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Educational Background and Industry Expertise Diversity of Top Management Teams and its Effect on Firm Performance in Eurozone Companies

Hofmann, Julius: Educational Background and Industry Expertise Diversity of Top Management Teams and its Effect on Firm Performance in Eurozone Companies – An Analysis across Economic Sectors

Standhartinger, Felix: Educational Background and Industry Expertise Diversity of Top Management Teams and its Effect on Firm Performance in Eurozone Companies – An Analysis across Countries

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Trotha, Johannes von: Educational Background and Industry Expertise Diversity of Top Management Teams and its Effect on Firm Performance in Eurozone Companies – Comparing Effects across High-tech and Low-tech Economic Sector

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Abstract

This thesis investigates the effect of educational background diversity (EDUDIV) and industry expertise diversity (INDIV) within Top Management Teams (TMTs) on firm performance measured by Tobin`s Q in 150 Eurozone companies. Using an advancement of the Shannon Diversity Index, econometric models evaluate three dimensions of the diversity effects: main, sector-specific, and country-specific. Grounded in Upper Echelons Theory (UET) and Resource Dependence Theory (RDT), the findings reveal that EDUDIV generally has a positive effect on firm performance, though this effect varies based on the company´s economic sector. High-tech (HT) sectors and countries with advanced talent ecosystems, as reflected in the Global Talent Competitiveness Index (GTCI), particularly benefit from EDUDIV by enhancing strategic adaptability and fostering innovation. In contrast, INDIV demonstrates a negative relationship overall, with exceptions in certain economic sectors, specifically within HT areas. The benefits from diverse perspectives might be outweighed by coordination challenges, resulting in varying levels of significance. These results underscore the nuanced role of TMT diversity, suggesting that its effect differs across contexts and excessive heterogeneity can hinder cohesion and decision-making. This research provides actionable insights for companies and policymakers seeking to optimize TMT composition to enhance firm performance.

Keywords: TMT, TMT Diversity, Board Heterogeneity, Firm Performance, Educational Background Diversity, Industry Expertise Diversity, Tobin's Q, Eurozone, Economic Sectors, High-tech, Low-tech

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1 Introduction

There has been increasing pressure on firms to improve their efforts and concentrate on non-financial aspects of their performance. Specifically, stakeholders expect organizations to take measures and report accordingly across three broad categories: Environmental, Social, and Governance (ESG) (Aydoğmuş, Gülay, and Ergun 2022; Shaikh 2022).

Taking corporate responsible actions and practicing non-financial reporting has become vital to investment decisions (Li et al. 2021). It is a relevant indicator of how firms serve the interests of their stakeholders and provide value for society at large. Globally, ESG performance has evolved into a metric for analyzing commitment to environmental protection and social responsibility. ESG is a multidimensional construct, encompassing various issues such as a company's carbon footprint, fair wages, or the diversity of board members. It provides a broad framework supporting investor's decision-making (Serafeim and Yoon 2022). A company with a high ESG score demonstrates social and environmental responsibility, reducing market volatility and information asymmetry between management and shareholders (Chen, Song, and Gao 2023). Information asymmetry is an inherent issue of the principal-agent relationship within Agency Theory. Due to differing objectives and information access, management might not always act in the best interest of shareholders, positioning them at a disadvantage. Thus, ESG disclosure is critical to bridge that gap and align interests, as managers are incentivized to act in ways that serve the company and society (Jensen and Meckling 1976).

One of the three critical components of ESG is corporate governance, which structures and guides decision-making within a firm (Shaikh 2022). Governance mechanisms like the supervisory board, oversight processes, and reporting ensure that businesses are managed responsibly and effectively (Chen, Song, and Gao 2023). These governance mechanisms also include Top Management Teams (TMTs), as they simultaneously execute shareholder and company interests.

Diversity within TMTs and a company's workforce has emerged as a critical component of corporate governance. Heterogeneous teams bring various experiences and perspectives that enrich decision-making and corporate strategy (Mansoor et al. 2013) discussions. From a stakeholder perspective, such diversity reduces risk and addresses the principal-agent problem.

1.1 Business Case for ESG

The growing emphasis on ESG issues inevitably raises questions about the associated costs and benefits for companies. While firms excelling in ESG are often associated with improved operating performance, higher returns, and lower firm-specific risk, researchers' findings remain inconclusive. Some studies report positive correlations between ESG performance and financial outcomes, while others find limited or no significant effects (Carnini Pulino et al. 2022; Shaikh 2022; Aydoğmuş, Gülay, and Ergun 2022).

Within the broader discussion on the "business case" for ESG, research has increasingly examined the role of governance in impacting firm performance, focusing on the effect of diversity within TMTs. In general, as first proposed by Hambrick and Mason (1984) in Upper Echelons Theory (UET), it is suggested that the characteristics of TMT members influence firm outcomes, with TMT diversity specifically often contributing positively through enhanced innovation, broader knowledge networks, greater adaptability in volatile environments, and unique team dynamics arising from the interplay of diverse attributes (Kilduff, Angelmar, and Mehra 2000). In academia, scholars have analyzed this diversity within TMTs across various characteristics, including demographic differences in gender, age, or nationality, as well as occupational factors like educational background or industry expertise (Chen and Hassan 2022; Wei and Zhang 2022; Aboramadan 2021; Wasike and Joseph 2020; Bolo, Muchemi, and Ogutu 2011).

1.2 Problem Statement, Research Question, Significance, and Structure of the Thesis

However, research on TMT diversity characteristics and their impact on firm performance has predominantly focused on social, readily observable factors, such as age and gender. More complex characteristics, such as an individual's professional background, have only recently garnered attention and, consequently, have not been examined as extensively. Additionally, as gathering data on these complex characteristics is often time-intensive, existing studies have concentrated on specific settings, typically within a single country or a limited number of companies within one industry. This paper aims to expand the literature by analyzing these complex characteristics of TMT members in a broader context. Explicitly, we utilize educational background diversity and industry expertise diversity as measures of TMT heterogeneity and investigate how these dimensions influence firm performance. This analysis is conducted across a sample encompassing 150 large companies in all major industries within the Eurozone. This paper contributes to the current body of research on TMT diversity and seeks to provide practical insights into TMT composition. The findings are particularly relevant for nomination committees, highlighting the potential risks of homogeneous leadership and providing guidance for firms to optimize TMT composition to achieve specific outcomes, such as higher innovation, resilience, and strategic agility.

The remainder of this paper is structured as follows: First, we review the existing literature on TMT heterogeneity and its impact on firm performance, leading to the development of our hypotheses. We then outline our methodology, present the empirical results, and test the proposed hypotheses. This is followed by a discussion of the findings and their implications. Finally, we conclude by offering practical applications, acknowledging the limitations of our study, and providing recommendations for future research.

2 Literature Review

The section begins by outlining key theoretical frameworks to provide a foundation for the literature review. It then examines existing research on TMT heterogeneity, starting with social characteristics and progressing to occupational characteristics, including educational background diversity and industry expertise diversity. The literature review concludes by developing the study's hypotheses.

2.1 Theoretical Background

TMTs oversee daily operations, manage the company, and implement strategies by continuously analyzing complex information and responding to external stimuli within the company's environment. Given the sheer volume of available information, it is impossible for managers to fully comprehend and effectively utilize all the data at their disposal. Consequently, they often rely on cognitive frameworks, like rules of thumb, to synthesize different pieces of information and facilitate decision-making (Bolo, Muchemi, and Ogutu 2011). This bounded rationality of managers strongly affects decision-making and, ultimately, a firm's performance (Nielsen 2010) because managers cannot always act rationally but are influenced by limitations as human beings (Cyert and March 1963). The Behavioral Theory of the Firm lays out valuable insights into how TMT members' backgrounds shape decision-making, elaborating on how cognitive and social factors affect team interactions (Nielsen 2010). It serves as a framework to evaluate how TMT diversity potentially drives or diminishes firm outcomes. Following the Theory, TMT members' actions are guided by personal experiences, social interactions, and values, which can install biases that impact how priorities are set, and strategic reactions are formed. Additionally, the Behavioral Theory proposes that these cognitive differences impact team dynamics, thereby executive team decision-making processes and overall corporate governance (Kaczmarek 2017). Yet, Behavioral Theory also urges caution as cognitive and experiential variances potentially lead to disagreements that stimulate disputes about corporate vision and strategic approach (Cui, Wang, and Zhang 2023).

Building on the concepts of bounded rationality and Behavioral Theory of the Firm, Hambrick and Mason (1984) developed UET. At its core, it states that "organizational outcomes – strategic choices and performance levels – are partially predicted by managerial background characteristics" (Hambrick and Mason 1984, 193). This Theory challenged prevailing views that organizational performance was primarily shaped by environmental forces and structural inertia (Liu, Fisher, and Chen 2018; Hannan and Freeman 1977) or by social and institutional pressures driving organizations toward similar structures and strategies over time (DiMaggio and Powell 1983). Since its development, UET has provided a foundation on how diversity in TMTs – including C-level executives, managing or executive directors, and presidents (Carpenter and Fredrickson 2001; Mbaya 2017) – influences various dimensions of organizational performance.

2.2 Business Case for TMT Heterogeneity

The literature has increasingly examined the relationship between supervisory and executive board characteristics and firm performance. To contribute to the discussion, we focus on the executive board, referred to as TMT, anticipating more precise insights given their direct involvement in strategy, decision-making, and financial outcomes. Research has explored heterogeneity across attributes of TMT members, including gender, age, race, educational background, and industry expertise. TMT diversity is commonly defined as the variation in TMT composition concerning these specific attributes (Akram et al. 2020).

High team heterogeneity offers access to diverse skills and experiences, while low heterogeneity may result in rapid consensus, potentially leading to limited or inaccurate results. Diversity fosters constructive discussions and multidimensional problem-solving (Wei and Zhang 2022). Additionally, as individuals bring unique networks and connections, diversity enhances access to a broader range of contacts and resources vital for the firm (Nkundabanyanga 2016), facilitating engagement with and leverage of various stakeholders. This is in line with Resource Dependence Theory (RDT) (Pfeffer and Salancik 1978) which argues that companies rely on external resources and managing this dependency is a crucial part of corporate strategy (Díaz-Fernández, González- Rodríguez, and Simonetti 2020; Wang, Ma, and Wang 2015; Colombo and Grilli 2005). Scholars suggest that heterogeneous teams are potentially better equipped to manage these dependencies due to their broader range of skills and expertise (Anderson et al. 2011).

2.3 Factors of TMT Heterogeneity: Social and Occupational Diversity Characteristics

To advocate for diversity in TMTs, examining the types that influence firm performance is essential. Scholars generally distinguish between social diversity (e.g., gender, age, nationality) and occupational diversity (e.g., education and professional expertise), which shape decision-making and performance. The following sections explore their impact on organizational outcomes.

2.3.1.1 Social Diversity Characteristics

Social heterogeneity primarily describes readily observable or superficial factors, sometimes called demographic characteristics (Bolo, Muchemi, and Ogutu 2011). Demographic diversity among executive members is thought to influence firm performance by offering a broader range of cognitive perspectives (Homberg and Bui 2013), but results have been inconclusive. Tanikawa, Kim, and Jung (2017), for instance, found that age diversity in Korean manufacturing companies has a significantly negative effect on Return on Equity (ROE), but not on Return on Assets (ROA). At the same time, Richard and Shelor (2002) detect that age heterogeneity diminishes ROA. Additionally, they conclude that the connection may be curvilinear, illustrating that there is a threshold for the beneficial effects of age diversity. The varying results signal that this relationship might be highly contextual dependent which is in line with Wasike and Joseph (2020), who assert that age diversity is beneficial in dynamic, uncertain environments where adaptability and idea generation are crucial.

Regarding gender diversity and firm performance, researchers report a negative relationship among Chinese companies (Chen and Hassan 2022). Female representation in TMTs decreases firm performance, as measured by Tobin's Q. However, these results contrast with other findings from China, where scholars found a positive effect of gender diversity on firm performance (Y. Liu, Wei, and Xie 2014). Other studies find no significant correlation between gender diversity and firm performance (Eulerich, Velte, and Uum 2014). While gender diversity benefits dynamic and innovative industries, it can be detrimental in others due to communication barriers and lack of cohesion, where inefficiencies may outweigh the benefits, leading to neutral or negative outcomes (Mutuku, K'Obonyo, and Awino 2013; Homberg and Bui 2013).

The impact of nationality diversity is mixed, with some studies highlighting benefits in international market access and cross-cultural understanding. In contrast, others cite communication barriers that can hinder efficiency and decision-making (Aboramadan 2021; Eulerich, Velte, and Uum 2014). Eulerich, Velte, and Uum (2014) associate a high number of foreign executives with diminished operating profitability. In contrast, Nielsen and Nielsen (2013) measure a significantly positive impact on ROA. This indicates that having a variety of nationalities represented in TMTs may enhance information processing and problem-solving, especially in globalized environments.

The literature review reveals significant variation in findings across economic sectors, countries, and methodologies, limiting study comparability. These mixed outcomes suggest that the relationship between social heterogeneity and firm performance is highly context-dependent, influenced by factors such as methodology, theoretical frameworks, region, period of analysis, or industry. Inconsistencies may also arise from mediating or moderating factors like firm size, age, market conditions, or leadership styles (Aboramadan 2021; Wasike and Joseph 2020).

2.3.1.2 Occupational Diversity Characteristics

Occupational diversity encompasses heterogeneity in terms of educational background and professional expertise diversity. It is generally assumed that diverse occupational backgrounds provide unique expertise, knowledge, and perspectives that enrich discussions and innovation generation processes, subsequently improving firm performance (Homberg and Bui 2013). This diversity enables firms to better navigate uncertain business environments by providing broader viewpoints and solutions to strategic challenges. Especially in times of crises, different industry expertise is vital for a firm's robustness and recovery (Putra 2024). Unlike social diversity, occupational diversity is influenced by choice, allowing it to be strategically managed, whereas social diversity is typically innate and may trigger social categorization processes (K. Dahlin, Weingart, and Hinds 2005). Social diversity is often influenced by political motivations rather than performance goals. Thus, while both forms of diversity are important, occupational diversity is likely to have a more direct impact on strategy implementation, decision-making, and, ultimately, firm performance (Anderson et al. 2011).

Both elements of occupational diversity align with Agency Theory, as heterogeneity in educational background and professional expertise among the TMT members helps mitigate principal-agent conflicts (Jensen and Meckling 1976). While UET focuses on how managerial characteristics – such as educational and professional background diversity – shape strategic outcomes, Agency Theory underlines how these characteristics mitigate principal-agent issues by reducing information asymmetry and supporting decision-making that includes shareholder interests (Agrawal and Knoeber 2012; Jensen and Meckling 1976). From an educational background diversity perspective, having executives with varied educational backgrounds promotes comprehensive discussions and analysis from multiple perspectives. This enhances alignment with shareholder interests by encouraging thorough oversight and reducing the risk of self-serving behavior or groupthink among executives (Goll, Sambharya, and Tucci 2001). Equivalently, professional expertise diversity enables TMTs to evaluate issues multifacetedly and via access to a broader knowledge base, improving a firm's ability to challenge assumptions and shared beliefs. By broadening the scope of experience within the TMT, the likelihood of the company acting in the best interest of shareholders is increased (Wei and Zhang 2022; Aboramadan 2021). Jointly, UET and Agency Theory highlight the critical role of TMT diversity in shaping corporate strategy and ensuring effective governance.

Occupational Diversity: Educational Background Diversity

Educational background diversity reflects the different collections of knowledge, skills, and abilities derived from the team members' academic qualifications (Dahlin, Weingart, and Hinds 2005). Education is one of several sources of knowledge that contribute to an individual's expertise. This expertise guides team members in determining how to prioritize and incorporate information into their decision-making processes (Cohen and Levinthal 1990). While research has extensively examined the impact of educational diversity within TMTs on behavior and firm performance (Zimmerman 2008), findings are mixed and highly context-dependent. Li, Zhang, and Zhang (2015) studied over 100 Chinese companies and found that educational diversity positively impacts firm performance when firms pursue diversification strategies. However, in companies with a single or dominant business strategy, educational diversity is negatively correlated with performance. The authors argue that diverse executive teams are better equipped to navigate complex, multi-industry environments, whereas homogeneous teams are more effective for companies focusing on a single industry, as they foster greater cohesion and alignment. Smith et al. (1994) find that educational heterogeneity, measured by the years of education, positively impacts return on investment (ROI) and sales growth, suggesting that the increase in creativity offsets potential problems associated with diverse education levels.

Educational background diversity has not only been studied in a direct context with firm performance but also related to underlying factors, such as strategic decision-making: Wiersema and Bantel (1992) find that firms with higher educational specialization heterogeneity are more likely to undergo strategic changes. Similarly, while researching TMTs in the retail banking industry, Bantel (1993) concludes that heterogeneity in educational majors enhances strategic clarity, emphasizing the value of cognitive diversity in high-level executive teams for strategic decision-making. Hambrick et al. (1996) suggest that educational background diversity positively affects a company's competitive behavior and strategic actions, particularly in terms of their propensity and scope, although it slows down execution speed. Knight et al. (1999) further note that demographic diversity, including educational background diversity, negatively impacts the strategic consensus in TMTs, underlining potential trade-offs between diversity and team cohesion. Educational background diversity has also been tested regarding its effect on international expansions, however, with limited success. Tihanyi et al. (2000) hypothesized that a diverse educational background would increase a firm's ability to address complex issues, such as internationalization, but ultimately found no significant effects. Similarly, Barkema and Shvyrkov (2007) argue that while educational diversity in TMTs can stimulate constructive debates and promote innovative solutions for foreign investment opportunities, tenure diversity exhibited a stronger correlation with these strategic choices. They posit that as managers ascend to higher levels within a firm, accumulated professional experience tends to overshadow educational diversity, reducing its impact on firm performance.

Occupational Diversity: Professional Expertise Diversity

As previously noted, educational background diversity is just one dimension of occupational heterogeneity, with professional expertise diversity representing another critical component.

Professional expertise diversity encompasses a TMT's range of functions and industries (Goll, Sambharya, and Tucci 2001). While educational background shapes how managers think, professional expertise reflects the external context in which they apply their knowledge. Experience within a specific function or industry enables executives to maneuver sector-specific hurdles and capitalize on market-specific opportunities. Complementing educational diversity, professional expertise diversity provides TMTs with contextual knowledge, derived from different functions and sectors (Chung, Cho, and Kang 2018).

Professional expertise is widely regarded as the root of high productivity, growth, and increased company value (Aboramadan 2021). Due to its complexity, encompassing an individual's entire professional background, it is typically further structured into industry and functional expertise, i.e., by Daellenbach et al. (1999). Industry expertise accounts for the different sectors an individual has worked in, while functional expertise focuses on the specific tasks and roles performed within a firm. Professional expertise diversity, therefore, captures the different industries and functional backgrounds represented within a TMT, providing access to a broader array of experiences, skills, and competencies across sectors (Goll, Sambharya, and Tucci 2001). Theoretically, professional expertise diversity can be directly linked to UET, as diverse professional experiences shape how executives interpret challenges, identify opportunities, and formulate corporate strategies (Hambrick and Mason 1984). Nonetheless, UET also underlines the potential conflicts arising from divergent perspectives and approaches inherent in varied professional backgrounds.

These mixed effects also hold in practice: Evaluating issues from multiple industry perspectives supports opportunity identification and risk mitigation, with industry-specific expertise offering value in market access and specialized product or process knowledge. However, while professional expertise diversity fosters innovation and strategic agility, it can also create challenges such as coordination difficulties, communication barriers, and potential conflict, underscoring the need for effective leadership to manage diversity within TMTs (Firk et al. 2022).

Functional and industry expertise heterogeneity are both essential in the broader discussion of TMT diversity, but much of the academic focus has been on functional diversity (Lo, Wang, and Zhan 2019). Studies show that functional diversity often aligns with better firm performance. Firk et al. (2022) find that managers with broad functional expertise are better at aligning different functional areas toward shared goals, facilitating information exchange, and making collaborative decisions. Similarly, Maschke and zu Knyphausen-Aufsess (2012) argue that firm performance increases when managers' functional backgrounds align with corporate strategy. This is further supported by various studies on functional background heterogeneity, which find that diverse, cross-functional expertise better supports firm performance when compared to homogenous teams (Chung, Cho, and Kang 2018; Goll, Sambharya, and Tucci 2001). According to Zimmerman (2008), TMT functional background heterogeneity is positively associated with the amount of capital generated at the IPO. The blending of diverse functional experts allows TMTs to analyze challenges from multiple perspectives, fostering creativity and innovation within the complex decision-making process of going public (Zimmerman 2008). Several researchers have studied the effect of functional diversity in the context of start-ups: Beckman, Burton, and O'Reilly (2007) show that TMT heterogeneity improves the likelihood of securing venture capital funding. Teams with mixed functional experiences are better equipped to navigate complex strategic hurdles as they can draw from a wider pool of knowledge and problem-solving skills, making them more agile and adaptable in turbulent environments. This adaptability is further emphasized by Smolinski, Sieweke, and Bostandzic (2018) who conclude that TMT functional heterogeneity has a positive effect on firm performance in such environments. However, diversity may also induce conflict and communication challenges if not managed effectively (Díaz-Fernández, González- Rodríguez, and Simonetti 2020). Wang, Ma, and Wang (2015) point out that functional heterogeneity does not constantly improve firm performance and might negatively impact short-term performance. As mentioned, the literature on industry expertise heterogeneity in TMTs is relatively recent and remains limited. For instance, Wiersema and Bantel (1992) highlight the need for further research concerning industry expertise diversity and its effect on corporate strategy. Industry expertise diversity is often tested in specific contexts. Chung, Cho, and Kang (2018) find that knowledge diversity, measured as the degree of heterogeneity in industry expertise, positively impacts firm-level innovation. Similarly, Díaz-Fernández, González-Rodríguez, and Simonetti (2020) demonstrate that TMTs with diverse industry expertise, combined with diversity in age, functional and educational backgrounds, achieve higher firm performance. Bengtsson, Raza-Ullah, and Srivastava (2020) identify a positive and significant effect of industry expertise diversity on a firm's competition capabilities, enabling TMTs to balance cooperation and competition more effectively. Conversely, Colombo and Grilli (2005) observe that founders of new technology-based companies with homogenous industry expertise have a positive effect on firm growth, while prior diverse industry expertise does not.

Overall, the findings on functional and industry background diversity are mixed. Although a positive relationship between diverse professional backgrounds and firm performance is frequently suggested, the realization of these benefits relies on factors such as effective team management and alignment with corporate strategy (Wei and Zhang 2022).

In summary, the mixed effects of educational and professional expertise diversity on firm performance suggest a non-linear relationship. While greater diversity is often considered beneficial, it is not generally supported by empirical evidence. Instead, optimal levels of diversity may exist, where moderate heterogeneity improves corporate outcomes, but excessive heterogeneity could impair team cohesion and decision-making (Wei and Zhang 2022; Díaz-Fernández, González- Rodríguez, and Simonetti 2020). Educational background diversity can offer advantages for decision-making and strategic flexibility by providing cognitive perspectives that foster problem-solving and innovation, particularly in dynamic environments. Meanwhile, industry expertise diversity widens TMT's knowledge base, aiding in opportunity identification and threat recognition. However, the impact of these diversity dimensions depends on contextual factors, including market conditions, corporate strategy, and leadership style. A nuanced approach to managing heterogeneity is necessary to leverage its potential fully while avoiding negative outcomes.

2.4 Hypotheses Development

The literature review demonstrates that although TMT heterogeneity and its relationship to firm performance were studied thoroughly, research gaps remain.

2.4.1.1 H1.1 and H2.1: Effects of TMT Heterogeneity on Firm Performance

First, many scholars adopt a relatively broad approach to TMT heterogeneity, with most research in the field being descriptive. Additionally, studies in Europe are limited and often only concentrate on a specific country or a single economic sector, restricting the generalizability of findings. To address this gap, this thesis focuses on the largest Eurozone companies across sectors. Finally, given the relative scarcity of research on occupational background heterogeneity within TMTs, we specifically examine the effects of heterogeneity in educational backgrounds and industry expertise. We do not account for functional expertise, as this has already been the focus of most papers related to industry expertise.

Several studies highlight the positive effect of educational background diversity within TMTs on firm performance (Díaz-Fernández, González-Rodríguez, and Simonetti 2015; Boerner, Linkohr, and Kiefer 2011). The findings conclude that TMTs with diverse educational backgrounds are better equipped to achieve enhanced firm performance. The literature review revealed three main reasons for a positive link: First, educational background diversity unites individuals with distinctive cognitive frameworks who think and solve problems differently, thereby enriching discussions on strategy formation and decision-making (Bolo, Muchemi, and Ogutu 2011). Second, having people from various educational backgrounds enhances a company's ability to make strategic adaptations (Wiersema and Bantel 1992), which is especially important in turbulent environments as those require flexible alterations regularly (Li, Zhang, and Jing Zhang 2015). Third, educational diversity enhances innovation by ensuring access to expertise and knowledge bases (Aboramadan 2021; Bantel and Jackson 1989). These reasons are essential to firm performance and long-term sustainable growth.

Simultaneously, numerous studies hint at a positive impact of industry expertise diversity within TMTs on firm performance (Wei and Zhang 2022; Nielsen and Nielsen 2013; Auh and Menguc 2005). Specifically, the literature highlighted three main reasons: First, industry expertise diversity enables a company to rely on a broad knowledge base across sectors. Individuals with various industry experiences are better at identifying different sector-specific risks and opportunities (Chung, Cho, and Kang 2018). Second, companies are strategically more agile and innovative as they can puzzle together bits of expertise across sectors, generating novel solutions and enhancing creativity (Díaz-Fernández, González- Rodríguez, and Simonetti 2020). This strategic agility can be especially vital in rapidly evolving industries (Kilduff, Angelmar, and Mehra 2000). Lastly, drawing on RDT (Pfeffer and Salancik 1978), having diverse industry experts in the TMT provides access to a wide network of contacts and resources, which is beneficial for managing external dependencies and improving strategic positioning. In essence, the literature implies that educational background and industry expertise diversity in TMTs provide distinctive benefits that can significantly enhance firm performance. For clarity, the hypotheses are structured in pairs to reflect their similar design, differing solely in the independent variable – EDUDIV for H1 and INDIV for H2. This pairing ensures a systematic and consistent examination of the effects of both dimensions of diversity. Accordingly, we propose our first two hypotheses:

H1.1: *Educational Background Diversity has a significantly positive effect on Firm Performance*

H2.1: *Industry Expertise Diversity has a significantly positive effect on Firm Performance*

2.4.1.2 H1.2 and H2.2: Effects of TMT Heterogeneity across Economic Sectors

In addition to research gaps, the findings of existing literature have not been conclusive. Instead, it suggests that the effects of TMT heterogeneity on firm performance, to some extent, depend on other contextual factors of a company's environment. One of the most commonly quoted contextual factors, starting with Hambrick and Mason (1984, 197) in their initial paper on UET, is the economic sector a company competes in, with the authors noting that the effects of industry experience on firm performance differ between economic sectors. To contribute to the research on the contextual factor of economic sectors, we introduce the following hypotheses:

H1.2: *The effect of Educational Background Diversity on Firm Performance differs between economic sectors*

H2.2: *The effect of Industry Expertise Diversity on Firm Performance differs between economic sectors*

2.4.1.3 H1.3 and H2.3: Effects of TMT Heterogeneity in High-Tech (HT) and Low-Tech (LT) Economic Sectors

More specifically, we hypothesize that the impact of TMT heterogeneity on firm performance varies by economic sector based on its volatility and complexity. In more volatile environments, better governance mechanisms, which include diverse TMTs provide broader access to information, enhance decision-making quality, and reduce risk for stakeholders, strengthening the company's resilience (Putra 2024). Additionally, companies operating in high-velocity environments are likely to benefit more from diverse management teams as those environments demand rapid reactions, and diversity enhances both adaptability and innovation (Muithya and Kilika 2018). To measure the volatility and complexity of the economic sector, the sectors studied in this paper are grouped into High-tech (HT) and Low-tech (LT) sectors. HT sectors are widely considered to be more volatile, competitive, and fast-paced compared to LT sectors. Researchers, for example, found that, when compared to LT sectors, HT sectors are more likely to engage in mergers and acquisition (M&A) activity (Aydogan 2002), are more innovative (Fontenele et al. 2016), and experience a higher stock return volatility (Gharbi, Sahut, and Teulon 2014). Therefore, we introduce the following hypotheses:

> **H1.3:** *The effect of Educational Background Diversity on Firm Performance is enhanced in high-tech economic sectors compared to low-tech economic sectors*

> **H2.3:** *The effect of Industry Expertise Diversity on Firm Performance is enhanced in high-tech economic sectors compared to low-tech economic sectors*

2.4.1.4 H1.4 and 2.4: Effects of TMT Heterogeneity Based on Talent Development

Finally, the effect of TMT heterogeneity frequently depends on the company's location, with the cultural context of countries being emphasized in the literature (Díaz-Fernández, González-Rodríguez, and Simonetti 2020) and authors such as Daellenbach, McCarthy, and Schoenecker (1999) highlighting the need for cross-country comparison. While scholars have often focused on differences related to the cultural dimensions introduced by Hofstede (1983), e.g., power distance and its effect on Chinese TMTs (Zhou et al. 2023), we expand the research by focusing on country-specific differences in its approach to human capital. The Human Capital Theory states that an economic investment in individuals' skills, knowledge, and expertise reflects a competitive advantage and, therefore, contributes to organizational performance (Wuttaphan 2017). The Behavioral Theory supports this by emphasizing the role of bounded rationality and the importance of integrating external knowledge for strategic decision-making (Cyert, Feigenbaum, and March 1963). Therefore, an advanced talent ecosystem, including strong market-based talent support, may enhance access to this knowledge by growing human capital. Specifically, we explore how a country’s talent competitiveness, measured via the Global Talent Competitiveness Index (GTCI), influences the effect of TMT heterogeneity on firm performance. Countries ranking high on this index tend to exhibit advanced talent ecosystems characterized by robust educational frameworks, institutional quality, and solid lifelong learning and vocational training systems (INSEAD 2023). Through these ecosystems, countries provide attractive environments for talent, fostering strong innovation capabilities, social stability, professional development, and retention opportunities. In other words, a high-ranking GTCI country might ensure that the human capital entering the workforce is well-equipped and capable of comprehending complex strategic decision-making. Hence, we propose the following hypotheses:

> **H1.4:** *The effect of Educational Background Diversity on Firm Performance is enhanced by the Global Talent Competitiveness Index with stronger effects in countries with advanced talent development environments*

> **H2.4:** *The effect of Industry Expertise Diversity on Firm Performance is enhanced by the Global Talent Competitiveness Index with stronger effects in countries with advanced talent development environments*

2.4.1.5 H3: Comparison of the Effects of Educational Background and Industry Expertise Diversity

Finally, we aim to compare the distinct effects of educational background diversity and industry expertise diversity on firm performance. Educational background diversity within TMTs critically influences organizational behavior by fostering more comprehensive cognitive processes. This diversity enhances cognitive frameworks within TMTs, enabling managers to evaluate information more thoroughly and make well-rounded strategic decisions, thereby positively impacting firm performance. In contrast, while valuable for accessing sector-specific knowledge and networks, industry expertise diversity does not have the same impact on organizational behavior, resulting in a relatively weaker relationship. Hilgard and Bower (1977) established that people comprehend and obtain new knowledge as a function of the number of categories of prior knowledge, the extent of differentiation among these categories, and their linkages, specifically knowledge range, depth, and integration. It follows for TMTs, that the more previous knowledge a team or organization has the easier it is for them to absorb, evaluate, and apply novel information, which ultimately benefits firm performance. An academic degree implies obtaining a body of knowledge and, simultaneously, awareness of where to look for related information (Dahlin, Weingart, and Hinds 2005). A TMT with diverse educational backgrounds has broader knowledge categories that increase the team's cumulated knowledge and ability to innovate, contrary to teams with similar educational backgrounds with more overlapping knowledge, limiting their problem-solving potential and creative ability.

