

**Board Skill Sets and Firm Value:
The Influence of Monitoring and Advising Skills**

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Abstract

We examine how heterogeneity of board skills affects firm value. Using advanced machine learning tools, we extract director biographies from proxy filings of U.S. publicly listed firms from 2010 to 2022 and create measures of monitoring- and advising-related skill sets. We report that the heterogeneity of monitoring-related skills on the board is negatively related to firm value, whereas the heterogeneity of advising-related skills is particularly beneficial for firms facing greater operational complexity, companies operating in more innovative industries, and those at the earlier stage of the corporate life cycle. Additional tests show that board-level heterogeneity of advising skills contributes to higher takeover activity, improved deal efficiency, and the acquisition of more valuable targets. The findings have direct implications for director nomination practices, as companies face increased pressure to equip their boards with a broader range of skills.

Keywords: corporate governance, board of directors; board skills, monitoring and advising, firm value

JEL Classification: J24; G34

“...now is the time to bring in new competencies, fresh eyes, and perspectives to the board.”
P. Loftus, D. Chopping. Novo Nordisk to Shake Up Board After Obesity-Market Challenges.
Wall Street Journal, Oct. 21st, 2025

“Directors don't need technical expertise or professional experience as much as they need good character and sound judgment.”
A. Murray. What Makes a Great Board Director?
Wall Street Journal, May 19th, 2025

1. Introduction

The board of directors faces increasing scrutiny over its ability to monitor and advise the executive team. According to the Conference Board's and PwC's annual studies, only 28% of the top executives in U.S. public companies believe their boards have the right combination of skills (PwC and The Conference Board, 2023). While top executives expect boards to possess more diverse and specialized competencies, directors themselves emphasize the need for more traditional financial and industry-related skills (Corporate Board Member, 2023; PwC, 2024). These different views raise the fundamental question of whether there is an optimal composition of board skills that would maximize firm value. To shed light on this question, we examine how heterogeneity of director skill sets on the board affects corporate policies and firm value.¹

Extant research on board skills has predominantly focused on specific, single skills of corporate directors.² However, little is known about the impact of different board-level combinations of director skills. Adams et al. (2018) use a sample of firms from 2010 to 2013 and characterize boards by whether directors, as a group, have a diverse range of skills. They conclude

¹ An extensive body of research has examined other characteristics and effectiveness of the board of directors (e.g., see literature reviews by Adams, 2017; Adams et al., 2010; Coles et al., 2024; Hermalin & Weisbach, 2003).

² For instance, Agrawal & Knoeber, 2001 (law and politics); Guner, Malmendier, & Tate, 2008 (banking experience); Krishnan et al., 2011 (legal expertise); Francis et al., 2015 (academics); Drobetz et al., 2018 (industry experts); Colevecchio et al., 2024 (sustainability).

that skill diversity negatively affects firm value. We argue, however, that board effectiveness likely depends on how board skill sets contribute to the main board functions of monitoring and advising, as well as how board skill sets align with specific company needs. To the best of our knowledge, this is the first study to examine the multidimensional nature of director skill sets over a long sample period and in connection to the main functions of the board and firm characteristics.

Research on board skill sets is challenging due to data limitations. Existing studies rely on director employment history provided by proprietary datasets (e.g., BoardEx or ISS Governance). However, readily available datasets sometimes provide incomplete or incorrect information and tend to focus only on large companies (e.g., S&P 1500 firms). In 2009, an amendment to Regulation S-K introduced the requirement for U.S. public companies to report the background and specific skills of their nominated directors, thus providing researchers with a rich but unstructured textual data source. The lack of standardized reporting, however, resulted in remarkable heterogeneity in disclosing director backgrounds, making data extraction difficult. We overcome these limitations by exploiting advancements in unsupervised machine learning and natural language processing (NLP) methods.

Specifically, we use RoBERTa, a transformer-based large language model (Liu et al., 2019), to extract raw textual data from proxy statements that contain biographies and skills of directors of U.S. public companies from 2010 to 2022. This approach allows us to process an extensive corpus of proxy statements and compile a unique director-firm-year dataset of over 179,000 observations, capturing the biographies and skills of 39,270 directors across 3,050 firms. This is the first study to deploy a large-scale ML/NLP-based methodology for capturing board skills across a cross-section of companies and time. The resulting dataset makes it possible to

examine skill sets at both the individual director and board levels, moving beyond the single-dimensional skill perspective common in the prior literature.

We examine the relation between board skill sets and firm value based on board skill measures constructed through the following algorithm. To facilitate comparability, we use the list of twenty broad skill categories and corresponding keywords from Adams et al. (2018) to identify the skill categories present in each director's extracted biography and skill description. We count distinct skill categories of board members in each firm in a given year. Intuitively, this measure captures the breadth of skills on the board, i.e., the number of distinct competency areas present on the board. A board with a high skill count (a more varied skill set) has directors bringing many different competencies. In contrast, a board with a low skill count may have directors with largely overlapping backgrounds, thus resulting in board-level skill concentration. As shown by Adams et al. (2018), the number of skill categories effectively captures the essential variety in board skills, and unlike factor analysis-based measures, it allows for a more straightforward economic interpretation of regression results.³

We first report considerable variation in board skill sets across companies and over time. In the cross-section, an average board exhibits approximately 12 distinct skill categories, with some boards possessing only two skill categories and others covering the maximum possible number of skills of 20. The average number of skill categories represented on boards increases steadily over the sample period, rising from 11 in 2010 to about 13 in 2022, highlighting the growing variety of skills on corporate boards. Additionally, growth in the number of board skills has not been uniform across categories, suggesting that certain skill types have become more

³³ In robustness tests, we incorporate the factor-analysis-based measures of board skill composition.

prevalent. For example, the representation of legal skills on the board has remained relatively stable at around 32% of boards, whereas sustainability-related skills have increased from approximately 10% at the beginning of the sample period to 40% in 2022.

Next, we examine whether board skill breadth is related to firm value, as measured by Tobin's Q. As a first step, we replicate the main results of Adams et al. (2018) and demonstrate that their findings hold when we restrict our sample to the period analyzed in their study. We extend the analysis to the broader 2010 – 2022 period and find that, although more varied board skill sets are generally negatively associated with Tobin's Q, the association loses statistical significance as more controls are added to the analysis.

The traditional corporate finance and governance literature offers two distinct views on the board's primary functions and the importance of board competencies in fulfilling those functions. Specifically, agency theory views the board as a critical corporate governance mechanism in addressing the principal-agent problem that arises from the separation of company ownership (shareholders) and control (corporate managers) (Berle & Means, 1932; Jensen & Meckling, 1976; Fama & Jensen, 1983). In this context, the board's primary function is to act as a control and discipline mechanism monitoring management on behalf of shareholders (Fama, 1980; Fama & Jensen, 1983). On the other hand, the resource-dependence theory stipulates that board composition is influenced by the firm's external complexity and dependencies (Boyd, 1990; Hillman et al., 2000; Pfeffer, 1972). From this perspective, the board is expected to mitigate information asymmetry between the organization and its external environment, acting as an advisor to management (Hillman & Dalziel, 2003; Lester et al., 2008; Kor & Sundaramurthy, 2009).

