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INNOVATIVE SMES: THE ROLE OF INTELLECTUAL CAPITAL AND BOARD SIZE IN SHAPING FINANCIAL PERFORMANCE

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Abstract

Purpose. *Nowadays, intellectual capital (IC) is a crucial driver of value creation, particularly for innovative firms. This study investigates the relationship between IC efficiency and firm performance (FP), with Board of Directors (BoD) size acting as a moderating variable. Although, BoD size-FP relation has been extensively explored in the literature, findings remain inconsistent. Resource-based view suggests that larger BoDs offer diverse experiences, perspectives and knowledge, enhancing decision-making; conversely, agency theory suggests that larger BoDs may lead to higher communication and coordination costs.*
Design/methodology/approach. *Using ordinary least squares (OLS) regression, we analyze data from 2,166 Italian innovative small and medium-sized enterprises (ISMEs). We test the relationship between IC (proxied by value-added intellectual coefficient (VAIC)) and FP (proxied by return on assets and return on equity), considering the moderation role of BoD size. We also employ Lasso regression for robustness.*
Findings. *IC efficiency significantly and positively impacts FP, with BoD size playing a significant moderating role. These findings are robust across both OLS and Lasso regressions.*
Practical and social implications. *The findings are relevant for both managerial practice and scholars. They contribute to They contribute to resource-based and agency theories by offering insightful outcomes on a novel sample. Furthermore, these results can also inform corporate governance practices in innovative SMEs regarding IC orchestration.*

1. Introduction

Determining successful corporate governance (CG) mechanisms is an area of interest for scholars and practitioners (Bansal & Singh, 2022; Sharma et al., 2023). As shown in the literature (Sirmon et al., 2011; Wernerfelt, 1984), CG plays a priority role in strategically managing resources, among which intangible ones are always more relevant in the current knowledge-based economy.

In a highly dynamic environment, such as that of innovative small and medium enterprises (ISMEs), the proper and clever management of intellectual resources is a key driver for competitive advantage (Bansal & Singh, 2022; Barney, 1991; Van et al., 2022; Xu et al., 2023). Moreover, the Italian context seems to be particularly intriguing for this issue (Fiorentino et al., 2024). In fact, although Italian firms report innovation activity at rates similar to other European countries, the actual production of innovations remains lower, contributing to a long-standing stagnation in productivity (Finaldi Russo et al., 2016). In response, Italian policymakers are increasingly supporting the growth of innovative companies (both startups and SMEs), recognizing the central role of innovation in driving business success and sustainable development (Audretsch et al., 2020; Fiorentino et al., 2024).

In recent years, scholars have studied the intellectual capital (IC) – defined as "intangible assets or knowledge resources which can create value for firms as achieve and maintain a competitive edge for them" (Stewart, 1997; Sveiby, 1997) –, recognizing it as a strategic resource. IC efficiency (ICE) – firstly developed in the Skandia model (Edvinsson & Malone, 1997) is strictly related to CG, as it reflects the firm's ability to leverage its intangible assets to generate value. According to Pulic (Pulic, 2000, 2004), ICE can be measured through the Value Added Intellectual Coefficient (VAIC), which considers human, structural and capital resources. The VAIC method offers valuable insights into enhancing the efficiency of both tangible and intangible asset utilization within a firm. This approach is widely recognized for its relative simplicity – as it relies on financial statement data – and has been extensively employed in numerous research (Mulyasari & Murwaningsari, 2019).

BoD plays a crucial role in shaping ICE (Nadeem et al., 2017; Scafarto et al., 2021). Hillman and Dalziel (2003) suggest that board characteristics influence the board's ability to fulfil its monitoring and resource-provision roles, which in turn affects ICE (Berezinets et al., 2016). Moreover, the BoD is not only a source of IC but also a key driver in enhancing its effective utilization. Among the characteristics of BoD, prior research is limited regarding the size, offering inconsistent results (Abdallah et al., 2024).

