THE IMPACT OF BOARD DIVERSITY ON INVESTMENT EFFICIENCY ACROSS STAGES OF FIRM LIFE CYCLE IN THE MENA REGION

Ibrahim Saleh AL-Radaideh 1
Dr. Haslindar Ibrahim 2

1 School of Management, Universiti Sains Malaysia (USM), Malaysia, (E-mail: ibrahims.r@student.usm.my)
2 School of Management, Universiti Sains Malaysia (USM), Malaysia, (E-mail: haslindar@usm.my)

Article history
Received date : 1-8-2023
Revised date : 2-8-2023
Accepted date : 10-10-2023
Published date : 15-10-2023

To cite this document:

Abstract: This study investigates the dynamic impact of board diversity on investment efficiency across different stages of a firm's life cycle, drawing from the framework of firm life cycle theory. It explores two critical diversity variables - the diversity-of-board index and diversity-in-board index - and their correlation with investment efficiency across various stages of the firm's life cycle, assessed based on free cash flow. The analysis encompasses 332 non-financial firms listed in the Dow Jones MENA Index from 2010 to 2021, yielding 3984 firm-year observations. Data was gathered from the S&P Capital IQ database and analysed using STATA software, employing panel data techniques. The findings reveal a positive influence of the diversity-of-board index on investment efficiency throughout the MENA region's firm life cycle. Conversely, the diversity-in-board index exhibits varying effects, being insignificant during the introduction stage, positive during growth and decline stages, and negative during mature and shake-out stages. These results endorse firm life cycle theory, emphasizing the dynamic role of board diversity in investment efficiency. Furthermore, the study supports resource dependence theory, indicating that diverse board structural characteristics enhance effectiveness, subsequently enhancing firm investment efficiency. This research offers valuable insights for economists and policymakers, advancing our comprehension of how board characteristics and attributes impact a firm's investment efficiency in a dynamic context.

Keywords: Diversity-of-Board, Diversity-in-Board, Investment Efficiency, Firm Life Cycle, and The MENA Region.
Introduction

Investment efficiency, crucial for growth and profitability, stems from the delicate balance of risk, return, and management costs within the constraints faced by investors (Hodgson et al., 2000). In a world of perfect markets, investments would be made in all projects with positive Net Present Value (NPV) to maximize returns (Modigliani and Miller, 1958; Biddle et al., 2009). However, real-world frictions, such as agency issues and information asymmetries, can lead to inefficient investments, resulting in either over- or under-investment (Richardson, 2006).

Corporate governance, as highlighted by Cheng et al. (2013) and Chen and Chen (2017), acts as a potent tool to mitigate agency issues and align the interests of managers and shareholders, thus addressing inefficient investments. Among internal corporate governance mechanisms, board diversity, including Chief Executive Officer (CEO) duality, board independence, board nationality, and women representation, stands out. It enhances monitoring, reduces agency conflicts in line with agency theory (Jensen and Meckling, 1976; Carter et al., 2003), and connects the organization to external resources as posited by the resource dependence theory (Salancik and Pfeffer, 1978; Carter et al., 2010).

Hence, a diverse board should comprise members with distinct characteristics and attributes, bringing a spectrum of skills, knowledge, and expertise (Xie, 2015). While a homogenous board may expedite decision-making, it may lead to limited information acquisition (Marcel et al., 2011). In contrast, board diversity fosters information sharing, diminishes uncertainty, and enhances resource management, ultimately bolstering investment efficiency (Felix, 2018).

Nevertheless, recent research findings on the relationship between board characteristics/attributes and investment efficiency have presented conflicting outcomes (Mirza et al., 2020; Xie, 2015; Cheng et al., 2013). This divergence can be attributed to prior studies examining the impact of board diversity on firm investment efficiency from a static perspective. Therefore, the first gap in this study is the lack of studies that approach the influence of board diversity on investment efficiency from a dynamic perspective, considering the different stages of a firm’s life cycle (Habib and Hasan, 2019). Understanding how board diversity interacts with firm life cycle stages is crucial for providing more nuanced and tailored recommendations for firms at different points in their development (Esqueda and O’Connor, 2020; Li and Zhang, 2018).

According to firm life cycle theory, a company’s internal and external environments evolve over time (Faff et al., 2016; Dickinson, 2011). Consequently, ownership structure, organizational behaviour, and corporate strategies are intricately linked at various life cycle stages (Habib and Hasan, 2019). In theory, during the introduction stage of the firm life cycle, a diverse board may offer a more expansive viewpoint on emerging trends and technologies, reducing the risk of overlooking innovative opportunities (Pham and Pham, 2020).

In the growth stage, diverse perspectives may introduce fresh ideas and market insights, aiding in the identification of high-potential investment opportunities (Saravia, 2013). Conversely, in the mature stage, diversity may optimize resource allocation and risk management to sustain investment efficiency (Habib and Hasan, 2017). Finally, during the shake-out and declining stages, diverse perspectives and skills may lead to more informed decisions, adaptability, and risk mitigation, vital for navigating challenging times and ensuring long-term sustainability (Ahmed et al., 2021).
Despite the theoretical foundation established in the literature (Ribeiro et al., 2021; Habib and Hasan, 2019), there is a paucity of actual empirical studies examining these relationships, particularly in the context of the MENA region. Wherefore, the second study gap is the scarcity of empirical investigations regarding the theoretical link between firm life cycle, board diversity, and investment efficiency (O’Connor and Byrne, 2015; Habib et al., 2018). This study aims to bridge this gap by conducting a comprehensive empirical analysis of how board diversity impacts investment efficiency across various stages of a firm’s life cycle in the MENA region.