Building on the agency and resource dependence theories, we introduce two novel measures of skill sets that are explicitly related to the board monitoring and advising functions. To classify skills as monitoring or advising, we follow prior studies that adopt a single-dimensional view of board competencies and discuss whether specific competencies contribute to the monitoring or advising function. For example, directors with finance and accounting skills (Agarwal & Chadha, 2005; DeFond et al., 2005; Engel, 2005) or academic experience (Chen et al., 2019) are shown to be more effective monitors, while directors with an entrepreneurial background (Faleye et al., 2012) or with venture capital experience (Ewans & Malenko, 2024; Ivanov & Xie, 2010) tend to contribute to the board as advisors.

To examine the relationship between the variety in board monitoring and advising skill sets and firm value, we incorporate both measures within the same regression specification, along with a broad set of firm- and board-level control characteristics. This empirical approach allows us to disentangle the effects of monitoring and advising-related skill sets and estimate the effect of one while explicitly controlling for the other, a distinction that was not feasible in prior studies relying on structural board characteristics or single skills as proxies of board monitoring or advising capabilities.

Our approach reveals an important heterogeneity in how board skill composition relates to firm value. Specifically, a higher variety in monitoring-related skills is significantly negatively associated with firm value, whereas a variety in advising-related skills exhibits an insignificant positive association. These findings are consistent with the theoretical predictions by Adams & Ferreira (2007), Song & Thaker (2006), and Baldenius et al. (2014), who propose that overly strong monitoring by the board may inhibit the information flow, slow down decision-making, and

undermine the strategic counsel, thereby increasing the cost of intense monitoring at the expense of the advising function (Faleye et al., 2011).

To evaluate the role of the advising skill sets more specifically, we investigate how a firm's operational environment and life cycle moderate the relation between board skill sets and firm value. Consistent with the resource dependence theory, we argue that firms operating in more complex business environments or in more innovative industries benefit from greater heterogeneity in board advising skills. In addition, building on a life cycle theory of the firm, we propose that companies in the earlier stages of the life cycle derive greater value from more diverse advising-related skills.

We use the firm complexity measure developed by Loughran and McDonald (2024) that captures the various dimensions of a firm's business environment, such as size, age, or number of business segments⁴. We demonstrate that while a greater variety of board monitoring-related skills is consistently detrimental to firm value regardless of firm complexity, more advising-related skills have a statistically significant positive effect on firm value for more complex firms. Similarly, advising skill sets contribute to firm value in companies operating in more innovative industries and at the introductory and growth stages.

All our findings are robust to the inclusion of controls for measures of board composition (e.g., board size, independence, frequency of board meetings, etc.), firm characteristics, and year and industry fixed effects. Results are also robust to alternative measures of firm value and complexity. Furthermore, we address endogeneity concerns by using director retirement and death events as sources of exogenous shocks to board structure (e.g., Falato et al., 2014; Fracassi & Tate,

⁴ In robustness tests, we verify the findings based on alternative measures of firm complexity.

2012; Masulis et al., 2025; Nguyen & Nielsen, 2010). We conjecture that firm value should decrease following the death or retirement of a director when the newly appointed director possesses unique monitoring-related skills. We implement a quasi-natural framework and a stacked difference-in-difference design following Gormley and Matsa's (2011) approach. Consistent with the rest of the analyses, we find that firm value declines when monitoring-related board skill sets become more diverse.

Moreover, to better understand the mechanism through which board advising skill sets affect firm value, we examine one of the main corporate strategic decisions requiring substantial board counseling, namely mergers and acquisitions (M&A). We hypothesize that, controlling for board monitoring-related skills, boards that possess more advising-related skills should be more efficient in evaluating and acquiring targets with higher potential synergies. Using two-stage Heckman selection models, we find that the probability of becoming an acquirer increases in board advising-related skills. Furthermore, advising skill sets significantly decrease deal completion times, positively relate to takeover premiums, and reduce the probability of large loss deals, highlighting that companies with more advising skill sets acquire more valuable targets. Therefore, we conclude that a higher variety in board advising skills increases firm value by improving the quality of corporate decisions.

This study advances existing literature in multiple ways. First, we examine a novel measure of board composition, board skill sets, that incorporates a multidimensional view of board human capital, moving away from single-dimensional measures prevalent in existing studies. By applying advanced ML/NLP techniques and constructing an extensive dataset of individual directors and board skills, we extend the work of Adams et al. (2018) on board skill sets and contribute to the

associated existing literature on the importance of human capital in corporate finance (e.g., Edmans, 2011; Fedyk & Hodson, 2023; Kaplan et al., 2012; Zingales, 2000).

Second, the existing literature predominantly uses board structural dimensions (e.g., independence or size) or directors' demographic characteristics (e.g., gender) to proxy for the monitoring and advising effectiveness of the board.⁵ While these attributes provide important insights into our understanding of boards, they do not directly capture board monitoring or advising capabilities. In contrast, we introduce novel measures of board skill composition that explicitly connect to board monitoring and advising skills. As corporate directors bring sets of skills to their boards to support the board's advising and monitoring capabilities, failing to consider such "portfolios" of monitoring and advising skills undermines the empirical inference (Carter, 2025). Our approach directly addresses this concern, enabling the simultaneous yet distinct assessment of both board functions in empirical tests. We find that monitoring (advising) skill diversity decreases (increases) firm value.

Additionally, we contribute to the broader literature on the importance of the firm's business environment in shaping corporate outcomes (e.g., Boyd, 1990; Coles et al., 2008; Hillman et al., 2000; Larsen et al., 2020). By separately evaluating board monitoring and advising skill sets, this study is the first to demonstrate that broader advising-related skill sets are especially valuable for firms operating in more complex environments, more innovative industries, and at earlier stages of the corporate life cycle. We also extend the literature on corporate mergers and

⁵ For example, on board size and independence, see Adams, 2017; Coles et al., 2008; Coles et al., 2014; Guo & Masulis, 2007; Hermalin & Weisbach, 1991, 2003; Jensen, 1993; Yermack, 1996; and on board demographic characteristics, see Adams & Ferreira, 2009; Ahern & Dittmar, 2012; Bernile et al., 2018; Masulis et al., 2025.

acquisitions by demonstrating that boards possessing more advising-related skill sets are more efficient in deal-related strategic counseling and achieving better deal outcomes.

Finally, this study has practical implications for the board nomination process and for corporate governance practices, particularly as companies adopt a “skill matrix” based approach to select potential new board members. Companies face increased internal and external pressure to equip their boards with more capabilities, but there are currently very few studies examining the impact of increasingly varied director skill sets on firm value.

The rest of the paper is organized as follows. Section 2 reviews relevant literature and develops hypotheses. Section 3 describes data and identification strategy, including dataset construction, research methodology, and sample characteristics. Section 4 discusses the main empirical findings. Section 5 addresses robustness checks and endogeneity concerns, and Section 6 presents additional tests. Section 7 concludes.

2. Literature Review and Hypotheses Development

The board of directors plays a critical role in corporate governance, simultaneously fulfilling monitoring and advising roles (Becher et al., 2023; Hillman & Dalziel, 2003).⁶ Indeed, corporate boards are responsible for numerous complex and interactive tasks⁷ that require extensive communication and deliberation (Forbes & Milliken, 1999; Van Peteghem et al., 2018). Board composition is a critical element that determines the board's ability to perform its primary

⁶ Here, we refer to the *sole* or *unitary* board structures present in the U.S, as opposed to *dual* or *two-tier* board systems, where members of two tiers generally do not overlap.