Numerous studies have investigated the correlation between ICE and firm performance (FP), yet the moderating influence of CG characteristics has remained less explored among academics (Van et al., 2022), especially within the Italian market. Considering the relevance of CG mechanisms and IC, few studies have investigated the moderating influence of BoD size on the relationship between ICE and FP. Hence, a research gap still exists. This study aims to fill methodological, sample and empirical gaps by employing an innovative statistical approach on a relevant and previously unexamined cluster of firms.

Based on these premises, we aim to search the relationship between BoD size and FP as well as ICE (proxied by VAIC) and FP (proxied by return on equity (ROE) and return on assets (ROA)), considering also the moderation role of BoD size.

The analysis refers to Italian ISMEs for the year 2022, thereby neutralizing the distorting effects on financial data due to the Covid-19 emergency. We carried out a quantitative analysis on a dataset of 2,166 entities through a double estimation technique. First, we employed the OLS estimator to test the research hypotheses, and then we performed a Lasso regression. The adoption of this latter adds novelty elements to the methodology.

The findings suggest a negative and significant relationship between BoD size and FP, while a positive one is established between ICE and FP. The positive moderation role played by BoD size emerges regarding the latter.

Hence, we intend to contribute to the current debate on IC in a highly dynamic context, providing both practical and theoretical insights. On one hand, under the theoretical frameworks of resource-based and agency theories (Barney, 1991; Berle & Means, 1932; Jensen & Meckling, 1976; Wernerfelt, 1984), the study enriches the current literature stream on IC, CG and FP (Chen et al., 2005; Nawaz & Ohlrogge, 2023; Van et al., 2022). On the other hand, from a managerial perspective, the study provides intriguing implications in terms of governance practices and intangibles' management, highlighting the key role for BoD in the orchestration of resource management (Sirmon et al., 2011).

To achieve this aim, Section 2 provides the literature review to develop the research hypotheses; Section 3 details the empirical methodology applied; Section 4 describes results; Section 5, after the results' discussion, wraps up the main conclusions.

2. Literature review

2.1. Intellectual capital and firm performance

Various interpretations of IC are presented in literature (Dumay, 2012; Edvinsson & Malone, 1997; Stewart, 1997; Ur Rehman et al., 2022); researchers agree on including both the human capital (HC) and structural capital

(SC) (Evangelista et al., 2018; OECD, 1999). HC refers to individuals within the organization (Edvinsson & Malone, 1997), playing a significant role in enhancing ICE (Laing et al., 2010). SC relates to the operational frameworks and organizational structures of the company, intended to maximize intellectual capacities (Bollen et al., 2005).

Measuring IC has faced challenges. Starting from the Skandia model (Edvinsson & Malone, 1997), VAIC, introduced by Pulic (2000), is a widely used metric for assessing ICE, as it is based on available accounting data that is comparable across companies. VAIC consists of HCE, SCE and Capital Employed Efficiency (CEE), where the latter represents the efficiency in the use of financial and physical capital. Some studies have noted that relational capital—another component of IC—is not directly included (Ståhle et al., 2011); however, it can be indirectly reflected in the efficient management of resources, influencing both HCE and SCE (Iazzolino & Laise, 2013). Several studies have proposed alternative measures to assess ICE. Some authors have adopted qualitative approaches, such as analyses of company reports and models based on intangible indicators (Guthrie et al., 2012), while others have developed composite metrics in multidimensional frameworks, such as the Skandia Navigator (Edvinsson & Malone, 1997) and Balanced Scorecard (Kaplan, 1992). Despite its limitations (Ståhle et al., 2011), VAIC is the most used in empirical research (Iazzolino & Laise, 2013), as it allows a standardised comparison based on available accounting data (Chen et al., 2005; Iazzolino & Laise, 2013; Pulic, 2004).