**Why MENA Region?**
After the Arab Spring crisis of 2010 and amidst rapidly changing global economic conditions, companies, particularly those in the Middle East and North Africa (MENA) region, found it necessary to become more competitive by improving the efficiency of its investments (Arayssi et al., 2019). As a result, The MENA companies recognized the value of diversifying their board of directors as a means to improve the overall worth of their firms. Additionally, some MENA countries have enacted regulations promoting board diversity, offering insights for other regions contemplating similar reforms (Loukil and Yousfi, 2016). For instance, Saudi Arabia, a traditional Islamic country, has given women remarkable rights in various areas such as banking, driving, political roles. Since then, women are allowed to run for office and be elected as political office holders (Kamrava, 2012). As a result, board diversity research became highly prevalent after this period.

**Literature Review and Hypothesis Development**
The board of directors holds a pivotal role in overseeing managerial functions, providing strategic direction, ensuring legal compliance, and maintaining external relationships (Rajkovic, 2020). Notably, their influence extends to investment decisions, underscoring their significance in corporate governance. However, existing literature predominantly examines the nexus between board diversity and investment efficiency within a static firm framework, neglecting the crucial dynamics of the firm's life cycle (Habib and Hasan, 2019). The firm life cycle theory posits that companies traverse distinct developmental stages, each marked by distinctive characteristics, operations, and strategies (Dickinson et al., 2018). These phases, in turn, exert a discernible influence on the selection process of the board of directors (Li and Zhang, 2018), consequently shaping a company's investment efficiency across its life cycle.

In the introduction stage, firms grapple with high levels of managerial opportunism, revenue and cost unpredictability, and a paramount focus on gaining competitive advantage and market share (Hasan et al., 2015). Concerns about future cash flows and funding constraints often lead to heightened capital costs in this stage (Dickinson, 2011). Corporate governance dimensions such as complexity, managerial proficiency, and resource demands evolve throughout the life cycle phases. Notably, founders typically assume sole proprietorship in this initial phase, steering their ventures while they are in their infancy, with long-term success contingent on securing resources for market entry (Esqueda and O’Connor, 2020).

Wahba and Elsayed (2014), in their study of 84 listed Egyptian companies spanning from 2005 to 2010, found that a larger board size negatively impacts financial performance in the early stages of a company. In the introduction phase, independent directors possess limited managerial authority, predominantly assuming supportive oversight roles (Bonn and Pettigrew, 2009), resulting in a limited influence on corporate governance.
Transitioning into the growth stage, firms shift their focus towards profit maximization, substantial investments, positive operating cash flows, and a preference for debt financing to leverage tax advantages (Drobetz et al., 2015). Managers assume a pivotal role in propelling growth, leveraging their expertise, knowledge, and networks. At this juncture, augmenting managerial ranks can bolster organizational credibility and reassure external stakeholders of its sustainability (Perrault and McHugh, 2015). Pham and Pham (2020) delved into 442 publicly traded Vietnamese firms from 2012 to 2018, revealing a favourable impact of CEO duality on firm performance in this growth stage.

As companies progress into the mature stage, the emphasis shifts towards operational efficiency, and they generate consistent cash flows from core operations. Firms in this phase often allocate less towards new investments, placing greater emphasis on preserving profitability and market share (Faff et al., 2016). Consequently, there is an escalation in agency issues and a diminished reliance on external resources compared to the growth stage (Pham and Pham, 2020). Saravia (2013) noted that maturing firms institute anti-takeover measures to safeguard against hostile takeovers, affording them greater confidence in their investment decisions. Moreover, as firms mature and face heightened agency costs tied to excess cash, they are inclined to reinforce anti-takeover provisions and invest in projects with comparatively lower returns against their cost of capital. Furthermore, Ding and Zhang (2013) underscored that effective board governance can significantly enhance a company's investment efficiency, particularly in the mature stage of its development.

On the other hand, O'Connor and Byrne (2015) examined the relationship between corporate governance and firm value over different stages of a company's life cycle for 225 firms in China, Korea, Malaysia, Singapore, and Turkey, etc. from 2001–2002, and the results show that for mature firms, there does not appear to be a discernible correlation between governance and firm value.

The shake-out stage heralds a company's transition marked by declining sales, profitability, and operating cash flows (Dickinson, 2011). Firms in this phase, grappling with diminishing profits, are faced with the critical decision of downsizing or reinvigorating operations through reinvestment (Ahmed et al., 2021). The determinants of changes in cash sales and Property, Plant, and Equipment (PP&E) during this phase, whether influenced predominantly by cash flows or investment patterns, remain ambiguous (Akbar et al., 2020).

Jawahar and Mclaughlin (2001) posit that during the shake-out stage, the board of directors frequently revisits strategies for managing diverse stakeholder groups. Businesses in this phase, striving for survival and market reassertion, often adopt strategic measures such as product redevelopment, mergers, downsizing, and layoffs. Analysing 49 Brazilian listed companies between 2010 and 2019, Ribeiro et al. (2021) found that governance assumes heightened significance in reducing the cost of debt for companies in the shake-out stage, underscoring the salience of the company's life cycle in this relationship.

In the decline stage, companies experience cash outflows from operations and cash inflows from investments due to slowed growth and asset liquidation (Drobetz et al., 2015). Jawahar and Mclaughlin (2001) highlight a diminished focus on traditional operating activities, often accompanied by a reduction in board size. Additionally, Habib et al. (2018) found that, compared to firms in the mature stage, firms in the decline stage tend to have more advisory
directors but fewer monitoring directors in their study of listed Australian companies from 2001 to 2014.

Furthermore, Ribeiro et al. (2021) looked into the relationship between a firm's life cycle stage and the cost of debt for 49 non-financial firms in Brazil from 2010 to 2019 and discovered the importance of governance in lowering debt costs, particularly for businesses in the decline stage, underscoring the relevance of a firm's life cycle in this dynamic.

**H1:** There is a significant positive impact of the diversity-of-board index on investment efficiency at different stage of firm life cycle in the MENA region.

**H2:** There is a significant positive impact of the diversity-in-board index on investment efficiency at different stage of firm life cycle in the MENA region.