⁷ For example, management and corporate performance oversight, strategy implementation, CEO and top management performance evaluation and compensation, and access to strategic capital resources.

roles (Van Peteghem et al., 2018). Hence, it is unsurprising that a large body of literature in various academic disciplines has analyzed the structural characteristics of boards (e.g., board size, independence, and busyness). Still, there is little consensus on what an optimal board should look like and what attributes contribute to board effectiveness (Larcker & Tayan, 2023).

According to the resource dependency theory, the board's effectiveness in fulfilling its roles depends fundamentally on its human and relational capital (Hillman et al., 2000; Pfeffer & Salancik, 1978). Board capital consists of individual directors' human capital (expertise, reputation, and skills) and their social or relational capital (social ties to other individuals, firms, and public agencies). Together, these forms of capital enhance the board's ability to monitor and advise management effectively and secure critical resources for the firm (Hillman & Dalziel, 2003; Kor & Sundaramurthy, 2009; Lester et al., 2008). While the individual board members may not possess the comprehensive set of attributes required to meet the firm's needs, the board as a group can effectively build on the multiple perspectives of individual directors and fulfill advising and monitoring functions (Kor & Sundaramurthy, 2009).

Theoretically, boards composed of directors with diverse skill sets should offer a broader range of perspectives in the strategic decision-making process, ultimately enhancing corporate performance. Directors with varied professional backgrounds may contribute complementary knowledge that improves overall decision-making, reduces information asymmetries, and fosters corporate innovation (Forbes & Milliken, 1999; Hillman et al., 2000). However, some empirical evidence suggests that skill diversity does not necessarily translate into improved firm outcomes. For example, Adams et al. (2018) argue that a greater variety of distinct skills on the board is associated with decreased company value, as measured by Tobin's Q. Fedaseyeu et al. (2018) show

that a higher number of qualifications per se does not significantly affect cumulative abnormal returns. Therefore, based on Adams et al (2018), we propose the following (alternative) hypothesis:

H1: There is a negative association between the total number of board skills and firm performance.

The monitoring or disciplinary function of the board has received much attention in both academic research and media outlets, especially after the passage of the Sarbanes-Oxley Act of 2002 (SOX) and subsequent changes in the listing requirements of public stock exchanges (Coles et al., 2024). Most of these studies focus on the structural dimensions of board composition (e.g., board size) and on observable monitoring-related decisions of the board, e.g., CEO performance evaluation, compensation, succession, and dismissal events, to assess the board's effectiveness in performing its disciplinary role⁸.

Theoretically, a monitoring-intensive board may be detrimental to firm performance (Adams & Ferreira, 2007; Adams & Ferreira, 2009; Baldenius et al., 2014; Burkart et al., 1997; Song & Thaker, 2006), especially for firms operating in more complex and dynamic environments (Faleye et al., 2011). A key reason why intense monitoring may not translate into corporate performance improvements is the tradeoff between the monitoring and advisory functions of board members, where excessive oversight suppresses the advisory function of the board. Adams & Ferreira (2007) develop a „friendly boards“ theory, according to which “a management-friendly board” – the one that is less likely to monitor the CEO intensely - can be optimal as the CEO is more inclined to share information, therefore reducing directors’ information asymmetry and enhancing the advising function of the board. Conversely, a monitoring-intensive board induces

⁸ See academic literature reviews by Adams et al. (2010), Adams (2017), Coles et al. (2024), and Hermalin & Weisbach (2003).

the CEO to act defensively, becoming reluctant to share information. As the board relies on the CEO's insider information to provide informed counsel and strategic guidance, this increased information asymmetry between the board and management hampers the directors' advising role (Adams & Ferreira, 2007). As a result, intense board monitoring may negatively affect corporate decision-making and, subsequently, firm performance. For example, Adams and Ferreira (2009) show that while female directors contribute to the improved monitoring function of the board, e.g., through holding CEOs more accountable for poor stock price performance, such heightened monitoring does not result in improved company performance. Similarly, Baldenius et al. (2014) model the strategic interaction between a privately informed CEO and the board of directors and demonstrate that, in theory, a monitoring-intensive board can be detrimental to firm performance, especially in companies with more severe agency problems (e.g., those with a more powerful CEO). Overly strong monitoring by the board may inhibit the information flow, slow decision-making, and undermine the strategic counsel. Thus, it is important to consider the "dark side" of monitoring (Faleye et al, 2011).

We therefore propose the following hypothesis to test the association between the heterogeneity of board monitoring-related directors' skill sets and company performance.

H2: There is a negative association between the number of board monitoring-related skills and firm performance.

While corporate finance and governance literature has predominantly focused on the board's monitoring role, directors play an important advisory function, providing counsel to management and linking the company and the external environment (Pfeffer & Salancik, 1978; Hillman & Dalziel, 2003).

A few earlier corporate studies highlighted the advisory role of the board members, building on interviews with directors, specific cases, and field studies (e.g., Demb & Neubauer, 1992; Mace, 1971). Similarly, Adams (2009), based on the interviews with Swedish directors, records that directors view their advisory role as more valuable to the CEO and the company, as it facilitates the exchange of information between the CEO and directors and encourages directors to participate in strategic decision-making more actively. Importantly, the boards that primarily focus on monitoring and management oversight, rather than advising, are not necessarily more effective (Adams, 2009; Faleye et al, 2011).

It may seem intuitive that a board composed of directors with various specialized skills and qualifications would perform its advisory role better. However, theoretical and empirical evidence suggest that this might not be the case. On the one hand, a board with diverse specialized skills can provide more specific counsel on a broader range of topics, thus ultimately increasing firm value. For example, some studies on board occupational heterogeneity argue that directors' human capital diversity may facilitate resource access (Siciliano, 1996) and better sustain growth (Kor & Sundaramurthy, 2009). On the other hand, excessive skill heterogeneity may lead to coordination and communication challenges and misaligned strategic priorities, ultimately diluting the board's advisory effectiveness and adversely impacting value creation. Research on organizational faultlines and team dynamics highlights that informational faultlines may inhibit the team's expertise integration mechanisms, i.e., the ability of teams to successfully employ and integrate the individually held knowledge for collective decision-making processes (Qu & Liu, 2017; Tiwana & McLean, 2005). As such, strong faultlines within boards may strengthen the bonds

within a subgroup of directors, while creating a more distinct separation between the subgroups⁹. As a consequence, the board may be exposed to subgroups' conflicting *priors* and expectations, undermining its ability to function as a united decision-making body (Bezrukova et al., 2009; Harrison & Klein, 2007; Lau & Murnighan, 2005; Shin & You, 2023). Because the board's advisory responsibility concerns strategic guidance, it requires the involvement and active participation of the entire board as a team (Van Peteghem et al., 2018). In this context, higher advisory-related skill diversity among directors may create stronger faultlines that generate conflicts, inhibit the information flow, and alter overall board dynamics, thus neutralizing the positive effect of advisory skill diversity. Additionally, as firms face regulatory and societal pressures to nominate subject-matter expert directors, the boards may grow beyond their optimal size, increasing the costs to the company and reducing each director's motivation to contribute. Considering the limited candidate pool of high-quality directors who would also be experts in some specific area, the companies may end up nominating directors who are not optimally fit to contribute to a broader strategic agenda (Nili & Shapira, 2024).

Accordingly, we propose the following hypothesis as a two-sided hypothesis formulated in the alternative form as follows:

H3: There is a positive/negative association between the number of board advising-related skills and firm performance.