Pursuant to the resource-based theory, companies must have a good hold on resources “valuable, rare, inimitable and not substitutable” (Barney, 1991) which, when leveraged effectively, enable firms to gain a competitive advantage and attain sustainable performance (Rumelt, 1984; Wernerfelt, 1984). IC can meet these characteristics, representing an intangible resource able to bring a sustainable competitive strength (Barney, 1991; Stewart, 1997). Indeed, based on the second literature stream on IC (Guthrie et al., 2012), scholars widely share the positive effect of IC on FP (Bismuth & Tojo, 2008; Chen et al., 2005).

However, according to the resource orchestration theory (Sirmon et al., 2011), which serves as an extension of the resource-based theory, it is crucial for organizations to properly orchestrate their resources. Hence, the role of CG becomes crucial in leveraging firms’ resources to improve financial performance (Scafarto et al., 2021). As shown by previous studies, the ongoing research on governance and IC reports mixed and inconsistent results (Nawaz & Ohlrogge, 2023; Van et al., 2022).

2.2. The moderation role of board size

BoD is the most crucial internal governance instrument (Brennan, 2006). Literature agrees on a triple board function: i) strategic, as defining the strategic formula of the company; ii) monitoring, as safeguarding shareholders' interests; iii) service, as the ability to manage stakeholders' relationships (Galeotti & Garzella, 2013; Johnson et al., 1996). Basically, it is the link between those who bring financial resources (shareholders) and those who manage these resources in order to get company's value (top management) (Monks & Minow, 2012).

Prior research has widely suggested a strict connection between board size and corporate performance with mixed interpretations (Bansal & Singh, 2022; Kao et al., 2019; Kumar & Singh, 2013; Sharma et al., 2023). Literature shows both positive (Ganguli & Guha Deb, 2021; Kiel & Nicholson, 2003) and negative (Cheng, 2008; Eisenberg et al., 1998; Ghosh, 2006; Kao et al., 2019; Yermack, 1996) relations. Moreover, as noted by Sharma et al. (2023), the relation can be both linear and non-linear.

According to the agency theory (Jensen & Meckling, 1976), the relationship between CG and FP is explained by the idea that managers, driven by information asymmetries, may engage in opportunistic behaviours to serve their own interests rather than maximizing shareholders' returns (Berle & Means, 1932). Larger boards may face communication and coordination challenges, slowing down decision-making processes (Eisenberg et al., 1998; Scafarto et al., 2021). Furthermore, they might intensify issues related to free-riding, as incumbent directors may allocate less effort towards fulfilling their responsibilities compared to smaller board structures (Harris & Raviv, 2008).

Eisenberg et al. (1998) identify a significant negative correlation between BoD size and firm profitability in Finnish small and medium sized enterprises (SMEs). Similarly, Ghosh (2006) provides evidence that a gain in the BoD size adversely affects firm value based on 127 Indian manufacturing firms for the year 2003. More recently, Kao et al. (2019) corroborate these findings, demonstrating a negative relationship using a dataset of Taiwanese listed firms from 1997 to 2015.

Conversely, other documents report a positive connection between BoD size and performance. For instance, Bansal and Singh (2022), in their analysis of 92 software companies from 2011 to 2018, find that board size, the frequency of board meetings, and the presence of remuneration and nomination committee positively influence performance metrics such as Return on Assets and Tobin's Q. Similarly, Ganguli and Guha Deb (2021) further confirm this positive relationship showing that the larger BoD size enhance financial performance-measured through ROA, ROE and Tobin's Q, using a sample of 265 entities from the S&P 500 index. Ntim et al. (2015) report that for 169 South African enterprises, larger board sizes positively contributed to performance indicators.

3. Hypotheses development

Based on the theoretical frameworks outlined in the literature review, scholars have widely recognized a relationship between ICE and FP, leaving sample gaps, as the lack of investigations in ISMEs. Thus, the following null hypothesis is formulated:

H1 – IC efficiency has a positive effect on FP.

In addition, although scholars recognized mixed evidence between BoD size and FP. Given previous studies' inclusive evidence, the following hypothesis is proposed:

H2a – Board size has a significant effect on FP.