**Methodology**

**Dependent Variable**

This study adopts Biddle's et al. (2009) model to measure investment efficiency, which is a dependent variable of the current study. This involves estimating the amount of investment deviating from normal investment level. In other words, the residual of the model is utilized as a proxy variable for measuring investment efficiency. Here are the specific details:

To apply the methodology from Biddle et al. (2009), the first step involves estimating the expected investment, which is essentially the optimal level of investment expenditures based on the company's future growth opportunities. This estimation considers the relationship between investment and revenue growth, where the growth rate of the company's basic revenue plays a crucial role (García-Sánchez and García-Meca, 2018). Since this relationship can differ depending on whether revenue is increasing or decreasing (McNichols and Stubben, 2008), a piecewise linear regression model is employed to account for this difference. Additionally, various independent variables, including financial leverage, cash held ratio, firm size, and stock return, are factored in as they influence investment expenditures (Lei and Chen, 2019; Lai and Liu, 2018). Importantly, all these explanatory variables are lagged by one year (t-1) to prevent potential bias between them and the dependent variable. Moreover, it also includes the lagged investment expenditures. Provided that the optimal level of investment expenditures is estimated according to the following model:

\[ I_t = a + \beta_1 \text{Growth}_{t-1} + \beta_2 \text{LEV}_{t-1} + \beta_3 \text{Cash}_{t-1} + \beta_4 \text{Size}_{t-1} + \beta_5 \text{Returns}_{t-1} + \beta_6 I_{t-1} + \varepsilon \ldots (1) \]

Where \( I_{t} \) represents investment expenditures in year \( t \); \( \text{Growth}_{t-1} \) is the sales growth rate in year \( t-1 \); \( \text{LEV}_{t-1} \) is the debt-to-asset ratio at the end of year \( t-1 \); \( \text{Cash}_{t-1} \) is the ratio of cash to total assets at the end of year \( t-1 \); \( \text{Size}_{t-1} \) is the natural logarithm of total assets at the end of year \( t-1 \); \( \text{Returns}_{t-1} \) the annual stock returns expressed as the change in market value from year \( t-1 \) to \( t \); \( I_{t-1} \) represents the investment expenditures in year \( t-1 \).

The second step in applying Biddle's et al. (2009) methodology focuses on measuring investment efficiency by assessing the deviation from the expected investment level. This deviation is quantified using the residuals (\( \varepsilon \)) from the model. When this deviation is zero, it signifies that investment aligns perfectly with the estimated optimal level. To express investment efficiency, researchers use the absolute difference between the model's (1) estimated optimal investment level and the statistically calculated normal investment level (residuals \( \varepsilon \)).
Essentially, the higher the deviation of the normal value of investment expenditures from the optimal level of investment expenditures, this is an indicator on the low investment efficiency (Jin and Yu, 2018).

**Independent Variable**

Two indices—one measuring diversity-of-board index and the other measuring diversity-in-board index—are used as independent variables in this study.

**Procedure for Diversity-of-Boards Index**

The diversity-of-board index measures the dissimilarity among company boards. Therefore, the diversity-of-boards index are represented with three dimensions: the first dimension is CEO duality which means that CEO also acts as chairman or not. The second dimension is the percentage of independent directors of a given board; the third dimension represents the board size which is the number of directors sitting on each board. As such, diversity-of-board variable is composed of heterogeneous dimensions, in which the first dimension is of a dichotomous nature, the second dimension is continuous, and the third dimension is discrete.

As a result, this study is used the inter-sample distance-measurement method (Deza and Deza, 2014), which quantifies the structural differences between firm boards. This technique demonstrates the degree to which the three structural characteristics of a given firm's board of directors differ from those of other firm boards in the sample.

To build a matrix to keep track of the diversity-of-board index. First, this study assessed the dissimilarity in a given firm's structural board of directors (i.e., the three attributes in this study) between that firm and another firm simultaneously. Second, it calculates this dissimilarity for all other firms. Third, the diversity-of-board index for the given firm was calculated using the average of how dissimilar the given firm was from the other firms in the sample. Fourth, this study evaluated other firms' diversity-of-board indices. By comparing the diversity-of-board index between companies, it were able to determine how dissimilar (or diverse) a company was from the other companies in the sample (Hafsi and Turgut, 2013).

Since the structural attributes of a board of directors in this study have different data types (binary and ratio scale), it used a novel method to process all of the various data types simultaneously, as suggested by Han et al. (2022). This method places all relevant attributes on a single scale with a range of [0, 1], combining their various attributes into a single dissimilarity matrix. A higher scale indicates a board with more diversity. Comprehensive details about this index-building procedure are provided in the Appendix.

**Procedure for Diversity-In-Boards Index**

The diversity-in-board index quantifies differences in demographic attributes among board members. This index considers three specific attributes: firstly, board nationality, which represents the percentage of foreign directors on the board (García Martín and Herrero, 2018); secondly, woman representation, calculated as the ratio of female board members to the total number of directors (Benkraiem et al., 2017); and thirdly, board education level, which measures the diversity in director graduate qualifications across four categories: bachelor's, master's, PhD, and other. To assess the diversity in education level within the board, a coefficient of variation (σ / µ) is used, aiming to determine the proportion of the graduate level group (Hafsi and Turgut, 2013). It's important to note that these three board attributes are treated as continuous variables in the study (Hoang et al., 2018).
As a result, diversity-in-board is measured using the terciles split method. To create the diversity-in-board index, the sample is divided into three equal terciles for each attribute, ranking the levels of diversity for each one. These groups are assigned values: zero for the first tercile (indicating below average diversity), one for the second tercile (average diversity), and two for the third tercile (above average diversity). The diversity-in-board index is then calculated as the sum of these ranked attributes, providing a measure of demographic diversity within a board for each company. A higher value signifies greater diversity-in-boards (Hafsi and Turgut, 2013; Hoang et al., 2018).