Industry expertise diversity, however, provides a complementary yet different value. It refers to professional experience within a particular economic sector, defining a TMT member's ability to initiate strategic change, navigate sector-specific challenges, or leverage established networks (Fan 2024). While it involves similar knowledge sources, it does not influence cognitive frameworks to the same extent as educational background diversity. Precisely, industry expertise diversity does not fundamentally reshape cognitive structures like educational background diversity does, limiting its influence on performance outcomes (Mathuki and Zhang 2022). Working within a specific field for various years unlocks considerations and perspectives that might be unique and valuable when applied in another sector. Yet, we expect the extent to which an educational background shapes an individual's worldview and problem-solving approach to be more influential. Given the unique role of educational diversity in intensifying organizational behavior and supporting strategic decision-making within TMTs, we propose our final hypothesis:

> **H3:** *The effect of Educational Background Diversity on Firm Performance is stronger than that of Industry Expertise Diversity*

For a comprehensive overview of the conceptual framework underlying the hypotheses development and key drivers, please refer to *Appendix 4*.

3 Methodology

This section is divided into three parts. First, we set up the data sample and clarify our empirical analysis's geographical and time-related scope. Second, we define and justify all necessary variables for the empirical analysis and explain their application. Third, we describe the econometric model, which is intended to lead each hypothesis to a result.

3.1 Data Samples

In justifying and selecting our data sample, we note that most studies on board diversity and firm performance concentrate on non-European countries (mainly the U.S. and Asia), as indicated by Kontesa et al. (2020), Kagzi and Guha (2018) and Adams and Ferreira (2009). Therefore, focusing on European companies is valuable for addressing the research gap, especially in the context of diversity, which goes beyond gender, nationality, and age (DWF 2021). Furthermore, we fixated on Eurozone companies, as this allows a better comparison and a unique context for analyzing board diversity's influence on firm performance not only due to the EU-wide harmonized legal framework but also the extensive occurrence of a two-tier board system (where supervisory boards are separated from executive boards) (Eulerich, Velte, and Uum 2014). Such a comparatively homogenous economic and legal policy environment helps control external factors and isolate the drivers of firm performance.

We initially gathered secondary source data for 156 listed Eurozone companies from London Stock Exchange Group Workstream (LSEG WS) (LSEG Workspace 2024) to analyze and empirically test the relationship of educational background and industry expertise diversity on firm performance. However, six companies were excluded from the sample due to limited data availability or intercompany duplicates (e.g., two companies with similar board members due to holding structure). We selected companies using The Reference Data Business Classification (TRBC), which categorizes LSEG-listed companies into 13 economic sectors (LSEG Workspace 2024). We decided to filter out the sectors "Institutions, Associations &

Organizations", "Government Activity", and "Academic & Educational Services" as their companies differ in business purpose, are state-run, or tend to be comparatively smaller in market cap (see list of final sectors in *Appendix 5*). A multi-sector approach supports our empirical analysis by considering all sectors equally, ensuring we can test all hypotheses in general terms and between economic sectors. Based on our final classification, we chose the 15 largest companies by market cap (from 31/08/2024) for each economic sector as they reflect a demonstrative sample and ensure consistent data quality. In total, 150 companies were considered for the empirical analysis.

3.2 Independent Variables: Board Diversity

Our analysis examines two independent variables: educational background diversity and industry expertise diversity of TMT members[1]. Supervisory board members or Board of Directors (BoD) members with non-executive character were excluded from the original analysis. To adhere to the literature format, we referred to relevant executive board members as TMT members. From the 150 selected companies, 1,482 TMT members were identified and analyzed, with educational background diversity and industry expertise diversity calculated using consistent structures but distinct methodologies. Relevant data was mainly available via the TMT members' CVs on the company websites, with supporting résumé sources (such as LinkedIn) used to confirm TMT members' backgrounds.

3.2.1.1 Educational Background Diversity

To explore the educational background diversity of TMTs, the individual educational background of TMT members had to be considered when investigating the study area of the most relevant degree. We specifically focused on completed degrees starting from a (university/college) undergraduate degree to more advanced degrees, which Times Higher

[1] Account for C-suite executives, executive directors, (senior or executive) vice presidents and other executive leadership members

Education (2024) classified into 11 study areas (incl. sub-areas) (see complete list of areas in *Appendix 6*). Degrees that did not fit into these categories were grouped under "Other".

Moving on, we defined a structured, step-by-step assessment process to identify each individual's most relevant degree study area. The process followed a series of decision points to ensure a consistent approach (see *Appendix 7*). It was designed to evaluate the most recent degree and progress through prior degrees to determine the most relevant one. If no degree was qualified, the process ended with "No Assessment." If a TMT member had not completed a higher study program, comparable vocational training was considered if possible. If this was not the case, the assessment also ended with "No Assessment". As illustrated in the initial step, we verified if the most recent degree was supplementary (such as an MBA, EMBA, etc.) because these are primarily designed to build upon prior knowledge, provide a broad, leadership skill-oriented education, and do not set a core technical, subject-specific skillset (Mangum and Wruck 2011). If the degree was supplementary, we then looked at the second most recent degree to determine relevance. If the most recent degree was not supplementary, we assessed whether it provided the key technical skills needed for the individual's career. If it did, we considered it the most relevant degree. If not, we repeated the process for earlier degrees until a relevant degree was identified or none qualified. If not, we repeated this process for the second and third most recent degrees. If none of the degrees qualified as relevant, the process ended with "No Assessment".

For the empirical analysis, we created the variable EDUDIV to aggregate the individual study areas of TMT members and calculate the educational background diversity per board at the company level. EDUDIV is based on the Shannon Diversity Index (SDI), which accounts for the richness and evenness of study area occurrences and ranges from 0 (indicating no diversity) to higher values showing more diversity (Shannon 1948). Pandey et al. (2022), Campbell and

Mínguez-Vera (2008), and Yap, Chan, and Zainudin (2017) support the application of SDI to the research of board heterogeneity in firm performance.

$$SDI(p_i) = -\sum_{i=1}^{k} \frac{T_i}{T} \ln\left(\frac{T_i}{T}\right)$$

In the formula, k represents the number of unique study areas (=11), and p_i the proportion of TMT members within each study area. The proportion p_i represents the division of T_i – number of TMT members in study area i – by T – the total number of TMT members per company. Due to the small sample size and varying TMT member size, SDI alone tends to overestimate diversity and might be biased (Campbell and Mínguez-Vera 2008). Therefore, we used Zahl's unbiased estimator of SDI (Zahl's SDI), which compensates for this effect and helps to ensure that differences in TMT member size do not skew diversity comparisons across companies (Konopiński 2020).

$$EDUDIV\ (Zahl's\ SDI) = SDI * \left(1 - \frac{1}{2T}\right)$$

3.2.1.2 Industry Expertise Diversity

A similar structure, with a divergent assessment tree and a deviating calculation methodology, has been used to assess industry expertise on individual TMT member levels and calculate its diversity. The evaluation of individual TMT members' industry expertise is no longer limited to the most relevant industry expertise. However, it followed Ericsson, Krampe, and Tesch-Römer (1993) that it takes 10,000 hours (about five to ten years of full-time work) to master a subject area. In the leadership context, Noe et al. (2016) underline that an economic sector has a threshold level of maturity to contribute at strategic company levels. Given the limitations in data granularity, eight years was chosen as the decision criterion for industry expertise diversity, aligning with a median threshold between seven and eight years. The explanation for the assessment inclusion of multiple industry expertise is that diverse management experiences contribute to a broader range of perspectives and thus influence TMT diversity, showing a broader industry expertise picture out of the data of each TMT member (Hambrick and Mason 1984). We applied the same ten TRBC economic sectors used to select the sample companies from LSEG WS (see *Appendix 5*). If we could not assign the industry expertise to an economic sector, we created the category "Other". Based on that, we considered all TMT members' industry expertise from different economic sectors relevant, which matched or exceeded the eight-year threshold. In the specific case of a TMT member having relevant industry expertise in more than three different economic sectors, the sectors were ranked according to their relevance (see *Appendix 8*). The ranking of accumulated industry expertise of a sector is based on an iteration that checks whether one of the accumulated industry expertise (1) contained higher seniority roles (TMT-related roles), (2) incorporated a higher number of different roles, (3) was in the more recent past or (4) received special recognitions or notable awards in that specific sector.

For the empirical analysis to capture industry expertise diversity at the company level, we have formulated the variable INDIV. As with EDUDIV, the entries of the TMT members per company were aggregated, but in this case with a weighted aggregation. $T_{i,j}$ is the weighted proportion of TMT members with relevant industry expertise in the economic sector i. If a TMT member had relevant industry expertise in only one economic sector, their contribution was fully allocated to that sector ($T_{i,j}$= 1). In the case of two economic sectors, each sector was given a half weighting ($T_{i,j}$=1/2). In the case of three economic sectors, each sector was given a third weighting ($T_{i,j}$=$1/3$).

$$SDI(p_i) = -\sum_{i=1}^{k} \frac{\sum_{j=1}^{n} T_{i,j}}{T} \ln\left(\frac{\sum_{j=1}^{n} T_{i,j}}{T}\right)$$

Following the EDUDIV approach, INDIV also needed an SDI adaption based on Zahl's SDI.

$$INDIV\ (Zahl's\ SDI) = SDI * \left(1 - \frac{1}{2T_{i,j}}\right)$$

3.3 Dependent Variable: Firm Performance

To measure firm performance, we used Tobin's Q, which measures the market value of a company's assets relative to their replacement, in which context Tobin (1969) suggested that companies make investment decisions by comparing this ratio. If Q > 1, the market values of the company's assets exceed their replacement costs. This creates an incentive for new investments, ensuring they are evaluated based on their potential to generate additional value through the efficient use of available resources (Campbell and Mínguez-Vera 2008; Tobin 1969). Conversely, if Q < 1, replacement costs increase, suggesting that lower investment might be advantageous due to inefficient asset use (Campbell and Mínguez-Vera 2008; Tobin 1969). We selected Tobin's Q over accounting-based measurements because it captures future-oriented performance from a market perspective (Magnanelli, Paolucci, and Pirolo 2021) and accounts for risk (Campbell and Mínguez-Vera 2008). Unlike accounting-based metrics such as ROA, Tobin's Q is less susceptible to reporting distortions due to tax laws and accounting regulations (Lindenberg and Ross 1981). In light of this, Tobin's Q is especially suited for our empirical analysis because board heterogeneity might have a considerably strong influence on future strategic decision-making, and board background diversity might actively contribute to higher ESG ratings, positively impacting market valuation (Deloitte 2022b). Our decision is supported by prior research in various similar fields (Kagzi and Guha 2018; Magnanelli, Paolucci, and Pirolo 2021; Darmadi 2013; Jindal 2015; Yap, Chan, and Zainudin 2017; Campbell and Mínguez-Vera 2008; Shamsudin, Mohd Suffian, and Ab. Rahman 2022; Suffian, Sanusi, and Mastuki 2015).

Following insights from the literature, we gathered data on Tobin's Q from LSEG WS. We interpreted it as the ratio of the sum of the company's market cap and the company's book value of debt with the company's book value of total assets: (Market Cap + Book Value of Debt) / Book Value of Total Assets. Because a well-comparable market value of debt is difficult to obtain, we used the book value of debt to calculate the company's market value, which is a widely accepted approximation (Perfect and Wiles 1994) also applied by Yap, Chan, and Zainudin (2017). To reduce firm performance volatility caused by individual companies' short-term conditions and to dampen the impact of macroeconomic, periodic events (such as an economic recession) (Gompers, Ishii, and Metrick 2003), we have derived Tobin's Q from three-year average data. Finally, we applied a natural logarithm transformation to control for outliers from a few companies, reducing skewness and normalizing the distribution (Benoit 2011). Therefore, we refer to (ln)Tobin's Q in the following.

3.4 Control Variables

Our empirical analysis controls for several variables with different impact levels. To cover this, we designed a pyramidal structure to address the multi-level influence points on firm performance, from a broad macroeconomic level over a company-specific level to a board-specific level (see overview in *Appendix 9*). Using a hierarchical structure of control variables follows UET by Hambrick and Mason (1984) capturing the influence of external environmental and internal organizational factors on firm performance.

On the macroeconomic level, we included the "Ease of Doing Business" Index which captures the regulatory environment of assessed countries and its impact on companies' business operations (World Bank Group 2020). According to the methodology of this index, a more business-friendly policy environment tends to mitigate operational inefficiencies by reducing the risk of market failure (World Bank Group 2020). We, therefore, matched the score of the 2020 index to our sample company's HQ countries to show whether company-level effects cause variations in (ln)Tobin's Q.

On the company-specific level, we inserted company size as a significant potential contributor to firm performance. On the accounting-based side, Total Assets is widely used by prior research (Kagzi and Guha 2018; Yap, Chan, and Zainudin 2017; Jindal and Jaiswall 2015;

Campbell and Mínguez-Vera 2008) because the effect of it on firm performance has already been investigated (Yermack 1996). Apart from Total Assets, we decided on Market Cap and Revenue, which might cover similar firm performance effects but also account for investor perception, market development, and operational scale, contributing to a more robust, unbiased model. When testing our model, we had to ensure that these company size variables do not cause multicollinearity, which we found out with stability and robustness tests (see chapter *3.6*). Subsequently, we added the Leverage Ratio (Kagzi and Guha 2018) to consider the company's financial risk and capital structure. All company-specific control variables were obtained from LSEG WS, retaking the three-year average values.

Lastly, on the board-specific level, we differentiated between the TMT level, which we obtained from our TMT background diversity data set, and the BOD level, which we again extracted from LSEG WS. TMT level based, we included Board Size because Yermack (1996) observed that a larger board member size indicated favorable financial ratios. Next, Yap, Chan, and Zainudin (2017) underpin the positive influence of gender diversity on firm performance, including it as TMT Gender Diversity. BOD level based, we chose Average Board Tenure, CEO-Chairman-Duality, and three-year average Independent Board Member focussing on a one-tier board system. Even though two-tier boards were more common in our sample company's structures, we wanted to shed light on the oversight characteristics of BODs. For example, Bremert and Schulten (2009) found that the characteristics of German-listed companies' supervisory boards positively influence firm performance. The three selected variables thus offer a holistic view of the BOD member's experience, balanced power structure, and objective oversight and, therefore, complement the governance factors from a supervisory perspective.

3.5 Contextual Factors and Interaction Terms

The hypotheses to our empirical analysis are designed to not only show the isolated effect of EDUDIV (H1.1) and INDIV (H2.1) on firm performance and their direct comparison (H3) but also test if this potential diversity-performance relationship varies across different contexts (H1.2-4; H2.2-4). Thus, we set contextual factors on (1) the economic sectors, (2) the technology intensity of these sectors, and (3) the national talent competitiveness to show if there are conditions that moderate the effect of EDUDIV and INDIV on firm performance. Based on these factors, we created interaction terms composed of EDUDIV or INDIV with the respective contextual factors.

As mentioned earlier, the economic sectors are derived from the TRBC classification for contextual factor setting. For hypothesis testing of H1.2 and H2.2, we applied effect coding in R to set the interaction term between EDUDIV and INDIV and each of the ten economic sectors. Effect coding ensures that the effect of a single economic sector is compared to the overall mean of all sectors rather than to a specific reference sector. This allows us to capture the unique influence of each economic sector and its moderation effect on the diversity-performance relationship.

3.5.1.1 High-Tech (HT) and Low-Tech (LT) Economic Sector

For H1.3 and H2.3, we separated TRBC economic sectors into HT and LT sectors. Instituto Nacional de Estadistica (2024, 3) defines HT as “rapid renovation of knowledge, very superior to other technologies and due to its degree of complexity that requires continued effort in research and a solid technological base”. According to the OECD, two indicators mainly define HT sectors: direct intensity as the relation of R&D expenses compared to production, and indirect intensity, which considers that one sector also benefits from the R&D intensity of other sectors (e.g., Original Equipment Manufacturer (OEM) company buys machinery from a software company) (Hatzichronoglou 1997). Since TRBC economic sectors are not classified by prior research, we assign them independently and refer to existing literature. Based on this classification scheme, we assigned the following four sectors as HT (see *Appendix 10*):

(1) Technology, represented by telecommunication, electronic equipment, and software companies, and heavily dependent on innovation cycles and consistent R&D spending (Hatzichronoglou 1997). (2) Healthcare, incorporating the development of medical devices, biotechnology, and pharmaceuticals, which companies spend on OECD average about 12% of their gross value added on R&D (leading behind “Electronic & optical products” and “Air & spacecraft”) (OECD 2019). (3) Energy, with particular emphasis on renewables and clean technology, its critical dependence on technology advancements and accountability of 5-10% on total public R&D spending in OECD countries (Energy Technology Perspectives 2023). (4) Consumer Cyclicals (CC), which includes, on the one hand, HT-intensive sub-sectors such as Automobile & Auto Parts, but on the other hand, also Cyclicals Consumer Services and Retailers with slower innovation cycles. Since the largest CC companies in our sample are OEMs, we still classify this sector as HT, which aligns with Hatzichronoglou (1997). The remaining economic sectors were grouped under LT for the sake of simplification. Overall, the remaining sectors can be described as, on average, more focused on operational efficiency than technological advancement with slower innovation cycles.

To implement the interaction term, we created a categorical dummy variable that assigns a value of 1 to companies belonging to HT sectors and a value of 0 to those from LT sectors.

3.5.1.2 Global Talent Competitiveness Index (GTCI)

Finally, for H1.4 and H2.4, the analysis focuses on the GTCI from INSEAD (2023), which highlights how economies compete globally to attract, develop, and retain talent, thereby boosting their competitiveness, innovation, and economic growth (see *Appendix 11*). The GTCI is presented annually for over 130 countries and is made up of 69 indicators that fall into the following three categories: (1) 34 indicators of hard/quantitative data based on a variety of public sources, such as UNESCO, OECD and the World Bank, (2) 17 indicators of indices / composite indicators data such as the Social Progress Index or the Global Innovation Index and

(3) 18 indicators on survey / qualitative data from the World Economic Forum's Executive Opinion Survey (INSEAD 2023).

Testing the hypotheses, we created the interaction term by deriving the GTCI of each HQ country and matching it to the respective companies.

3.6 Econometric Model

After establishing the hypotheses and explaining the data sample along with all necessary variables (see overview in Appendix 12), the final step was to outline our econometric model. This model is supposed to address each hypothesis using a structured approach that conducts a series of statistical tests to ensure a reliable outcome.

Before applying the model, we specified the mathematical composition to generate a formula for each hypothesis. Each formula shows the relation we aimed to test—including dependent variables, independent variables, control variables, and interaction terms—serving as the starting point of our regression analysis. We have detailed the formula for each hypothesis in *Appendix 3*. To decide on approving our hypotheses, we set the following significance levels for the p-values of all our tests: p-value < 0.1 = marginally significant; p-value < 0.05 = significant; p-value < 0.01 = highly significant. The following provides a detailed explanation of the five steps that each hypothesis formula undergoes in "R" (RStudio Team 2024) – our chosen programming language – to determine significance levels and hypothesis approval (see approach overview in *Appendix 13*):

Step 1 – Linear Regression: A linear model was used to grasp the overall diversity effect on firm performance, offering a general insight into its impact across all companies. Therefore, we established a linear model for all hypotheses and conducted a forced stepwise regression. This approach enabled us to incorporate essential variables for each regression needed to evaluate the hypotheses (EDUDIV, INDIV, (ln)Tobin's Q, and/or interaction terms) while retaining only the significant control variables. This minimizes potential distortions from insignificant variables, resulting in a more straightforward and interpretable model. As mentioned above, for H1.2 and H2.2, we ran forced stepwise regression twice due to the nature of effect coding, which ensured that all ten sectors were included.

If the model was significant and revealed a significant effect of EDUDIV/INDIV (moderated by interaction terms) on (ln)Tobin's Q, it provided evidence for the hypothesis, depending on the effect's direction. If not significant, we proceeded to run a quantile regression to see if there was significance in distinctive (ln)Tobin's Q quantiles (more in *Step 4*).

Step 2 – Inference Test for Linear Regression: This step was applied only to hypotheses with an interaction term (H1.2-1.4 and H2.2-2.4) or two independent variables (H3). We used the ANOVA test for hypotheses with interaction terms to confirm that the interaction term significantly improved the model's explanatory power. For H3, we conducted the WALD test to observe if EDUDIV contributed significantly more to (ln)Tobin's Q than INDIV. A quantile regression was required if neither test was significant.

Step 3 – Stability and Robustness Tests: A series of tests were carried out to ensure that our models were stable and robust to obtain meaningful results. These included a multicollinearity test using the VIF factor to confirm that predictor variables were not correlated (VIF factor < 5). Furthermore, we ensured heteroscedasticity and conducted a Breusch-Pagan test, which shows that residual variance is non-constant (p-value < 0.05). Testing for normality was deemed unnecessary because, due to our sample size of 150 companies, the Central Limit Theorem assumption of a normal distribution of residuals applied. If the tests were approved, we considered our model robust and stable. If one of the tests failed, we applied quantile regression to address violations in linear model assumptions.

Step 4 – Quantile Regression: Quantile regression was used to provide a more nuanced view of the diversity-performance relationship by capturing how the effect of EDUDIV/INDIV on firm performance varied across different levels (quantiles) of (ln)Tobin's Q. For instance, it could reveal whether the impact of EDUDIV/INDIV is stronger for high-performing companies than for low-performing ones. We applied quantile regression if we failed significance tests in Step 1 and Step 2 or failed robustness and stability tests in Step 3. If all prior steps met the significance and stability criteria, we conducted quantile regression to complement our model. The control variables Market Cap, Total Assets, and Revenue were scaled to ensure comparability across quantiles when conducting the quantile regression. Subsequently, nine quantiles, ranging from 10^{th} to 90^{th} quantile, were determined and mapped in the regression.

Step 5 – Inference Test for Quantile Regression: To determine the effectiveness and necessity of quantile regression, we applied the WALD test, which demonstrated that EDUDIV/INDIV differed significantly across the quantiles of (ln)Tobin's Q. This step was essential when the average effect in linear models did not fully capture the impact of diversity on firm performance. If quantile regression was needed due to non-significance or failed tests in prior steps, the WALD test confirmed its application.

This chapter provided the data sample's background, each variable's methodological structure, and a step-by-step approach to a consistent econometric framework for all our hypotheses, ensuring rigorous standards were maintained by integrating linear models, quantile models, and necessary stability and robustness tests. It sets a strong foundation for analyzing our results and empirically testing our hypotheses.

4 Empirical Analysis and Results

This section comprises two parts: First, descriptive statistics offer an overview of key variables such as diversity metrics (EDUDIV, INDIV), firm performance ((ln)Tobin’s Q), and control variables, highlighting, i.e., distributions, variability, and correlation. Second, hypothesis testing and regression analysis evaluate the impact of TMT diversity on firm performance through regression models and contextual interactions, supported by robustness checks and quantile regression to ensure model stability and explore effects across performance levels.

4.1 Descriptive Statistics

This section overviews our key variables and examines distributions, central tendencies, and variability affecting regression. A correlation matrix offers preliminary insights into the relationships among diversity indices, firm performance, and controls. Furthermore, diversity patterns across the categorical variables Economic Sector, Economic Sector High Low, and HQ Country are analyzed, laying the groundwork for hypothesis testing.

4.1.1.1 Central Tendencies and Summary Statistics

This part includes continuous and categorical variables analyses, covering their key distributional characteristics and diversity patterns.

We start by examining the continuous variables, highlighting their central tendencies, variability, and distributional characteristics while identifying skewness and potential outliers that may influence results. The primary variables are shown in *Appendix 14*. Detailed distributional characteristics, including skewness and outliers, were assessed using tools like histograms and box plots, providing critical context for subsequent statistical analysis. *Appendix 15* summarizes the main descriptive statistics.

Board Diversity Metrics: Both EDUDIV (mean = 1.151) and INDIV (mean = 0.792) exhibit low skewness (-0.763 and 0.213), indicating roughly symmetrical distributions with medians near their means. EDUDIV shows a slight left skew, peaking around average diversity levels with a few outliers at the lower end. INDIV is more concentrated at the lower end, clustering near zero, with a higher count of companies showing no diversity (13 for INDIV vs. 8 for EDUDIV).

Firm Performance Metric: (ln)Tobin's Q ranges from -2.41 to 3.06, with a high standard deviation of 0.98, indicating substantial variability. An average slightly above zero (0.09) and a skewness close to zero (0.016) show a nearly symmetrical, bell-shaped distribution around the mean, suggesting that the LN transformation balances firm performance values. This symmetry, along with minimal outliers and central clustering, supports its suitability for regression analysis. By contrast, the untransformed Tobin´s Q is heavily right-skewed (skewness = 4.607), as a few companies exhibit notably high performance. The LN transformation effectively normalizes this skewness, making (ln)Tobin´s Q a more stable basis for statistical analysis.

Company-specific, Board-specific, and Macroeconomic: Company-specific metrics reveal significant size variation, with market cap averaging $50.37bn but being heavily skewed by a few large companies, while total assets show even greater skewness due to extreme outliers. Board structures are diverse, averaging 10 members with moderate gender diversity (25.51% female representation) and varying levels of independence and tenure, reflecting different governance strategies. Macroeconomic factors display clustering around the median but highlight disparities in business and talent competitiveness, with notable outliers like Luxembourg and Croatia emphasizing environmental differences across countries. The two indices exhibit bimodal and multimodal patterns, respectively, indicating distinct clusters within the data. Outliers, such as Luxembourg, Italy, and Croatia, highlight business and talent competitiveness challenges across companies.

Following the analysis of continuous variables, we turn to categorical variables, identifying patterns and potential imbalances that could affect interpretation.