Following the resource-based theory, BoD can effectively leverage intellectual resources, boosting financial performance. The literature is rich in analyses concerning the relationship between IC and FP, as well as the effect of BoD size on IC efficiency (Nawaz & Ohlrogge, 2023; Scafarto et al., 2021; Van et al., 2022). Both relations are investigated, reaching mainly a positive relationship (Ho & Williams, 2003; Shahzad et al., 2019). Less investigated is the moderating role of board size on the relationship between IC and FP (Van et al., 2022). Hence, the following hypotheses are formulated:

H2b – Board Size, treated as an interaction variable, positively moderates the relationship between IC efficiency and FP.

4. Methodology

4.1. Sample

We retrieved the dataset from AIDA Bureau van Dijk; it includes 2,756 Italian ISMEs established before 2022. After discarding entities for which financial and governance data were unavailable or incomplete regarding the year 2022, the final dataset comprises 2,166 ISMEs, comprising 59% micro, 32% small, and 9% medium-sized enterprises.

As defined by DL 3/2015, ISMEs must be compliant with a series of specific objective and subjective requirements.

Italy was selected as a country of research due to numerous reasons, including the top rank as a global manufacturer leader and exporter. In addition, the sample provides interesting peculiarities not yet faced in previous literature. Indeed, this kind of companies is receiving quite great attention from policymakers, who guarantee a series of benefits in terms of, for example, funding facilities and fiscal incentives.

4.2. Variables

4.2.1. Dependent variables

We applied two accounting-based indicators for financial performance. In particular, we used Return on ROE and ROA to assess FP as the dependent variables (Bansal & Singh, 2022; Ghosh, 2006; Ntim et al., 2015). Moreover, to ensure results' robustness, we employed a linear combination of ROA and ROE, in which each one has the same weight (arithmetic mean) (Morrone et al., 2022). Due to the nature of the sample, which includes non-listed companies, we did not consider any market-based indicator (e.g., Tobin's Q).

4.2.2. Explanatory variables

Our explanatory variable is the ICE, proxied by VAIC (Pulic, 2000). The latter is derived from the firm's value-added (VA), commonly employed in the literature as a proxy for ICE (Chen et al., 2005; Laing et al., 2010; Scafarto et al., 2021). VAIC calculation comprises HC, SC and employed capital (EC) and combines the efficiency of both intangible and tangible assets.

$$\text{VAIC}^{\text{TM}} = \text{HCE} + \text{SCE} + \text{CEE}$$

HCE stands for human capital efficiency, computed as the ratio of VA to employees' costs. SCE stands for structural capital efficiency, computed as the ratio of the difference between VA and employees' costs to VA. CEE stands for capital employed efficiency, computed as the ratio of VA to total assets, excluding intangible assets.

Hence, we calculated value added as follows:

$$\text{VA} = \text{OP} + \text{EC} + \text{D\&A} + \text{P}$$

We determined VA by the algebraical sum of operating profit (OP), employees' costs (EC), depreciation and amortization (D&A) and provisions (P).

Board size (BOD_SIZE) is represented by the total members of the BoD as of 31st December 2022. However, we used the logarithmic specification of BoD size to avoid multicollinearity issues among regressors.

4.2.3. Control variables

In addition, we included several control variables: Return on Sales, firm size, leverage and industry sectors. In particular, ROS_adj (Return on Sales) is the ratio of EBITDA to sales, serving as a key indicator of profitability of the firm. SIZE (firm size) is considered using the natural logarithm of sales, providing a standardized metric for the firm scale. LEV is represented by financial leverage, capturing the proportion of both short-term and long-term debt. Finally, we controlled industry-specific effects through the inclusion of ad hoc dummy variables (industry) (Scafarto et al., 2021). The full set of variables included in the models is shown in Table 1.