Classification Variables

In Dickinson's (2011) work, who addresses the limitations of Anthony and Ramesh's (1992) methodology for assessing a firm's life cycle, whom draws insights from economic literature covering various aspects of a firm's behavior, such as production, learning, investment, entry/exit patterns, and market share (Spence, 1981; Wernerfelt, 1985; Jovanovic and MacDonald, 1994). Dickinson (2011) then creates a simplified proxy for a firm's life cycle, relying on the prediction of how operating, investing, and financing cash flows behave at different stages of a firm's life cycle. These stages are determined by a firm's performance and resource allocation, who argues that cash flows can indicate differences in a firm's profitability, growth, and risk, making them useful for categorizing firms into life cycle stages like introduction, growth, mature, shake-out, and decline.

In this study classified all the sample firms into different life cycle stages on the basis of the following cash flow pattern:
(1) Introduction: if OCF < 0, INVCF < 0 and FINCF > 0;
(2) Growth: if OCF > 0, INVCF < 0 and FINCF > 0;
(3) Mature: if OCF > 0, INVCF < 0 and FINCF < 0;
(4) Decline: if OCF < 0, INVCF > 0 and FINCF ≤ or ≥ 0; and
(5) Shake-out: the remaining firm years will be classified under the shake-out stage.

Where OCF is cash flow from operations; INVCF is cash flow from investment; FINCF is cash flow from financing. In addition, to reduce the impact of single-year effects, we use three-year moving averages of each cash flow type rather than fiscal year-end values to obtain the final life cycle classification (Drobetz et al., 2015).

Measurement of Control Variables

The regression analysis took into account several other firm-specific variables were included as controls, namely firm size, debt ratio, slack, market-to-book ratio, tangible assets ratio, and loss. These variables are considered influential factors in assessing a firm's investment efficiency, as highlighted in previous literature. Therefore, the researcher identified the control variables and the method of measuring them as follows:

Firm size, determined as the natural logarithm of total assets, signifies a firm's influence and capability. Larger firms tend to enjoy more accessible and favorable financing terms (Shen et al., 2015), potentially enabling greater investment capacity. Debt ratio, calculated as total liabilities divided by total assets, accounts for potential investment distortions and financing obstacles due to high indebtedness (Lei and Chen, 2019). Slack, measured as the total cash balance divided by total assets, affects future sales growth and, consequently, a firm's investment efficiency (Argilés-Bosch et al., 2018). The Market-to-Book ratio, derived from the market value divided by the book value of equity, reflects a firm's growth prospects, potentially
facilitating external financing for investments (Nugroho, 2020). Tangible assets ratio, calculated as fixed assets divided by total assets, inversely relates to a firm's investment efficiency; an increase in it typically corresponds to decreased investment efficiency (Jeon and Oh, 2020). Lastly, the Loss is a dummy variable, equaling 1 when a firm reports negative net income and 0 otherwise, allowing for the consideration of profitability's impact on investment efficiency (Lei and Chen, 2019).

Data and Sample Selection
The sample selection encompasses non-financial firms listed in the Dow Jones MENA Index, spanning a duration of twelve years from 2010 to 2021. The Dow Jones MENA Index was selected due to its comprehensive coverage of companies operating across eleven nations in the MENA region. It aims to encapsulate approximately 95% of the market capitalization within the region, rendering it a robust indicator of prevailing market trends. The Dow Jones MENA Index comprised a total of 790 constituent companies during the specified period. However, 178 financial companies and 280 entities lacking complete data on firm life cycle, board diversity, and other pertinent variables were excluded from the sample. Consequently, the final sample size consisted of 332 non-financial firms, yielding a total of 3984 firm-year observations. Refer to Table 1 for a breakdown of constituents by country.

Data for this research was procured from the S&P Capital IQ database, which houses comprehensive annual reports (encompassing both financial and corporate governance reports) for companies listed in the Dow Jones MENA Index. Financial reports were utilized to compute investment efficiency and various control variables, including firm size, debt ratio, slack, market-to-book ratio, tangible assets ratio, and loss. Moreover, cash flow data extracted from financial reports was employed to ascertain the stages of the firm's life cycle. Corporate governance reports were instrumental in sourcing data pertaining to board diversity. These encompassed measurements based on six distinct characteristics and attributes: CEO duality (the amalgamation of chairman and CEO roles in a single individual), board independence (the proportion of independent board members), board size (the total count of directors on the board), board nationality (count of foreign board members), women representation (count of female board members), and board education level (the educational qualifications of board members).

<table>
<thead>
<tr>
<th>Country</th>
<th>Number of Constituents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Saudi Arabia</td>
<td>86</td>
</tr>
<tr>
<td>Kuwait</td>
<td>35</td>
</tr>
<tr>
<td>UAE</td>
<td>45</td>
</tr>
<tr>
<td>Qatar</td>
<td>20</td>
</tr>
<tr>
<td>Oman</td>
<td>45</td>
</tr>
<tr>
<td>Bahrain</td>
<td>11</td>
</tr>
<tr>
<td>Egypt</td>
<td>37</td>
</tr>
<tr>
<td>Morocco</td>
<td>21</td>
</tr>
<tr>
<td>Tunisia</td>
<td>19</td>
</tr>
<tr>
<td>Jordan</td>
<td>12</td>
</tr>
<tr>
<td>Lebanon</td>
<td>1</td>
</tr>
<tr>
<td><strong>Sum</strong></td>
<td><strong>332</strong></td>
</tr>
</tbody>
</table>
Empirical Model
To test the proposed relationship, we proposed the following regression model. The model is mathematically expressed as follows:

\[
\text{absI}_{ij} = \beta_0 + \beta_2 \text{DoB}_{ij} + \beta_2 \text{DiB}_{ij} + \beta_3 \text{FSIZE}_{ij} + \beta_4 \text{DRATIO}_{ij} + \beta_5 \text{SLACK}_{ij} \\
+ \beta_6 \text{MTB}_{ij} + \beta_7 \text{TAR}_{ij} + \beta_8 \text{LOSS}_{ij} + \epsilon_{ij} \quad \ldots \ldots \quad (2)
\]

Where \( \text{absI}_{ij} \) investment efficiency is the absolute value of the regression residual of model (1); \( \text{DoB}_{ij} \) diversity-of-board index is measured using the inter-sample distance-measurement method; \( \text{DiB}_{ij} \) diversity-in-board index is measured using the terciles split method; \( \text{FSIZE}_{ij} \) firm size, determined as the natural logarithm of total assets; \( \text{DRATIO}_{ij} \) debt ratio, calculated as total liabilities divided by total assets; \( \text{SLACK}_{ij} \) slack, measured as the total cash balance divided by total assets, affects future sales growth and; \( \text{MTB}_{ij} \) market-to-Book ratio, derived from the market value divided by the book value of equity; \( \text{TAR}_{ij} \) tangible assets ratio, calculated as fixed assets divided by total assets; Lastly, \( \text{LOSS}_{ij} \) loss is a dummy variable, equaling one when a firm reports negative net income and zero otherwise.