Theoretically, firms operating in more complex and dynamic environments should have higher advising needs (Klein, 1998). Such firms (larger, more diversified, or operating in rapidly

⁹ Lau and Murnighan (1998) introduced the concept of “faultlines,” defined as hypothetical dividing lines that may divide a group into subgroups, based on the alignment of multiple attributes (Bezrukova et al., 2009).

changing environments) would benefit the most from the broader access to diverse knowledge and external networks that can significantly affect the firm's ability to adapt and compete effectively (Boyd, 1990; Hillman & Dalziel, 2003; Dalziel et al., 2011). For example, Coles et al. (2008) show that the Tobin Q increases in board size for complex firms, and the relationship is driven by the number of outside directors on the board. At the same time, for R&D-intensive companies, firm performance increases are driven by the number of insiders, which highlights the importance of firm-specific knowledge for firms operating in dynamic environments. Similarly, Klein (1998) highlights that inside directors may add value to the companies if assigned to finance and investment committees. More recently, Field and Lowry (2022) show that optimal governance structures (classified boards and dual class shares) vary in the firm life cycle, reflecting differences in information asymmetry and agency costs.

However, the aforementioned studies solely consider one-dimensional characteristics of the board, and a single, one-size-fits-all model of board structure may not be an optimal solution for most companies (McConnell, 2003). We posit that the skills and qualifications contributed by the individual directors to board capital may have a different effect on corporate value creation and performance, depending on the firm's strategic business needs and operational complexity. Moreover, this relationship may vary depending on whether the particular skills are associated with the monitoring or advising functions of the board. For instance, the importance of advising-related skills may be especially pronounced for firms in more innovative or dynamic environments, where strategic decisions must be made relatively quickly to stay ahead of the competition. In these circumstances, a board focusing on monitoring at the expense of advising may be especially value-detrimental, as opposed to a board that contributes more advising-related skill sets. Therefore, we propose the following hypothesis:

H4: Firm value increases with advising-related board skill heterogeneity for more complex companies, for companies operating in more innovative industries, and for younger firms.

3. Research Design

3.1. Board Skill Sets

3.1.1. Skills Disclosure

In 2009, the SEC updated Item 401 of the Regulation S-K that outlines the mandatory disclosure requirements for all U.S. publicly listed companies. Item 401 mandates companies to disclose all control persons related to the firm (i.e., company directors, executive officers, and other significant employees), their ownership in the company, and family relationships to company employees (SEC Regulation S-K, 2025¹⁰) as part of their annual DEF 14A form (proxy statement) filing. The 2009 amendment required companies to expand the disclosed information and include details on the directors' business experience and background related to their nomination to the board.

While the 2009 disclosure requirement was an essential regulatory milestone enhancing transparency around public companies' key controlling persons, it provided no specific standard format or requirements to report directors' professional skills. Typically, companies disclose qualifications-related information under the "Nominees for Election" section. However, the level of depth and specificity in describing the relevant skills and biographical backgrounds varies

¹⁰ <https://www.sec.gov/rules-regulations/staff-guidance/compliance-disclosure-interpretations/divisionscorpfinguidanceregs-kinterp.htm> (last updated March 2025).

significantly across companies. For example, while some companies provide lengthy biographical information with a detailed record of each director’s professional biography, others only provide brief statements on the reason for a particular director’s nomination. More recently, companies have started incorporating image-based skill matrices of director names and skills with checkmarks indicating if a director possesses a particular skill. While such matrices may be informative for outsiders, they are not necessarily aligned with directors’ textual biographies and may incentivize window dressing-type behavior by firms (Becher et al., 2023).

3.1.2. Board Skills Dataset and Measures

We collect raw textual data on director biographies from proxy statements (DEF 14A filings) in a multi-step procedure. First, we retrieve the *cikcode* designations for all U.S. publicly traded companies from the Compustat data universe for all sample years. Then, we use the *sec-edgar-downloader* package in Python to download the annual proxy statements for all companies with filings available in the SEC EDGAR database. We utilize deep learning methods and natural language processing (NLP) tools to extract the biography and skills-related text for board members from the available DEF 14A filings. In particular, we use *LinkTransformers* and the RoBERTa model (Liu et al., 2019) to identify and collect all paragraphs containing the names of board directors. In the next step, based on the pre-trained RoBERTa model,¹¹ we classify and save the paragraphs containing biographies and qualification-related descriptions of individual directors. After collecting, cleaning, and verifying the quality of the textual data, we have over 179,000 director-firm-year observations covering 3,050 distinct firms and 39,270 individual directors.

¹¹ We use the year 2010 extracted biographies as a training dataset to pre-train the RoBERTa classifier.

We construct board skill set measures based on the following algorithm. We incorporate a list of twenty skill categories and corresponding keywords from Adams et al. (2018) and identify specific skill types mentioned in the biographical descriptions of individual directors. A complete skill dictionary can be found in the Appendix. We create a set of dummy variables, each equal to one if a director biography description contains keywords or phrases assigned to a specific skill category.

[Insert Table 1 here]

For example, suppose a director is classified as having a “Marketing” skill. In that case, it indicates that a company stresses that this director has either marketing or sales skills or is knowledgeable in marketing activities (see Table 1). Similarly, if a company specifies that a director has any risk management-related experience, this director is assigned a value of one for a “Risk Management” indicator variable.

After constructing director-level sets of skills, we derive board-level measures. In particular, a board-level measure of each skill category in each year equals one if this specific skill is assigned to at least one director on the board in this year, and zero otherwise. Then, the total number of skills present on the board of each firm in a particular year (*Board_Skills*) equals the count of the board-level skill categories.

To test our hypotheses, we divide the twenty skill categories into two mutually exclusive groups: monitoring-related and advising-related skills. Monitoring (advising)-related skills are shown in the literature to support the board's monitoring (advising) role. For example, directors with general finance and accounting skills (Agarwal & Chadha, 2005; DeFond et al., 2005; Engel, 2005) or academic experience (Chen et al., 2019) are shown to be more effective monitors, while

directors with an entrepreneurial background (Faleye et al., 2012) or international experience (Chen et al., 2020; Gianetti et al., 2015) tend to contribute to the board as advisors. We define *Monitoring_Skills* (*Advising_Skills*) as a total count of monitoring (advising)-related skill categories on a company's board in a given year.

3.2.Other Firm / Board Characteristics

Data on firm and board characteristics come from multiple sources. We collect data on firm-level financial and accounting variables from Compustat and CRSP. Board-related characteristics are sourced from BoardEx, while information on CEO age is obtained from Execucomp, supplemented by our calculations based on the BoardEx Individual Director Profile table and executives' dates of birth. Additionally, we source data on the number of annual board meetings from Adams et al. (2021) and on staggered boards from the Matthew Serfling dataset (Guernsey et al., 2022).

3.3.Sample Construction

The final sample used in this study is constructed as follows. We begin with the Director Skills dataset extracted from the DEF 14A filings. We use a combination of exact and fuzzy matching approaches to merge the Director Skills dataset with the BoardEx Organization Summary table. The company-year level observations are merged based on a precise match, and individual director level observations within the merged company-year observations are subsequently matched based on the fuzzy matching algorithm that accounts for director name variations in DEF 14A filings versus the BoardEx Organization Summary table. The fuzzy string matching for director names is required due to differences in director name reporting in proxy statements versus Boardex, including variations in first names, presence/absence of middle names, generational and

professional suffixes. We retain the matched observations with a cosine similarity score of above 0.85 and manually verify the quality of matched observations.