Table 1. Variables specification

Variable	Definition	Measurement	Literature
ROE	Return on Equity	Net income / shareholders' equity	(Bansal & Singh, 2022; Ghosh, 2006; Isola et al., 2020; Xu et al., 2023)
ROA	Return on Assets	Net income / total assets	(Isola et al., 2020; Van et al., 2022; Xu et al., 2023)
LC_FP	Linear combination of ROA and ROE	(ROA+ROE) / 2	(Aryani et al., 2023; Morrone et al., 2022)
VAIC	Value added intellectual coefficient	HCE+SCE+CEE	(Laing et al., 2010; Pulic, 2000; Xu et al., 2023)
HCE	Human capital efficiency	Value-added / total personnel cost	(Nadeem et al., 2017; Pulic, 2000)
SCE	Structural capital efficiency	(Value-added – personnel cost) / value added	(Pulic, 2000)
CEE	Employed capital efficiency	Value-added / capital employed	(Nadeem et al., 2017; Pulic, 2004)
LEV	Financial leverage	Total liabilities / shareholders' equity	(Ganguli & Guha Deb, 2021; Van et al., 2022; Xu et al., 2023)
BOD_SIZE	Board size	Log of number of BoD members	(Buallay & Hamdan, 2019; Ganguli & Guha Deb, 2021; Ntim et al., 2015; Van et al., 2022)
SIZE	Firm size	Log of annual sales	(Ganguli & Guha Deb, 2021)
ROS_ADJ	Return on Sales (adjusted)	EBITDA / Sales	(Barak & Sharma, 2024; Lim, 2025)
industry	Industry dummies	Set of eight dummies which code 1 if the company belongs to the industry and 0 otherwise	(Scafarto et al., 2021)

4.3. The functional form

We used the Ordinary Least Squares (OLS) method to evaluate the research hypotheses, given the static nature of the dataset (fixed year = 2022). The econometric formulations of the linear models are the following:

$$(1) \quad FP_i = \beta_0 + \beta_1 VAIC_i + \beta_2 ROS\_adj_i + \beta_3 SIZE_i + \beta_4 LEV_i + industry + \varepsilon_i$$

$$(2) \quad FP_i = \beta_0 + \beta_1 VAIC_i + \beta_2 BOD\_SIZE_i + \beta_3 ROS\_adj_i + \beta_4 SIZE_i + \beta_5 LEV_i + \beta_6 (VAIC * BOD\_SIZE)_i + industry + \varepsilon_i$$

where FP stands for financial performance and represents the stochastic error.

4.4. Machine Learning approach: Lasso regression

We applied Lasso (least shrinkage and selection operator) regression that is a machine learning–based regularization method useful for improving the prediction accuracy and interpretability (Tibshirani, 1996). In addition, this technique is considered suitable for large datasets (Cerulli, 2023), as ours. This methodological choice strengthens the contribution of the study in multiple ways. First, to the best of our knowledge, Lasso regression has not yet been applied to Italian firms to assess the impact of IC on FP, providing new empirical insights. Second, recent studies highlight the effectiveness of machine learning techniques in FP forecasting (Lim, 2025), especially in the field of accounting and finance (Ding et al., 2020; Mousa et al., 2022). Compared to OLS regression, Lasso offers significant advantages by simultaneously performing variable selection and regularization, reducing multicollinearity and improving model interpretability (Cerulli, 2023).

5. Results

5.1. Descriptive statistics and correlation analysis

In Table 2, we show summary statistics of used variables. Italian ISMEs registered a good general level of FP in 2022, in line with market trends.

Table 2. Descriptive statistics

Variables	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
ROE	2233	0.4034259	35.46947	-147.70	146.63
ROA	2424	-2.061708	27.9662	-626.49	180.71
LC_FP	2233	0.83	25.19	-111.41	82.71
VAIC	2207	19.89	693.71	-1,380.99	32,261.08
BOD_SIZE	2639	3.28	2.33	1.00	16.00
VAIC*BOD_SIZE	2207	1.96	63.41	-1,670.52	594.60
ROS_ADJ	2337	-14.82	97.67	-971.46	117.09
LEV	2412	5.84	97.06	-1,711.54	4,009.88
SIZE	2424	12.94	3.42	0.00	18.63

In Table 3, we present the Pearson's correlation matrix with significance levels useful in identifying multicollinearity among the set of variables, as well as in recognizing any prior associations between the variables. Following Kennedy (1985), a value of 0.8 may represent multicollinearity issues, suggesting the absence of multicollinearity among the set of regressors. Anyway, we perform an additional test in the following section.