The study categorizes the companies of the study sample into five stages based on Dickinson’s (2011) classification: introduction, growth, mature, shake-out, and decline, each determined individually. Subsequently, model (2) was used for each stage to assess how the diversity-of-board index and diversity-in-board index affects investment efficiency during different stages of a firm's life cycle.

Results and Discussion

Descriptive Analysis
The table 2 presents descriptive statistics of the sample used in the study, categorized by different life cycle stages of the firms.

<table>
<thead>
<tr>
<th>FLC Stage</th>
<th>Introduction</th>
<th>Growth</th>
<th>Mature</th>
<th>Shake-Out</th>
<th>Decline</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
<td>(285 Obs.)</td>
<td>(795 Obs.)</td>
<td>(2,241 Obs.)</td>
<td>(513 Obs.)</td>
<td>(150 Obs.)</td>
</tr>
<tr>
<td></td>
<td>Mean (Std. Dev.)</td>
<td>Mean (Std. Dev.)</td>
<td>Mean (Std. Dev.)</td>
<td>Mean (Std. Dev.)</td>
<td>Mean (Std. Dev.)</td>
</tr>
<tr>
<td>Investment Efficiency ( i,t )</td>
<td>0.003 (0.001)</td>
<td>0.002 (0.001)</td>
<td>0.001 (0.001)</td>
<td>0.002 (0.001)</td>
<td>0.005 (0.002)</td>
</tr>
<tr>
<td>( \text{IDoB}_{i,t} )</td>
<td>0.233 (0.082)</td>
<td>0.241 (0.087)</td>
<td>0.232 (0.088)</td>
<td>0.223 (0.08)</td>
<td>0.236 (0.092)</td>
</tr>
<tr>
<td>( \text{IDiB}_{i,t} )</td>
<td>2.839 (1.328)</td>
<td>2.686 (1.292)</td>
<td>2.853 (1.231)</td>
<td>2.945 (1.173)</td>
<td>2.64 (1.48)</td>
</tr>
<tr>
<td>( \text{FSIZE}_{i,t} )</td>
<td>8.453 (0.728)</td>
<td>8.674 (0.693)</td>
<td>8.635 (0.733)</td>
<td>8.548 (0.669)</td>
<td>8.345 (0.693)</td>
</tr>
<tr>
<td>( \text{DRATIO}_{i,t} )</td>
<td>0.545 (0.212)</td>
<td>0.496 (0.197)</td>
<td>0.421 (0.199)</td>
<td>0.411 (0.251)</td>
<td>0.46 (0.222)</td>
</tr>
</tbody>
</table>
Investment Efficiency shows a fluctuating trend, with the mean descending from 0.003 (Std. Dev. = 0.001) in the Introduction stage to 0.001 (Std. Dev. = 0.001) in Mature, and then ascending in Decline to 0.005 (Std. Dev. = 0.002). The Diversity-of-Board Index (IDoB) exhibits minor variability, with mean values ranging from 0.233 (Std. Dev. = 0.082) in Introduction to 0.236 (Std. Dev. = 0.092) in Decline. Its counterpart, the Diversity-in-Board Index (IDiB), peaks at the Shake-Out stage with a mean of 2.945 (Std. Dev. = 1.173). Firm Size (FSIZE) remains relatively stable throughout the cycle yet decreases to a mean of 8.345 (Std. Dev. = 0.693) in Decline. Debt Ratio (DRATIO) initially starts at a high mean of 0.545 (Std. Dev. = 0.212) and generally reduces over time. The metric of Slack rises until the Shake-Out stage, where it reaches a mean of 0.082 (Std. Dev. = 0.086), before decreasing. Market-to-Book Ratio (MTB) varies significantly, plunging to a low mean of 1.218 (Std. Dev. = 0.768) in Shake-Out. Tangible Assets Ratio (TAR) also demonstrates variation, peaking in the Growth stage with a mean of 0.619 (Std. Dev. = 0.216). Lastly, the LOSS variable, indicating Negative Net Income, starts at a mean of 0.337 (Std. Dev. = 0.473) and shows substantial fluctuations, reaching a mean of 0.353 (Std. Dev. = 0.48) in Decline. These metrics collectively reveal the evolving financial and strategic positions of firms at different life cycle stages.

**Variance Inflation Factor (VIF)**

The Variance Inflation Factor (VIF) test is a statistical tool used in regression analysis to assess multicollinearity among predictor variables, which can cause instability in coefficient estimates. It calculates a VIF value for each predictor, with a threshold typically set at 5 or 10. A VIF exceeding this threshold indicates significant multicollinearity, prompting researchers to take corrective actions such as removing correlated variables or employing dimensionality reduction techniques. (Hair, 2009). The VIF values for the constructs in the different stages are relatively close to (1-5), suggesting no problems of multicollinearity. As a result, the independent variables within each construct are not strongly correlated, which is desirable for regression analysis.