Next, we merge the dataset with the Compustat Fundamentals Annual table and, following corporate finance and governance literature, drop companies in the financial and utilities sector (#sic 4900-5000 and 6000s). We then merge the file with CRSP to add annual stock returns and volatility. The merged sample contains 152,639 director-firm-year level observations (see Table 2). We then add the BoardEx Board and Director Committees table, board meetings data from Adams et al. (2021), companies' business segments based on the Compustat Business Segments table, and CEO age data based on the Execucomp and Boardex Individual Profile tables.

[Table 2 here]

The final sample contains 125,538 director-firm-year level observations, including 20,154 distinct directors. After collapsing the sample to firm-year level, we have 16,596 observations for 2,419 distinct companies in 2010 – 2022.

3.4. Empirical Approach

To examine the influence of board skill heterogeneity on firm value, we use the following baseline model:

$$TOBIN_Q_{it} = \alpha + \beta Board_Skills_{it} + \gamma X_{it} + \eta Y_i + \theta Z_t + \varepsilon, \quad (1)$$

where $TOBIN_Q_{it}$ is the dependent variable of interest, computed as the sum of total assets and market value of equity minus book equity, divided by total assets. $Board_Skills_{it}$ represents measures of board skill sets. X_{it} is a vector of firm- and board-related control variables. Y_i

represents the industry indicators based on the Standard Industry Classification (SIC) two-digit codes; Z_t represents the year indicator variables.

We follow Faleye et al. (2011) and Adams et al. (2018) and incorporate the following variables to control for firm-level observable characteristics. We control for the firm size (*Size*), measured by the natural logarithm of the firm's total assets (Compustat variable *#at*), and for the firm age (*Firm_Age*), which is a natural logarithm of the number of years a company has been present in the CRSP universe at the time of the DEF 14A proxy statement. We control for corporate diversification measured by the number of business segments (*Business_Segments*) and for profitability based on return on assets (*ROA*), defined as operating income before depreciation (*#oibdp*) scaled by total assets (*#at*). Additional firm-related control variables include capital expenditures (*#capx*), scaled by the level of annual sales (*#sale*), stock return volatility (*Volatility*) based on the standard deviation of the firm's daily stock returns during the year, and *Leverage*, measured as total long-term debt (*#dltt*) scaled by total assets.

As per board-level control variables, we follow Adams et al. (2018) and include *Board_Size* as the total number of directors on the board, *Board_Independence* as a ratio of outside directors (based on the *#ned* variable classifications in BoardEx) to the total number of directors, and *Board_Committees* representing the number of distinct committees. Additionally, we incorporate the annual number of board meetings (*Board_Meetings*). All variable definitions and data sources can be found in the Appendix.

3.5.Descriptive Statistics

Table 3, Panel A, presents the firm-level summary statistics of the final sample, where continuous variables are winsorized at the 1st and 99th percentiles. The sample captures companies

of very different ages, from some that only recently entered the CRSP data universe (as of year 2022) to firms with almost a century-old operations. The average firm is 25 years old and has over \$7,000 million in total assets. The sample is substantially heterogeneous, with the median firm size being \$1,107 million and a maximum of \$551,669 million. On average, the companies operate in 2.9 business segments. Return on Assets (ROA) ranges from negative 0.72 to 0.40, with an average of 0.08. Regarding the governance-related variables, the median board has eight members, is on average 85% independent, and meets seven times per year.

Table 3, Panel B, shows a selection of director-level summary characteristics. Approximately 60% of the sample directors are members of the audit committees, and 17% of board members are female. The average director is 62 years old and has served on the board for an average of 8.4 years. These statistics presented in Table 3 correspond to those reported in the corporate governance and finance literature (e.g., Adams, 2017; Adams et al., 2018).

[Insert Table 3 here]

Figure 1 displays the pairwise Pearson correlation matrix for the firm-level variables. As expected, board size (*Board_Size*) is positively correlated with company size (correlation coefficient of 0.62), implying that larger companies, on average, have larger boards. Similarly, larger companies are associated with a greater number of board committees (0.34), higher ROA (0.31), and lower stock return volatility (-0.42). None of the coefficients are close to the conventional threshold of $|\rho| < 0.7$, which would suggest potential multicollinearity issues¹².

¹² We test for the presence of multicollinearity based on the baseline regression specification. The average VIF value across the variables in the model is below 4.0, and none of the variables exhibit a VIF above 3.0, indicating acceptable levels of potential multicollinearity according to conventional thresholds (e.g., O'Brien, 2007).

With respect to board skill measures, the pairwise correlation between *Monitoring_Skills* and *Advising_Skills* is 0.49, suggesting that while these dimensions of board skill sets are related, they capture distinct aspects of director qualifications. Importantly, *Board_Size* is moderately correlated with all three measures of board skills (ranging from 0.39 to 0.31), indicating that while larger boards tend to be associated with higher variety in both monitoring and advising skill sets, board size alone does not mechanically determine the heterogeneity in skills.

[Insert Figure 1 here]

Table 4 displays the distribution of skill averages across categories at the director and board levels. Across directors, the most prevalent skill categories are *Management* (46.93%), *International* (44.13%), and *Finance/Accounting* (41.02%) related skills. The least common skills include *Scientific* (2.37%), *Entrepreneurial* (3.04%), *Sustainability* (4.77%), and *Legal* (5.90%). Notably, the skill sets differ substantially between insider and outsider directors¹³. For example, while more than 44% of outside directors possess *Finance/Accounting* skills, only 22% of insiders have the same qualifications. Similarly, outside directors are more likely to bring to the board *Risk Management* skills (8.40% vs. 3.62%), *Government Policy* (11.57% vs. 6.52%), and *Compensation* (20.39% vs. 6.63%).

[Insert Table 4 here]

At the board level, all boards have at least one director with *Finance/Accounting* skills, which is expected as per Sarbanes-Oxley (SOX) requirements for having at least one financial expert on the board. Similarly, all boards have *Company Business* skills, as all inside directors

¹³ In supplementary tests, we exclude monitoring-related skills possessed by insider directors when computing the total number of board skills. All results remain robust to this alternative specification.

automatically qualify as company experts by definition. Most of the boards have at least one director with *Management* skills (93.94%), *International* (88.06%), and *Outside Board* experience (70.71%). Interestingly, almost 65% of boards have *Academic*-related skills, and 70% have at least one director with *Technology* skills.

The overall distribution of the total number of skills present on the boards is similar to the one reported by Adams et al. (2018), with the average number of skill categories ranging between 10 and 12 (Figure 2). As evident from Figure 3, which shows the time trends in skill averages by category, the demand for *Technology*-related skills has grown substantially over the sample period, ranging from approximately 62% at the beginning to around 78% in the most recent years (Figure 3, Panel A). Other skill categories that grew substantially during the sample period include *Sustainability*, *Risk Management*, and *Government Policy*.

[Insert Figure 2 here]

[Insert Figure 3 here]

4. Empirical Results

4.1. Baseline Results and Board Monitoring and Advising Functions

To evaluate the association between board skill sets and firm value (Hypothesis 1), we first replicate the main findings from the Adams et al. (2018) study and then re-run the results based on the entire sample from 2010 to 2022. The results are presented in Table 5. The dependent variable in all model specifications is Tobin's Q, defined as the sum of total assets and market value of

equity less book equity, scaled by total assets. The independent variable of interest is *Board_Skills*, computed as the total count of skill categories existing on the board of the company *i* in year *t*. All model specifications include industry and year indicator variables, as well as heteroscedasticity-robust standard errors clustered at the firm level.