Table 3. Correlation matrix

	ROE	LC_FP	VAIC	BOD_ SIZE	VAIC* BOD_ SIZE	ROS_ ADJ	LEV	SIZE	ROA
ROE	1								
LC_FP	0.9837 ***	1							
VAIC	0.0356	0.0344	1						
BOD_SIZE	-0.184 ***	-0.1982 ***	-0.0262	1					
VAIC*BOD_SIZE	0.104 ***	0.1121 ***	0.0701 ***	0.0253	1				
ROS_ADJ	0.4204 ***	0.4636 ***	0.0145	-0.197 ***	0.0499 **	1			
LEV	0.0791 ***	0.0601 ***	0.0323	-0.028	0.2835 ***	0.0207 **	1		
SIZE	0.2232 ***	0.2374 ***	0.004	0.097 ***	0.0205	0.3964	-0.0014	1	
ROA	0.8413 ***	0.9248 ***	0.0270	-0.170 ***	0.0626 ***	0.7925 ***	0.0067	0.1938 ***	1

5.2. OLS results

In Table 4, we display regression results of model 1 and model 2, in order to test the research hypotheses H1, H2a and H2b. Prior to running the regression models, we computed various diagnostics among the variables. Firstly, the Variance Inflator Factor (VIF) is used to verify multicollinearity issues among regressors. Thus, by setting a cut-off value of mean VIF = 5 (Weisberg, 2005), no serious concern of multicollinearity among regressors was detected. Additionally, we employed robust standard errors to mitigate issues of heteroscedasticity and autocorrelation by utilizing the "robust" option in STATA. This decision is grounded in the resilience demonstrated in prior research (White, 1980), which underscores the efficacy of this approach in mitigating bias in scenarios where heteroscedasticity is observed (Long & Ervin, 2000). Consistent with previous literature on IC, VAIC produces a significant and positive effect on financial performance, proxied by ROE and ROA (Bismuth & Tojo, 2008; Chen et al., 2005). In accordance with resource-based theory, this evidence supports the H1. Overall, each control variable produces a strongly significant association with the dependent variable. Furthermore, the F-test associated with each model confirms the overall significance of the models. Moving to the role of board size, it is evident a direct negative relationship between the number of BoD members and FP. According to model 2, the connection is strongly significant and consistent if tested on both ROE and ROA, supporting H2a. These findings support the idea that a larger board may suffer from communication and coordination problems, as demonstrated by previous studies on CG (Eisenberg et al., 1998; Kao et al., 2019; Yermack, 1996). Finally, turning to moderation analysis, we included the interaction between VAIC and board size in model 2. Results support H2b, demonstrating that larger boards may improve financial performance by leveraging intellectual resources. The t-test confirms the significance of the result with 99% confidence. Our findings are consistent if tested on both dependent variables and are in line with previous research (Ho & Williams, 2003; Shahzad et al., 2019).

Table 4. OLS regression results

model	(1)		(2)	
dependent variable	Y = ROE	Y = ROA	Y = ROE	Y = ROA
VAIC	.001473***	.00050304*	.0010229***	.0002772*
BOD_SIZE			-6.801734***	-3.163528***
c.VAIC#c.BOD_SIZE			.0497349***	.0272719***
ROS_adj	.1517705***	.0911111 ***	.1359834***	.083538***
SIZE	1.407598***	.5104855**	1.853368***	0.7202078***
LEV	.2992377***	-0.0290164 *	.2789009***	-0.409416*
industry	yes	yes	yes	yes
_CONS	-12.43769	-2.528328	-17.22155***	-2.43654
Observations	2,006	2,006	2,006	2,006
F-statistics (Prob.>F)	11.20***	10.05***	18.46***	19.31***
R-Sq (between)	0.1954	0.2693	0.2188	0.2951
Robust Std. Err.	yes	yes	yes	yes
VIF	1.10	1.10	1.10	1.10

5.3. Lasso results

We performed the lasso regression, including a linear combination of ROA and ROE as the dependent variable (arithmetic mean). Firstly, following Cerulli (2023), the sample is split into two subsets randomly of 75% and 25%, respectively (Table 5).