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Introduction</th>
<th>Growth</th>
<th>Mature</th>
<th>Shake-Out</th>
<th>Decline</th>
</tr>
</thead>
<tbody>
<tr>
<td>Investment Efficiency Model</td>
<td>VIF</td>
<td>VIF</td>
<td>VIF</td>
<td>VIF</td>
<td>VIF</td>
</tr>
<tr>
<td>Growth i,t</td>
<td>1.082</td>
<td>1.036</td>
<td>1.072</td>
<td>1.023</td>
<td>1.071</td>
</tr>
<tr>
<td>LEV i,t</td>
<td>1.162</td>
<td>1.219</td>
<td>1.221</td>
<td>1.222</td>
<td>1.46</td>
</tr>
<tr>
<td>Cash i,t</td>
<td>2.603</td>
<td>1.454</td>
<td>2.948</td>
<td>3.69</td>
<td>2.541</td>
</tr>
<tr>
<td>Size i,t</td>
<td>1.153</td>
<td>1.13</td>
<td>1.152</td>
<td>1.19</td>
<td>1.443</td>
</tr>
<tr>
<td>Returns_i,t</td>
<td>1.073</td>
<td>1.048</td>
<td>1.066</td>
<td>1.014</td>
<td>1.072</td>
</tr>
<tr>
<td>I_i,t</td>
<td>2.552</td>
<td>1.347</td>
<td>2.855</td>
<td>3.549</td>
<td>2.438</td>
</tr>
</tbody>
</table>
Study Model

| IDOB_{i,j} | 1.218 | 1.103 | 1.065 | 1.06 | 1.492 |
| DiB_{i,j}  | 1.057 | 1.063 | 1.008 | 1.015 | 1.071 |
| FSIZE_{i,j} | 1.357 | 1.409 | 1.461 | 1.422 | 2.43 |
| DRATIO_{i,j} | 1.481 | 1.378 | 1.362 | 1.464 | 2.096 |
| Slack_{i,j}  | 1.143 | 1.242 | 1.182 | 1.236 | 1.303 |
| MTB_{i,j}   | 1.154 | 1.167 | 1.068 | 1.071 | 1.263 |
| TAR_{i,j}   | 1.464 | 1.323 | 1.36 | 1.292 | 1.527 |
| LOSS_{i,j}  | 1.222 | 1.084 | 1.128 | 1.126 | 1.323 |

Table 4: Model Specification Test of investment Efficiency

<table>
<thead>
<tr>
<th>Tests / Stage</th>
<th>Introduction</th>
<th>Growth</th>
<th>Mature</th>
<th>Shake-Out</th>
<th>Decline</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lagranigian Multiplier Test</td>
<td>0.000(1)</td>
<td>0.000(1)</td>
<td>0.000(1)</td>
<td>0.000(1)</td>
<td>0.000(1)</td>
</tr>
<tr>
<td>Hausman Test</td>
<td>183.23(0.000)</td>
<td>219.54(0.000)</td>
<td>484.390(0.000)</td>
<td>163.62(0.000)</td>
<td>45.49(0.000)</td>
</tr>
<tr>
<td>Autocorrelation Test</td>
<td>26.423(0.000)</td>
<td>44.243(0.000)</td>
<td>246.800(0.000)</td>
<td>19.688(0.000)</td>
<td>37.969(0.000)</td>
</tr>
<tr>
<td>Heteroscedasticity</td>
<td>1.60E+05(0.000)</td>
<td>2.2e+06(0.000)</td>
<td>1.8e+06(0.000)</td>
<td>4.0e+06(0.000)</td>
<td>2.6e+07(0.000)</td>
</tr>
<tr>
<td>Cross-Sectional Dependence</td>
<td>0.78(0.435)</td>
<td>0.34(0.731)</td>
<td>1.19(0.235)</td>
<td>-0.32(0.747)</td>
<td>-0.57(0.569)</td>
</tr>
</tbody>
</table>

In table 4 this study conducted panel data analysis across different firm life cycle stages and consistently found that the Fixed Effect model was the most appropriate choice, as indicated by the Hausman Test. However, the presence of autocorrelation and heteroscedasticity in all stages necessitated the use of the Feasible Generalized Least Squares (FGLS) model, a robust method capable of addressing these issues by estimating error covariance. Cross-Sectional Dependence varied across stages, suggesting that firm behaviour may be influenced by others in some stages, highlighting the need to consider this dependence when interpreting results. Overall, this study demonstrated a robust approach to statistical analysis and model selection, ensuring the reliability of their panel data research findings.

Table 5: Investment efficiency models

<table>
<thead>
<tr>
<th>I_{i,t}</th>
<th>Coef.</th>
<th>Growth</th>
<th>Coef.</th>
<th>Mature</th>
<th>Coef.</th>
<th>Shake-Out</th>
<th>Coef.</th>
<th>Decline</th>
</tr>
</thead>
<tbody>
<tr>
<td>I_{i-1}</td>
<td>0.004</td>
<td>0.019***</td>
<td>-0.005***</td>
<td>-0.004***</td>
<td>0.008***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LEV_{i-1}</td>
<td>0.017*</td>
<td>-0.029***</td>
<td>-0.003</td>
<td>-0.019***</td>
<td>-0.041***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cash_{i-1}</td>
<td>0.3***</td>
<td>0.234***</td>
<td>0.33***</td>
<td>0.269***</td>
<td>-0.183***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Size_{i-1}</td>
<td>0.003</td>
<td>0.002**</td>
<td>0.003***</td>
<td>-0.004***</td>
<td>-0.004</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Returns_{i-1}</td>
<td>0.005</td>
<td>0.025***</td>
<td>0.007***</td>
<td>0.013***</td>
<td>0.009***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I_{i-2}</td>
<td>0.542**</td>
<td>0.552***</td>
<td>0.543***</td>
<td>0.520***</td>
<td>0.664***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.017</td>
<td>0.049***</td>
<td>0.005</td>
<td>0.072***</td>
<td>0.085***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.5691</td>
<td>0.3953</td>
<td>0.643</td>
<td>0.5563</td>
<td>0.4783</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 5 displays the regression results for different models used to calculate the dependent variable (investment efficiency) in various firm life cycle stages (Introduction, Growth, Mature, Shake-Out, Decline). The R-squared values in these models reflect the degree to which they account for variance in different stages of a firm's life cycle. Among these stages, the Mature stage stands out with the highest R-squared value (0.643), indicating robust explanatory capability. It is followed by the Introduction stage with the second-highest R-squared value (0.569), the Shake-Out stage with the third highest (0.556), the Decline stage with the fourth highest (0.478), and finally, the Growth stage with the lowest R-squared value (0.395). The Wald chi-squared test and associated p-values assess the overall significance of each model. Moreover, the large chi-squared values for all models indicate a strong overall explanatory power.