In columns (1) and (2), we report the results for the specifications used by Adams et al. (2018) and for the same sample period of 2010 – 2013. The remaining columns report results for the extended sample period from 2010 to 2022. Column (3) reports the results of the parsimonious Q regression over the total count of board skills; the model in column (4) includes firm-related control variables; column (5) contains additional board-related controls; and column (6) adds additional control variables (*Leverage*, *Classified_Board*, *Board_Age*, and *Board_Female*).

Across all model specifications, the coefficient of the primary variable of interest (*Board_Skills*) remains consistently negative. Importantly, the magnitude of the coefficient remains consistent. However, the significance weakens when we extend the sample period beyond the years initially examined by Adams et al. (2018) and add additional controls.

[Insert Table 5]

Regarding control variables, we find that older firms and firms with more business segments are negatively associated with firm value. Notably, the coefficients on governance-related variables are consistent with the prior literature. For example, as earlier studies show, board size is significantly negatively related to Tobin's Q (Yermack, 1996; Eisenberg et al., 1998). Also, the number of board committees and the frequency of board meetings are negatively related to Tobin's Q, suggesting that the complexity of board structure does not necessarily add to firm value and may be associated with higher coordination and alignment costs. Similarly, in line with

previous studies, higher board independence has an inverse relationship with Tobin's Q (Agrawal & Knoeber, 1996; Bhagat & Black, 2002; Klein, 1998).

Table 6 presents the results related to hypotheses 2 and 3, which examine the relationship between firm value and monitoring and advising skill sets. We define *Monitoring_Skills* (*Advising_Skills*) as the board-level count of monitoring (advising)-related skills, where the choice of the skill type associated with each role follows the previous literature on how specific director qualifications relate to the board monitoring or advising roles.

[Insert Table 6]

As shown, *Monitoring_Skills* is consistently negative and statistically significant at the 1% level in all model specifications, suggesting that a higher variation in monitoring-related skill sets is associated with decreased firm value. In contrast, the advising-related skills (*Advising_Skills*) seem to be insignificantly related to firm value proxied by Tobin's Q. While the coefficient in the parsimonious model (column (1)) is positive and statistically significant, the addition of the firm- and governance-related control variables subsumes the significance of the advising-specific board skills. The results suggest that the contribution of advisory-specific skills is not uniform across firms. For example, Nili & Shapira (2024) mention that the optimal value-enhancing composition of board skills may vary greatly depending on the company's industry, life cycle stage, and reputational threats. This proposition aligns with the predictions from resource dependence theory regarding the importance of a firm's unique operational environment in driving firm advising needs (Boyd, 1990; Hillman & Dalziel, 2003).

4.2. Firm Complexity and Board Skill Sets

To examine the role of the business environment in driving the relationship between monitoring- and advising-related skill sets and firm value, we incorporate a measure of firm complexity (*Complexity*) developed by Loughran and McDonald (2024). This measure is based on the textual analysis of companies' 10-K reports and captures the multidimensionality of operations, strategy, accounting practices, and other aspects of a firm's business. Loughran and McDonald (2024) show that this proxy for the operational complexity is differentiated from the firm size and other conventional complexity measures.

First, we re-run the baseline model specifications with an additional variable, *Complexity*, and the interaction term of *Complexity* and *Board_Skills*¹⁴. As shown in Table 7, the coefficient on *Complexity* is significant and negative in all model specifications, indicating the inverse relationship between complex business operations and firm value. This finding aligns with Larsen et al.'s (2022) conclusion that firm complexity may negatively influence profitability due to increased coordination costs. Notably, while *Board_Skills* remains consistently negative, it is now statistically significant at 1%-5% levels, highlighting the importance of controlling for firm complexity beyond conventional measures (e.g., number of business segments or firm size). The interaction term (*Complexity x Board_Skills*) is positive and significant: as firm complexity increases, the adverse effect of additional board skills diminishes.

[Insert Table 7]

¹⁴ We test for the presence of multicollinearity based on the baseline regression specification by performing the Variance Inflation Factor (VIF) analysis. The average VIF value across the variables in the model remains below 4.0, and none of the variables exhibit a VIF of above 3.0, indicating acceptable levels of potential multicollinearity as per conventional thresholds (e.g., O'Brien, 2007).

To illustrate this moderation effect further, we split the sample based on the industry-year median values of firm complexity. The results are shown in Table 8. For low-complexity firms (those with a complexity measure less than the industry-year median value), the estimated coefficient on *Board_Skill* is negative and statistically significant. In contrast, the estimated coefficient is positive for high-complexity firms (those with a complexity measure equal to or higher than the industry-year median value); however, it is insignificant and of lower magnitude. This pattern reinforces the previous conclusion that the adverse effect of higher variation in board skills is not uniform across firms and may be dependent on firm-specific needs and characteristics.

[Insert Table 8]

First, we examine the association between board monitoring and advising skill sets and firm value in the context of firm complexity, by running the model specifications for subsamples of low- and high-complexity firms (Table 8, columns 1 and 2). Remarkably, the coefficient of the monitoring-related skills variable remains consistently significantly negative in both subsamples, providing further evidence of the detrimental effect of excessive monitoring. On the contrary, the higher variation in advising-related skill sets appears especially valuable for more complex firms (the coefficient of *Advising_Skills* is positive and significant at 1% level), emphasizing the importance of advising skills for companies operating in more complex and dynamic business environments.

Similarly, we find that firms operating in more innovative industries (Table 8, column 4) and firms in the early stages of the corporate life cycle (Table 8, column 6) benefit from a higher variety in advising skill sets.

5. Robustness and Endogeneity

In this section, we consider a range of robustness tests of the results. We examine alternative measures of firm value, complexity, and board skill sets, and explore the exogenous changes to board composition around unexpected director departures. Also, we verify the initial list of skill categories suggested by Adams et al. (2018) to address concerns of potential measurement error, subjective skill classification, and the omission of prominent skill categories.

5.1. Alternative measures of firm performance

The baseline dependent variable, Tobin's Q, defined as the sum of total assets and market value of equity less book equity, all scaled by total assets, is a firm value measure commonly used in the corporate governance and finance literature (e.g., Adams et al., 2018; Coles et al., 2008, 2014; Dass et al., 2013; Faleye et al., 2018; Field et al., 2013; Yermack, 1996, etc.). To examine the sensitivity of the earlier results to the definition of firm value, in Table 9, Panel A, we present the results from several sensitivity tests of alternative measures of firm value.

As in Table 8, we use subsamples of high and low complexity companies based on industry-year median values of Loughran and McDonald's (2024) firm complexity measures. All tests follow the baseline model specification, including the complete set of firm and governance control variables, industry and year fixed effects, and firm-level clustered standard errors.

In columns (1) and (2) of Table 9, Panel A, we estimate the Tobin's Q regressions based on the $t+1$ values of Tobin's Q rather than t . While the standard method in the literature has been to estimate contemporaneous regressions (see Mitton, 2022 for a survey of the literature), this approach is subject to a simultaneity bias, occurring when dependent variable and one or more of

the regressor's are determined in equilibrium so that it can plausibly be argued that x causes y or that y causes x (Roberts & Whited, 2012). While the introduction of forward-looking y or lagged regressors does not fully resolve the simultaneity problem in the corporate governance setting (Wintoki et al., 2012), scholars adopt the approach as a robustness check to strengthen the temporal ordering of a hypothesized relationship and mitigate the reverse causality issues (e.g., Bebchuk et al., 2011; Coles et al., 2012; Dass et al., 2013).