Table 5*. Sample split*

Sample	Freq.	Percent	Cum.
Training	1,979	74.99	74.99
Validation	660	25.01	100
Total	2,639	100	

We performed the OLS regression using the training and, subsequently, we employed the lasso postestimation to generate two different sub-samples: the in-sample (i.e., training) and out-of-sample (i.e., testing or validation) that estimate the mean square errors (MSE).

Table 6. *OLS regression on training and validation subsets*

Sample	MSE	R-Sq.	Obs
Training	423.1826	0.3247	1,686
Validation	426.8876	0.3509	547

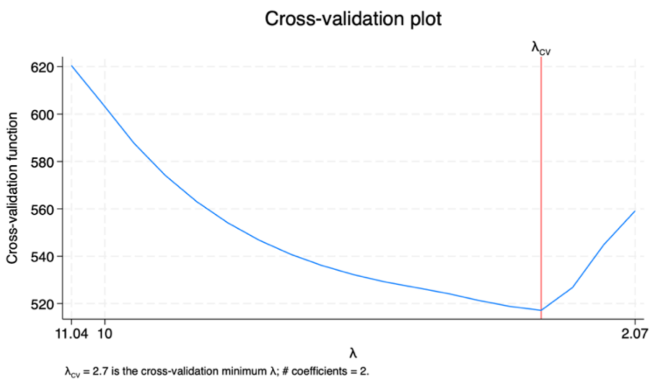
In Figure 1, we report the cross-validation plot of lasso regression, displaying the cross-validation (CV) optimal λ identified by the red mark. Thus, the optimal λ is equal to 2.73 and the CV MSE is 517.1386, associated with an out-of-sample R-squared of 0.1724.

Finally, we employed double-selection lasso linear regression to make inference on the variable of interest, demonstrating results highly consistent with the OLS regression (Table 6).

Table 7*. Inference on full sample (Lasso regression)*

LC_FP	Coefficient	P>z	[95% conf.	interval]
VAIC	0.0006505	0.002	0.0002423	0.0010586
BOD_SIZE	-4.987361	0.000	-6.420785	-3.553937
interaction	0.0386182	0.000	0.0248397	0.0523967

Figure 1. *Cross-validation plot*



5.4. Robustness checks

We assessed the reliability of the outcomes derived from the regressions, and we validated them using various control methodologies. In particular, the estimation of models using two different performance indicators, ROE and ROA, led to consistent and similar results, as shown in Table 4 and confirmed in Table 8. We gave an implicit and double control check by the Lasso regression application. Following this machine learning-based technique, results are robust in both different subsets randomly split. The last stage of control consists of including VAIC components in regression models to test robustness on H1 (Pulic, 2000). In Table 9, we display regression results, providing further support for H1.

Table 8*. OLS regression results (y = LC_FP*

	Model 1	***Model 2***
dependent variable	Y = LC_FP	
VAIC	.0009867**	.0006505***
BOD_SIZE		-4.987361***
c.VAIC#c.BOD_SIZE		.0386182***
ROS_adj	.1218587 ***	.1101092***
SIZE	.9617182***	1.290599***
LEV	.135564***	.1183738**
industry	yes	yes
_CONS	-11.51238***	-11.42302**
Observations	2,006	2,006
F-statistics (Prob. > F)	11.87***	21.02***
R-Sq (between)	0.2289	0.2547
Robust Std. Err.	yes	yes
VIF	1.10	1.10