Economic Sector: The dataset includes 10 sectors with equal representation (15 companies each), supporting cross-sector comparisons. Still, with only 15 companies per economic sector, the statistical power to detect trends is limited, so findings should be interpreted cautiously.

Economic Sector High Low: The dataset has more LT companies than HT companies, which could impact any conclusions drawn regarding diversity and performance in technology-intensive sectors.

HQ Country: The uneven distribution of headquarters, with some countries represented by only one company, reduces statistical reliability for those nations. Such limited representation may reflect company-specific characteristics rather than broader national trends, emphasizing the need for cautious interpretation. The distribution of HQ Country in our dataset can be seen in *Appendix 16*.

Diversity Indices

Building on the earlier analysis, this section explores diversity patterns within the three categorical variables. It then proceeds to use statistical tests to assess the significance of these differences.

EDUDIV and INDIV are evaluated across Economic Sector, Economic Sector High Low, and HQ Country to identify potential sectoral, technological, or regional influences on board diversity and their implications for firm performance. Full results are provided in *Appendix 17*.

Economic Sector and Board Diversity Metrics: Healthcare has the highest EDUDIV scores, emphasizing educational diversity, while Real Estate is lower, reflecting specialization. Moreover, Energy shows the highest interquartile range for EDUDIV, indicating variability. For INDIV, Utilities and Industrials lead, highlighting the value of industry expertise, while Financials scores lowest. Real Estate has a significant INDIV spread, indicating varied strategies for expertise diversity.

Economic Sector High Low and Board Diversity Metrics: HT economic sectors have a slightly higher mean in EDUDIV, emphasizing varied educational backgrounds to drive innovation. Additionally, the diversity spread is broader in HT, with notable outliers, such as Healthcare companies, showing the highest EDUDIV values. LT sectors, on the other hand, exhibit a more consistent, narrower EDUDIV range, as they have lower overall variability. For INDIV, LT sectors report a higher mean and broader spread, with some companies demonstrating high expertise diversity. HT sectors have a higher median INDIV score, indicating a generally higher baseline of expertise diversity but less variability than LT sectors.

HQ Country and Board Diversity Metrics: Italy and Luxembourg lead in EDUDIV, strongly emphasizing educational diversity, while Croatia scores the lowest. Ireland shows the widest EDUDIV spread, indicating diverse strategies among its companies. On the other hand, INDIV is highest in Portugal and Austria but lowest again in Croatia. Its variability across countries surpasses that of EDUDIV, with Italy displaying the highest INDIV spread, highlighting significant diversity across its companies.

To ensure a robust analysis of diversity indices across different categorical variables, statistical tests were employed to assess the significance of the observed differences. For Economic Sectors and HQ Country, where there are multiple categories, ANOVA test followed by Tukey´s HSD post-hoc tests were conducted to pinpoint significant differences between specific groups. For Economic Sector High Low, an independent T-test suffices to compare the two categories.

Board Diversity Metrics by Economic Sector: ANOVA for EDUDIV yields significant results ($p = 0.011$), with significant pairings for Healthcare and Consumer Non-Cyclicals (CNC) (+0.484) and Healthcare and Real Estate (-0.593). For INDIV, the ANOVA test confirms sector-level differences, with Utilities showing significantly higher INDIV scores compared to multiple sectors.

Board Diversity Metrics by Economic Sector High Low: T-tests for EDUDIV indicate marginal significance regarding differences between HT and LT sectors (p-values = 0.073), while for INDIV ($p = 0.716$), technology classification does not substantially influence diversity levels.

Board Diversity Metrics by HQ Country: ANOVA results for EDUDIV and INDIV show no significant differences by HQ Country (p-values of 0.196 and 0.22), suggesting a stable distribution of diversity indices across countries.

Building on the analysis of categorical variables and their impact on EDUDIV and INDIV, we examined interactions between these diversity indices and (ln)Tobin's Q to assess potential links between diversity and firm performance. A correlation matrix (*Appendix 18*) offers insights into how diversity metrics may correlate with financial outcomes. Additionally, key financial controls - Market Cap, Revenue, Total Assets, and Leverage Ratio – were analyzed to further understand their influence on (ln)Tobin's Q. This enables us to quantify these relationships and gives us a better understanding of the strength and direction of the relations between variables.

EDUDIV shows a weak positive correlation with (ln)Tobin's Q (R = 0.15), suggesting only a slight association between educational diversity and firm performance. This relationship appears weak, as evidenced by scattered data points around the trend line in the scatter plot.

INDIV's correlation with (ln)Tobin's Q is even lower (R = 0.06), indicating a minimal positive connection between industry expertise diversity and firm performance. Notably, the spread of the data points hints at a very weak relationship, which could imply that other factors may play a more crucial role in determining (ln)Tobin´s Q.

The correlation matrix shows a moderate positive correlation between Market Cap and (ln)Tobin´s Q (R = 0.29). Revenue, Total Assets, and Leverage Ratio all have negative correlations, with Total Assets showing the strongest (R = -0.58), indicating that higher values of these company characteristics are associated with lower Tobin´s Q values.

The weak correlations between EDUDIV, INDIV, and financial variables suggest that diversity indices are mainly independent of company size and structure.

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Following the correlation matrix overview, this advanced interaction analysis examines whether EDUDIV and INDIV relate differently to (ln)Tobin’s Q across categories such as economic sectors and HT and LT sectors. Facet plots reveal possible relationship variations influenced by sector-specific or regional factors. Furthermore, in addition to the visual analysis, *Appendix 19* presents the correlation values between EDUDIV and INDIV and (ln)Tobin´s Q across each economic sector, for HT and LT sectors, as well as for countries. While interpretation requires caution, given the limited sample size, the table remains a valuable supplementary resource, offering additional insights into the relationship between diversity metrics and firm performance.

Board Diversity Metrics and (ln)Tobin´s Q by Economic Sector: In sectors such as Basic Materials, Financials, and Healthcare, EDUDIV and (ln)Tobin’s Q show slight positive trends, indicating potential performance benefits from educational diversity in these sectors. However, the trends are mild and may require further analysis for significance. Conversely, Technology shows a negative trend with EDUDIV, hinting at a complex relationship, while sectors like Energy and Real Estate display minimal correlation, suggesting that other factors might drive firm performance. For INDIV, CC, Industrials, and Energy exhibit positive trends with (ln)Tobin’s Q, indicating that a broader industry expertise diversity may benefit these sectors. In contrast, Technology, CNC, and Healthcare display negative trends, suggesting that these sectors may benefit from specialized expertise over a broad industry background. Interestingly, CNC, Energy, Healthcare, Industrials, and Utilities show opposite trends when comparing EDUDIV and INDIV, which will be explored in further analysis.

Board Diversity Metrics and (ln)Tobin´s Q by Economic Sector High Low: In both HT and LT economic sectors, the trend lines indicate a positive relationship between EDUDIV and (ln)Tobin´s Q. The effect appears to be almost equal across the two classifications. However, due to the relatively small trend slope in both cases, this correlation might be weak and could reflect other contextual sector characteristics rather than a strong effect of EDUDIV alone. For INDIV, LT sectors also show a weak positive trend, however, in contrast, HT sectors display a nearly flat line, suggesting no clear relationship between INDIV and (ln)Tobin´s Q in this sector.

Board Diversity Metrics and (ln)Tobin´s Q by HQ Country: As previously mentioned, the analysis of EDUDIV and INDIV in relation to (ln)Tobin’s Q by HQ Country is constrained by the limited representation of some countries. This reduces the robustness and generalizability of country-specific diversity-performance insights. However, we will still examine the six most represented countries with a sample size of eight or more—France, Germany, Ireland, the Netherlands, Spain, and Italy—to gain insight into potential trends and relationships in these regions. France shows a negative correlation between EDUDIV and (ln)Tobin´s Q, while for Germany, the trend line indicates a positive relationship between the two variables. Similar results can be found for Ireland and the Netherlands. For INDIV, the trend is more modest for Germany and the Netherlands, while France exhibits, contrary to EDUDIV, a slight positive relationship between INDIV and (ln)Tobin´s Q, suggesting that local companies may benefit from a broad industry expertise background.

4.2 Hypotheses Testing and Regression Analysis

Building on descriptive statistics, we now move to the core of the empirical analysis, focusing on hypothesis testing using regression analysis. To evaluate each hypothesis systematically, we employed regression models that test the direct effects of EDUDIV and INDIV on firm performance and interaction effects with key contextual variables. These models enable us to investigate the overall effect of diversity and whether certain environments or conditions enhance or reduce its effects. This analysis builds on the patterns observed in the descriptive statistics, using statistical testing to validate the hypotheses and provide insights into how diversity may shape firm performance across different contexts. Each hypothesis was tested individually, following the structured approach set out in the methodology. This approach ensures that our findings are robust and aligned with the theoretical framework and research questions set out in the earlier sections of this study. The results of the hypotheses testing can be found in *Appendix 20*, while detailed quantile regression results are provided in *Appendix 21*.

For each hypothesis, we ran diagnostic tests for multicollinearity and heteroscedasticity (Breusch-Pagan test). Except where explicitly stated, these tests confirm model stability with no multicollinearity issues and homoscedasticity. Similarly, unless otherwise specified, both inference tests are significant. Each model´s adjusted R-squared, ranging from 0.559 to 0.665, indicates moderate to strong explanatory power, showing that diversity indices and control variables account for a substantial portion of the variability in (ln)Tobin´s Q. Additionally, the F-statistic consistently indicates high model significance across hypotheses, underscoring that the overall models are statistically robust.

The linear model for H1.1 shows a p-value of 0.094 for EDUDIV, with an estimate of 0.215, therefore indicating marginal significance. Quantile regression results across various quantiles show that EDUDIV´s effect on (ln)Tobin´s Q is generally positive but only marginally significant at the 90^{th} quantile. This indicates that its impact may be stronger among high-performing companies. However, the ANOVA ($p = 0.204$) highlights that the effect of diversity does not significantly differ across different quantiles of firm performance. In summary, EDUDIV shows a marginally significant positive effect on (ln)Tobin´s Q.

The linear regression analysis of H2.1 shows no significant linear relationship ($p = 0.141$) between INDIV and (ln)Tobin's Q with a negative estimate of -0.174, suggesting limited direct association. In quantile regression, INDIV shows a statistically significant negative relationship with (ln)Tobin's Q at the 60^{th} and 70^{th} quantiles and a marginally significant negative relationship at the 50th and 80th quantiles, suggesting an inverse effect on middle-level performance. Overall, INDIV does not exhibit a consistent positive effect on firm performance, instead, it shows a negative impact among mid-level performers, indicating that INDIV may influence performance differently across firm performance levels.

The regression model of H1.2 includes interactions between EDUDIV and each economic sector to assess how the impact of educational diversity varies across economic sectors. Our approach reveals sector-specific effects, with varied coefficients indicating that EDUDIV's impact on (ln)Tobin's Q differs by sector. Notably, interactions for CC, Financials, Real Estate, and Technology are highly significant while CNC and Utilities are significant, showing that EDUDIV's influence is more pronounced in these sectors. Notably, only CC, CNC, and Technology demonstrate a positive impact, while effects in other sectors are negative. Quantile regression analysis further highlights that the sectors CC and Technology exhibit significant effects across multiple quantiles, reinforcing sector-specific patterns and indicating that EDUDIV's impact on (ln)Tobin's Q is not uniform across sectors but varies significantly.

Following the approach in H1.2., the results for H2.2 reveal both highly significant and significant interactions between INDIV and specific economic sectors, notably Financials, Real Estate, Technology, CC, and Industrials, with positive effects observed in the latter three. The findings support the importance of the interaction terms and indicate that INDIV's effect on (ln)Tobin's Q varies by sector. Quantile regression analysis reveals stronger sector-specific effects, particularly at higher quantiles. In conclusion, the results indicate that INDIV's effect on firm performance varies significantly by economic sector, highlighting the importance of sectoral context in assessing management diversity impacts on firm performance.

Despite the smaller sample size per economic sector (n = 15), potential issues do not compromise the validity of the results, as the overall sample size (n = 150) allows the CLT to apply to the model residuals, supported by a highly significant F-statistic indicating model robustness.

The linear model of 1.3 includes an interaction term between EDUDIV and HT/LT sectors to examine if EDUDIV's impact on (ln)Tobin's Q varies by sector type. Linear regression results show that the main effect of EDUDIV (indicating LT) is not significant ($p = 0.5873$), while the interaction term (showing the difference in the effect of HT sectors) is highly significant (p-value = 0.005) with a positive estimate of 0.255. Quantile regression shows significant interaction at the 40^{th}, 70^{th}, 80^{th}, and 90^{th} quantiles, with EDUDIV alone remaining non-significant. Overall, the results indicate that EDUDIV's positive impact on firm performance is stronger in HT sectors.

The regression results for H2.3 reveal a significant negative main effect of INDIV on firm performance in LT sectors (p-value = 0.049; estimate = -0.239) and a significant positive interaction term (p-value = 0.035; estimate = 0.273), indicating variation depending on the environment. Quantile regression shows marginal significance for the interaction term at the 50^{th} and 90^{th} quantiles, suggesting a stronger INDIV effect in HT sectors. For LT sectors, INDIV alone is significant but negatively estimated at the 40^{th}-80^{th} quantiles. ANOVA for quantile regression ($p = 0.344$) suggests these differences are not statistically robust. In conclusion, INDIV's impact on (ln)Tobin's Q appears stronger in HT sectors, though the ANOVA results indicate these effects are inconsistent across quantiles.

The linear model consists of (ln)Tobin's Q, EDUDIV, control variables, and an EDUDIV-GTCI interaction term. The results show that the main effect of EDUDIV has a marginally significant coefficient ($p = 0.072$) and a negative effect (–1.088) on (ln)Tobin's Q. The interaction term is significant ($p = 0.028$, estimate = 0.019), suggesting that GTCI moderately enhances the

EDUDIV-Tobin's Q relationship. Quantile regression reveals marginal significance of the interaction term at the 30th and 90th quantiles, with positive estimates indicating some influence of GTCI on firm performance at different levels. In summary, GTCI enhances EDUDIV's impact on Tobin's Q, though the effect is modest and varies across quantiles.

The linear regression analysis of H2.4 shows that the main effect of INDIV has a negative coefficient (-0.769) and is statistically insignificant ($p = 0.343$). Similarly, the interaction term between INDIV and GTCI is also not significant ($p = 0.457$) with a weak positive estimate (0.009), indicating that GTCI does not significantly influence the INDIV-performance relationship. ANOVA results further confirmed that including the interaction term does not improve the model's explanatory power. This suggests a minimal direct impact of GTCI on the INDIV-Tobin's Q relationship. Quantile regression finds no significant interaction effect across quantiles, and the inference test on quantiles ($p = 0.019$) reveals differences unrelated to the GTCI interaction. Overall, INDIV's effect on performance appears stable across talent competitiveness levels, with no significant GTCI moderation observed.

The regression model, which includes both EDUDIV and INDIV alongside control variables, aims to assess the comparative impact of these diversity indices on (ln)Tobin's Q. EDUDIV shows a marginally significant positive effect ($p = 0.061$), while INDIV, also marginally significant ($p = 0.09$), indicates a weaker, negative effect (estimate = -0.2). This suggests that EDUDIV has a stronger effect on firm performance than INDIV. Quantile regression highlights that EDUDIV's positive impact becomes significant at the 90th quantile ($p = 0.04$), suggesting greater influence in high-performing companies. INDIV, however, shows significance at the 40th and 60th to 80th quantiles, with a persistent negative effect. Overall, EDUDIV positively affects firm performance more strongly than INDIV, especially in higher-performing companies.

5 Discussion

The hypothesis testing and regression analysis revealed that diversity in TMTs, measured through EDUDIV and INDIV, significantly influences firm performance, with sectoral and contextual variations. Overall, EDUDIV appears to have a stronger effect on firm performance than INDIV. For eight out of nine hypotheses, the model used to test the hypothesis was significant or marginally significant. In the succeeding section, the results of the hypotheses testing will be analyzed and discussed.

5.1 Hypotheses 1.1 and 2.1 (Alissa Thomfohrde)

This section explores the results for H1.1 and H2.1, which analyzed the relationship between EDUDIV and firm performance, as well as INDIV and firm performance within TMTs. The discussion examines these relationships in depth, linking the findings to the broader literature, theoretical reasoning, and practical implications.

UET provides a foundational understanding of the relationship between EDUDIV and firm performance (Hambrick and Mason 1984). As stated in UET, executives' academic backgrounds shape their cognitive perspectives, influencing strategic decisions and corporate outcomes, hence EDUDIV introduces unique sets of knowledge, abilities, and beliefs (Dahlin, Weingart, and Hinds 2005). This is further supported by empirical research, which suggests that educational diversity enhances strategic adaptability (Wiersema and Bantel 1992), innovation (Auh and Menguc 2005), and strategic decision-making by broadening cognitive frameworks and knowledge sources (Díaz-Fernández, González-Rodríguez, and Simonetti 2015; Bell et al. 2011). Collectively, these frameworks indicate that diversity enables executives to analyze challenges from multiple perspectives, thereby developing innovative and superior solutions. For instance, a lawyer's distinct problem-solving approaches differ significantly from those of an engineer or psychologist. In practical terms, EDUDIV leads to richer discussions and reduced risk of groupthink (Bantel 1993; Wiersema and Bantel 1992).

Similarly, INDIV in TMTs has demonstrated a positive effect on firm performance, as executives accumulate a lot of invisible knowledge over the course of their professional careers (Chung, Cho, and Kang 2018; Auh and Menguc 2005; Goll, Sambharya, and Tucci 2001; Zhou et al. 2023). This prior professional experience builds social capital, which plays a vital part in securing relevant resources and fostering business relationships (Zhou et al. 2023). By providing sector-specific social capital and facilitating access to respective networks and resources, INDIV enhances a company's strategic agility (Pfeffer and Salancik 1978). TMT members often rely on routine-based frameworks shaped by their professional experiences, enabling them to make qualified decisions and navigate in dynamic environments effectively (Miner, Gong, and Baker 2011). For instance, managers with prior industry expertise consistently outperform their less experienced counterparts in M&A, attaining superior returns (Custódio and Metzger 2013). These expertise-based benefits align with RDT, which underscores the value of external resources and networks in overcoming organizational hurdles (Pfeffer and Salancik 1978). Moreover, TMTs with international professional past experiences serve as valuable advice networks, utilizing their diverse industry backgrounds to inform strategic international decisions (Athanassiou and Nigh 2002). However, the relationship between INDIV and firm performance is not uniformly positive, as it seems to be contingent on contextual and organizational factors (Díaz-Fernández, González- Rodríguez, and Simonetti 2020; Wang, Ma, and Wang 2015; Colombo and Grilli 2005).

Overall, the literature emphasizes the individual contributions of EDUDIV and INDIV to firm performance: EDUDIV widens cognitive perspectives, while INDIV provides sector-specific expertise and social capital.

Results and Hypothesis Evaluation

The theoretical insights set the stage for evaluating the empirical results of H1.1. H1.1 proposed that EDUDIV within TMTs significantly improves firm performance. As shown in the descriptive analysis, this relationship is marginally significant. Although the evidence is not strong, the results support the hypothesis, suggesting that educational diversity within TMTs positively effects firm performance. This finding is in line with previous studies where scholars attribute educational diversity's positive impact to its contributions to cognitive variety, adaptability, strategic decision-making, and innovative potential. The weak statistical significance hints at possible moderating factors that may influence this relationship. However, generally, we approve H1.1.

In contrast to EDUDIV, the effects of INDIV reveal a more nuanced dynamic. H2.1 posited a positive relationship between INDIV and firm performance. However, the empirical results indicate a negative but non-significant overall effect. It follows that INDIV does not significantly influence firm performance across the entire sample. Yet, insights from quantile regression portray a different picture, revealing significant variations in INDIV's effects. For middle-performing companies (60^{th}-70^{th} quantile), as seen in the hypothesis testing and linear regression part, INDIV demonstrated a significant negative effect. For the 50^{th} and 80^{th} quantiles, the relationship was marginally significant, which suggests weaker or context-dependent effects. For companies in the 10^{th} quantile (lowest-performing group), 13 out of 15 companies are from the Financials sector. This heavy representation hints that sector-specific dynamics may also impact the relationship between INDIV and firm performance. Notably, the sample consists of the top 15 companies by market capitalization in ten industries within the Eurozone, thereby these findings mirror relative performance differences among elite companies. In this group, middle-performing companies seem particularly vulnerable to negative effects, such as strategic misalignment and communication difficulties, as these outperform any potential advantages. However, high-performing companies exhibit more resilience, potentially prioritizing stability over risk-taking. As evidenced by the negative effect of INDIV on firm performance for middle-performing companies, we reject H2.1.

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The marginally significant results of H1.1 necessitate a closer examination of the mechanisms driving EDUDIV's effect. Educational background diversity enhances cognitive variety within TMTs by shaping members' cognitive styles through their academic backgrounds. The choice of an academic degree reflects an individual's personality and worldview, while the academic journey further shapes their perspectives and knowledge base (Wiersema and Bantel 1992). Each TMT member with a distinct educational background adds a unique cognitive base, including assumptions regarding the future, knowledge of alternatives, and the consequences attached to those (Hambrick and Mason 1984). Hence, EDUDIV fosters distinctive knowledge and approaches, thereby increasing the likelihood of generating well-analyzed and innovative solutions. This perspective aligns with research by Díaz-Fernández, González-Rodríguez, and Simonetti (2015) who link educational diversity with enriched intellectual capital. Intellectual capital encompasses the collective skills, knowledge, and cognitive resources within a TMT that drive firm performance. A more diverse intellectual base provides a broader range of cognitive tools and perspectives, which can enhance a company's ability to navigate complex challenges. EDUDIV also improves strategic adaptability by introducing contrasting perspectives, methods, and solutions stemming from diverse academic backgrounds. This enables TMTs to respond swiftly to changing market demands (Talke, Salomo, and Kock 2011). Drawing on the Behavioral Theory of the Firm, the diversity of cognitive frameworks within a TMT strengthens strategic decision-making processes, which are essential in today's fast-evolving market environment. Strategic adaptability provides a competitive advantage, as it equips TMTs to better identify opportunities and threats, thereby leveraging boundary-spanning competencies that enhance market responsiveness (Talke, Salomo, and Kock 2011; Wiersema and Bantel 1992).

Innovation is another potential factor explaining the positive relationship between EDUDIV and firm performance. Innovation is essential for firm survival and long-term performance, as it drives continuous reinvention and adaptation. Educationally diverse TMTs are more likely to engage in creative deconstruction and construction, with heterogeneity fostering a proactive orientation toward innovation (Yoon, Kim, and Song 2016; Talke, Salomo, and Kock 2011; Schumpeter 1942). Diverse viewpoints generate fresh ideas and challenge existing ones, which might otherwise inhibit innovation (Auh and Menguc 2005).

Studies illuminate that EDUDIV promotes greater risk-taking and openness to change, empowering TMTs to pursue novel strategic directions and realize superior performance (Wei and Zhang 2022; Firk et al. 2022). Finally, EDUDIV further improves strategic decision-making by providing a wide range of perspectives. This is particularly vital for companies engaging in complex strategies, such as product diversification (Díaz-Fernández, González-Rodríguez, and Simonetti 2015). Given the irregular and multifaceted nature of strategic decision-making, the perceptions and judgments of individual TMT members significantly shape outcomes (Wiersema and Bantel 1992). By enriching the decision-making process, EDUDIV enhances a company's ability to evaluate and respond to intricate market challenges, thereby supporting sustainable growth (Díaz-Fernández, González-Rodríguez, and Simonetti 2015).

The results of H2.1 also demand further interpretation to understand the conditions shaping INDIV's effect. The surprisingly negative effect of INDIV among middle-performing companies and its variability across quantiles could be explained by several factors: First, sector-specific expertise might become outdated and misaligned with current industry dynamics, particularly in fast-paced environments. TMT members with extended tenure (8+

years) within a particular economic sector may develop a strong reliance on ingrained practices, which may lead to a reluctance to adopt innovative strategies or reform existing approaches. This can diminish a company's strategic agility and impede its capacity for innovation. Vinding (2006) finds that the work experience of executives in the science-based and ICT-intensive sectors is negatively related to innovation. In these sectors, knowledge might become outdated rapidly due to the fast-evolving nature of the economic sector. In this context, the value of INDIV erodes and could potentially turn harmful, explaining the observed effect. Second, the requirement of at least eight years of prior experience in a different economic sector suggests that TMT members with substantial industry expertise are often older. This age-related characteristic may partly explain the negative effect of INDIV, as older executives in dynamic sectors such as ICT may not be skilled or familiar with recent sector advancements (Vinding 2006). Moreover, research by Wiersema and Bantel (1992) points out that organizations going through strategic change are usually led by TMTs characterized by lower average age, higher educational specialization heterogeneity, and shorter organizational tenure. This indicates that TMT members in such contexts probably have had less time to build up industry expertise, thereby reinforcing the notion that INDIV might not be advantageous for companies navigating strategic transformations. Notably, middle-performing companies could represent companies undergoing such strategic change, further supporting this finding. Third, these companies might lack sufficient integration mechanisms to effectively align divergent perspectives and foster consensus within their TMTs. Boerner, Linkohr, and Kiefer (2011) point out that misalignment within TMTs reduces efficiency by slowing down decision-making. Companies positioned in the 60^{th}-70^{th} quantile may face challenges in leveraging the potential benefits of INDIV due to underdeveloped absorptive capacities and limited ability to integrate and align varying areas of expertise.

Another important aspect potentially explaining this finding is the conditional effect of diversity (Dhaouadi 2014; Nielsen 2010). Like EDUDIV, INDIV requires active efforts to manage and integrate multiple perspectives within the team. While INDIV can increase access to resources and provide a wider network of contacts, its benefits depend on the company's capacity to foster collaboration and align divergent viewpoints. Wei et al. (2023) urge that the impact of expertise diversity varies with team dynamics and depends on cooperation openness and absorptive capacity. This is consistent with Roh et al. (2019) who assert that INDIV requires effective team processes to avoid inefficiencies and conflict. High-performing companies usually already have optimized strategies and streamlined processes, which make them less dependent on leveraging diversity. In addition, they might prioritize stability over risk-prone behavior, leading to INDIV having less of an effect, which might even be disruptive when introducing unnecessary complexity (Roh et al. 2019; Custódio and Metzger 2013). Low-performing companies within our elite sample might exhibit simplified decision-making processes centered around necessities.

Finally, the Financials economic sector's dominance in the 10^{th} quantile points to sector-specific dynamics. This sector is typically characterized by conservative decision-making and highly regulated environments, suggesting that these circumstances block INDIV's potential advantages by valuing compliance and operational efficacy over out-of-the-box thinking (Bontis and Serenko 2009).

and Practice

This section highlights critical implications for theory and practice. Notably, to the best of our knowledge, this study offers the first in-depth investigation of EDUDIV and INDIV within TMTs and their distinct effects on firm performance. By concentrating on diversity in academic qualifications and sector-specific expertise through industry tenure, we contribute a novel perspective to current discussions that goes beyond conventional diversity metrics. First, the findings for H1.1 expand UET by suggesting that related diversity-performance frameworks should account for the nuanced and potentially non-linear effects of educational diversity within TMTs. While the observed marginal significance highlights the positive potential of EDUDIV, it also underscores its context-dependent nature. Factors such as sector type, environmental context, and team dynamics may significantly influence the relationship (Turi et al. 2022; Díaz-Fernández, González-Rodríguez, and Simonetti 2015; Wiersema and Bantel 1992). Future theoretical models should include these contingencies to better capture the complex dynamics of EDUDIV.

The findings for H2.1 extend the application of RDT by emphasizing that resource access alone is insufficient; leveraging mechanisms are necessary for translating diversity into performance gains. Similarly to EDUDIV, the conditional effects (Dhaouadi 2014) of INDIV on firm performance align with the emerging notion of an inverted U-shaped relationship (Singh, Gaur, and Schmid 2010). Balanced levels of INDIV can optimize performance, but excessive diversity may introduce inefficiencies (Roh et al. 2019; Singh, Gaur, and Schmid 2010). The negative effect observed in middle-performing companies may reflect these inefficiencies.

For practitioners, our findings related to H1.1 suggest that EDUDIV within TMTs is advisable, as it contributes positively to firm performance. Yet, balancing diversity within TMTs is equally critical to mitigate the potential drawbacks of excessive heterogeneity. For H2.1, while the results might suggest that INDIV should not be prioritized due to its observed negative effect, a more nuanced interpretation is needed. The potential benefits of INDIV, such as access to sector-specific insights and networks, may fail to materialize without active and deliberate efforts to leverage this form of diversity (Zhou et al. 2023).

