	0.386	1.168	0.675	0.379	1.202

Validations of predicted probabilities: As we explained earlier, logistic regression predicts the logit of an event outcome from a set of predictors. Because the logit is the natural log of the odds, it can be transformed back to the probability scale. The resultant predicted probabilities can then be revalidated with the actual outcome to determine if high probabilities are indeed associated with events and low probabilities with non-events. The degree to which predicted probabilities agree with actual outcomes is expressed in terms of four measures: Goodman-Kruskal's Gamma, Somers's D statistic, and the c statistic.

Goodman-Kruskal's Gamma statistic is preferred over the Kendall's Tau-a statistic as the former is more useful and appropriate than the latter when there are ties for both outcomes and predicted probabilities (See DeMaris, 1992). Thus, if we examine the Gamma statistic values in the contemporaneous effect models, which run from the lowest of 0.367 in Model 2 to the highest value of 0.462 in Model 4 (Table 5), we interpret this as 36.7% fewer errors made in predicting a firm's competitive advantage position by using the estimated probabilities than by chance alone (See DeMaris, 1992). The theoretical range of 'c' statistic lies between 0.5 and 1. A 'c' statistic value of 0.5 indicates that the model is no better than assigning observations randomly into outcome categories. A 'c' value of 1 indicates that the model assigns higher probabilities to all observations with the event outcome as compared to non-event observations. Looking at the results in Table 5, it is observed that its value runs from the lowest of 0.682 in Model 2 to the highest of 0.73 in Model 4 (Table 5). This means that 68.2% of firms in Model 2 and 73% of cases in Model 4 correctly assign a higher probability to those firms which are competitive advantaged. Though the goodness-of-fit statistics reported across the models seem low, but they are still in an acceptable range. In our context comparing the 'c' statistic value across the contemporaneous models, it is confirmed that Model 4 is the best model as it is associated with the highest c statistic.

Table 5. Model validation statistics for the firms competitive advantage model

Statistic	Model 1	Model 2	Model 3	Model 4	Model 5
Panel A: Contemporaneous effect					
Percent Concordant	68.6	68	71.6	72.9	72
Percent Discordant	30.8	31.5	28.1	26.8	27.7
Percent Tied	0.6	0.6	0.3	0.3	0.3
Pairs	522699	522699	522699	522699	522699
Somers' D	0.378	0.365	0.434	0.461	0.443
Gamma	0.381	0.367	0.436	0.462	0.444
Tau-a	0.186	0.179	0.213	0.226	0.217
C	0.689	0.682	0.717	0.73	0.721
Panel B: Lag Effect					
Percent Concordant	69.3	68.5	72.1	73.5	72.5
Percent Discordant	30.1	31	27.6	26.2	27.1
Percent Tied	0.6	0.5	0.3	0.3	0.3
Pairs	422433	422433	422433	422433	422433
Somers' D	0.392	0.375	0.445	0.473	0.454
Gamma	0.394	0.377	0.446	0.474	0.455
Tau-a	0.192	0.184	0.218	0.232	0.222
C	0.696	0.688	0.722	0.736	0.727

From the above analysis it can be concluded that the odds of the firms' competitive advantage position is both reasonably and positively explained by the composite VAIC measure and the individual based intellectual capital component measures i.e. VACA, HCVA and SCVA as well. The results here lend support only to our hypotheses H1-1a, H2-1a, H2-2a and H2-3a at least at 5% level of significance. However the effectiveness of deliberate engagement of RDBV and SDBV are questioned as both of the variables fail to influence significantly the odds of the firms' competitive advantage position in India in the expected direction, thus we don't find evidence supporting H3-1a, H3-2a H3-3a and H3-4a.

Industry wise examination is carried out to choose the best explained model and the finding here suggests that Model 4 turns out to be the best model irrespective of the industry category, where adjusted R^2 value found to be higher. Thus, it is inferred that the composite VAIC based models fail to explain better the competitive advantage conditions of the selected Indian industries compared to the individual component based intellectual capital models. Further, it is also evident that VACA plays the most significantly role in influencing competitive advantage condition of Indian firms for all industry categories under investigation except banking and financial services. The results here suggest that the competitive conditions of the emerging market industries in general and India in particular draw their competitive advantage strength mostly from the physical capital. Keeping the academic brevity in mind we haven't provided the estimated results in the tabular format. Interested readers may request to authors for such results.