Table 6: Model Specification Test of Study Model

<table>
<thead>
<tr>
<th>Tests / Stage</th>
<th>Introduction</th>
<th>Growth</th>
<th>Mature</th>
<th>Shake-Out</th>
<th>Decline</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lagranigian Multiplier Test</td>
<td>22.70 (0.000)</td>
<td>110.33 (0.000)</td>
<td>340.97 (0.000)</td>
<td>40.51 (0.000)</td>
<td>1.39 (0.1192)</td>
</tr>
<tr>
<td>Hausman Test</td>
<td>8.63 (0.3747)</td>
<td>13.80 (0.0873)</td>
<td>91.80 (0.000)</td>
<td>31.96 (0.0001)</td>
<td>10.44 (0.2353)</td>
</tr>
<tr>
<td>Autocorrelation Test</td>
<td>16.925 (0.0002)</td>
<td>49.999 (0.000)</td>
<td>230.075 (0.000)</td>
<td>72.150 (0.000)</td>
<td>21.753 (0.000)</td>
</tr>
<tr>
<td>Heteroscedasticity</td>
<td>10.86 (0.001)</td>
<td>9.54 (0.0020)</td>
<td>70.56 (0.000)</td>
<td>2.3e+06 (0.000)</td>
<td>1.53e+06 (0.000)</td>
</tr>
<tr>
<td>Cross-Sectional Dependence</td>
<td>—</td>
<td>2.32 (0.020)</td>
<td>-0.19 (0.847)</td>
<td>1.550.122</td>
<td></td>
</tr>
</tbody>
</table>

Table 6 summarizes this study's approach to data analysis in different firm life cycle stages. Notably, this study utilized panel data analysis in the Mature, Shake-Out, and Decline stages, while opting for pooled data analysis in the Introduction and Growth stages. The choice of fixed and random effect models for various firm life cycle stages suggests the researcher's diligence in accounting for unobserved individual-specific effects and variations within the dataset. Moreover, the consistent presence of heteroscedasticity and autocorrelation across all models underscores the importance of addressing these issues. To mitigate these concerns, the researcher wisely applied the Feasible Generalized Least Squares (FGLS) model in panel data analysis and employed robust standard errors in the pooled data analysis. This approach enhances the reliability and robustness of the statistical analyses, ultimately contributing to the validity of the research findings.
In table 7 the R-squared values and the associated F-tests in each firm life cycle stage reveal the explanatory power and significance of the models. Among these stages, the Shake-Out stage exhibits the highest R-squared value (0.530), indicating that the model explains a substantial portion of the variance in this stage. It is followed by the Decline stage with the second-highest R-squared value (0.407), suggesting a moderately strong explanatory capability. The Mature stage follows with a relatively lower but still notable R-squared value (0.329). The Introduction stage follows with a relatively lower but still notable R-squared value (0.306). The Growth stage demonstrates the lowest R-squared value (0.195), indicating a weaker ability to explain variance. Importantly, all F-tests have p-values less than 0.000, signifying the overall significance of the models across all firm life cycle stages. Therefore, the models are statistically significant in explaining variations in the dependent variable in each firm life cycle stage.

In this section, it tests two hypotheses regarding the impact of board diversity on investment efficiency in the MENA region across different firm life cycle stages.

**Hypothesis 1 (H1):** This study hypothesizes that there is a significant positive impact of the diversity of the board (IDOB) on investment efficiency at different stage of firm life cycle in the MENA region.

**Hypothesis 2 (H2):** This study hypothesizes that there is a significant positive impact of the diversity in the board (IDiB) on investment efficiency at different stage of firm life cycle in the MENA region.

To assess these hypotheses, it conducted regression analyses for each firm life cycle stage (Introduction, Growth, Mature, Shake-Out, Decline) using absolute investment efficiency (absI) as the dependent variable and the diversity-of-board (IDOB) and the diversity-in-board (IDiB) as independent variables. The significance levels for the coefficients were set at p<.01 for highly significant, p<.05 for significant, and p<.1 for marginally significant.

The results indicate that in the Introduction stage, IDOB has a highly significant positive impact on investment efficiency (p<.01), supporting H1. However, IDiB is not statistically significant, failing to support H2.
In the Growth and Mature stages, both IDOB and IDiB have highly significant positive impacts on investment efficiency (p<.01 and p<.05), confirming both H₁ and H₂.

In the Shake-Out stage, IDOB significantly impacts investment efficiency at the 5% level (p<.05), supporting H₁, while IDiB is marginally significant at the 10% level (p<.1), providing partial support for H₂.

In the Decline stage, both IDOB and IDiB have significant positive impacts on investment efficiency (p<.05), confirming both H₁ and H₂.

The findings suggest that the influence of board diversity on investment efficiency varies across firm life cycle stages in the MENA region. Both diversity-of-board (IDOB) and diversity-in-board (IDiB) play significant roles in enhancing investment efficiency in different stages, emphasizing the importance of considering the specific firm life cycle context when assessing the impact of board diversity.