The findings for INDIV underscore the critical role of diversity management practices, especially for middle-performing companies. Developing organizational absorptive capacities is essential to fully realize the value of diversity, as these capacities enable companies to integrate diverse perspectives, foster collaboration, and minimize inefficiencies (Wei et al. 2023). In practical terms, the results provide valuable guidance for hiring strategies. Companies should actively promote EDUDIV within TMTs to enhance cognitive variety and strategic decision-making. Yet, in terms of INDIV, caution is required, as poorly managed diversity or misaligned team dynamics can yield harmful outcomes (Turi et al. 2022).

In essence, H1.1 and H2.1 explored the relationship between EDUDIV and INDIV within TMTs and their respective effects on firm performance. Although both forms of diversity are theoretically associated with enhanced firm performance, the findings reveal a more nuanced picture shaped by organizational context and performance levels. EDUDIV exhibited consistent marginal benefits across performance levels, reflecting its role in increasing intellectual capital through diverse perspectives and cognitive variety (Díaz-Fernández, González-Rodríguez, and Simonetti 2015). INDIV, in contrast, displayed significant variability across quantiles, potentially due to the differing capacities of companies to effectively integrate and manage this diversity. For middle-performing companies, the challenges of leveraging INDIV outweighed its potential benefits, resulting in a negative effect on firm performance.

These findings underscore that diversity within TMTs, whether in terms of educational background or industry expertise, does not inherently guarantee positive effects on firm performance. Its impact depends substantially on effective management practices, potentially more so for INDIV than EDUDIV. Homberg and Bui (2013, 17) accurately noted that "the benefits of diversity do not occur from the simple fact of having a diverse workforce", emphasizing that TMT diversity can either be an asset or a liability depending on how it is approached. The findings illuminate the contingent nature of diversity's effect on firm performance, underscoring the difficulty of generalizing its effects. Nonetheless, these findings highlight the necessity for practitioners to conduct a thorough "contextual diagnosis" (Joshi and Roh 2009, 24) when defining their diversity strategy.

Research

The findings must be considered alongside the study's limitations. For H1.1, while the empirical results primarily support the research model, the relationship between EDUDIV and firm performance is only marginally significant. The findings of H2.1 lack overall statistical significance, albeit significant effects were observed in the 60^{th}-70^{th} quantile. Although the sample size in this study is generally considered appropriate for the scope of the analysis, the focus on a sample of top companies limits the generalizability of the results to smaller and less competitive companies. A larger sample size and a longer study period are recommended to increase robustness and extend applicability beyond this elite subset.

This study employs a quantitative approach, which inherently limits the analysis to the numerical data collected and the literature reviewed. As a result, the findings are constrained by theoretical assumptions and correlations. These hypotheses do not account for potentially critical contextual and team-specific factors, such as industry environment, diversity management practices, and team dynamics, which might moderate the diversity-performance link (Homberg and Bui 2013; Nielsen 2010; Cyert, Feigenbaum, and March 1963).

These limitations simultaneously reveal several opportunities that could yield promising results but remained unaddressed by this study. Future research should adopt a mixed-method approach, integrating qualitative and quantitative methodologies. This could enable researchers to leverage both structured and unstructured data, consequently increasing the depth and richness of insights. To gain a more profound understanding of the conditions under which diversity influences performance, future studies should investigate the role of moderating variables such as team cohesion, leadership styles, and organizational culture. These factors may help explain the negative effects observed in INDIV, particularly among middle-performing companies. Wei et al. (2023) point out that past professional experiences are particularly valuable in navigating turbulent environments, as they provide a means to mitigate the risks brought by environmental uncertainty. This observation highlights the potential benefits of INDIV in specific contexts, suggesting that it might yield more favorable results under certain environmental conditions, thereby pointing to a compelling avenue for future research. In addition, scholars should explore potential synergy effects between diversity dimensions. While most scholars have analyzed diversity attributes in isolation, these dimensions might not be independent of each other (Nielsen 2010). INDIV might yield better results when considered as a complementary variable. The inconclusive findings in prior research on TMT diversity may stem from a failure to account for such interactions. Notably, the dominance of the Financials economic sector in the 10th quantile demands closer investigation. Financial companies reveal both the lowest performance and the most pronounced negative effects of EDUDIV and INDIV. In literature, many scholars assign financial companies a special place primarily due to a lack of data or significance. Those who have examined financial companies specifically revealed contrasting findings (Ratzan and Lant 2019; Mutuku, K'Obonyo, and Awino 2013). However, to the best of our knowledge, no comprehensive explanations have been provided to account for these observations, leaving a critical gap in understanding the underlying mechanisms within this economic sector.

5.2 Hypotheses 1.2 and 2.2 (Julius Hofmann)

H1.2 was proposed as "The effect of Educational Background Diversity on Firm Performance differs between economic sectors", while H2.2 was proposed as "The effect of Industry Expertise Diversity on Firm Performance differs between economic sectors".

The literature review revealed that previous studies focusing on educational background and industry expertise and their influence on firm performance did not show consistent results, both with regard to significance and the direction of the effects, indicating that contextual factors play a significant role. Hambrick and Mason (1984) in their introduction of UET, identified one such contextual factor: the composition of TMTs and the influence of its members are likely shaped by the company's sector. However, past research has often focused on only a single sector, making an analysis across sectors hard. In contrast, we compared the ten economic sectors of our data set, in order to explore sector-specific trends and propose possible drivers.

5.2.1.1 Summary of Empirical Results and Hypothesis Evaluation

As expected, results for EDUDIV and INDIV across sectors show differing levels of significance and directional effects: For EDUDIV, the sectors of Basic Materials, Energy, and Healthcare show non-significant results. For INDIV, these three sectors, as well as CNC and Utilities, are non-significant. Therefore, for the respective independent variable, these sectors will not be further interpreted. Interestingly, sectors where both variables are significant did not differ in their directional effects between EDUDIV and INDIV and show either only positive (e.g., Technology) or negative (e.g., Financials) effects for both variables. Since effects differ between sectors for both EDUDIV and INDIV, we can approve H1.2 and H2.2.

5.2.1.2 Interpretation and Reasoning

In the following, we will discuss the results of our testing of EDUDIV and INDIV and their effect on firm performance. Specifically, this part will explore possible sector-specific characteristics and drivers, which, at least to some extent, might be able to explain the varied sector-specific results found during our hypotheses testing.

Economic Sector: Technology

The Technology sector showed significant positive estimates for both variables, suggesting that sector characteristics amplify the advantages of diverse TMTs. Examining these drivers might offer insights into how our variables impact firm performance.

As we explored earlier, Bantel and Jackson (1989) and other scholars have shown a positive association between EDUDIV and innovation activities. Innovation is particularly critical in the highly competitive and fast-evolving Technology sector (Gomez 2023), especially in topperforming companies, such as the companies in our sample, whose growth is significantly more influenced by innovation compared to average companies (Coad and Rao 2008). The importance of innovation in the tech sector is also evident in its global share of R&D spending. The Information and Communication Technology (ICT) sector alone accounts for approximately 44% of total R&D expenditures globally (European Commission et al. 2023, 39). The importance of innovation in the Technology sector is also reflected by patent activity, with Digital Communication, Medical Technology, and Computer Technology collectively accounting for 25% of all patents in Europe (European Patent Office 2023). However, while high R&D spending and patent activity underscore the sector's focus on innovation, these do not guarantee success, as innovation outcomes remain inherently uncertain (Schumpeter 1942; Coad and Rao 2008), highlighting the importance of broader innovation focuses to mitigate risks associated with missed opportunities or market shifts. Furthermore, research by Bain & Co (2020) shows that companies in the tech-sector face the second-highest likelihood of being disrupted among all industries and are relatively unlikely to recover from such disruptions. This dynamic environment requires strategic adaptability, a trait that EDUDIV can help foster.

Additionally, the benefits of TMT heterogeneity in this sector extend into industry expertise diversity. As we showed earlier, one of the main advantages of having a TMT with high INDIV is creating a broad knowledge base, which helps companies identify opportunities and challenges in different sectors (Chung, Cho, and Kang 2018). The tech sector especially has become increasingly intertwined with traditional LT sectors due to the rapid integration of technologies like Internet of Things (IoT) connectivity or, more recently, artificial intelligence (AI), with many of these technologies becoming essential tools for driving competitiveness in these LT sectors. McKinsey & Co (2024) outlined 15 key technology trends and their relevance to different sectors, demonstrating how technology already impacts traditional LT sectors: Advanced Robotics or Connectivity technology, for example, are shown relevant for more than

10 sectors, including manufacturing, retail, agriculture or mining. Meanwhile, generative AI has become a transformative tool across virtually every sector, with applications spanning 22 sectors. As technology becomes critical to sectors once considered LT, companies in those industries are investing heavily in digital transformation. By 2027, companies in EMEA are projected to invest $1.1 trillion in digital transformation, nearly doubling their 2023 spending (IDC 2023). Additionally, the growing interdependence between tech and non-tech sectors is also starting to become evident in the M&A and strategic partnership market. In the US, tech giants like Amazon and Google have pursued large-scale moves into non-tech sectors (Whole Foods 2017; Verily 2019). In Europe, similar activity is emerging, albeit on a smaller scale and often through strategic partnerships rather than M&A, e.g., demonstrated by Ericson's strategic partnership with the automotive OEM Volvo (Volvo 2021). For tech companies, this growing interdependence demands a TMT equipped with diverse industry expertise to navigate this complexity. Leaders with backgrounds in non-tech sectors are better positioned to understand the market complexities, unique needs, opportunities, and risks of partner sectors, tailor solutions effectively, and build effective strategic partnerships using their existing economic sector network.

In summary, by combining diverse cognitive frameworks, TMTs with high EDUDIV enhance a company's ability to diversify innovation strategies and adapt quickly, while INDIV is crucial for helping tech companies navigate and profit from an increasingly interconnected landscape.

Economic Sector: Industrials

Industrials also showed significant, positive results for both EDUDIV and INDIV. Again, examining sector-specific characteristics might help explain these positive effects.

As mentioned earlier, EDUDIV brings together individuals with different cognitive frameworks, enabling diverse approaches to problem-solving and decision-making. This capability is particularly valuable for Industrials, as they rely heavily on production processes, distribution networks, and the procurement of raw materials from global supply chains. The sector's complexity and pressure to maintain efficiency make operational excellence a critical determinant of success (Handoyo et al. 2023). Companies that can achieve operational efficiency benefit from cost reductions, resource optimization, and enhanced ability to cope with disruptions. Research has demonstrated the positive impact of operational efficiency on firm performance, with Hardcopf, Liu, and Shah (2021) showing a direct link between efficiency and improved manufacturing outcomes. By uniting diverse problem-solving approaches, TMTs with varied educational backgrounds are better equipped to identify inefficiencies, assess alternatives, and implement strategies to streamline operations. For instance, these teams can devise innovative supply chain solutions, integrate predictive maintenance technologies, and optimize resource allocation more effectively.

Moreover, Industrials frequently face the challenge of making substantial upfront investments, whether due to capital-intensive equipment (Fernando 2024) or because of extended production cycles, e.g., for aerospace companies (Vandaele 2023). Additionally, companies face long lead times between order placement and delivery (Wagner 2023), creating substantial sunk costs and consequently path-dependencies, and finally, a "lock-in" effect, where an organization becomes constrained by established patterns, making alternative actions increasingly difficult and more expensive (Sydow, Schreyögg, and Koch 2009). INDIV can play a key role in helping companies break these path dependencies. Brekke et al. (2024) identified several mechanisms to break dependencies in manufacturing companies, such as Organizational Reconfiguration, where INDIV can act as a catalyst by broadening perspectives on how companies adapt to external changes. A new TMT member with experience in a more dynamic sector can, for instance, offer expertise on organizational inefficiencies often found in large industrial conglomerates and provide valuable insights for improving organizational structures, such as through spin-offs or carve-outs. These organizational reconfigurations have shown to increase productivity through cost savings and other efficiency increases (Chemmanur, Krishnan, and Nandy 2014).

In conclusion, EDUDIV and INDIV can significantly improve Industrials' ability to respond to internal and external pressures. EDUDIV fosters efficiency improvements, while INDIV enhances the company's ability to break path dependencies and adapt to new opportunities.

Economic Sector: Consumer Cyclicals (CC)

The CC sector represents the final sector with significant positive results for both EDUDIV and INDIV. Two defining characteristics of this sector may help explain these results: its consumer-centric nature and its strong dependence on economic cycles.

The theoretical basis for consumer centricity lies in the Integration-Responsiveness (IR) Framework, which examines how companies balance the pressures of global integration with local responsiveness, adapting to cultural and market-specific demands (Prahalad and Doz 1987). Companies in the CC sector typically adopt transnational or multinational strategies, balancing high local responsiveness with the centralization of key functions such as production or R&D. This is, for example, common with luxury goods brands, where brands frequently tailor their products and marketing campaigns to align with specific cultural and market demands (Bai, McColl, and Moore 2021), e.g., to reflect local traditions in China or to connect with local culture in India (Li 2023; AFP 2011). Similarly, automotive companies inside the CC sector face significant barriers implementing purely global strategies due to regional variations in environmental regulations and cultural preferences, such as vehicle size or performance (Rugman and Collinson 2004), leading to companies offering bespoke features tailored to these preferences (McKinsey & Co 2022). Local responsiveness in the CC sector underscores the need to interpret cultural nuances, adapt strategies swiftly, and foster creative, cross-disciplinary problem-solving, all of which are capabilities that EDUDIV enhances by bringing together diverse cognitive frameworks.

INDIV, on the other hand, might play a crucial role in navigating the fluctuations that the CC sector experiences due to its strong dependency on discretionary spending by consumers, which makes CC companies bound to economic cycles (Saxo Bank 2024). Following the 2008 financial crisis, besides the financial and housing sector, the automotive sector was the sector hit most sever, with vehicle production dropping by 4% in 2008 (Sturgeon and Van Biesebroeck 2010, 6; OICA 2024). Similarly, during the current economic downturn, leaders in the fashion sector view economic uncertainty due to high inflation and low consumer confidence as the most prominent threat (McKinsey & Co 2023). INDIV enhances a company's ability to navigate these fluctuations by equipping TMTs with diverse perspectives that are critical for managing economic volatility. Leaders with varied industry expertise bring practical knowledge of how different sectors respond to economic downturns. This allows for robust scenario and contingency planning, as well as agile decision-making, and underscores how INDIV allows CCs to navigate economic cycles.

Economic Sector: Financials

The Financial sector showed significant negative results for both EDUDIV and INDIV, suggesting that TMT diversity may not align with the strategic needs of Financial companies.

The negative relationship between EDUDIV and firm performance in the Financial sector is consistent with findings from Li, Zhang, and Zhang (2015), who showed that in companies employing a single or dominant business strategy, educational background heterogeneity was negatively correlated with firm performance. Interestingly, companies in the Financial sector typically focus on a single or dominant business strategy, as they often specialize in one core area, such as retail banking, insurance services, or asset management, and usually not operate major diversification strategies outside their industries. For example, Allianz generates about 95% of its revenue from insurance services (Allianz Group 2023, 173), while Banco Santander generates ca. 88% of its revenue from retail banking (Santander 2023, 379). According to the authors, companies operating in a single sector are more focused on gaining a competitive edge over their competitors and, therefore, profit more from a homogeneous board with similar understandings and capabilities, which fosters greater strategic alignment and cohesion. This insight may help explain the observed negative EDUDIV effect, as greater educational diversity in the Financial sector may introduce complexity or reduce alignment within the TMT.

Additionally, the sector is particularly characterized by substantial regulation, which emerged as a response to the 2008 global financial (GFC) crisis, shaping both the banking, as well as other Financial sub-sectors, such as the insurance sector (Smoleńska 2021; Zaidi, Md Aris, and Mohamed Yusof 2018). While these regulations ensure stability, they also increase complexity, imposing significant compliance and operational burdens. This complexity is further heightened by the need to comply with both EU and local market regulations, as member states retain discretion over certain compliance matters (Oliver Wyman 2023). The regulatory complexity requires specialized knowledge in areas like risk and compliance, which outside executives might find hard to acquire. Additionally, TMTs with diverse industry expertise may struggle to align on regulatory matters, as differing perspectives could complicate decision-making. In this context, a more homogeneous TMT with shared expertise in finance might be better equipped to navigate these complexities. Thus, INDIV may hinder performance by reducing the cohesion needed to effectively manage regulatory burdens.

Economic Sector: Real Estate

The Real Estate Sector also showed significant negative effects for both variables. We will analyze the sector characteristics to give possible reasons for these effects in the following.

The sector is characterized by complex, multi-year development cycles that include stages such as land acquisition, design, permitting, construction, and leasing. Additionally, to ensure the property remains profitable long-term, Real Estate companies must consider the entire useful life of a project, often spanning 50 to 100 years (Urban Land Institute 2012). These extended timelines make Real Estate investments highly capital-intensive, requiring significant upfront capital and careful, long-term planning (Xiaoguang and Zhanjun 2015; Gehner and Peek 2009). This requires companies to maintain a consistent strategic vision throughout the development process. However, EDUDIV, via the cognitive diversity it brings, may lead to misalignment in how long-term goals are approached, caused by disagreements on priorities or a lack of unity for a long-term vision. This may lead to resource misallocations or missed opportunities. The combination of long development cycles and consistent, long-term strategy needs makes the sector particularly susceptible to the negative effects of EDUDIV.

Furthermore, the Real Estate sector is sensitive to economic cycles, though unlike in the CC sector, INDIV doesn't seem to mitigate these dependencies for Real Estate companies, as seen by the negative effect found. One explanation could be the specialized knowledge needed to understand the connection between macro- and microeconomic cycles, which is considered "the foundation of understanding" in the Real Estate market (Pyhrr, Roulac, and Born 1999, 7). Therefore, having diverse knowledge resources, a characteristic of TMTs with high INDIV, might negatively influence the performance of a Real Estate company. Additionally, given the size and scope of the Real Estate companies in our sample, they are likely to operate similarly to large asset managers that optimize their portfolio and use value-add management (see, e.g., Vonovia SE 2023, 46). This similarity in strategic approaches aligns with our findings in the Financial sector, where negative INDIV effects were also observed, as both sectors manage complex portfolios and face significant regulatory and risk management demands (PwC 2022), suggesting that homogeneous TMTs with sector-specific knowledge may be better equipped to handle complexities like regulatory challenges and portfolio management.

In summary, the outlined sector characteristics, including long-term focus, economic sensitivity, and regulation help explain why both variables showed negative effects in Real Estate sector.

Economic Sector: Consumer Non-Cyclical (CNC)

Unlike the previous sectors, CNC only showed significant results for EDUDIV. In the following, we will examine sector characteristics that might explain the positive EDUDIV effect. Since, INDIV did not show significant results, it will not be further analyzed.

Unlike CC, the CNC sector, due to the essential nature of its products, is less dependent on economic cycles. However, it is still affected by broader economic pressures, such as high inflation, which drives consumers to seek cheaper alternatives (Shuleva 2023). To remain competitive, companies must innovate to lower costs, by, e.g., introducing new, more efficient processes or technologies (Chen 2021). As shown in the literature review, TMTs with diverse educational backgrounds unite individuals who, through their unique educational pathways, have learned to think and solve problems differently and, therefore, may be beneficial for finding new, cost-effective processes. On the other hand, when price pressure is lower, CNCs often compete through product differentiation. Successful CNC companies have, therefore, built up their capacities for innovation in order to cater to increasingly shorter product cycles, e.g., driven by sustainability trends (Colella, Pardo, and Hindo 2022). As shown by Bantel and Jackson (1989) or more recently Schubert and Tavassoli (2020), EDUDIV plays a key role here, as TMTs with high EDUDIV are more likely to engage in innovation activity and facilitate it by incorporating varied perspectives and expertise, enabling companies to move faster than disruption and stay competitive.

Economic Sector: Utilities

The final economic sector with significant results was the Utilities sector, for which our analysis showed a negative relationship between EDUDIV and firm performance.

Utilities are characterized by large, capital-intensive investments, like power plants or distribution networks (Casalta et al. 2024), requiring efficient use of capital and long-term strategic planning. Setting strategic priorities that ensure investments being made in line with future needs and market shifts, have shown to significantly increase capital productivity (McKinsey & Co 2019). A recent example highlighting both the capital intensity and the establishment of strategic priorities in the utility sector is Iberdrola's decision to shift focus toward power grid investments in the US while scaling back investments in renewable energy., entailing a capital expenditure of ca. €40bn over the coming years (Lombardi 2024). These enormous investments emphasize the need for careful and sustainable planning. EDUDIV, which brings diverse cognitive frameworks and problem-solving approaches, may not always be beneficial in this context. The long-term nature of investments in Utilities requires consistent, coherent strategic alignment across the TMT, which might be disrupted by diverse perspectives and approaches, as shown i.a. by Knight et al. (1999). Additionally, while the sector traditionally relies on long-term strategic decisions, disruptions in energy policy and technology, such as the growing need for electric vehicle (EV) infrastructure, require more dynamic, frequent planning (Deloitte 2022a). EDUDIV in this context, as shown by Hambrick, Cho, and Chen (1996) might impede timely decision-making due to competing educational perspectives.

In conclusion, while high, long-term capital investments in the Utilities sector require strategic prioritization, new developments in the sector showcase the necessity of adapting quickly. However, TMTs with educational diversity have shown to impede these challenges.

5.2.1.3 Implications for Theory and Practice

Our findings across economic sectors align with existing theoretical research on UET, in that TMT composition influences firm performance, but emphazise that results and direction of effects are heavily context-dependent on a sector's strategic demands, such as innovation importance, capital intensity or regulatory levels. The drivers identified in the literature, such as educational diversity fostering a unification of differing cognitive perspectives and industry expertise broadening knowledge resources, remain relevant as potential explanations for the effects we observed.

In practice, our findings suggest that having TMT diversity in a company is neither inherently advantageous nor disadvantageous. Instead, companies must tailor their diversity strategies to fit the specific context of their sector. For example, for sectors that place high value on innovation, such as Technology or CC, adding TMT members with diverse educational backgounds seems reasonable, while it seems a disadvantage in sectors with high capital intensity, like Real Estate or Utilties. Furthermore, adding outside industry expertise seems to harm firm performance in highly regulated sectors, such as Financials and Real Estate. Consequently, understanding a company's specific environmental context before developing TMT diversity strategies.

5.2.1.4 Limitations and Future Research

Limitations for H1.2 and H2.2 mainly stem from its scope. Due to the nature of our overall sample, 150 companies in 10 economic sectors, only 15 companies are analyzed per sector in the two hypotheses. While interpretations for specific sectors are still possible within the broader model, caution is warranted in drawing strong conclusions. We, therefore, refrain from analyzing the size of the effects in these hypotheses and rather focus on directional effects. Additionally, the sector-specific characteristics are only a potential explanation for the observed effects, as proving causality is outside the scope of this thesis.

Our limitations simultaneously present intriguing opportunities for future research. Beyond increasing the sample size within each sector to strengthen our results across different sectors, empirically testing the sector-specific characteristics identified in this thesis, such as regulatory burden and high capital intensity, could yield valuable insights into which characteristics actually prove to have a significant influence on the effects of EDUDIV and INDIV.

5.3 Hypotheses 1.3 and 2.3 (Johannes von Trotha)

H1.3 predicted that the effect of EDUDIV on firm performance is enhanced in HT economic sectors compared to LT sectors. Similarly, H2.3 suggested that INDIV has a greater effect on firm performance in HT sectors.

These hypotheses assumed HT sectors require adaptability, creativity, and governance mechanisms leveraging diverse perspectives for better decision-making (Putra 2024; Muithya and Kilika 2018). In such dynamic and innovation-driven contexts, EDUDIV and INDIV offer unique advantages by enhancing cognitive diversity and access to external networks, respectively (Anderson et al. 2011; Bell et al. 2011; Pfeffer and Salancik 1978). Conversely, LT sectors prioritize operational efficiency over strategic flexibility, where excessive diversity may introduce inefficiencies and coordination challenges, diminishing its impact (Wei and Zhang 2022; Gharbi, Sahut, and Teulon 2014). These differences set the stage for examining how sectoral characteristics mediate the effect of EDUDIV and INDIV on firm performance, as explored in the subsequent analyses.

Results and Hypothesis Evaluation

Regression analysis for H1.3 shows that the main effect of EDUDIV on (ln)Tobin´s Q is not statistically significant for LT sectors, indicating no meaningful impact on firm performance in these environments. However, the significant interaction term highlights a context-dependent effect, with EDUDIV significantly enhancing firm performance in HT sectors (overall effect: 0.328[2]). Therefore, H1.3, which states that the effect of EDUDIV on firm performance is enhanced in HT sectors compared to LT sectors, is approved.

[2] HT effect EDUDIV = main effect + interaction effect = 0.0727 + 0.255 = 0.328

The regression results for H2.3 reveal a significant negative main effect of INDIV on firm performance in LT sectors and a significant positive interaction term, indicating variation depending on the environment. The overall effect of INDIV in HT sectors (0.034[3]) suggests a small but positive influence, while LT sectors experience a negative effect. Therefore, H2.3, which states that INDIV is enhanced in HT compared to LT sectors, is approved.

oning

As discussed in previous sections, both the UET and RDT emphasize the strategic value of diversity. UET highlights the cognitive benefits of EDUDIV, which fosters broader problem-solving capabilities (Dahlin, Weingart, and Hinds 2005; Hambrick and Mason 1984), while RDT underscores how INDIV enhances access to external resources, reducing dependency risks and fostering strategic agility (Anderson et al. 2011; Pfeffer and Salancik 1978). Absorptive capacity enables companies to integrate external knowledge, enhancing decision-making, risk evaluation, and opportunity identification (Cohen and Levinthal 1990; Tushman and Katz 1980). Building on these theoretical foundations, the regression analyses for H1.3 and H2.3 provide empirical evidence of the context-dependent effect of diversity on firm performance. These results show how both UET and RDT differ depending on the environmental demands of each sector. EDUDIV significantly enhances firm performance in HT sectors but shows no significant effect in LT environments, reflecting the unique demands of volatile and dynamic sectors. Similarly, INDIV has a slightly positive influence on firm performance in HT sectors while negatively affecting performance in LT sectors. These results underscore the importance of tailoring TMT diversity to the specific demands of HT and LT sectors, highlighting the need to explore these dynamics.

[3] HT effect INDIV = main effect + interaction effect = -0.239 + 0.273 = 0.034

HT Sector

HT sectors, accounting for 84% of global R&D spending in 2022 (European Commission et al. 2023), are defined by rapid innovation cycles, technological advancements, and intense strategic cooperation (Fontenele et al. 2016; Zakrzewska-Bielawska 2010). Their high R&D intensity drives continuous breakthroughs, fostering company-level dynamism (Thornhill 2006). Furthermore, HT companies dominate patent applications in fields such as Computer Technology and Digital Communication (WIPO 2023), relying on diversity to sustain innovation and market leadership. EDUDIV enhances cognitive diversity, promoting problem-solving through varied perspectives and fostering cross-disciplinary innovation by encouraging creative rethinking and rebuilding (Yoon, Kim, and Song 2016). This focus on innovation strengthens collaboration within teams, enabling them to tackle complex challenges effectively. INDIV, on the other hand, supports cross-sector collaboration and competitiveness through external networks. These distinctions enable companies to capitalize on emerging opportunities and navigate volatility (Muithya and Kilika 2018; Hambrick and Mason 1984). Thornhill (2006) further highlights that innovation drives revenue growth most effectively in HT sectors when knowledge assets are high, consistent with the Resource-Based View of knowledge as a competitive resource (Wernerfelt 1984). Knowledge serves as the cornerstone of HT sectors, driving innovation, enabling the integration of scientific research into practical applications, and fostering continuous adaptation to rapidly evolving technological landscapes (Zakrzewska-Bielawska 2010). Educationally diverse TMTs thrive in innovation-intensive environments by managing uncertainty and driving innovation (Bodla et al. 2018; Li, Zhang, and Zhang 2015).

HT companies´ lean and agile structures (average total assets: $70.5bn vs. $215.3bn in LT companies in our dataset, see *Appendix 23*) enable faster decision-making and integration of diverse inputs compared to the asset-heavy operations of LT sectors, where capital-intensive business models prioritize stability over innovation. EDUDIV further strengthens strategic decision-making in HT sectors by expanding the breadth of knowledge sources (Díaz-Fernández, González- Rodríguez, and Simonetti 2020). This agility, reflected in higher (ln)Tobin`s Q values (0.492 vs. -0.185), potentially indicates market acknowledgment of their innovative capabilities and adaptability. With a higher average market cap ($67.6bn vs. $ 38.9bn) and revenue (41.6bn vs. $30.2bn), HT companies can invest in innovation-driven strategies, leveraging EDUDIV.

Furthermore, operating at the intersection of multiple fields, HT companies benefit from EDUDIV in TMTs, which integrates diverse insights to create competitive advantages. For instance, the pharmaceutical industry combines educational backgrounds such as physical sciences, life sciences, and clinical & health, while renewable energy companies leverage knowledge in engineering, physical sciences, and computer science. EDUDIV fosters internal team collaboration, enabling HT companies to integrate diverse insights and address complex challenges, maintaining competitiveness in fast-evolving sectors with short product life cycles (Felin 2014; Hazir and Autant-Bernard 2014).