As can be seen from the regression results, the findings are robust to the inclusion of a forward-looking measure of Tobin's Q ; i.e., a higher variety in monitoring-oriented skill sets has a negative association with firm value, regardless of firm complexity. As in the main results, advising-related skill sets are significantly and positively related to the Tobin's Q for more complex firms.

Similarly, findings remain robust when using an industry-adjusted measure of Tobin's Q (columns 3 and 4) and *total q* , an alternative measure of Tobin's Q that accounts for intangible capital (columns 5 and 6). A growing share of intangibles in the capital structures has sparked a scholarly debate about Tobin's Q as a proxy for firm value. As U.S. firms have persistently increased their investment in intangible assets, accounting for intangibles may mitigate the measurement error associated with a traditional Tobin's Q (Peters & Taylor, 2017).

Additionally, we use abnormal returns based on the Fama-French 4-factor model. We regress daily excess stock returns obtained from CRSP on the daily four factors to capture the intercept, which is the Fama-French alpha. As evident from Table 9, columns 7 and 8, findings remain robust, and monitoring-related skill sets are consistently negatively associated with firm value. In contrast, advising-related skills significantly increase value for highly complex

companies. We obtain similar results when estimating the 3-year buy-and-hold abnormal returns (columns 9 and 10).

[Insert Table 9]

5.2. Alternative measures of firm complexity

The baseline measure of complexity is based on the Loughran and McDonald (2024), who perform the textual analysis of companies' 10-K reports to capture the multidimensionality of operations, strategy, accounting practices, and other aspects of a firm's business. The authors show that this proxy of firm complexity is differentiated from the firm size and other conventional complexity measures. To alleviate the measurement error concerns, we re-estimate the main results based on alternative measures of firm complexity commonly used in the finance and accounting literature. The results are reported in Table 9, Panel B.

The first alternative complexity measure incorporates the sample's median number of business segments. We categorize companies with fewer than three business segments as low complexity firms, and companies with at least three as high complexity firms.

Following Coles et al. (2008, 2020), we compute the second alternative complexity measure as the factor score of firm sales, number of business segments, and leverage. Each component separately represents a commonly used proxy of firm complexity, and a firm-year level factor score captures the estimate of the common part of these three variables to reduce the dimensionality of the variables and circumvent the multicollinearity issue.

Finally, we adopt a firm complexity measure based on accounting reporting complexity, which is defined as the count of accounting items disclosed in eXtensible Business Reporting

Language (XBRL) filings (Hoitash & Hoitash, 2018). The results in Table 9, Panel B, are consistent across different measures of firm complexity and confirm the main findings.

5.3. Alternative measure of board skill diversity

We follow Kaplan et al. (2012), Custodio et al. (2013), Kaplan and Sorensen (2017), and Adams et al. (2018) and use principal component analysis to capture the primary dimension of variation across the monitoring and advising-related skill categories. Table 9, Panel C reports the Tobin's Q regression results, where the main variables of interest are the first principal component of monitoring and advising-related skill sets. While assessing the economic magnitude of the coefficients on the factor scores is challenging, the results confirm the main findings and show that higher variation in monitoring-related skills has a negative relationship with firm value as measured by Tobin's Q. In contrast, a higher variation in advising-related skill sets has a significant positive association with Tobin's Q for highly complex firms.

5.4. Stacked Difference-in-Difference

As noted in Adams et al. (2010), empirical studies on corporate boards are difficult, and the causality of relationships is often impossible to determine. As a result, most of the empirical studies have focused on the structural dimensions of the board, such as size and the fraction of outside directors, as these measures are observable and easily quantifiable. The major challenge with this approach is that the boards themselves are endogenously determined structures, which are chosen to address the governance-related issues they face (Adams et al., 2010; Hermalin & Weisbach, 1988; Weisbach, 1998). While a significant body of scholarly research argues that certain governance characteristics are related to firm performance, it is practically implausible to

prove that causation is not reverse or that it is not another unobserved factor that determines the choice of the board structure and simultaneously drives corporate outcomes (Wintoki et al., 2012).

We implement a quasi-natural framework to mitigate endogeneity concerns using an event study methodology and the stacked difference-in-difference approach (Gormley & Matsa, 2011). Following Fracassi and Tate (2012), Nguyen and Nielsen (2010), and Masulis et al. (2025), we exploit director death and retirement events as plausibly exogenous shocks to board skill composition. A limitation of this design stems from the measurement of the key explanatory variables - board-level counts of monitoring- and advising-related skills - which, by construction, often exhibit a limited within-firm variation. As a result, the departure of a director with only overlapping skills does not lead to a subsequent detectable change in the board-level skill composition. Furthermore, even when a director with non-overlapping skills departs, if she is replaced by an individual with a different set of unique skills, the total count of skill categories may remain unchanged, masking the underlying changes in board skill composition.

To mitigate this concern, we define a firm as exposed to a shock when a director exits the board due to retirement or death in year t , and the subsequent board-level count of monitoring-related (advising-related) skills in year $t+1$ increases (decreases). For consistency, we focus on the plausibly negative exogenous shocks to board skill sets (an increase in monitoring skills or a reduction in advising skills). To evaluate the changes in firm value around the treatment (director departure and subsequent shift in board skill composition), we construct a cohort of exposed and unexposed firms using firm-year observations four years before and four years after the event. Then, we pool the data across cohorts and estimate the average treatment effect.

Table 10 presents the results of the stacked difference-in-difference tests. We include firm-cohort fixed effects to ensure that the model estimates the impact of exposure after controlling for any fixed differences between firms. We include year-cohort fixed effects as a nonparametric control for secular time trends. Following Gormley and Matsa (2011), we allow the industry and year fixed effects to vary by cohort. All model specifications include firm-level clustered robust standard errors.

Columns (1) – (3) show the coefficient estimates for the model specifications focusing on the changes in monitoring-related skill sets around director exit. The first column presents the estimation results of a parsimonious model with only firm-cohort and year-cohort fixed effects. The second column includes firm and governance control variables from the baseline specification, and the third column adds an advising-related skill set measure. The addition of controls does not quantitatively alter the results; in all three specifications, the *Post_Mon* variable, which denotes the post-treatment dummy, remains significantly negative, indicating an adverse effect on firm value after the treatment event.

Columns (4) – (6) show the coefficient estimates for the model specifications exploiting the same treatment design but focusing on the decrease in advising-related skill sets around director exit. In all specifications, the *Post_Adv* treatment dummy is significantly negative, indicating an adverse effect of the reduction in advising-related skill sets on firm value.

[Insert Table 10]

6. Additional Tests: Corporate Acquisition Decisions

To further evaluate the impact of board skill composition on board effectiveness, we investigate the importance of advising skill sets in major corporate decisions. Corporate mergers and acquisitions are among the most critical corporate strategic investment decisions, where boards play a central role in evaluating, designing, and approving corporate acquisition strategy (Masulis et al., 2025). Acquisitions are expected to create shareholder value through potential synergies; however, a substantial portion of deals are the outcome of agency problems and destroy firm value (Harford & Li, 2007; Masulis et al., 2007, 2025; Moeller et al., 2005). Acquisitions fail due to poor evaluation of targets, overpayment relative to the target's quality, a poor integration process post-implementation, or management entrenchment and overconfidence (Amihud & Lev, 1981; Malmendier & Tate, 2008; Schleifer & Vishny, 1989; Stahl & Voigt, 2008).