In each firm life cycle stage within the MENA region, specific control variables have been observed to exert varying degrees of significance on investment efficiency (absI). In the Introduction stage, Firm Size (FSIZE) demonstrates marginal significance at the 5% level, indicating a somewhat positive influence on investment efficiency for larger firms. However, other control variables such as Debt Ratio (DRATIO), Slack, Market-to-Book Ratio (MTB), Tangible Assets Ratio (TAR), and Net Income (LOSS) do not exhibit statistically significant impacts on investment efficiency during this stage. In the Growth stage, several control variables prove highly significant: Slack, MTB, and TAR are all highly significant at the 1% level, suggesting that firms with greater slack resources, higher market-to-book ratios, and increased tangible assets tend to experience improved investment efficiency. Firm Size (FSIZE) and Net Income (LOSS) are marginally significant at the 5% and 10% levels, respectively, implying their potential influence. In the Mature stage, Firm Size (FSIZE) emerges as highly significant at the 1% level, indicating a positive impact on investment efficiency. Debt Ratio (DRATIO), Slack, MTB, and Net Income (LOSS) also significantly affect investment efficiency, albeit at varying levels of significance (p<.01, p<.05, and p<.1), highlighting their roles in this stage. In the Shake-Out stage, control variables such as Slack, MTB, Tangible Assets Ratio (TAR), Debt Ratio (DRATIO), and Net Income (LOSS) significantly influence investment efficiency, further emphasizing their significance in this stage. Lastly, in the Decline stage, Debt Ratio (DRATIO) and Slack exhibit high significance at the 1% level, indicating substantial impacts on investment efficiency, while Firm Size (FSIZE) marginally influences investment efficiency at the 10% level. These results underscore the varying roles and importance of control variables in shaping investment efficiency within specific firm life cycle contexts.

Conclusion and Recommendation
This study has shown how important diversity-of-board and diversity-in-board indexes are for investment efficiency throughout a firm's life cycle in the MENA region. The diversity-of-board index emerged as a key element, favouring the efficiency of investments at all stages. The diversity-in-board index also boosts a firm's investment efficiency during its growth and decline stages, but when it is mature and going through a shake-out, it has the opposite effect. The diversity-in-board index also demonstrated nuanced effects, favouring growth and decline stages while being detrimental to mature and shake-out phases. However, diversity-in-board index had no effect on firm investment efficiency in the MENA region during the introduction
stage. Future studies can compare the results with those from the current study using different study samples, such as the Jones MENA Ex-Saudi Index, Dow Jones GCC Index, and Dow Jones GCC Ex-Saudi Index. The suggestion to combine quantitative data with qualitative analysis to create and validate new metrics for evaluating board diversity. Finally, by using flexible accelerator models, future studies can examine the sustained effectiveness of investment. These models provide important insights for economists and policymakers, assisting in the understanding of how economic conditions affect investment patterns and enabling predictions about how economic policies will affect investment and overall economic growth.

Appendix. Technique for Measuring the Diversity-of-Board Index
First, we measured the dissimilarity between a given firm and another firm, and we then measured such dissimilarity for all other firms, using a mathematical distance function defined by Han and Kamber (2006) as follows:

\[ d_{ij} = \frac{\sum_{f=1}^{P} d_{ij}^{(f)}}{\sum_{f=1}^{P} g^{(f)}} \] … … (3)

Where \( i \) and \( j \) are two p-dimensional data points represented as \( (x_{i1}, x_{i2}, ..., x_{ip}) \) and \( (x_{j1}, x_{j2}, ..., x_{jp}) \) respectively, and \( d_{ij} \) is a distance function (metric) used to express the (dis)similarity between two data points (i.e., \( i \) and \( j \) in this case). Then, the contribution of dimension \( f \) to the dissimilarity between \( i \) and \( j \) (i.e., \( d_{ij}^{(f)} \)) is computed dependent on its type:

1. If \( f \) is binary or nominal: \( d_{ij}^{(f)} = 0 \) if \( x_{if} = x_{jf} \), or otherwise \( d_{ij}^{(f)} = 1 \)
2. If \( f \) is interval-scaled: \( d_{ij}^{(f)} = \frac{|x_{if} - x_{jf}|}{\max_{h} x_{hf} - \min_{h} x_{hf}} \)
3. If \( f \) is ordinal or ratio-scaled: compute ranks \( r_{if} \) and \( z_{if} = \frac{r_{if} - 1}{M_{f} - 1} \), and treat \( z_{if} \) as interval-scaled \((r_{if} \in \{1, ..., M_{f}\})\).

In this function, the contribution of all different types of dimensions to the dissimilarity (i.e., \( d_{ij}^{(f)} \)) are normalized, and hence expressed on a common scale of (0, 1).

In our analysis, this study will individually compute the distance of each data point (i.e., company board) to all other data points in our data set using the above-mentioned metric. Here, this study has given equal weights to the relative contributions of each variable to the distance function (i.e., \( d_{ij}^{(f)} = 1 \)). Then, this study averages the computed distances of each data point to all other data points using the formula below:

\[ d_{(i,j)} = \frac{\sum_{f=1}^{P} d_{ij}^{(f)}}{s} \] … … (4)

And for the average distance to all the other boards we use:

\[ D_{(i)} = \frac{\sum_{z=1}^{k} d_{(i,z)}}{k - 1} \] … … (5)
where, $x_{i1}$, the board size $i$; $x_{i2}$, the percentage of independent directors $i$; $x_{i3}$, the fact that whether CEO of company board $i$ also acts as chairman or not; $s$, the number of dimensions representing diversity of boards (i.e., board size, independence and duality); $k$, the number of company boards; $d_{ij}^{(f)}$, the distance of company board $i$ to company board $j$ with respect to the variable $f$; $d_{ij}^{(f)}$, the relative contribution of the dimension $f$ to the distance between the company board $i$ and the company board $j$; $d_{(i,j)}$, the distance of company board $i$ to company board $j$; $D_{(i)}$, the average distance of company board $i$ to all other boards.

The output of this distance-measurement metric provides information on how (dis)similar a given board, taken into consideration three dimensions at the same time, from all other boards in our sample. This information represents the nature of diversity of boards.

References


Hoang, T. C., Abeyseker, I., & Ma, S. (2018). Board Diversity and Corporate Social


O’Connor, T., & Byrne, J. (2015). When does corporate governance matter? Evidence from