These fast-changing markets further highlight the importance of INIDV, as it enables TMTs to identify trends and secure first-mover advantages by leveraging external networks and market insights. It supports the cross-pollination of ideas by integrating methodologies and insights from different fields (Jarzabkowski and Searle 2004), such as leveraging expertise from consumer electronics to design user-friendly interfaces for mobile health devices in the pharmaceutical industry. Such synergies broaden strategic capacity, equipping TMTs to develop and implement strategies effectively (Jarzabkowski and Searle 2004).

These factors validate the hypotheses that both EDUDIV and INDIV enhance firm performance in HT sectors. Notably, EDUDIV has a stronger positive effect (H1.3), aligned with the innovation-driven demands of HT sectors. The importance of cognitive diversity in fostering cross-disciplinary innovation and enhancing absorptive capacity is emphasized by the high

R&D intensity that characterizes the HT sector. INDIV, while valuable for external perspectives, plays a secondary role in core innovation processes (H2.3). EDUDIV´s ability to enhance strategic adaptability (Wiersema and Bantel 1992) further strengthens its relevance in dynamic environments, as its general skills are less likely to become outdated compared to INDIV´s industry-specific expertise (Kato 2020). From a team dynamics perspective, EDUDIV activates elaboration-based processes that enhance the cognitive resource base, while INDIV may trigger categorization-based biases that limit its effectiveness in fostering cohesive innovation-focused teamwork (Joshi and Roh 2009). Consequently, the disadvantages associated with INDIV contribute to its smaller impact in HT contexts compared to EDUDIV.

Despite its benefits, integrating EDUDIV and INDIV into TMTs in HT sectors presents challenges. The rapid pace of innovation and intense competition mean that even minor divergences in approaches or delays in decision-making can have significant consequences, such as losing first-mover advantages to competitors. EDUDIV, while broadening cognitive resources, may exacerbate such delays by introducing conflicting priorities (Wei and Zhang 2022; Knight et al. 1999). Social Identity Theory (Tajfel 1978) suggests that demographic attributes such as education may lead to self-categorization, forming in-groups and out-groups that hinder collaboration (Bodla et al. 2018; Veltrop et al. 2015), particularly detrimental in high-pressure HT environments where seamless coordination is critical. Moreover, while diversity fosters strategic innovation, it can also lead to task conflict, which, if poorly managed, may escalate into destructive social conflict, undermining team cohesion and performance (Jarzabkowski and Searle 2004). However, the cross-disciplinary nature of HT sectors, where professionals often collaborate on innovation projects, helps mitigate some of these challenges.

LT Sector

EDUDIV´s non-significant effect in LT sectors (H1.3) underscores its inconsistent and marginal impact in these settings. In LT sectors, the focus on operational efficiency and incremental innovation limits the utility of diversity (Putra 2024; Nouman et al. 2022). These environments prioritize standardized processes, routine decision-making, and predictability, which align poorly with the broader cognitive diversity EDUDIV offers. Structural constraints, including limited R&D budgets, technological resources, and smaller organizational sizes[4], reduce the capacity of LT companies to effectively use the benefits of cognitive diversity (Nouman et al. 2022). In these environments, the complexities introduced by EDUDIV in TMTs, such as increased decision-making time or conflict, are more likely to introduce inefficiencies, hindering performance rather than enhancing it (Wei and Zhang 2022; Boerner, Linkohr, and Kiefer 2011). These inefficiencies are reflected in lower (ln)Tobin´s Q values in capital-intensive LT sectors, such as Financials and Utilities, which may be increased by the challenges EDUDIV introduces in these environments. Utilities and Industrials, for instance, prioritize operational stability, cost efficiency, and long-term investments over transformative innovation (Fernando 2024; Handoyo et al. 2023). Within Industrials, particularly the manufacturing sector, reliance on stable supply chains, predictable operations, and high capital expenditures favors specialized expertise and homogeneity (Fernando 2024; Handoyo et al. 2023).

While EDUDIV´s non-significant effect in LT sectors highlights its challenges, INDIV presents distinct yet related issues (H2.3). The following analysis explores the limited utility of INDIV in LT sectors, where its benefits often fail to align with sector-specific demands. Established markets in LT sectors depend on long-term, stable supplier-buyer relationships with extended lead times, as seen in Utilities and Industrials (Boston Consulting Group 2024; Aghazadeh and Maleki 2024; Li et al. 2022). In these contexts, external networks are important, but the focus is on networks that evolve over the years within the supply chain rather than dynamic, cross-industry networks. INDIV, which introduces connections from unrelated sectors, adds little value in these settings. Highly regulated sectors, such as Utilities, are governed by regulatory

[4] Smaller organizational sizes limit the knowledge absorptive capacity of LT companies (Nouman et al. 2022)

entities that enforce compliance, tariff regulation, and predictable service delivery (Bundesnetzagentur 2024; FERC 2024). These regulatory demands reduce the need for dynamic external networks, limiting the utility of INDIV (Nouman et al. 2022).

Joshi and Roh (2009) suggest that diversity, including INDIV, can trigger biases and negative opinions among TMTs, potentially disrupting team cohesion. In such cases, networks introduced by INDIV may become distractions rather than assets, especially when existing partnerships already meet operational needs. Incremental innovation, common in LT sectors, reduces the significance of cross-sector insights that INDIV typically offers, as opposed to the value such insights might provide in driving disruptive changes (Kwak, Kim, and Heo 2023; Nouman et al. 2022).

Furthermore, similar to the HT sector, labor market tightness affects LT sectors, with nearly three-quarters of manufacturing executives citing workforce attraction and retention as a primary challenge (Deloitte 2024b; Brower 2024; McKinsey & Co 2024). Cross-sector hires can offer a viable option to address skills gaps and support operational efficiency. Companies avoiding INDIV risk stagnation, particularly where missed opportunities outweigh the risk of inclusion. However, while such hires have potential, they also carry risks. INDIV may misalign with the stability-focused needs of LT sectors, negatively impacting performance. This is exemplified by Ron Johnson´s failed tenure at J. C. Penney, where strategies drawn from his prior experience at Apple conflicted with retail´s value-driven priorities (Mourdoukoutas 2021), leading to a drop in sales from $17bn in 2011 to $13bn in 2013 and over $1bn in losses (JC Penney 2013).

Nevertheless, diversity could provide value during strategic transformations (Jackson 2022). For instance, as LT companies adopt HT capabilities (McKinsey & Co 2024), EDUDIV and INDIV may help modernize processes and enhance customer experiences. EDUDIV introduces fresh perspectives on technological integration, while INDIV offers insights into external networks that have navigated similar transitions.

Future Trends

The HT sector is set for transformative growth, driven by advancements in AI, cloud computing, and cybersecurity (Deloitte 2024a; Accenture 2023), which demand interdisciplinary approaches and diverse leadership teams to navigate technological integration. Generative AI is expected to enhance decision-making and collaboration within TMTs, leveraging the cognitive diversity of EDUDIV to address challenges such as AI ethics and regulatory compliance while fostering innovation and strategic flexibility (McKinsey & Co 2024). INDIV can further support cross-sector ecosystems, integrating insights from traditionally non-HT sectors to drive advancements in areas such as IoT or automation (McKinsey & Co 2024). Advancements in governance frameworks and digital tools, such as AI-driven platforms, could help optimize EDUDIV and INDIV. These tools improve communication, resolve coordination challenges, and maximize the impact of diversity, particularly in LT sectors transitioning toward higher innovation capacity. Beyond financial outcomes, TMT diversity fosters sustainable innovation and inclusivity, bridging knowledge gaps and enabling companies to capitalize on emerging opportunities in interconnected markets. By strategically shaping TMT composition, companies can position themselves to capitalize on these trends, ensuring diverse teams maximize innovation potential and adaptability.

In conclusion, the contextual dependency of EDUDIV and INDIV´s impact on firm performance underscores the need to align TMT composition with sector-specific demands. In HT sectors, EDUDIV fosters innovation and adaptability, while INDIV enhances external access and strategic agility. Conversely, LT sectors require careful alignment to leverage diversity´s benefits while mitigating challenges.

and Practice

This study highlights diversity´s sector-specific impact, advancing both UET and RDT. It confirms UET´s proposition that EDUDIV fosters innovation and adaptability in HT sectors and extends RDT by illustrating how INDIV facilitates external resource access in dynamic environments. For LT sectors, the findings challenge the assumption of universally positive diversity effects, emphasizing that operational cohesion and sectoral stability can constrain its benefits. Diversity´s mixed impacts underscore the need for alignment with sector-specific demands, bridging a gap in diversity literature and encouraging explorations of its contextual dimensions.

For HT sectors, prioritizing EDUDIV and INDIV in TMT recruitment can enhance cross-disciplinary collaboration and absorptive capacity, driving innovation and adaptability. In contrast, LT sectors should adopt a more cautious approach, aligning diversity initiatives with operational priorities to avoid inefficiencies. Structured frameworks, such as conflict-resolution frameworks, can help integrate diverse perspectives to mitigate coordination challenges and align TMT contributions with sector-specific goals. Effective onboarding processes tailored to integrate diverse perspectives are equally crucial, particularly for INDIV. Such processes can expedite the adjustment period for TMT members with varied industry backgrounds, ensuring they contribute meaningfully and align with organizational priorities while effectively applying their expertise from previous industries. While companies cannot change external factors such as global competition or economic conditions (Kagzi and Guha 2018; Thornhill 2006), they can strategically shape TMT composition to leverage EDUDIV and INDIV as a competitive advantage. Recognizing that recruitment outcomes vary across sectors, organizations can optimize diversity initiatives by tailoring them to align with their specific operational and strategic demands.

The regression analysis of H1.3 quantifies the impact of EDUDIV on firm performance in HT sectors. Specifically, adding one board member with a diverse educational background is associated with an estimated 8.86% increase in Tobin´s Q (see *Appendix 22*), reflecting the potential benefits of diverse TMT compositions. This finding, which is based on historical data, underscores how EDUDIV could enhance market valuation by aligning TMT capabilities with the innovation-driven demands of HT sectors. The results in H2.3 underscore the contextual dependency of INDIV in shaping firm performance. Based on the historical data in our dataset, an additional industry expertise diverse executive board member demonstrates a modest positive effect in HT sector, contributing to a 0.97% increase in Tobin´s Q (see *Appendix 22*), highlighting its value in utilizing external insights. However, in LT sectors, INDIV is associated with an 8.62% decrease in Tobin´s Q, reflecting the potential for coordination challenges and misalignment in stable, efficiency-oriented contexts.

These results highlight that diversity´s impact is highly contingent on sector characteristics, underscoring the need for sector-specific strategies to effectively leverage its benefits. HT companies should actively leverage diversity as a competitive asset, while LT companies must carefully balance integration against their operational demands. Strategic recruitment and governance practices tailored to sector-specific contexts are essential for maximizing the value of EDUDIV and INDIV.

Research

The limitations of this study primarily come from its sectoral scope and generalizability. First, the binary classification into HT and LT sectors fails to differentiate medium-tech sectors, which combine elements of innovation and operational stability. Grouping these with LT sectors limits the applicability of findings to intermediate companies. Hatzichronoglou (1997) notes that the OECD categorizes sectors into high, medium, and LT based on R&D intensity, a classification that could even be expanded to four categories. Second, sector misclassification within the sample introduces variability, as some LT companies may exhibit HT characteristics and vice versa. This issue aligns with broader concerns of traditional sector classification. Potters (2009) critiques the widely used R&D intensity-based classification, highlighting inadequacies in contexts where LT products integrate HT technologies. This variability impacts the interpretation of EDUDIV and INDIV across diverse contexts, such as HT (e.g., Healthcare vs. Energy) or LT (e.g., Utilities vs. Real Estate) sectors. Lastly, while the analysis identifies associations between EDUDIV and INDIV with firm performance, potential endogeneity raises causality concerns. High-performing companies may attract diverse talent, making diversity a consequence rather than a cause of success (Matos, Lopes, and Matos 2012). As Wooldridge (2010) emphasized, correlations rarely imply causation without controlling for influencing factors, necessitating robust econometric methods. These limitations suggest caution when generalizing results and highlight opportunities for more refined future research.

Future research could expand on the findings of this study in several ways. First, examining medium-tech sectors could reveal how EDUDIV and INDIV interact in hybrid environments, potentially revealing nuanced patterns of diversity´s impact. Second, disaggregating HT and LT classifications could provide more granular insights into sector-specific diversity impacts. Moreover, the reliance on Tobin´s Q as a sole proxy for firm performance may not fully capture the multidimensional effects of diversity in the context of H1.3 and H2.3. ROA, as used by e.g., Shehata, Salhin, and El-Helaly (2017) and Erhardt, Werbel, and Shrader (2003), could offer a more direct measure of operational efficiency, potentially addressing Tobin´s Q limitations in reflecting diversity´s tangible impacts across sectors. Future research should also explore diversity´s limited or negative effects, such as challenges posed by EDUDIV and INDIV in LT sectors, and the modest positive effect of INDIV in HT sectors. Investigating EDUDIV and INDIV interaction effects could clarify whether their combined influence creates synergies or exacerbates coordination challenges. Furthermore, studying the interplay between UET and

RDT could guide governance models aligning diversity with sector-specific demands and improve its management in HT and LT sectors. Cultural and institutional contexts likely moderate these relationships, and examining their influence could refine strategies for diversity management. Finally, exploring the role of digital tools and AI in managing diversity offers exciting opportunities. Technologies that improve communication and analyze diverse insights could enhance EDUDIV´s and INDIV´s value, particularly in sectors facing coordination challenges. Addressing these gaps will refine the theoretical understanding of TMT diversity in HT and LT sectors and provide further actionable insights for organizations.

5.4 Hypotheses 1.4 and 2.4 (Felix Standhartinger)

H1.4 states that the positive effect of EDUDIV on firm performance is strengthened in countries with higher talent competitiveness, as reflected in the GTCI, while H2.4 suggests a similar moderating effect of the GTCI on the relationship between INDIV and firm performance.

The relationship between TMT heterogeneity and firm performance is shaped by cross-country effects that move beyond cultural dimensions. Instead, we focus on differences in human capital development by concentrating on essential influence factors directly affecting strategic decision-making. Both Human Capital Theory and Behavioral Theory highlight the importance of a robust talent ecosystem, which can improve decision-making capacity and offer external knowledge, especially for diverse TMTs. These perspectives suggest that such ecosystems, measured by GTCI, moderate the positive effect of EDUDIV and INDIV on firm performance in countries with well-developed talent enhancement frameworks.

Results and Hypothesis Evaluation

Based on the empirical analysis for H1.4 and the relation of EDUDIV to (ln)Tobin’s Q moderated by GTCI, we can generally observe that countries – except for France – show a positive correlation between EDUDIV and (ln)Tobin’s Q. Furthermore, the linear model explains that the main effect of EDUDIV has a marginally significant and markedly negative impact on (ln)Tobin's Q in countries with lower levels of talent competitiveness (low GTCI countries). Most relevant, the interaction term of EDUDIV and GTCI is statistically significant with a positive estimate. For every unit increase in a country's GTCI score, the negative impact of EDUDIV is offset, resulting in a net positive effect on (ln)Tobin's Q in high GTCI countries. Based on these results, after running the econometric step-by-step approach, we can state that high GTCI countries enable firms to unlock the benefits of educational background diversity and, therefore, approve H1.4.

However, the results regarding the GTCI moderating effect on INDIV in H2.4 are less meaningful. In the linear model, the main effect of INDIV reveals a negative impact with evident statistical insignificance. A similar picture emerges looking at the INDIV and GTCI interaction term, with a weak positive effect and statistical insignificance. The results of the quantile model do not change this picture either. This shows that the data does not support H2.4 and, hence, is not approved.

5.4.2.1 Interpretation and Reasoning

Interpretation – Educational Background Diversity

Overall, touching on diversity in educational backgrounds, the positive interaction term between EDUDIV and GTCI displays that in high-ranking GTCI environments, TMTs with educational background diversity demonstrate better firm performance. Based solely on this, we can presume that high GTCI countries provide a robust institutional framework (via regulatory, openness, educational, and sustainability aspects) that moderates the ability of diverse TMTs to take up and apply external knowledge, as Behavioral Theory implies (Cyert, Feigenbaum, and March 1963). On the other hand, the negative main effect of EDUDIV on firm performance indicates that low GTCI countries might leave room for interpretation, what hinders a company from capitalizing on firm performance due to higher TMT heterogeneity. In fact, Huggins and Thompson (2016) mention that localities in less economically developed, more communal- and collective-values-oriented regions are generally less individualistic, less diverse, and struggle to encourage new ideas and effective knowledge-sharing. Based on this consideration, companies may struggle to extract external knowledge grounded on entrepreneurship and diverse solutions in a country with a weaker talent ecosystem reflected by high communal- and collective values.

Consequently, countries with high GTCI scores, such as the Netherlands, Ireland, and Germany, have well-developed talent ecosystems that may drive impacts of TMT diversity, although they have different patterns. The Netherlands, which has the highest GTCI performance and second highest EDUDIV, demonstrates an efficient school-to-work transition, with 60% of skills acquired through real-life workplace settings in the upper secondary vocational system (OECD 2016). This creates a consistent pipeline of high-quality talent equipped with practical and theoretical knowledge, which supports Dutch companies in maintaining a high EDUDIV baseline. However, high GTCI and EDUDIV performance is affected by a saturation effect. Adding a potentially diverse TMT member to Dutch companies would not yield a substantial Tobin's Q boost compared to weaker-performing countries like Germany (see *Appendix 22*). Higher baseline EDUDIV would lead to diminishing returns, as further diversity may create integration challenges that outweigh benefits, a concept described as "suboptimal stable equilibria" (March 1991,71). Additionally, while the Netherlands demonstrates a relatively small average TMT size compared to other countries (see *Appendix 26*), this concentration increases the measurable impact of diversity within the team. However, at higher diversity levels, the marginal benefit of adding diverse TMT members might diminish due to potential integration challenges, limiting the moderating effect of GTCI. In Ireland, where EDUDIV is comparatively low, companies benefit from one of Europe's highest educational attainment rates, with 95% of 20-24-year-olds completing higher secondary education and 64% of 30–34-

year-olds holding tertiary qualifications (Central Statistics Office 2024). This institutional strength may compensate for lower initial diversity, enabling a significant Tobin's Q boost (see A*ppendix 22*). The gap between Ireland's low baseline EDUDIV and its high GTCI highlights that countries with room for diversity improvements can effectively leverage a broad institutional talent ecosystem. Moving on, Germany would provide the highest Tobin's Q boost (see *Appendix 22*) among observed countries, attributed to its moderate EDUDIV and smallest average TMT sizes, which increases the impact of additional TMT member diversity on strategic decision-making. J.G. March and Simon (1958) agree with this by using the concept of "bounded rationality" to explain that in smaller groups, more effective decision-making and communication are carried out, as they minimize coordination challenges and compromise-finding problems. Furthermore, Germany's high Revenue-to-Total-Assets ratio reflects effective resource utilization (see *Appendix 26*). This may indicate that German companies achieve better operational productivity through more effective strategic decision-making, which could explain a higher Tobin's Q boost.

Emphasizing moderate GTCI countries, France, with a high baseline EDUDIV, results in a smaller Tobin's Q boost compared to peers (see *Appendix 22*). The French talent ecosystem displays inefficiencies in talent utilization, with OECD's third-highest expenditures on "Continuing Vocational Training" relative to labor costs but below-average participation in non-formal job-related training (OECD 2023). Further, the negative correlation between EDUDIV and (ln)Tobin's Q suggests that challenges in integrating diverse perspectives within larger TMTs may attenuate the effect of diverse members.

Countries with lower GTCI, such as Spain and Italy, may face systemic barriers that hinder the effective translation of EDUDIV into improved firm performance, showing the lowest Tobin's Q boost (see *Appendix 22*). In Spain, second highest EU youth unemployment (10.8%, compared to the EU average of 6.3%) and a significant "brain drain," with 8% of PhD graduates emigrating, cause a reduced talent pool and enormous economic losses ($10bn annually on PhD brain drain) (Eurostat 2024; Xartec Salut 2022). Spain's corporate sector has already identified the inability to retain and upskill young professionals, acknowledging a talent knowledge gap (Foro Recursos Humanos 2023). Similarly, Italy, despite having the highest median EDUDIV, may struggle to leverage its diversity due to weak institutional support and limited international knowledge inflows. The Italian education system is well-developed and can provide young talents with necessary skills – which explains the high median EDUDIV – but it is tailored to domestic markets. For example, Italian universities only attract 4.2% of students from abroad, below the EU average of 9% (Eurostat 2022). Low rankings in GTCI pillars like "International Students" (69^{th}) and "Brain Gain" (97^{th}) further highlight its domestically focused talent ecosystem (INSEAD 2023). Moreover, Italy's largest average TMT size (see *Appendix 26*) may contribute to coordination challenges within TMTs, reducing the potential benefits of its high baseline EDUDIV in improving firm performance (Bolo, Muchemi, and Ogutu 2011). All in all, both Spain and Italy are exposed to a limited talent pool, which restricts the ability of companies to benefit from diverse TMTs and limits the potential performance advantages of EDUDIV.

Based on overall and country-level observations, we can tentatively conclude that GTCI results on EDUDIV complement the literature. These show that a country's macroeconomic environment and institutional landscape significantly influences its ability to achieve higher firm performance. Hence, GTCI reflects a country's ability to create and transfer knowledge, enabling educationally diverse TMTs to convert this into firm performance.

Reasoning – Educational Background Diversity

A causal explanation of how GTCI moderates EDUDIV to enhance firm performance remains absent. Addressing this and building on the Behavioral Theory, we focus on external knowledge volume and its integration through "absorptive capacity" (Cohen and Levinthal 1990).

External knowledge volume represents the pool of knowledge available outside the company. This knowledge is essential for driving innovation and maintaining competitiveness in a global environment (Cohen and Levinthal 1990). In that light, TMTs are a vital channel for identifying, interpreting, and leveraging this knowledge for strategic decision-making. The GTCI from INSEAD (2023) shows which countries can generate and harness external knowledge by capturing how they can produce and acquire talents (= input pillars, see *Appendix 11*). Especially the “Grow” pillar with its factors “Formal Education” (via e.g., vocational enrollment) and “Lifelong Learning” (via e.g., prevalence of training in firms) contributes to our Theory by suggesting that in high-ranking countries, investing in these aspects ensure consistent development of individual’s knowledge quality which further expands the external knowledge pool (INSEAD 2023). Consequently, high-ranking countries seek to utilize the skills and knowledge gained by future talents (=output pillars, see *Appendix 11*).

To combine with our results, without sufficient external knowledge volume (low GTCI countries), EDUDIV’s potential remains untapped, as reflected in its negative main effect. It demonstrates how an advanced talent ecosystem increases external knowledge and explains how much companies can absorb. In high GTCI environments, TMTs can act as “boundary spanners” (establish connections between outside and inside an organization; Ejim 2024) with the ability to absorb and integrate such knowledge into firm strategies. The significant interaction between GTCI and EDUDIV precisely evidences this, highlighting the role of absorptive capacity in enabling companies to convert increased external knowledge volume into actionable insights.

Absorptive capacity (AC) refers to a company’s ability to identify, assimilate, and apply knowledge and derive value from it (Cohen and Levinthal 1990). This capability is essential for maintaining competitiveness and enhancing organizational performance. At its core, AC depends on the internal knowledge base, which absorbs external knowledge volume, relying on individual and systemic factors.

At the individual level, TMT members contribute to absorptive capacity through their diverse experiences and educational backgrounds, which enhance their ability to integrate external knowledge. For instance, TMT members with diverse educational backgrounds act as gatekeepers, connecting external knowledge with internal organizational units and promoting strategic decision-making (Tushman and Katz 1980). Moreover, Chung, Cho, and Kang (2018) state that a TMT's broader knowledge base—moderated by the diversity of its members' educational backgrounds—contributes to organizational innovation.

At the company level, AC extends beyond individual contributions. It depends on systemic factors like effective communication structures, knowledge distribution, and expertise integration, which amplify how well knowledge volume from the external environment is absorbed (Cohen and Levinthal 1990).

Returning to our analysis, TMT heterogeneity can significantly moderate a company's AC. Diverse TMTs bring a broader knowledge base (Chung, Cho, and Kang 2018), facilitate communication and expertise integration, and signal inclusivity, enhancing a firm's ability to attract a skilled workforce in competitive talent markets (Dauth et al. 2023). This diversity enables them to utilize external knowledge sources better, making heterogeneous TMTs particularly impactful in high GTCI environments, where strong talent ecosystems enhance external knowledge volume and the ability to absorb it. High GTCI countries strengthen better talent environments, which drive knowledge creation and expand external knowledge volume. Latukha (2018) highlights that talent development in such environments positively influences an organization's AC and enables companies to convert external knowledge into strategic advantages effectively. In this process, environments with high GTCI act as catalysts, providing the infrastructure for TMTs from different educational backgrounds to succeed.

Pinned down to our hypothesis, it means how much knowledge a company can accumulate through the size of its knowledge volume (replicated by GTCI) and the strength of its AC (reinforced by EDUDIV). Countries with high GTCI and high EDUDIV (e.g., the Netherlands) benefit from stronger AC.

However, the key question arises regarding how this additional knowledge flow toward a company is integrated and converted into firm performance. The Behavioral Theory and the concept of "bounded rationality" have already provided theoretical reasoning that an enriched knowledge pool enables companies to overcome organizational obstacles such as informational constraints and decision biases to enhance performance (Nielsen 2010; Cyert, Feigenbaum, and March 1963). To better understand the effects thereof, we want to split firm performance into financial and non-financial performance:

Financially, we have demonstrated the impact on a market-related metric like (ln)Tobin's Q and seek to explain the positive moderation effect on financial performance. Expanding and focusing on talent ecosystems, we connected the GTCI of Eurozone countries with the respective labor productivity, expressed as GDP per hour worked, in a separate analysis to highlight the relationship between national talent competitiveness and economic output (see *Appendix 24*), comparing data from INSEAD (2023) and ILOSTAT (2023). The results show a moderate-to-strong correlation (0.687), suggesting that high GTCI countries may be better positioned to utilize human capital efficiently. For companies operating in these environments, access to a skilled workforce and stable institutional frameworks can increase operational efficiency, reduce costs, and support strategic decision-making, which supports the idea that advanced talent ecosystems moderate the relationship between TMT heterogeneity and financial performance.

Considering non-financial performance, we also conducted further analysis to demonstrate how GTCI positioning affects performance beyond a company's economic value in comparing a

Eurozone country's GTCI with its sustainability performance (reflected by the Environmental, Social and Governance Index (ESGI) showing a country's ESG risk profile (INSEAD 2023; Risk Watch Initiative 2023). The comparison shows a strong negative correlation (-0.784), indicating that countries with higher GTCI are associated with lower ESGI risk scores, demonstrating a more favorable risk environment (see *Appendix 25*). This aligns with the idea that competitive talent ecosystems are closely associated with better risk management and stronger sustainability performance. The findings imply that lower ESGI risk scores in high GTCI countries indirectly contribute to financial performance. For companies operating in these environments, external factors such as supportive policies and institutional frameworks can lead to improved corporate sustainability practices. Consequently, companies in low-risk ESGI environments can better align their activities with their stakeholders' demands, thus indirectly supporting their financial performance through greater market confidence affecting valuation metrics (Gregory 2022).

Based on this deep dive, we can state that high GTCI countries create environments where firms can effectively turn diverse educational knowledge into financial but also non-financial gains, supporting better decisions and stronger firm performance.

Interpretation – Industry Expertise Diversity

Having concentrated entirely on EDUDIV so far, we also want to explain why GTCI, combined with industry expertise, could not provide meaningful results. For EDUDIV, we have already provided a rationale that high GTCI countries increase the volume of external knowledge. We also hold this view in the context of INDIV. On the contrary, a comparison of the estimates of the EDUDIV and INDIV linear models shows that the moderation effect of GTCI is significantly lower. However, this should be treated with caution due to the non-significant INDIV p-values, demonstrating that TMTs with high industry expertise diversity cannot benefit from high GTCI countries (smaller interaction term estimate in H2.4, see *Appendix 20*).

Reasoning – Industry Expertise Diversity

The main reason for INDIV's non-significance in H2.4 may be derived from the principles of AC. According to Cohen and Levinthal (1990), AC is primarily based on prior related knowledge, especially in cognitive domains. Industry expertise may build essential competencies but does not necessarily enhance an individual's cognitive capacity for knowledge absorption. TMT members from diverse sectors might lack a shared framework for processing complex knowledge. Similarly, Milliken and Martins (1996) contribute to the observation that TMTs with a high degree of industry expertise diversity lead to more formal communication and that these teams are less integrated, making strategic decision-making more difficult. Additionally, Thatcher, Jehn, and Zanutto (2003) recognize that TMTs with considerable industry experience diversity risk splitting into siloed expertise background groups. These “diversity faultlines” can lead to less collaboration and increased competition within a TMT, resulting in ineffective decisions and lower cohesion.