In addition to the aforesaid result discussions, we also investigate the robustness of our results segregating the data of each firm into two equal halves before and after 2008. The results obtained from such segmented models corroborate our main findings. However, we have not presented the robustness results due to space constraints in the journal and the interested readers may receive such estimated results from the authors.

4.2 Findings from the lagged models

While examining the lagged effect of the intellectual capital efficiency (LVAIC) on firms' competitive advantage in a logistic regression framework, it is observed from the Models 1 and 2 that the coefficient attached to the LVAIC is statistically significantly higher than zero ($\beta > 0$). Furthermore, it is inferred from the coefficients of the lagged relational capital (LSDBV) in Model 2 that it shows the complementarities and positively influences the odds of firms' competitive advantage position. While examining the sign of the lagged physical and financial capital efficiency (LVACA), lagged Human capital efficiency (LHCVA) and lagged structural capital efficiency (LSCVA) in Models 3, 4 and 5, it is revealed that all three individual components of intellectual capital are observed to be positive and statistically significant at the 1% level of significance. These results suggest that the deployment of LVACA, LHCVA and LSCVA are creating a condition for odds of firms having a competitive advantage in the Indian industry space. The sign of the lagged innovative capital efficiency (LRDBV) and the level of significance confirms a negative and somewhat weak association with firms' competitive advantage, which means the investment on research and development in Indian firms in general fails to create a condition for odds of firms' competitive advantage. However, comparing the sign and coefficients of the relational capital in the composite VAIC models (Models 1 and 2) and component based models (Models 3, 4 and 5), the sign do not conform to each other (Table 6).

The confidence interval estimates of the odds ratio for the LVAIC suggests that the probability of the odds of a firm being in the situation of competitive advantage is 1.121 [=exp(0.114); Table 4 and Table 6] times greater than the odds for a firm being at a competitive disadvantage in the industry 'i' at time 't' at the 95% level of confidence in Model 1. If LVAIC increases by 10 points, the odds increase from 1.0 to 1.121 [= exp10*(1.121)]. Similarly the examination of the odds ratios attached with variables related to one period LVACA, LHCVA and LSCVA evidenced that the probability of the odds of a firm being in the situation of competitive advantage is relatively greater than the odds for a firm being at a competitive disadvantage. However the odd ratios of the innovative capital affirms that the probability of the odds of a firm being in the situation of competitive advantage is relatively lower than the odds for a firm being at a competitive disadvantage.

Overall model evaluation: The overall model evaluation test for the lag models remains in conformity with the analysis of contemporaneous models documented in previous sub-sections. All three statistical tests - the likelihood ratio, score, and Wald tests inferred that, all five lag logistic models are observed to be more effective than their corresponding null models. The quality of the model specification test which is examined through AIC across the lag models also reveals that the models including intercepts and covariates seem to perform better compared to the models with intercepts only. However, in the case of lag models also the fourth logit model appears to be the best according to the AIC value (Table 2).

Table 6. Logistic regression parameter estimation for the firms' competitive advantage obtained from the lagged model

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-1.044*** (-10.07)	-0.985*** (-9.29)	-1.992*** (-10.66)	-2.012*** (-10.25)	-1.636*** (-11.12)
LVACA			1.500***(7.61)	1.670***(7.69)	1.623***(7.61)
LHCVA			0.092***(5.65)	0.085***(5.28)	0.116***(7.75)
LSCVA			0.664**(2.55)	0.814***(2.98)	
LRDBV		-6.026**(-2.40)		-3.349(-1.26)	-3.517(-1.33)
LSDBV		0.216*(1.75)		-0.613*(-1.92)	-0.393(-1.33)
LVAIC	0.114***(7.94)	0.107***(7.43)			
Number of obs	1314	1314	1314	1314	1314
Chi Square	127.60***	197.08***	194.08***	203.40***	190.74***
Pseudo R^2	0.071	0.109	0.108	0.113	0.106
Log likelihood	-832.916	-797.680	-799.680	-795.019	-801.348

Notes: 1. *L* stands for one period lag in each explanatory variable;

2. ***, ** and * indicate 1% , 5% and 10% level of statistical significance, respectively.

Goodness-of-fit statistics: While examining the results of the goodness-of-fit statistics for the lagged model it is observed that the Pseudo R Square values and their corresponding Chi Square statistics for all the lagged models fit to the data well. Model 4 is found to be the best fit model as its Pseudo R Square value is 0.113, which is the highest across the models.