Table 9. VAIC split into its three components as regressors

	Model (1)		
Dependent Variable (ROE)			
HCE	.0013042***		
SCE		.076044***	
CEE			3.524372***
ROS_adj	.1549334***	.1547971***	.1500004***
SIZE	1.155224***	1.171545***	.7806431***
LEV	.2288596*	.2291482***	-.6169548**
industry	yes	yes	yes
_CONS	-10.91587***	-14.34146***	-10.91587***
Observations	2,166	2,166	2,006
F-Statistics (Prob. > F)	14.32***	31.91***	14.32***
R-Sq (Between)	0.2273***	0.2010***	0.2273
Robust Std. Err.	yes	yes	yes
VIF	1.38	1.09	1.38

6. Discussion and conclusion

The increasing dynamism and the rapid innovation within companies are fostering intense hypercompetition in the global marketplace (Galeotti & Garzella, 2013). ISMEs fully embody this concept, making them a particularly relevant sample that is underexplored in literature. Innovation has emerged as a central theme in contemporary research (Fiorentino et al., 2024), with numerous studies emphasizing its critical role in driving business success and sustainable growth (Audretsch et al., 2020). ISMEs stand out as they must meet specific innovation criteria. This provides an intriguing sample to investigate business internal dynamics, with specific regard to the BoD composition and IC management.

Research has extensively surveyed the relationship between the BoD and FP, revealing both linear and nonlinear associations (Sharma et al., 2023) as well as positive or negative correlations (Eisenberg et al., 1998; Ghosh, 2006; Ntim et al., 2015; Yermack, 1996). Furthermore, literature has broadly examined the link between IC and financial performance, suggesting a positive association.

This study investigates the complex relationship between IC efficiency, BoD size, and FP in innovative Italian SMEs. The results confirm the significant positive impact of ICE on FP (H1), aligning with the resource-based view, which emphasizes the role of valuable intangible assets (Barney, 1991; Sirmon et al., 2011; Wernerfelt, 1984). These findings underscore the importance of organizations strategically managing and leveraging their IC for competitive advantage and financial success (Nawaz & Ohlrogge, 2023; Scafarto et al., 2021).

The findings of this study also demonstrate a significant negative association between BoD size and FP (H2a), consistent with agency theory's prediction regarding increased communication and coordination challenges in larger boards (Eisenberg et al., 1998; Kao et al., 2019; Yermack, 1996). This implies that smaller, more agile BoDs may prove more effective in driving firm performance in this context.

Crucially, an interesting and novel finding of this study is that the negative relationship between BoD size and FP is moderated by IC efficiency (i.e., mitigated in firms with higher IC)(H2b). Specifically, in firms with higher IC efficiency, the negative impact of larger boards is attenuated. This underscores the significance of resource orchestration and suggests that firms with strong IC can mitigate the potential negative effects of a larger BoD by efficiently leveraging their resources (Van et al., 2022).

6.1 Theoretical and practical implications

This study offers both theoretical and practical contributions. From a theoretical standpoint, it integrates resource-based and agency theories to enhance our understanding of how IC and BoD size jointly affect FP. The role played by IC clarifies the conditions under which the negative effects of larger boards are mitigated (Jensen & Meckling, 1976; Wernerfelt, 1984). The findings extend and refine existing research on CG, resource management, and FP, particularly in the context of ISMEs.

From a practical standpoint, the findings provide actionable insights for stakeholders in ISMEs, highlighting the importance of aligning board composition with ICE and the need to effectively orchestrate IC resources to achieve superior financial outcomes (Barney, 1991).

6.2 Limitations and future trends

The study has certain limitations. The quantitative analysis is based on data from a single year. Analysing a more extended timeframe would provide more robust insights into the dynamic interplay of variables investigated. The reliance on the VAIC as the primary measure of ICE presents another limitation (Ståhle et al., 2011). Hence, future research could address these limitations. Furthermore, the sample consists of Italian ISMEs; therefore, caution is advised in generalizing these results to other contexts and firm types.

Future studies might also investigate other moderating factors that could influence the relationship between ICE, BoD size and FP, such as market-based or disclosure-related indicators.

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