Another perspective of this result lies behind the GTCI focus on the quality of education systems and skills development through indicators such as “Formal Education”, “Lifelong Learning,” “Access to Growth Opportunities,” and “Global Knowledge Skills” (INSEAD 2023). Since industry expertise diversity tends to reflect different professional and economic sector-specific experiences rather than educational attainment, the GTCI does not adequately consider or reward industry expertise. Moreover, the effectiveness of talent ecosystems themselves may play a critical role in explaining non-significance. Zahra and George (2002) explain that companies in countries with high GTCI find it easy to acquire external knowledge (=PACAP) but often fail to implement and apply it effectively (=RACAP), thus reducing its impact (resulting in a low “efficiency ratio”). Van Wijk, Jansen, and Lyles (2008) emphasize this in stating that such environments intensify challenges in knowledge transfer by making it too tacit, specific, and complex, resulting in a lack of coordination, which hinders companies’ ability to align diverse industry expertise with the knowledge they acquire. This misalignment makes the GTCI moderator weaker for INDIV than for EDUDIV because, in high GTCI environments, external knowledge often replaces rather than increases the value of industry expertise diversity (e.g., hiring external consultancy for horizontal sector expansion), leading to insignificant or adverse net effects in many countries.

and Practice

Our results contribute to the existing literature in several ways: First, by integrating GTCI, this paper is among the first to discover country-specific effects of TMT heterogeneity by showing how national talent ecosystems influence outcomes at the company level. We show that the effects of TMT heterogeneity are highly context-dependent and vary depending on institutional conditions such as the education system and the quality of skills development. Second, we fill a gap in Behavioral and Human Capital Theory by showing how advanced talent ecosystems reduce bounded rationality and enhance the role of human capital. Environments with high GTCI help TMTs access, process, and apply external knowledge, improving decision-making and aligning with objectives. Third, we show that GTCI represents a country's external knowledge volume, enabling companies to use a diverse TMTs AC to extract this knowledge for better performance. Our results show that environments with high GTCI increase the value of educational background diversity but do not significantly affect industry expertise diversity, highlighting the need for tailored strategies for different diversity types. Considering practical implications, on the one hand, companies may invest in external knowledge mechanisms by collaborating with national institutions to increase the country-wise knowledge volume level. For example, a company could partner with local universities and technical schools to develop vocational training tailored to industry needs (as the Dutch system lays out). In this way, they not only support the flow of knowledge between educational institutions and industry but can also attract talent still in education, thus generating efficiencies in their recruiting. Furthermore, (multinational) companies may adjust to country-specific contexts, offsetting weak national talent systems by tailoring their internal knowledge mechanisms. In low GTCI environments, companies could implement in-house training academies (e.g., corporate universities to create the knowledge quality necessary (especially if multinational companies do business in emerging markets, as stated by Han et al. (2024)). On the other hand, policymakers – especially in low GTCI environments – may prioritize reforms in the education system (such as tax incentives for vocational training) to prepare for long-term economic challenges. The "Draghi-Report" (Draghi 2024) about "The future of European competitiveness" highlights the urgent need for the EU to enhance its workforce's adaptability by prioritizing education and retraining opportunities. This aligns with the objective of solid vocational training systems, promoting lifelong learning, and enhancing the digital literacy of future talents to stay competitive in a disruptive economic environment. Adopting such approaches would enable companies and policymakers to build robust talent ecosystems that support innovation, productivity, and economic growth.

Research

Based on the analysis and discussion framework in the context of GTCI, we can identify three main limitations and propose future research fields: First, the data sample includes an unequal proportion of companies from respective countries, as it focuses on the Eurozone's 150 largest companies across its economic sectors. Therefore, to ensure robust and stable results, we included only those countries in the discussion, with at least eight companies in the sample (Netherlands, Ireland, Germany, France, Spain, Italy). However, this approach does exclude companies from countries with smaller sample sizes. It potentially limits the generalizability of the findings to the overall GTCI effect, particularly for variations in high/low GTCI countries (Nielsen 2010). Future studies could ensure a meaningful and equally weighted number of companies in the sample selection to include countries with lower GTCI, regardless of company size (e.g., Eastern Europe). Second, although GTCI is a comprehensive measure of a country's talent competitiveness, it leaves out country-specific factors that moderate firm performance (such as a country's degree of industrialization) and does not measure how effectively firms adapt to national talent ecosystems. By focusing exclusively on GTCI, our paper assumes a homogeneous impact of talent ecosystems across all economic sectors and geographies, which may not be the case. Future research could expand the scope across regions (e.g., Europe vs. Asia) to understand how cultural and institutional differences modify the role of a country or focus on broader measurements of a country's effectiveness (e.g., World Economic Forum's Global Competitiveness Index). Third, the paper's reliance on cross-sectional rather than longitudinal data limits the ability to establish causality between GTCI, TMT heterogeneity, and firm performance. Although we provided theoretical backing for our results using knowledge volume and AC, their practical effects remain unobserved. Therefore, we can only provide indicative but not definitively conclusive results in GTCI. We recommend that future scholars use panel data to observe the effectiveness of GTCI over time and whether patterns can be discerned between changes in GTCI and TMT heterogeneity and/or firm performance.

5.5 Hypotheses 3

This section discusses the results for H3, comparing the effects of EDUDIV and INDIV on firm performance within TMTs.

The literature review emphasized that a stronger EDUDIV effect stems from its ability to build cognitive frameworks and broaden problem-solving capacities within TMTs. Drawing on the Behavioral Theory of the Firm (Cyert and March 1963) and UET (Hambrick and Mason 1984), diverse educational backgrounds cultivate cognitive diversity within TMTs, enabling them to analyze issues from varying perspectives and strengthening strategic adaptability. In contrast, INDIV, while valuable for sector-specific knowledge, can foster silo-creation and introduce coordination challenges, ultimately limiting its effect on firm performance. However, both diversity factors represent distinct forms of human capital according to the Resource-Based View (Wernerfelt 1984). Teams with a broader range of prior knowledge, as suggested by Hilgard and Bower (1977), are better equipped to absorb, integrate and apply new information, thereby facilitating strategic decision-making and innovation creation. While EDUDIV and INDIV propose distinct strengths and challenges, they also have the potential to complement each other. By fostering both broad and specialized strategic insights, they underscore the importance of understanding their unique contributions and their combined effects on firm performance (Nielsen 2010).

5.5.1.1 Summary of Empirical Results and Hypothesis Evaluation

H3 proposed that the effect of EDUDIV on firm performance is stronger than that of INDIV. Both factors were significant with EDUDIV showing a positive coefficient and INDIV a negative coefficient. The difference in the strength of their effects is moderate, with EDUDIV surpassing INDIV. A WALD test was conducted to compare the coefficients of EDUDIV and INDIV, testing their equality. The test was significant, confirming a statistically stronger effect of EDUDIV on firm performance. Therefore, we approve H3. Yet, the outcome demands closer examination to fully understand the mechanisms driving these effects and their implications.

5.5.1.2 Interpretation and Reasoning

The results of H3 provide a unique opportunity to directly compare the effects of EDUDIV and INDIV within the same model, offering insights into how these two dimensions of TMT diversity effect firm performance. While previous hypotheses isolated the effects of EDUDIV and INDIV, this analysis reveals their relative contributions and emphasizes the consistently stronger positive effect of EDUDIV compared to INDIV. The findings highlight several key factors driving this difference.

First, in literature, human capital can be divided into general and specific human capital. Formal education is considered general human capital and captures analytical and problem-solving abilities that are transferable to other areas. In contrast, industry-specific work experience is considered specific human capital, encompassing skills directly tied to acquiring and applying new knowledge rooted in expertise developed within a particular field (Kato 2020). In this sense, EDUDIV may be considered more beneficial as it is more versatile and applicable to a wider range of issues. Moreover, EDUDIV´s value lies in its sustainability. General cognitive frameworks provided by diverse educational backgrounds are less likely to become obsolete in rapidly changing environments compared to the more narrow and distinct industry-related expertise. Also, formal education provides the basis for specific knowledge or expertise to be developed and proven to be more resilient in rapidly changing environments (Kato 2020).

Second, the stronger positive effect of EDUDIV can be attributed to its activation of elaboration-based processes. Joshi and Roh (2009) identify two distinct mechanisms through which team diversity impacts performance. The first, elaboration-based processes, refers to the cognitive resource base of a firm, which comprises the exchange of knowledge and perspectives among group members. This process involves individuals actively engaging with, processing, and integrating shared information while receiving and responding to feedback. Thereby, knowledge is a social construct that is developed and advanced through shared interactions and joint endeavors (Bolo, Muchemi, and Ogutu 2011). The second mechanism, categorization-based processes, is primarily socially motivated and externalizes as negative attitudes or biases toward other team members. While elaboration-based processes enhance performance by leveraging diverse resources, categorization-based processes hinder performance by fostering interpersonal tensions and conflict. In the context of EDUDIV and INDIV, this might suggest that educational diversity fosters performance improvements by extending the team's cognitive base and combining numerous intellectual frameworks (Joshi and Roh 2009). Conversely, the impact of INDIV may be less positive or even negative due to the potential activation of categorization-based processes. The more specific, task-oriented nature of INDIV may not significantly expand the cognitive resource base in the same way as EDUDIV, while simultaneously increasing the likelihood of interpersonal biases or conflict stemming from industry-specific assumptions and norms. This dynamic lowers the potential for INDIV to contribute to firm performance (Joshi and Roh 2009).

Third, as highlighted in earlier analyses, EDUDIV enhances AC (Cohen and Levinthal 1990), enabling TMTs to integrate external knowledge and respond to environmental changes. While INDIV offers network access and sector-specific insights, it lacks the same breadth, resulting in diminishing returns when collaboration is constrained.

The positive effect of EDUDIV on firm performance stems from mechanisms like strategic adaptability, innovation, and decision-making. While INDIV contributes through knowledge resources, network access, and agility, its impact is less pronounced at the firm level. EDUDIV’s broader applicability and versatility allow for a stronger, more positive influence, whereas INDIV’s negative effects highlight coordination challenges and biases within TMTs.

5.5.1.3 Implications for Theory and Practice

The findings of H3 align with broader themes discussed earlier. EDUDIV consistently demonstrates a positive relationship with firm performance, while INDIV’s effects are more variable, highlighting the context-dependent nature of industry-specific expertise. This comparison reinforces that EDUDIV’s versatility and cognitive diversity make it a more reliable predictor of firm performance across scenarios. The simultaneous presence of EDUDIV and INDIV in the model reflects real-world TMT dynamics, emphasizing the need for nuanced strategies to optimize their combined impact. For example, companies may benefit from leveraging INDIV to address specific industry challenges while relying on EDUDIV to drive cross-functional innovation and long-term strategic adaptability. Finally, our findings highlight the limitations of treating educational background and prior industry expertise diversity as a single category under the broader term of task-related diversity or similar terms, as used by some scholars (Horwitz and Horwitz 2007; Zhou and Rosini 2015; Jarzabkowski and Searle 2004). By revealing distinct, and at times, counteracting effects of these two dimensions, this study raises questions about the appropriateness of such categorizations. A re-evaluation of diversity frameworks to distinctly differentiate between these constructs could enable more precise analyses of their individual and combined effects on firm performance.

5.5.1.4 Limitations and Future Research

These findings are subject to several limitations. The assumption of independence between EDUDIV and INDIV may oversimplify their relationship, as potential synergies or conflicts between the two forms of diversity remain unexplored. While multicollinearity diagnostics showed no linear dependence, the linear model's assumption of additivity may miss nuanced interactions, which risks overlooking potential synergies or conflicts between the two forms of diversity, potentially biasing the results by failing to fully capture their deeper interactions. Additionally, comparing effect sizes of coefficients relies on the robustness of measurement methods and sample representativeness, which may limit the generalizability of findings.

Building on these limitations, several future arrays of research can be derived from the investigation. First, future research could investigate whether the interaction between EDUDIV and INDIV creates synergies, optimizing outcomes by combining diverse educational insights with specific industry expertise. INDIV may play a complementary role to EDUDIV (Joshi and Roh 2009). For instance, does INDIV enhance EDUDIV’s effectiveness in sectors with high environmental dynamism? Exploring these dynamics is critical for developing strategies to optimize diversity in TMTs. Finally, future studies could incorporate alternative performance measures, such as organizational resilience or long-term sustainability, providing a more holistic view of how EDUDIV and INDIV contribute to company success. These methods may reveal contexts where the complementary effects of EDUDIV and INDIV manifest more prominently in non-financial outcomes, offering deeper insights into their broader contributions to organizational adaptability and team cohesion.

6 Conclusion

This study analyzed the effect of TMT diversity, specifically EDUDIV and INDIV, on firm performance within Eurozone companies. Employing comprehensive statistical methods on a sample of 150 large companies, we showed how these diversity metrics impact firm performance through their central effects, sector-specific effects, and country-specific effects.

6.1 Summary of Key Findings

Three overarching effects of EDUDIV are identified. The main effect demonstrates that EDUDIV enhances strategic adaptability and innovation by leveraging cognitive perspectives, particularly in dynamic markets. The sector-specific effect suggests that TMT diversity is not inherently positive or negative; however, the results show that sectors with significant findings for both variables exhibited the same directional effects. This underscores that companies must first understand their sector's key characteristics: EDUDIV significantly enhances firm performance in HT sectors characterized by rapid innovation cycles and technological complexity, whereas its effect is negligible in LT sectors focused on operational stability and predictability. Meanwhile, we find that country environments matter in an advanced talent ecosystem and enhance external knowledge volume, boosting firm performance via the AC of a heterogeneous TMT. However, in high EDUDIV contexts (e.g., Netherlands), additional diversity brings diminishing returns, limiting improvements.

Similarly, the INDIV findings present mixed results. Its main effect is not significantly related to firm performance except for middle-performing companies, which experienced negative effects due to conflicts outweighing benefits. Sector-specific effects show modest positive effects in HT sectors due to external network access and industry insights but negative effects in LT sectors, where coordination challenges and misalignments diminished its value. Country-specific observations demonstrate INDIV's insignificance, as countries with high GTCI emphasize education-based skills and cognitive knowledge, which may be misaligned with the framework needed to integrate diverse sector expertise effectively. Finally, comparing the effects of EDUDIV and INDIV, we find evidence of their complementary potential, as observed in H3. Moderate levels of diversity across both dimensions could foster innovation and agility, driving superior performance. However, excessive diversity in either dimension can reduce effectiveness and team cohesion. Findings underscore the importance of active diversity management to mitigate negative effects.

6.2 Contributions to Literature

Our research expands the literature by addressing notable gaps. We make several contributions: First, to the best of our knowledge, this is the first study conducting a thorough analysis of EDUDIV and INDIV within TMTs and their respective effects on firm performance. Focusing on the diversity of academic qualifications and tenure across distinct industries, this research departs from traditional diversity measures. It contributes a more nuanced and multi-faceted perspective to the current discussion. In this way, the analysis also considers macro-levels, showing how national talent ecosystems (measured by GTCI) influence the relationship between TMT diversity and firm performance, indicating the importance of contextual factors. Second, this study introduces a novel data collection method for analyzing TMT profiles by systematically examining member CVs across Eurozone countries and economic sectors. This addresses the limitations of previous studies, which lacked in-depth data and often concentrated merely on a single sector or region. Our findings demonstrate a broader and more generalizable application. Third, our findings strengthen UET (Hambrick and Mason 1984) by empirically linking EDUDIV – and, to some extent, INDIV – with firm performance. We provide empirical evidence that educational and past professional experience shape decision-making processes and overall firm performance. In addition, the observed effects in our study advance Resource-based Theories (Pfeffer and Salancik 1978) by demonstrating that the mere possession of resources, such as knowledge or industry expertise, is insufficient to translate into a competitive advantage. Instead, the effectiveness of these resources depends on how diversity is managed and strategically leveraged to drive firm performance. Lastly, this research challenges the prevailing assumptions of existing theories, which often emphasize the advantages of heterogeneity, suggesting that greater diversity consistently enhances decision-making quality and organizational outcomes (Wei and Zhang 2022). However, on the contrary, our findings indicate that diversity can sometimes block decision-making and decrease firm performance, especially when not aligned with contextual factors like sector dynamics or organizational strategy. These insights align with and expand emerging theories, as supported by Roh et al. (2019), emphasizing that there might be an optimal level of diversity within TMTs.

6.3 Practical Implications

Our findings offer actionable insights for companies. First, this study highlights the critical role of EDUDIV in driving firm performance, often outperforming INDIV effects. Human Capital Theory complements this by positing that companies benefit from their executive's cumulative cognitive capabilities (e.g., independent thinking) driven by their educational qualifications (Weiss 2015; Brown 2005; Singh, Terjesen, and Vinnicombe 2008). However, industry-specific experience topped the list of board recruitment priorities in Deloitte (2018) on US companies. Similarly, Heidrick & Struggles (2024) findings on European companies indicate that professional experience remains a critical selection criterion. Educational background plays a subordinate role in the appointment of TMT members. To address this concern, companies could place greater emphasis on educational diversity when assembling TMTs. Supervisory bodies of large companies should look beyond industry experience and actively target TMT members from diverse educational backgrounds. Rey (2022) highlights the key role of the nominating committee as a lever for ensuring diversity on the board, emphasizing its potential to promote EDUDIV through transparent and strategic selection processes.

Second, the negative effect of INDIV might initially suggest its limited value. However, the findings in the study highlight the potential for enhancement if appropriate diversity management practices and organizational structures are implemented. By establishing mechanisms to integrate and utilize diverse industry expertise effectively, INDIV´s effect on firm performance could improve. While it may not match the consistently positive effect of EDUDIV, these adjustments could enhance INDIV´s contribution to organizational outcomes.

Third, this study helps understand the double-edged nature of TMT diversity, as highlighted by Zhou et al. (2023), where its effects are conditional and context-dependent, varying significantly by sector and country. Our findings underscore that diversity is not universally beneficial. It can foster innovation and adaptability but may also introduce inefficiencies or conflicts if not managed effectively within the organizational and cultural context. To address this complexity, companies should perform a “contextual diagnosis” (Joshi and Roh 2009, 24) to develop tailored diversity strategies in treating diversity as a potential asset and liability.

6.4 Research Limitations

This study must acknowledge several limitations. First, our analysis employs cross-sectional data, limiting the ability to capture temporal relationship changes. The absence of panel data restricts insights into dynamic causal relationships, such as how EDUDIV and INDIV influence firm performance under varying conditions or over time. Studies, such as Labra and Torrecillas (2018) and Bond (2002) highlight the importance of panel data in capturing longitudinal changes and dynamic effects in organizational contexts. Second, data collection relied on CVs and LinkedIn due to unavailable alternative sources, introducing potential biases, such as outdated profiles, incomplete career histories, and reliance on self-reported data, which may affect data reliability. Third, the study focused on 150 companies within the Eurozone, selecting the top 15 companies by market capitalization across ten industries, limiting generalizability to other regions with differing economic and regulatory contexts. The focus on large market capitalization companies excludes mid-sized or smaller companies, potentially overlooking diversity dynamics in such organizations. Additionally, analyzing TMTs instead of boards of directors or other governance bodies reduces applicability to contexts like the US, where governance structures often integrate TMTs and boards. Last but foremost, while the study identifies associations between EDUDIV, INDIV, and firm performance, it does not establish causality. Reverse causation, where already high-performing companies attract diverse TMT members, remains a concern. As Wooldridge (2010) highlights, correlation does not imply causation, particularly without accounting for influencing factors, emphasizing the need for robust econometric methods. These limitations call for caution in extending results to broader contexts and underscore the need for refined future research.

6.5 Future Research Directions

The limitations highlight future research directions. Expanding with panel data could assess temporal changes and longitudinal diversity effects, as shown by Kagzi and Guha (2018) and Gordini and Rancati (2017) who demonstrate how panel data facilitates exploring diversity effects across organizational growth stages and external shocks. Broader studies across sectors, regions, and additional diversity dimensions, like personality traits, could enhance understanding of diversity's impact on performance. Qualitative methods could deepen the understanding of interactions between EDUDIV and INDIV. To address endogeneity, approaches like instrumental variables (Shatnawi et al. 2022) and propensity score matching (Uwizeye 2023) can isolate causal impacts. Incorporating non-financial metrics like ESG scores or brand reputation highlights diversity's broader effect (Homberg and Bui 2013). Examining mediators, moderators, and synergy effects may explain inconsistencies in prior research and refine strategies for optimized diversity's performance benefits.

References and Appendices

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Appendix 1 – List of Contents

Appendix 2 – List of Abbreviations

AI	Artificial Intelligence
BoD	Board of Directors
CC	Consumer Cyclical
CNC	Consumer Non-Cyclical
EDUDIV	Educational Background Diversity
EMEA	Europe, Middle East and Africa
ESG	Environmental, Social and Governance
ESGI	Environmental, Social and Governance Index
EU	European Union
EV	Electric Vehicle
GFC	Global Financial Crisis
GTCI	Global Talent Competitiveness Index
H	Hypothesis
HT	High-tech
ICT	Information and Communication Technology
INDIV	Industrial Expertise Diversity
IoT	Internet of Things
IR	Integration Responsiveness
LSEG WS	London Stock Exchange Group Work Stream
LT	Low-tech
M&A	Mergers & Acquisitions
OEM	Original Equipment Manufacturer
R&D	Research and Development
RDT	Resource Dependence Theory

ROA	Return on Assets
ROE	Return on Equity
ROI	Return on Investment
TMT	Top Management Team
TRBC	The Reference Data Business Classification
UET	Upper Echelons Theory

Appendix 3 – Regression Model Equations

Hypotheses 1.1

$$(\ln)Tobin's\ Q_i = \beta_0 + \beta_1 * EDUDIV_i + \beta_2 * \ Easeof\ Doing\ Business\ Index_i + \ \beta_3 * Market\ Cap_i + \beta_4 * Total\ Assets_i + \beta_5 * Revenue_i + \beta_6 * Leverage\ Ratio_i + \beta_7 * Board\ Size_i + \beta_8 * Gender\ Diversity_i + \beta_9 * Av.Board\ Tenure_i + \beta_{10} * \ CEO\ Chairman\ Duality_i + \beta_{11} * Independent\ Board\ Members_i + \epsilon_i$$

Hypothesis 1.2

$$(\ln)Tobin's\ Q_i = \beta_0 + \beta_1 * EDUDIV_i + \sum j = 1^9 \delta_j * (EDUDIV_i * Economic\ Sector_j) + \beta_2 * \ Easeof\ Doing\ Business\ Index_i + \ \beta_3 * Market\ Cap_i + \beta_4 * Total\ Assets_i + \beta_5 * Revenue_i + \beta_6 * Leverage\ Ratio_i + \beta_7 * Board\ Size_i + \beta_8 * Gender\ Diversity_i + \beta_9 * Av.Board\ Tenure_i + \beta_{10} * \ CEO\ Chairman\ Duality_i + \beta_{11} * Independent\ Board\ Members_i + \epsilon_i$$

Hypothesis 1.3

$$(\ln)Tobin's\ Q_i = \beta_0 + \beta_1 * EDUDIV_i + \delta * (EDUDIV_i * Economic\ Sector\ High\ Low_i) + \beta_2 * \ Easeof\ Doing\ Business\ Index_i + \ \beta_3 * Market\ Cap_i + \beta_4 * Total\ Assets_i + \beta_5 * Revenue_i + \beta_6 * Leverage\ Ratio_i + \beta_7 * Board\ Size_i + \beta_8 * Gender\ Diversity_i + \beta_9 * Av.Board\ Tenure_i + \beta_{10} * \ CEO\ Chairman\ Duality_i + \beta_{11} * Independent\ Board\ Members_i + \epsilon_i$$

Hypothesis 1.4

$$(\ln)Tobin's\ Q_i = \beta_0 + \beta_1 * EDUDIV_i + \delta * (EDUDIV_i * GTCI_i) + \beta_2 * \ Easeof\ Doing\ Business\ Index_i + \ \beta_3 * Market\ Cap_i + \beta_4 * Total\ Assets_i + \beta_5 * Revenue_i + \beta_6 * Leverage\ Ratio_i + \beta_7 * Board\ Size_i + \beta_8 * Gender\ Diversity_i + \beta_9 * Av.Board\ Tenure_i + \beta_{10} * \ CEO\ Chairman\ Duality_i + \beta_{11} * Independent\ Board\ Members_i + \epsilon_i$$

Hypothesis 2.1

$$(\ln)Tobin's\ Q_i = \beta_0 + \beta_1 * INDIV_i + \beta_2 * \ Easeof\ Doing\ Business\ Index_i + \ \beta_3 * Market\ Cap_i + \beta_4 * Total\ Assets_i + \beta_5 * Revenue_i + \beta_6 * Leverage\ Ratio_i + \beta_7 * Board\ Size_i + \beta_8 * Gender\ Diversity_i + \beta_9 * Av.Board\ Tenure_i + \beta_{10} * \ CEO\ Chairman\ Duality_i + \beta_{11} * Independent\ Board\ Members_i + \epsilon_i$$

Hypothesis 2.2

$$(\ln) Tobin's\ Q_i = \beta_0 + \beta_1 * INDIV_i + \sum j = 1^9 \delta_j * (INDIV_i * Economic\ Sector_j) + \beta_2 * \ Easeof\ Doing\ Business\ Index_i + \ \beta_3 * Market\ Cap_i + \beta_4 * Total\ Assets_{\,i} + \beta_5 * Revenue_i + \beta_6 * Leverage\ Ratio_i + \beta_7 * Board\ Size_i + \beta_8 * Gender\ Diversity_i + \beta_9 * Av.Board\ Tenure_i + \beta_{10} * \ CEO\ Chairman\ Duality_i + \beta_{11} * Independent\ Board\ Members_i + \epsilon_i$$

Hypothesis 2.3

$$(\ln) Tobin's\ Q_i = \beta_0 + \beta_1 * INDIV_i + \delta * (INDIV_i * Economic\ Sector\ High\ Low_i) + \beta_2 * \ Easeof\ Doing\ Business\ Index_i + \ \beta_3 * Market\ Cap_i + \beta_4 * Total\ Assets_{\,i} + \beta_5 * Revenue_i + \beta_6 * Leverage\ Ratio_i + \beta_7 * Board\ Size_i + \beta_8 * Gender\ Diversity_i + \beta_9 * Av.Board\ Tenure_i + \beta_{10} * \ CEO\ Chairman\ Duality_i + \beta_{11} * Independent\ Board\ Members_i + \epsilon_i$$

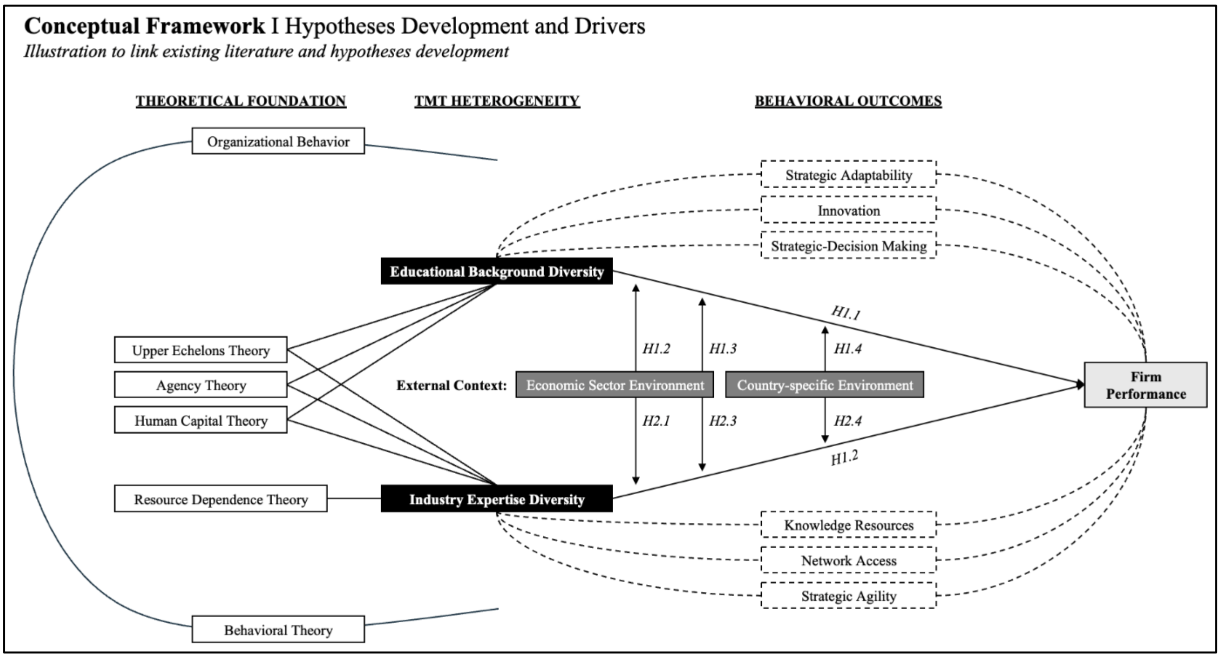
Hypothesis 2.4

$$(\ln) Tobin's\ Q_i = \beta_0 + \beta_1 * INDIV_i + \delta * (INDIV_i * GTCI_i) + \beta_2 * \ Easeof\ Doing\ Business\ Index_i + \ \beta_3 * Market\ Cap_i + \beta_4 * Total\ Assets_{\,i} + \beta_5 * Revenue_i + \beta_6 * Leverage\ Ratio_i + \beta_7 * Board\ Size_i + \beta_8 * Gender\ Diversity_i + \beta_9 * Av.Board\ Tenure_i + \beta_{10} * \ CEO\ Chairman\ Duality_i + \beta_{11} * Independent\ Board\ Members_i + \epsilon_i$$