Validations of predicted probabilities: Examining the Gamma statistic values in the lagged models, it can be seen that they run from the lowest of 0.375 in Model 2 to the highest of 0.473 in Model 4 (Table 5). This is interpreted as 37.5% and 47.3% fewer errors are made in predicting a firm's competitive advantage position by using the estimated probabilities than by chance alone in lagged Model 2 and lagged Model 4 respectively. While examining the c statistic, it is observed that its value runs from the lowest of 0.688 in Model 2 to the highest of 0.736 in Model 4 (Table 5). This means that 68.8% of firms in the lagged Model 2 and 73.6% of cases in lagged Model 4 correctly assign a higher probability to those firms who are competitively advantaged. Though the goodness-of-fit statistics reported across the models seem low, but they are still in an acceptable range. In our context comparing the 'c' statistic value across the lagged models, it is confirmed that Model 4 is chosen as the best lagged model as this model is associated with the highest c statistic value.

Thus, the above analysis suggests that the odds concerning the firms' competitive advantage position is reasonably and positively explained by the LVAIC and the individual based lagged intellectual capital component measures i.e. LVACA, LHCVA and LSCVA. Also the results here lend support only for the hypotheses H1-1a, H2-1a, H2-2a and H2-3a at least at the 5% level of significance. However the effectiveness of deliberate engagement of LRDBV and LSDBV are questioned as both of the variables fail to influence significantly the odds of a firms' competitive advantage position in India in the expected direction, thus we do not find evidence supporting H3-1a, H3-2a H3-3a and H3-4a.

Industry wise findings for lag models also suggest that Model 4 turns out to be the best model irrespective of the industry category for the lagged models. It is also evident that LVACA plays the most significantly role in influencing competitive advantage condition of Indian firms for all industry categories except for banking and financial services and information technology industries. The results here further support our earlier finding that the emerging market industries in general and India in particular draw their competitive advantage strength mostly from the LVACA. Keeping the academic brevity in mind we haven't provided the estimated results in the tabular format. Interested readers may request to authors for such results.

5. Conclusion

The aim of this paper was to use a binary response model to examine firms' competitive advantage and disadvantage outcomes in terms of the intellectual capital predictors. Five logit models were estimated. Out of the five models, two models were based on the composite intellectual capital efficiency index and 3 models were based on having individual intellectual capital components as explanatory variables. The fit of the model was illustrated with data obtained from 146 companies from seven different Indian industry segments. The tested models performed differently depending on the categorization of outcome, adequacy in relation to assumptions, goodness of fit and parsimony. It is observed that the firms' competitive advantage is reasonably well explained by individual intellectual capital component based models rather than the composite VAIC index based models. The variable VACA has an odd large value compared to others, which may suggest that VACA plays a significant role in influencing competitive advantage condition of Indian firms in most of the Indian industry under investigation. It is thus inferred that the competitive advantage conditions of the emerging market industries in general and India in particular draw their competitive advantage strength mostly from the VACA. However in a few specific industries such as automobiles, consumer goods, health and pharmaceuticals and information technology industries, VACA, structural capital and HCVA are found to be significant determinants.

The findings of this study have potential implications for firms, governments and scholars interested in studying intellectual capital in emerging market. The Indian firms in most of the industry segments derive their competitive strengths from the VACA and ultimate HCVA and SCVA remain unexplored. To remain competitive in this market, the firms should strengthen their human and structural capital base with immediate effect. To do so, there is need for renewed thinking in part of the Indian business managers to identify measure, promote and align their firms' strategy with the intellectual capital so as to leverage competitive advantages in the industry. The governments are also having important roles in creating conditions for identifying, nurturing and promoting intellectual capital in the emerging market space. While designing the policy for the promotion of emerging economies government should rebalance resources investing in diverse intellectual capital components so as to avoid the lopsided development. The study also extends the understanding of scholars how VAIC and other associated components determine competitive advantage of firms in the emerging market industry. To the best of our knowledge, the competitive advantage condition is modeled for the very first time in a VAIC framework in this study.

This study is not free from limitations. First, the sample firms include exclusively Indian enterprises, so the conclusions are directly important only for the domestic economy. Second, we excluded other industry segments of the Indian industries due to non-availability of reliable data. These limitations provide a future scope of this research, where scholars may explore the effect of intellectual capital on firms 'competitive advantage condition including other left out Indian industries such as the textile industry, food processing, etc. Further, the hypotheses tested in this study may be reexamined in a broader international context so as to establish a strong empirical evidence on the effect of intellectual capital on firms' competitive advantage condition.

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