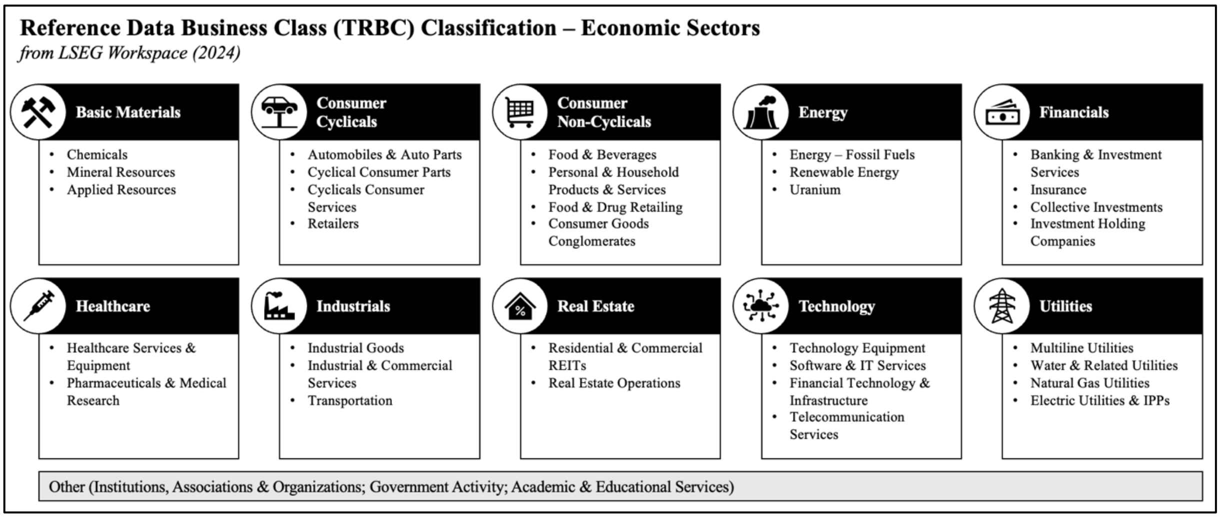
Hypothesis 3

$$(\ln) Tobin's\ Q_i = \beta_0 + \beta_1 * EDUDIV_i + \beta_2 * INDIV_i + \beta_3 * \ Easeof\ Doing\ Business\ Index_i + \ \beta_4 * Market\ Cap_i + \beta_5 * Total\ Assets_{\,i} + \beta_6 * Revenue_i + \beta_7 * Leverage\ Ratio_i + \beta_8 * Board\ Size_i + \beta_9 * Gender\ Diversity_i + \beta_{10} * Av.Board\ Tenure_i + \beta_{11} * \ CEO\ Chairman\ Duality_i + \beta_{12} * Independent\ Board\ Members_i + \epsilon_i$$

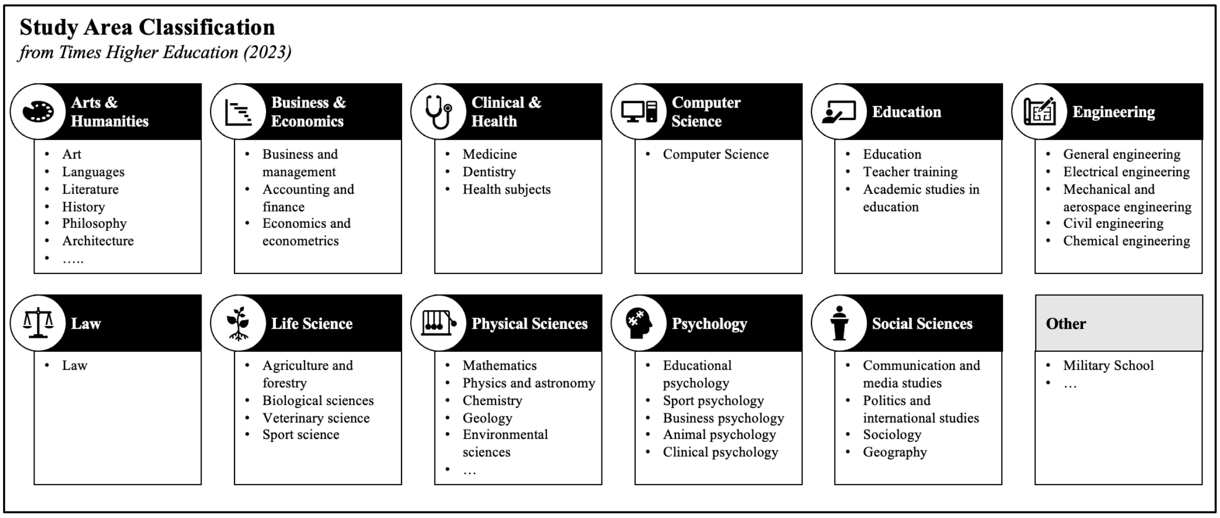
Appendix 4 – Conceptual Framework of Hypotheses Development and Drivers



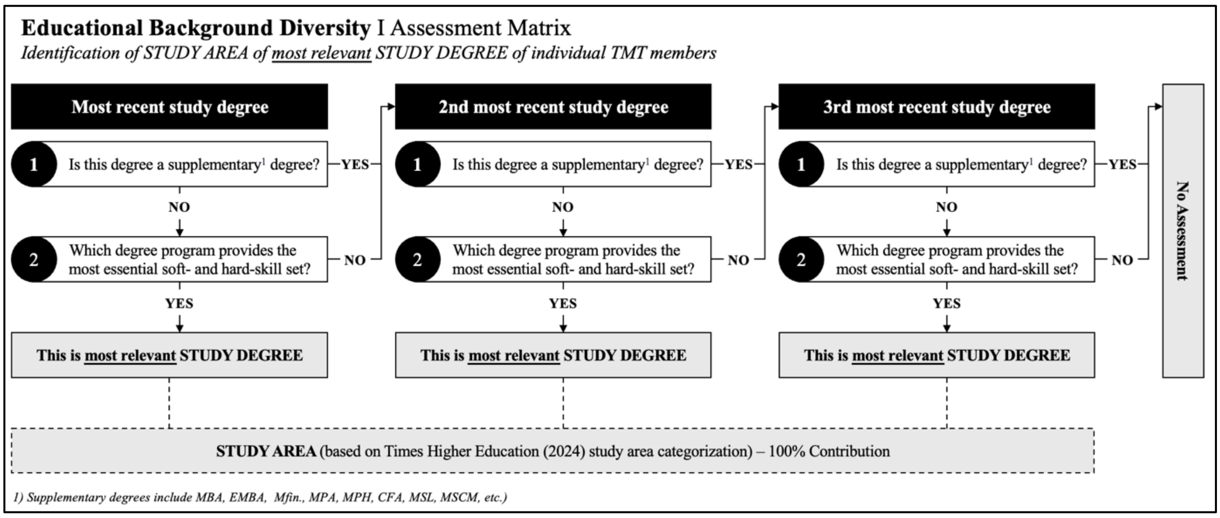
Appendix 5 – Reference Data Business Class (TRBC) Classification



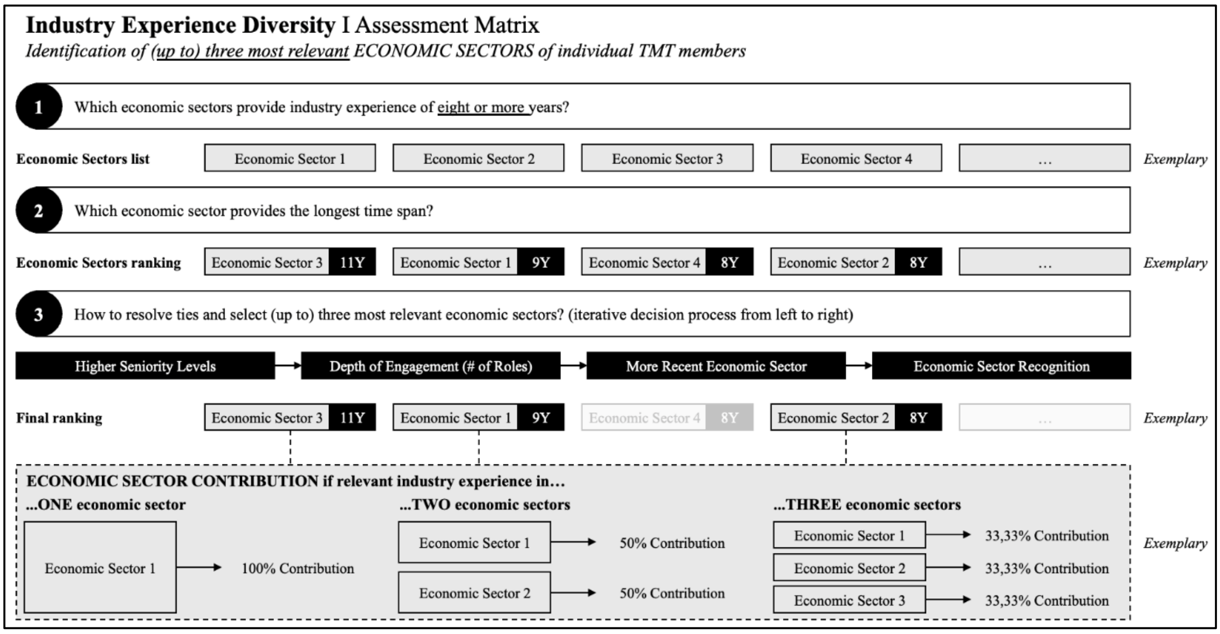
Appendix 6 – Study Area Classification



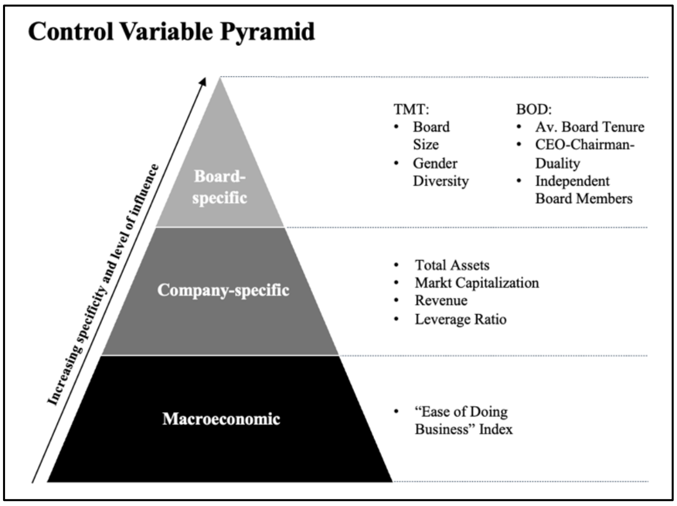
Appendix 7 – Educational Background Diversity Assessment Matrix



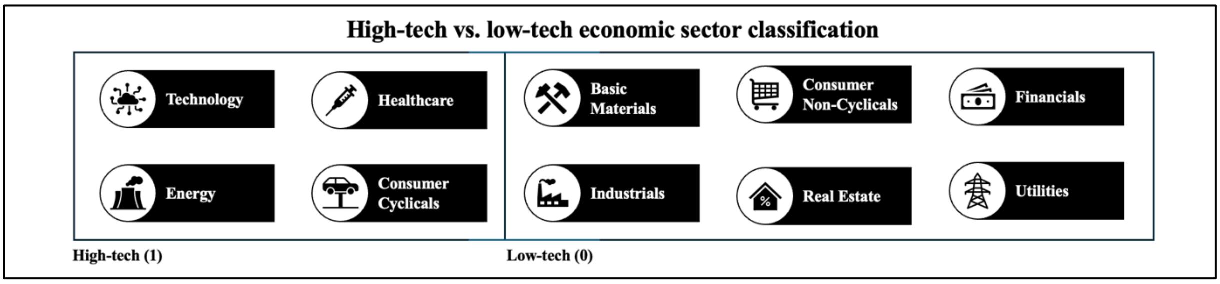
Appendix 8 – Industry Expertise Diversity Assessment Matrix



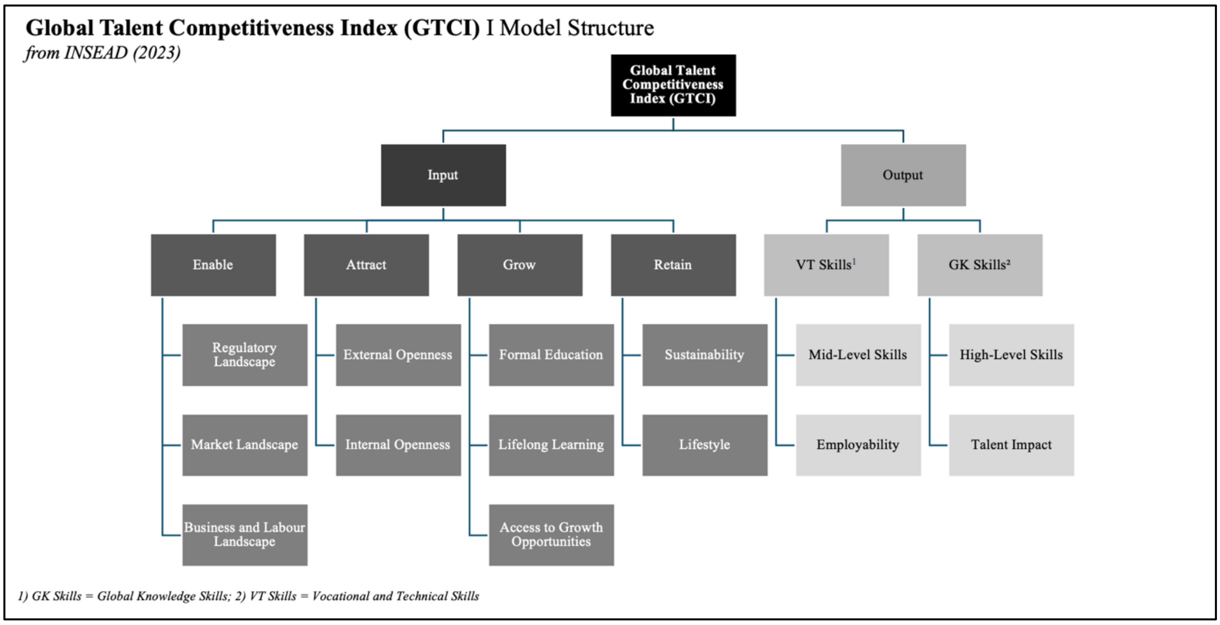
Appendix 9 – Control Variable Pyramid



Appendix 10 – High-Tech vs. Low-Tech Economic Sector Classification



Appendix 11 – Global Talent Competitiveness Index (GTCI)

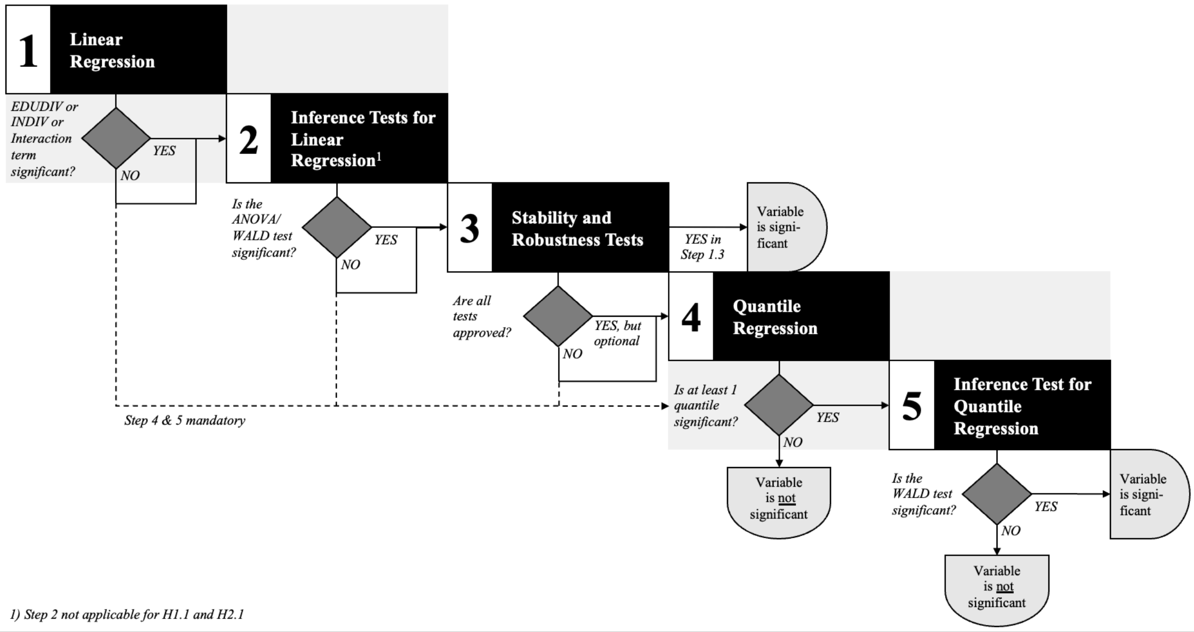


Appendix 12 – Overview of Control Variables and Contextual Factors

Variables	**Definition**
Independent Variable	
Educational Background Diversity (EDUDIV)	Zahl's SDI measuring TMT educational background diversity derived from original analysis
Industry Expertise Diversity (INDIV)	Zahl's SDI measuring TMT industry expertise diversity derived from original analysis
Dependent Variable	
(ln)Tobin's Q	LN-transformed 3Y average market-based firm performance indicator from LSEG WS
Control Variable	
Macroeconomic	
Ease of Doing Business Index	World Bank index ranking countries business regulatory environment
Company-specific	
Market Cap	3Y average of company's market value from LSEG WS
Total Assets	3Y average of company's total assets from LSEG WS
Revenue	3Y average of company's revenue from LSEG WS
Leverage Ratio	3Y average of company's leverage ratio from LSEG WS
Board-specific	
Board Size	Total number of TMT members per company from original analysis
Gender Diversity	% of female TMT members per company from original analysis
Av. Board Tenure	Average years served by BOD members per company from LSEG WS
CEO Chairman Duality	BOD dummy variable (1 = CEO also Chairman, 0 = not) from LSEG WS
Independent Board Members	3Y average % of independent BOD members from LSEG WS
Contextual Factors	
Economic Sector	Classifying company's economic sector in TRBC from LSEG WS
Economic Sector High Low	Dummy variable assigning economic sector to high-tech and low-tech sectors (1 = high, 0 = low)
Global Talent Competitiveness Index (GTCI)	INSEAD index assessing company's HQ Country talent competitiveness

Appendix 13 – Econometric Model

Econometric Model I Step-by-Step Approach



1) Step 2 not applicable for H1.1 and H2.1

Appendix 14 – Overview of Continuous Variables

Category	Variables			
Board Diversity Metrics	EDUDIV	INDIV		
Firm Performance Metric	(ln)Tobin´s Q			
Company-specific	Market Cap	Total Assets	Revenue	Leverage Ratio
Board-specific	Independent Board Members	Average Board Tenure	Gender Diversity	Board Size
Macroeconomic	Ease of doing Business Index	GTCI		

Appendix 15 – Summary Statistics of Continuous Variables

Variable (n = 150)	Mean	SD	Median	Mad	Min	Max	Skew	Kurtosis	SE
(ln)Tobin's Q	0.086	0.985	0.045	0.780	-2.407	3.062	0.016	0.352	0.080
EDUDIV	1.151	0.427	1.255	0.327	0.000	2.119	-0.763	0.954	0.035
INDIV	0.792	0.469	0.773	0.516	0.000	1.777	0.213	-0.760	0.038
Ease of Doing Business Index	77.323	2.388	76.800	2.669	69.600	80.200	-1.025	1.147	0.195
GTCI	68.239	4.948	69.880	4.403	50.380	74.760	-0.840	0.397	0.404
Market Cap (in $bn)	50.371	56.960	31.947	30.873	3.255	369.835	2.543	8.202	4.651
Total Assets (in $bn)	157.362	390.116	37.467	37.520	0.517	2931.726	4.593	24.227	31.853
Revenue (in $bn)	34.643	46.707	20.344	22.747	0.300	312.913	2.786	10.095	3.814
Leverage Ratio	0.942	0.852	0.759	0.498	0.005	5.968	3.147	13.996	0.070
Ind. Board Members	0.652	0.215	0.635	0.233	0.000	1.000	-0.140	-0.454	0.018
Average Board Tenure	6.425	2.512	6.171	2.137	1.818	15.425	0.920	1.408	0.205
Gender Diversity	0.255	0.122	0.250	0.124	0.000	0.600	0.221	-0.027	0.010
Board Size	9.880	5.387	9.000	5.930	2.000	33.000	1.228	2.177	0.440

Appendix 16 – Frequency Distribution and Macroeconomic Indices of HQ Country

Countries	Number of Companies	Ease of Doing Business Index	GTCI
Germany	35	79.7	69.88
France	34	76.8	66.91
Netherlands	21	76.1	74.76
Ireland	15	79.6	70.45
Spain	12	77.9	60.36
Italy	9	72.9	58.07
Belgium	7	75	69.12
Finland	5	80.2	74.35
Luxembourg	4	69.6	72.88
Portugal	4	76.5	61.6
Austria	2	78.7	69.05
Croatia	1	73.6	50.38
Cyprus	1	73.4	59.46

Appendix 17 – Summary Statistics by Categorical Variables

	EDUDIV					INDIV				
Economic Sector	**Mean**	**Median**	**SD**	**Min**	**Max**	**Mean**	**Median**	**SD**	**Min**	**Max**
Basic Materials	1.192	1.263	0.315	0.600	1.636	0.711	0.598	0.419	0.000	1.496
Consumer Cyclicals	1.103	1.290	0.520	0.000	1.671	0.683	0.785	0.395	0.000	1.269
Consumer Non-Cyclicals	1.018	1.050	0.389	0.000	1.761	0.631	0.462	0.511	0.000	1.641
Energy	1.021	1.099	0.469	0.000	1.745	0.802	0.850	0.454	0.000	1.617
Financials	1.068	1.048	0.393	0.482	1.850	0.430	0.404	0.293	0.000	1.110
Healthcare	1.503	1.333	0.396	0.773	2.119	0.891	0.820	0.384	0.370	1.572
Industrials	1.209	1.272	0.376	0.000	1.519	0.946	0.990	0.472	0.000	1.728
Real Estate	0.910	1.150	0.520	0.000	1.458	0.839	0.773	0.567	0.000	1.765
Technology	1.288	1.320	0.240	0.818	1.593	0.728	0.720	0.335	0.000	1.291
Utilities	1.193	1.178	0.385	0.534	1.998	1.260	1.290	0.435	0.358	1.777
Economic Sector High Low										
Low-tech	1.098	1.183	0.405	0.000	1.998	0.803	0.699	0.516	0.000	1.777
High-tech	1.229	1.294	0.450	0.000	2.119	0.776	0.789	0.392	0.000	1.617
HQ Country										
Germany	1.161	1.255	0.359	0.000	2.009	0.736	0.793	0.482	0.000	1.635
France	1.179	1.281	0.454	0.000	2.045	0.817	0.798	0.461	0.000	1.765
Netherlands	1.178	1.320	0.516	0.000	2.119	0.633	0.576	0.478	0.000	1.496
Ireland	1.147	1.147	0.385	0.585	1.914	0.855	0.646	0.500	0.000	1.728
Spain	1.059	1.156	0.450	0.000	1.567	0.638	0.617	0.400	0.000	1.210
Italy	1.493	1.533	0.322	0.739	1.850	1.037	0.785	0.515	0.487	1.696

Notes: Finland and Belgium not included due to small sample size; Not enough data available for Luxembourg, Portugal, Austria, Croatia, and Cyprus

Appendix 18 – Correlation Matrix

Variables	1	2	3	4	5	6	7
1. EDUDIV	1.00	0.12	0.15	0.18	0.11	-0.02	0.04
2. INDIV		1.00	0.06	-0.04	-0.08	-0.24	0.11
3. (ln)Tobin´s Q			1.00	0.29	-0.34	-0.58	-0.32
4. Market Cap				1.00	0.28	0.10	-0.13
5. Revenue					1.00	0.23	0.03
6. Total Assets						1.00	0.32
7. Leverage Ratio							1.00

Appendix 19 – Correlation of EDUDIV / INDIV on (ln)Tobin´s Q

	Economic Sectors									
	Basic Materials	**Consumer Cyclicals**	**Consumer Non-Cyclicals**	**Energy**	**Financials**	**Healthcare**	**Industrials**	**Real Estate**	**Technology**	**Utilities**
EDUDIV on (ln)Tobin´s Q	0.20	0.11	0.12	-0.04	0.24	0.31	-0.05	0.06	-0.48	-0.06
INDIV on (ln)Tobin´s Q	0.15	0.29	-0.46	0.20	0.15	-0.16	0.24	0.02	-0.41	0.18
	Economic Sector High Low									
	High-tech sectors		**Low-tech sectors**							
EDUDIV on (ln)Tobin´s Q	0.12		0.10							
INDIV on (ln)Tobin´s Q	0.01		0.11							
	HQ Countries									
	France	**Germany**	**Ireland**	**Netherlands**		**Spain**	**Italy**			
EDUDIV on (ln)Tobin´s Q	-0.13	0.45	0.30	0.35		0.11	0.49			
INDIV on (ln)Tobin´s Q	0.09	0.08	0.26	-0.03		0.51	0.08			

Notes: Finland and Belgium not included due to small sample size; Not enough data available to calculate correlation for Luxembourg, Portugal, Austria, Croatia, and Cyprus

Appendix 20 – Results of Hypotheses Testing

		Step 1				Step 2	Step 3		Step 4	Step 5
Hypotheses	**Variable**	**p-Value**	**Estimate**	**Adj. R^2**	**F-statistic**	**ANOVA**	**Multicollinarity**	**Heteroscedasticity**	**Quantile**	**ANOVA**
Topic 1										
H1.1	EDUDIV	0.094*	0.215	0.562	48.78; p-value < 0.05	-	Approved	Approved	Please refer to Appendix 21 for detailed overview over the results of the quantile regression	0.204
H1.2	EDUDIV	0.075*	0.210	0.665	22.08; p-value < 0.05	0.000***	Approved	Approved		0.000***
	EDUDIV_Basic Materials	*0.883*	*0.017*							
	EDUDIV:Consumer Cylicals	*0.005****	*0.370*							
	EDUDIV:Consumer Non-Cyclicals	*0.019***	*0.308*							
	EDUDIV:Energy	*0.815*	*0.031*							
	EDUDIV:Financials	*0.000****	*-0.758*							
	EDUDIV:Healthcare	*0.447*	*0.075*							
	EDUDIV:Industrials	*0.066**	*0.209*							
	EDUDIV:Real Estate	*0.002****	*-0.444*							
	EDUDIV:Technology	*0.000****	*0.433*							
	EDUDIV:Utilities	*0.040***	*-0.240*							
H1.3	EDUDIV	0.587	0.073	0.591	36.87; p-value < 0.05	0.005***	Approved	Approved		0.000***
	EDUDIV:Economic_Sector_High_Low	*0.005****	0.255							
H 1.4	EDUDIV	0.072*	-1.088	0.574	41.06; p-value < 0.05	0.028**	Approved	Approved		0.036**
	EDUDIV:Global_Talent_Competitiveness_Index	*0.028***	0.019							
Topic 2										
H2.1	INDIV	0.141	-0.174	0.560	48.4; p-value < 0.05	-	Approved	Approved		0.089**
H2.2	INDIV	0.109	-0.194	0.636	21.04; p-value < 0.05	0.000***	Approved	Approved		0.000***
	INDIV_Basic Materials	*0.611*	*0.093*							
	INDIV:Consumer Cylicals	*0.004****	*0.601*							
	INDIV:Consumer Non-Cyclicals	*0.228*	*0.224*							
	INDIV:Energy	*0.953*	*0.010*							
	INDIV:Financials	*0.000****	*-1.488*							
	INDIV:Healthcare	*0.285*	*0.167*							
	INDIV:Industrials	*0.027***	*0.324*							
	INDIV:Real Estate	*0.032***	*-0.340*							
	INDIV:Technology	*0.008****	*0.528*							
	INDIV:Utilities	*0.355*	*-0.118*							
H2.3	INDIV	*0.049***	-0.239	0.570	40.57; p-value < 0.05	0.035**	Approved	Approved		0.344
	INDIV:Economic Sector_High_Low	*0.035***	0.273							
H2.4	INDIV	0.343	-0.769	0.559	38.71; p-value < 0.05	0.457	Approved	Approved		0.019**
	INDIV:Global_Talent_Competitiveness_Index	0.457	0.009							
Topic 3										
H3	EDUDIV	0.061*	0.241	0.568	40.12; p-value < 0.05	0.017**	Approved	Approved		0.035**
	INDIV	0.090*	-0.200							

Notes: N = 150 companies; *p<0.1; **p<0.05; ***p<0.01

Appendix 21 – Results of Quantile Regression

			Quantile Regression	
Hypotheses		Variable	p-Value	Estimate
Topic 1				
H1.1	10th Quantile	EDUDIV	0.848	0.041
	20th Quantile	EDUDIV	0.616	0.078
	30th Quantile	EDUDIV	0.989	0.002
	40th Quantile	EDUDIV	0.793	0.034
	50th Quantile	EDUDIV	0.308	0.148
	60th Quantile	EDUDIV	0.276	0.176
	70th Quantile	EDUDIV	0.675	0.074
	80th Quantile	EDUDIV	0.219	0.183
	90th Quantile	EDUDIV	0.051*	0.400
H1.2	10th Quantile	EDUDIV	0.965	-0.007
		EDUDIV_Basic Materials	*0.824*	*0.047*
		EDUDIV:Consumer Cylicals	*0.053**	*0.333*
		EDUDIV:Consumer Non-Cyclicals	*0.302*	*0.186*
		EDUDIV:Energy	*0.097**	*-0.223*
		EDUDIV:Financials	*0.144*	*-0.966*
		EDUDIV:Healthcare	*0.832*	*0.047*
		EDUDIV:Industrials	*0.030***	*0.290*
		EDUDIV:Real Estate	*0.431*	*-0.109*
		EDUDIV:Technology	*0.015***	*0.561*
		EDUDIV:Utilities	*0.154*	*-0.319*
	20th Quantile	EDUDIV	0.746	0.050
		EDUDIV_Basic Materials	*0.963*	*0.009*
		EDUDIV:Consumer Cylicals	*0.073**	*0.300*
		EDUDIV:Consumer Non-Cyclicals	*0.396*	*0.144*
		EDUDIV:Energy	*0.027***	*-0.338*
		EDUDIV:Financials	*0.013***	*-0.909*
		EDUDIV:Healthcare	*0.961*	*0.009*
		EDUDIV:Industrials	*0.001****	*0.380*
		EDUDIV:Real Estate	*0.067**	*-0.208*
		EDUDIV:Technology	*0.006****	*0.517*
		EDUDIV:Utilities	*0.714*	*-0.065*
	30th Quantile	EDUDIV	0.642	0.063
		EDUDIV_Basic Materials	*0.153*	*0.227*
		EDUDIV:Consumer Cylicals	*0.152*	*0.257*
		EDUDIV:Consumer Non-Cyclicals	*0.066**	*0.264*
		EDUDIV:Energy	*0.036***	*-0.404*
		EDUDIV:Financials	*0.016***	*-0.947*
		EDUDIV:Healthcare	*0.191*	*0.227*
		EDUDIV:Industrials	*0.001****	*0.339*
		EDUDIV:Real Estate	*0.019***	*-0.244*
		EDUDIV:Technology	*0.028***	*0.423*
		EDUDIV:Utilities	*0.416*	*-0.113*
	40th Quantile	EDUDIV	0.592	0.084
		EDUDIV_Basic Materials	*0.148*	*0.195*
		EDUDIV:Consumer Cylicals	*0.065**	*0.362*
		EDUDIV:Consumer Non-Cyclicals	*0.098**	*0.237*
		EDUDIV:Energy	*0.469*	*-0.146*
		EDUDIV:Financials	*0.006****	*-1.116*
		EDUDIV:Healthcare	*0.223*	*0.195*
		EDUDIV:Industrials	*0.083**	*0.205*
		EDUDIV:Real Estate	*0.022***	*-0.259*
		EDUDIV:Technology	*0.005****	*0.466*
		EDUDIV:Utilities	*0.481*	*-0.081*
	50th Quantile	EDUDIV	0.643	0.080
		EDUDIV_Basic Materials	*0.154*	*0.230*
		EDUDIV:Consumer Cylicals	*0.039***	*0.469*
		EDUDIV:Consumer Non-Cyclicals	*0.298*	*0.213*
		EDUDIV:Energy	*0.495*	*-0.204*
		EDUDIV:Financials	*0.021***	*-1.172*
		EDUDIV:Healthcare	*0.182*	*0.230*
		EDUDIV:Industrials	*0.090**	*0.232*
		EDUDIV:Real Estate	*0.003****	*-0.319*
		EDUDIV:Technology	*0.002****	*0.564*
		EDUDIV:Utilities	*0.213*	*-0.131*
	60th Quantile	EDUDIV	0.872	-0.033
		EDUDIV_Basic Materials	*0.293*	*0.160*
		EDUDIV:Consumer Cylicals	*0.033***	*0.539*
		EDUDIV:Consumer Non-Cyclicals	*0.311*	*0.273*
		EDUDIV:Energy	*0.633*	*-0.136*
		EDUDIV:Financials	*0.017***	*-1.144*
		EDUDIV:Healthcare	*0.307*	*0.160*
		EDUDIV:Industrials	*0.188*	*0.254*
		EDUDIV:Real Estate	*0.000****	*-0.438*
		EDUDIV:Technology	*0.012***	*0.465*
		EDUDIV:Utilities	*0.223*	*-0.140*
	70th Quantile	EDUDIV	0.834	-0.041
		EDUDIV_Basic Materials	*0.607*	*0.089*
		EDUDIV:Consumer Cylicals	*0.070**	*0.475*
		EDUDIV:Consumer Non-Cyclicals	*0.543*	*0.197*
		EDUDIV:Energy	*0.631*	*-0.193*
		EDUDIV:Financials	*0.195*	*-0.799*
		EDUDIV:Healthcare	*0.586*	*0.089*
		EDUDIV:Industrials	*0.123*	*0.331*
		EDUDIV:Real Estate	*0.001****	*-0.485*
		EDUDIV:Technology	*0.046***	*0.434*
		EDUDIV:Utilities	*0.215*	*-0.174*
	80th Quantile	EDUDIV	0.380	0.144
		EDUDIV_Basic Materials	*0.715*	*0.064*
		EDUDIV:Consumer Cylicals	*0.021***	*0.591*
		EDUDIV:Consumer Non-Cyclicals	*0.657*	*0.223*
		EDUDIV:Energy	*0.855*	*-0.088*
		EDUDIV:Financials	*0.687*	*-0.216*
		EDUDIV:Healthcare	*0.731*	*0.064*
		EDUDIV:Industrials	*0.072**	*0.373*
		EDUDIV:Real Estate	*0.000****	*-0.740*
		EDUDIV:Technology	*0.289*	*0.231*
		EDUDIV:Utilities	*0.009****	*-0.451*
	90th Quantile	EDUDIV	0.025**	0.363
		EDUDIV_Basic Materials	*0.391*	*-0.171*
		EDUDIV:Consumer Cylicals	*0.004****	*0.769*
		EDUDIV:Consumer Non-Cyclicals	*0.044***	*0.991*
		EDUDIV:Energy	*0.847*	*-0.103*
		EDUDIV:Financials	*0.396*	*-0.437*
		EDUDIV:Healthcare	*0.388*	*-0.171*
		EDUDIV:Industrials	*0.345*	*0.176*
		EDUDIV:Real Estate	*0.000****	*-1.028*
		EDUDIV:Technology	*0.113*	*0.392*
		EDUDIV:Utilities	*0.002****	*-0.729*
H1.3	10th Quantile	EDUDIV	*0.990*	0.003
		EDUDIV:Economic_Sector_High_Low	*0.238*	0.157
	20th Quantile	EDUDIV	*0.996*	-0.001
		EDUDIV:Economic_Sector_High_Low	*0.366*	0.099
	30th Quantile	EDUDIV	*0.721*	-0.059
		EDUDIV:Economic_Sector_High_Low	*0.478*	0.070
	40th Quantile	EDUDIV	*0.444*	-0.119
		EDUDIV:Economic_Sector_High_Low	*0.028***	0.203
	50th Quantile	EDUDIV	*0.869*	0.025
		EDUDIV:Economic_Sector_High_Low	*0.113*	0.161
	60th Quantile	EDUDIV	*0.703*	0.056
		EDUDIV:Economic_Sector_High_Low	*0.178*	0.169
	70th Quantile	EDUDIV	*0.006****	-0.001
		EDUDIV:Economic_Sector_High_Low	*0.007****	0.408
	80th Quantile	EDUDIV	*0.207*	0.241
		EDUDIV:Economic_Sector_High_Low	*0.016***	0.396
	90th Quantile	EDUDIV	*0.541*	0.125
		EDUDIV:Economic_Sector_High_Low	*0.015***	0.470
H 1.4	10th Quantile	EDUDIV	0.367	-1.138
		EDUDIV:Global_Talent_Competitiveness_Index	0.283	0.020
	20th Quantile	EDUDIV	*0.165*	-1.283
		EDUDIV:Global_Talent_Competitiveness_Index	*0.146*	0.019
	30th Quantile	EDUDIV	*0.086**	-1.457
		EDUDIV:Global_Talent_Competitiveness_Index	*0.083**	0.021
	40th Quantile	EDUDIV	*0.229*	-0.911
		EDUDIV:Global_Talent_Competitiveness_Index	*0.198*	0.014
	50th Quantile	EDUDIV	*0.221*	-0.725
		EDUDIV:Global_Talent_Competitiveness_Index	*0.127*	0.013
	60th Quantile	EDUDIV	*0.301*	-0.731
		EDUDIV:Global_Talent_Competitiveness_Index	*0.221*	0.013
	70th Quantile	EDUDIV	*0.404*	-0.713
		EDUDIV:Global_Talent_Competitiveness_Index	*0.373*	0.011
	80th Quantile	EDUDIV	*0.224*	-1.270
		EDUDIV:Global_Talent_Competitiveness_Index	*0.153*	0.022
	90th Quantile	EDUDIV	*0.177*	-1.563
		EDUDIV:Global_Talent_Competitiveness_Index	*0.079**	0.028

Topic 2				
H2.1	10th Quantile	INDIV	0.951	-0.011
	20th Quantile	INDIV	*0.606*	*-0.053*
	30th Quantile	INDIV	*0.108*	*-0.144*
	40th Quantile	INDIV	*0.305*	*-0.100*
	50th Quantile	INDIV	0.089*	-0.192
	60th Quantile	INDIV	0.032**	-0.255
	70th Quantile	INDIV	0.008***	-0.295
	80th Quantile	INDIV	0.065*	-0.304
	90th Quantile	INDIV	0.786	-0.105
H2.2	10th Quantile	INDIV	0.550	-0.118
		INDIV_Basic Materials	*0.528*	*0.160*
		INDIV:Consumer Cylicals	*0.518*	*-0.243*
		INDIV:Consumer Non-Cyclicals	*0.131*	*0.304*
		INDIV:Energy	*0.761*	*-0.052*
		INDIV:Financials	*0.099**	*-1.368*
		INDIV:Healthcare	*0.518*	*0.160*
		INDIV:Industrials	*0.019***	*0.383*
		INDIV:Real Estate	*0.275*	*0.168*
		INDIV:Technology	*0.147*	*0.397*
		INDIV:Utilities	*0.889*	*0.036*
	20th Quantile	INDIV	0.994	-0.001
		INDIV_Basic Materials	*0.478*	*0.190*
		INDIV:Consumer Cylicals	*0.162*	*0.346*
		INDIV:Consumer Non-Cyclicals	*0.366*	*0.167*
		INDIV:Energy	*0.247*	*-0.280*
		INDIV:Financials	*0.056**	*-1.237*
		INDIV:Healthcare	*0.442*	*0.190*
		INDIV:Industrials	*0.038***	*0.311*
		INDIV:Real Estate	*0.762*	*-0.055*
		INDIV:Technology	*0.133*	*0.424*
		INDIV:Utilities	*0.743*	*-0.064*
	30th Quantile	INDIV	0.342	-0.143
		INDIV_Basic Materials	*0.237*	*0.253*
		INDIV:Consumer Cylicals	*0.289*	*0.332*
		INDIV:Consumer Non-Cyclicals	*0.211*	*0.242*
		INDIV:Energy	*0.397*	*-0.240*
		INDIV:Financials	*0.013***	*-1.490*
		INDIV:Healthcare	*0.266*	*0.253*
		INDIV:Industrials	*0.038***	*0.292*
		INDIV:Real Estate	*0.618*	*-0.081*
		INDIV:Technology	*0.059**	*0.506*
		INDIV:Utilities	*0.946*	*0.008*
	40th Quantile	INDIV	0.091**	-0.230
		INDIV_Basic Materials	*0.306*	*0.185*
		INDIV:Consumer Cylicals	*0.311*	*0.374*
		INDIV:Consumer Non-Cyclicals	*0.290*	*0.204*
		INDIV:Energy	*0.823*	*0.059*
		INDIV:Financials	*0.009****	*-1.488*
		INDIV:Healthcare	*0.417*	*0.185*
		INDIV:Industrials	*0.109*	*0.255*
		INDIV:Real Estate	*0.145*	*-0.197*
		INDIV:Technology	*0.100*	*0.452*
		INDIV:Utilities	*0.675*	*-0.044*
	50th Quantile	INDIV	0.188	-0.221
		INDIV_Basic Materials	*0.406*	*0.137*
		INDIV:Consumer Cylicals	*0.125*	*0.640*
		INDIV:Consumer Non-Cyclicals	*0.262*	*0.277*
		INDIV:Energy	*0.952*	*0.016*
		INDIV:Financials	*0.011***	*-1.559*
		INDIV:Healthcare	*0.490*	*0.137*
		INDIV:Industrials	*0.291*	*0.200*
		INDIV:Real Estate	*0.171*	*-0.194*
		INDIV:Technology	*0.265*	*0.397*
		INDIV:Utilities	*0.534*	*-0.090*
	60th Quantile	INDIV	0.115	-0.286
		INDIV_Basic Materials	*0.516*	*0.168*
		INDIV:Consumer Cylicals	*0.078**	*0.737*
		INDIV:Consumer Non-Cyclicals	*0.170*	*0.230*
		INDIV:Energy	*0.969*	*-0.011*
		INDIV:Financials	*0.028***	*-1.657*
		INDIV:Healthcare	*0.481*	*0.168*
		INDIV:Industrials	*0.091**	*0.374*
		INDIV:Real Estate	*0.104*	*-0.240*
		INDIV:Technology	*0.451*	*0.289*
		INDIV:Utilities	*0.860*	*-0.029*
	70th Quantile	INDIV	0.110	-0.331
		INDIV_Basic Materials	*0.804*	*0.064*
		INDIV:Consumer Cylicals	*0.100*	*0.795*
		INDIV:Consumer Non-Cyclicals	*0.666*	*0.134*
		INDIV:Energy	*0.808*	*-0.084*
		INDIV:Financials	*0.011***	*-1.788*
		INDIV:Healthcare	*0.829*	*0.064*
		INDIV:Industrials	*0.086**	*0.411*
		INDIV:Real Estate	*0.086**	*-0.303*
		INDIV:Technology	*0.080**	*0.696*
		INDIV:Utilities	*0.945*	*0.014*
	80th Quantile	INDIV	0.162	-0.287
		INDIV_Basic Materials	*0.563*	*-0.186*
		INDIV:Consumer Cylicals	*0.084**	*0.990*
		INDIV:Consumer Non-Cyclicals	*0.997*	*-0.002*
		INDIV:Energy	*0.863*	*0.090*
		INDIV:Financials	*0.047***	*-1.230*
		INDIV:Healthcare	*0.556*	*-0.186*
		INDIV:Industrials	*0.052**	*0.467*
		INDIV:Real Estate	*0.032***	*-0.414*
		INDIV:Technology	*0.207*	*0.552*
		INDIV:Utilities	*0.403*	*-0.174*
	90th Quantile	INDIV	0.543	0.169
		INDIV_Basic Materials	*0.835*	*-0.073*
		INDIV:Consumer Cylicals	*0.012***	*1.328*
		INDIV:Consumer Non-Cyclicals	*0.679*	*0.435*
		INDIV:Energy	*0.406*	*0.529*
		INDIV:Financials	*0.017***	*-1.714*
		INDIV:Healthcare	*0.830*	*-0.073*
		INDIV:Industrials	*0.696*	*0.106*
		INDIV:Real Estate	*0.000****	*-0.888*
		INDIV:Technology	*0.106*	*0.717*
		INDIV:Utilities	*0.073**	*-0.457*
H2.3	10th Quantile	INDIV	0.584	-0.635
		INDIV:Economic Sector_High_Low	0.416	-0.156
	20th Quantile	INDIV	0.617	-0.053
		INDIV:Economic Sector_High_Low	0.666	0.070
	30th Quantile	INDIV	0.195	-0.131
		INDIV:Economic Sector_High_Low	0.377	0.091
	40th Quantile	INDIV	0.044**	-0.201
		INDIV:Economic Sector_High_Low	0.124	0.168
	50th Quantile	INDIV	0.038**	-0.244
		INDIV:Economic Sector_High_Low	0.095*	0.202
	60th Quantile	INDIV	0.043**	-0.269
		INDIV:Economic Sector_High_Low	0.339	0.138
	70th Quantile	INDIV	0.023**	-0.299
		INDIV:Economic Sector_High_Low	0.611	0.111
	80th Quantile	INDIV	0.014**	-0.314
		INDIV:Economic Sector_High_Low	0.122	0.471
	90th Quantile	INDIV	0.299	-0.301
		INDIV:Economic Sector_High_Low	0.063*	0.940
H2.4	10th Quantile	INDIV	0.726	-0.476
		INDIV:Global_Talent_Competitiveness_Index	0.756	0.007
	20th Quantile	INDIV	0.719	-0.357
		INDIV:Global_Talent_Competitiveness_Index	0.769	0.004
	30th Quantile	INDIV	0.351	-0.815
		INDIV:Global_Talent_Competitiveness_Index	0.421	0.010
	40th Quantile	INDIV	0.324	-0.805
		INDIV:Global_Talent_Competitiveness_Index	0.406	0.010
	50th Quantile	INDIV	0.851	-0.130
		INDIV:Global_Talent_Competitiveness_Index	0.940	-0.001
	60th Quantile	INDIV	0.479	-0.483
		INDIV:Global_Talent_Competitiveness_Index	0.727	0.004
	70th Quantile	INDIV	0.482	-0.460
		INDIV:Global_Talent_Competitiveness_Index	0.817	0.002
	80th Quantile	INDIV	0.585	-0.555
		INDIV:Global_Talent_Competitiveness_Index	0.779	0.005
	90th Quantile	INDIV	0.156	-2.195
		INDIV:Global_Talent_Competitiveness_Index	0.174	0.032

Topic 3				
H3	10th Quantile	EDUDIV	0.885	0.039
		INDIV	0.964	-0.009
	20th Quantile	EDUDIV	0.501	0.106
		INDIV	0.515	-0.073
	30th Quantile	EDUDIV	0.899	0.017
		INDIV	0.172	-0.139
	40th Quantile	EDUDIV	0.414	0.126
		INDIV	0.091*	-0.161
	50th Quantile	EDUDIV	0.114	0.249
		INDIV	0.146	-0.153
	60th Quantile	EDUDIV	0.264	0.199
		INDIV	0.062*	-0.216
	70th Quantile	EDUDIV	0.402	0.143
		INDIV	0.002***	-0.39
	80th Quantile	EDUDIV	0.341	0.135
		INDIV	0.027**	-0.304
	90th Quantile	EDUDIV	0.040**	0.503
		INDIV	0.364	-0.257
Notes: N = 150 companies; *p<0.1; **p<0.05; ***p<0.01				

Appendix 22 – Translation of Diversity Indices and (ln)Tobin´s Q

H	Coefficient	Model Type	Median Zahl's SDI	Adjusted Median Zahl's SDI[1]	Median Change	Estimate from Regressions	Impact on Tobin´s Q	Effect on Tobin´s Q
	EDUDIV							
H1.1	EDUDIV	Linear Model	1.25	1.49	0.24	0.2151	0.05	5.24%
H1.2	Consumer Cyclicals	Linear Model	1.29	1.51	0.22	0.3703	0.08	8.51%
	Consumer Non-Cyclicals	Linear Model	1.05	1.30	0.25	0.3080	0.08	8.16%
	Financials	Linear Model	1.05	1.32	0.27	-0.7584	-0.20	-18.53%
	Industrials	Linear Model	1.27	1.51	0.24	0.2092	0.05	5.06%
	Real Estate	Linear Model	1.15	1.49	0.34	-0.4441	-0.15	-14.10%
	Technology	Linear Model	1.32	1.58	0.26	0.4326	0.11	11.88%
	Utilities	Linear Model	1.18	1.49	0.31	-0.2402	-0.08	-7.27%
H1.3	High-tech	Linear Model	1.29	1.55	0.26	0.3281	0.08	8.86%
H1.4[2]	Germany	Linear Model	1.25	1.58	0.32	0.2593	0.08	8.78%
	France	Linear Model	1.28	1.50	0.22	0.2020	0.05	4.61%
	Netherlands	Linear Model	1.32	1.51	0.19	0.3534	0.07	6.86%
	Ireland	Linear Model	1.15	1.36	0.21	0.2703	0.06	5.87%
	Spain	Linear Model	1.16	1.41	0.25	0.0757	0.02	1.95%
	Italy	Linear Model	1.53	1.71	0.18	0.0316	0.01	0.56%
	INDIV							
H2.1	INDIV (50th Quantile)	Quantile Model	0.84	1.23	0.39	-0.1923	-0.08	-7.30%
	INDIV (60th Quantile)	Quantile Model	0.85	1.11	0.26	-0.2549	-0.07	-6.36%
	INDIV (70th Quantile)	Quantile Model	0.90	1.21	0.30	-0.2953	-0.09	-8.59%
	INDIV (80th Quantile)	Quantile Model	0.53	0.89	0.35	-0.3037	-0.11	-10.20%
H2.2	Consumer Cyclicals	Linear Model	0.79	0.98	0.19	0.6009	0.11	12.17%
	Financials	Linear Model	0.40	0.70	0.30	-1.4880	-0.44	-35.82%
	Industrials	Linear Model	0.99	1.16	0.17	0.3240	0.05	5.61%
	Real Estate	Linear Model	0.77	1.18	0.41	-0.3404	-0.14	-12.88%
	Technology	Linear Model	0.72	1.03	0.31	0.5278	0.16	17.49%
H2.3	Low-tech	Linear Model	0.70	1.08	0.38	-0.2385	-0.09	-8.62%
	High-tech	Linear Model	0.79	1.07	0.28	0.0344	0.01	0.97%

1) One additional diverse board member was added to showcase the marginal effect
2) Countries with 8 or more companies are analyzed to avoid misleading results

Appendix 23 – Comparison of Selected Metrics for HT and LT Sectors

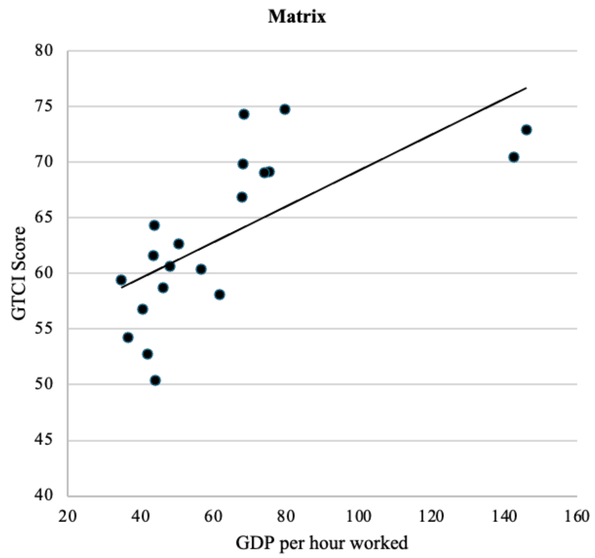
	EDUDIV	INDIV	(ln)Tobin´s Q	Market Cap (in $bn)	Revenue (in $bn)	Total Assets (in $bn)	Leverage Ratio	Board Size
HT Sector	1.229	0.776	0.492	67.640	41.359	70.456	0.702	9.133
LT Sector	1.098	0.803	-0.185	38.857	30.166	215.300	1.101	10.378

Appendix 24 – GTCI and GDP per hour worked Correlation Matrix

Country	GTCI Score[1]	GDP per hour worked[2]
Netherlands	74.76	79.80
Finland	74.35	68.60
Luxembourg	72.88	146.10
Ireland	70.45	142.50
Germany	69.88	68.10
Belgium	69.12	75.50
Austria	69.05	74.20
France	66.91	67.90
Estonia	64.29	43.90
Malta	62.66	50.70
Portugal	61.60	43.70
Slovenia	60.62	48.20
Spain	60.36	56.60
Cyprus	59.46	34.70
Lithuania	58.73	46.40
Italy	58.07	61.70
Latvia	56.78	40.70
Slovakia	54.24	36.70
Greece	52.75	41.90
Croatia	50.38	44.10

1) INSEAD 2023
2) ILOSTAT 2023

Correlation



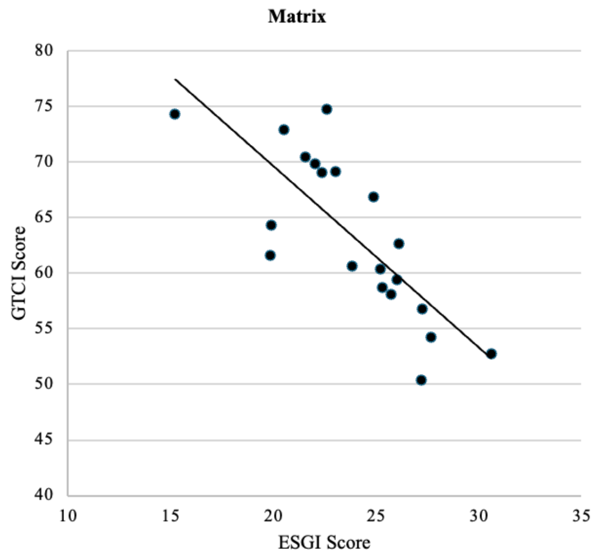
Correlation coefficient: 0.687

Appendix 25 – GTCI Score and ESGI Score Correlation Matrix

Country	GTCI Score[1]	ESGI Score[2]
Netherlands	74.76	22.61
Finland	74.35	15.21
Luxembourg	72.88	20.53
Ireland	70.45	21.57
Germany	69.88	22.05
Belgium	69.12	23.03
Austria	69.05	22.40
France	66.91	24.88
Estonia	64.29	19.89
Malta	62.66	26.10
Portugal	61.60	19.87
Slovenia	60.62	23.84
Spain	60.36	25.21
Cyprus	59.46	26.03
Lithuania	58.73	25.31
Italy	58.07	25.73
Latvia	56.78	27.28
Slovakia	54.24	27.68
Greece	52.75	30.63
Croatia	50.38	27.23

1) INSEAD 2023
2) Risk Watch Initiative 2023

Correlation



Correlation coefficient: -0.784

Appendix 26 – HQ Country Average Statistics on Empirical Variables

	Average								
HQ Country	(ln)Tobin's Q	Market Cap ($bn)	Revenue ($bn)	Total Assets ($bn)	Revenue-to-Total-Assets ratio	Leverage Ratio	Board Size	Gender Diversity	Av. Board Tenure
Netherlands	0.70	60.83	24.46	84.04	29.10%	0.87	10.29	0.19	5.53
Ireland	0.58	60.35	22.76	150.33	15.14%	0.68	11.47	0.25	7.22
Germany	-0.24	46.67	52.46	139.30	37.66%	0.77	6.31	0.26	6.28
France	0.09	69.35	38.43	239.58	16.04%	0.79	11.59	0.29	6.70
Spain	-0.33	39.55	21.94	248.82	8.82%	1.19	12.08	0.27	6.34
Italy	-0.20	43.92	39.57	231.91	17.06%	2.38	14.78	0.29	5.91