We hypothesize that firms where boards possess more advising-related skills should be more efficient in evaluating and acquiring targets. To test the hypothesis, we collect data on mergers with deal announcement dates from the Thompson/SDC U.S. Merger and Acquisitions database (SDC). For each acquisition to be included in our sample, we require that the deal is valued at \$1 million or more and involves a U.S. acquirer. We exclude multiple deals announced by the same acquirer on the same date. After eliminating acquirers with no data in the Compustat, CRSP, BoardEx, and board skill sets dataset, we obtain 2,120 acquisitions made by the firms from 2010 to 2022.

Extant literature argues that the decision to attempt an acquisition is non-random (Li & Prabhala, 2007); therefore, following Faleye et al. (2011), we estimate two-stage Heckman selection models, where the first stage estimates the choice to attempt a bid as a function of variables suggested by prior literature. We include industry and year fixed effects, as well as board skill set variables. The first column in Table 11 indicates that larger and better-performing firms

are more likely to become acquirers. Importantly, the probability of acquisition increases for firms with a higher heterogeneity in board advising-related skill sets.

[Insert Table 11]

The second column of Table 11 presents the results of the second stage of the regression of time to deal completion on the board skill sets measures and control variables, accounting for potential self-selection in the decision to make a bid. Time to deal completion is defined as the natural logarithm of one plus the number of days from the deal announcement date to the deal effective date. As the results show, the estimated marginal effect of advising-related skill sets is negative and statistically significant at the 5% level. Thus, acquisitions are completed in a significantly shorter time when the board possesses more advising-related skills. Importantly, the coefficient on the monitoring-related skill sets variable is significantly positive, which directly aligns with the previous literature (e.g., Faleye et al., 2011) and suggests that deal completion time increases with more intense board oversight.

In column (3), the dependent variable of interest is *Cumulative_Deals*, defined as the natural logarithm of one plus the number of deals the acquirer has successfully completed. As expected, advising-related skill set heterogeneity is negatively associated with the cumulative number of deals. We conjecture that firms where boards have more varied advisory skill sets acquire fewer but more valuable targets, with higher potential synergistic gains. To test this proposition, we follow Field and Mkrtchyan (2017) and define a *Large_Loss* as an indicator variable that equals one if the acquisition generated a loss of over \$500 million, and zero otherwise. As shown in column (4), the probability of an acquisition resulting in a large loss is significantly lower when the board possesses broader advising skill sets.

Additionally, we define the variables related to the final-offer takeover premium. To compute final-offer premiums, we collect stock prices for the common shares of target companies and perform adjustments for stock splits and dividends. We follow Dimopoulos and Sacchetto (2014) and measure offer premiums as follows:

$$\omega (p_b / p_{-28} - 1) \quad (2)$$

where ω is the percentage of target shares sought by the bidder, p_b is the price per target share offered, and p_{-28} is the target stock price 28 days prior to the announcement date, as reported in CRSP. Additionally, we measure offer premiums based on the 42 days prior to the announcement date.

We report the results of the second-stage regressions from a Heckman selection model in Table 11, columns (6) and (7). The findings are consistent across specifications and show that higher variety in advising-related skill sets is associated with higher takeover premiums. Prior literature posits that the takeover price offered by an acquirer should reflect both the underlying value of the target and potential synergistic gains a bidder expects from a takeover (Crawford & Lechner, 1996; Ferris et al., 2016; Varaiya, 1987). We may therefore expect bidders to offer higher takeover premiums for more valuable targets with more expected synergies.

7. Conclusion

We examine the influence on firm value of a novel measure of board composition, board skills. We depart from the existing literature by adopting a multidimensional view of board human capital, thus moving away from the structural and single-dimensional measures prevalent in

current studies. We exploit the 2009 amendment to Regulation S-K and compile a unique dataset of board members' biographies and qualifications to examine the association between board skill composition and firm value over the 2010-2022 period.

We initially find some evidence that board skill set heterogeneity is negatively related to firm value, consistent with the finding of Adams et al. (2018) based on a short sample period. However, when we distinguish between the two main functions of the board, we find that heterogeneity in board monitoring skill sets is negatively related to firm value, while heterogeneity in advising skills is positively related to firm value, especially for more complex firms, firms operating in more innovative industries, and firms in the earlier stages of the corporate life cycle. These results are consistent with the notion that excessive monitoring negatively affects companies by limiting the effectiveness of the board advising function. The findings are robust to alternative measures of firm value and other sensitivity checks. Moreover, we argue that results demonstrate a causal effect by reporting similar results based on stacked difference-in-difference tests around exogenous director departure events. Additional tests show that advising skill sets contribute to higher takeover activity, improved deal efficiency, and acquisition of more valuable targets.

The results of this study contribute to the ongoing debate on director competencies and provide practical implications for the board nomination process, as companies face increased regulatory and societal pressures to add skills. We show that merely “ticking off the credentials” to comply with a “one-size-fits-all” approach may be detrimental to firm value, especially for companies adopting a simplified “skill matrix” approach to fill the gaps in board skill composition. Overall, the findings call for a more nuanced approach to determining the optimal composition of director skills at the board level.

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Tables and Figures

Table 1. Skill Categories.

This table lists 20 skill categories per Adams et al. (2018).

Skill Category	Description
Academic	The director is from academia or has a higher degree (such as a Ph.D.)
Company Business	The director is experienced in the firm's business or industry (or a closely related industry)
Compensation	The director has compensation and benefits experience
Entrepreneurial	The director has entrepreneurial experience
Finance/Accounting	The director has experience in banking, finance, accounting, or economics-related activities
Governance	The director has corporate governance experience
Government Policy	The director has governmental, policy, or regulatory experience
International	The director has international experience
Leadership	The director is someone who has leadership skills/experience
Legal	The director has legal expertise
Management	The director has management and communications skills/experience
Manufacturing	The director has manufacturing experience
Marketing	The director has marketing and sales skills/experience or is knowledgeable in marketing activities
Outside Board	The director has outside board experience
Outside Executive	The director is an executive of another company
Risk Management	The director has risk management experience
Scientific	The director has engineering, scientific, or research & development (R&D) skills/experience
Strategic Planning	The director is someone who has strategy skills or strategy planning experience
Sustainability	The director has experience in environmental and sustainability issues
Technology	The director has technology skills/experience

Table 2. Sample Construction.

This table outlines the sample construction steps and merging algorithm for the final sample of this study.

	Director-firm-year level	Firm-year level
Directors' Skills Dataset	179,026	25,961
Merge with BoardEx Organization Summary	176,900	
Merge with Compustat Fundamentals Annual	166,741	
less utilities and financial companies	153,635	
Merge with CRSP	152,639	
Merge with BoardEx Committees and Meetings	128,689	
Merge with Compustat Business Segments, the CEO age dataset, and the Classified Board data	125,967	
less missing observations	122,538	
Collapse to firm-year level		16,596

Table 3. Summary Statistics.

The table below presents the descriptive statistics for the sample of the U.S. non-financial and non-utility firms between 2010 and 2022. Panel A shows firm-level characteristics, and Panel B reports individual director-level attributes. Variable definitions are provided in Appendix A1.

Panel A: Firm-level Summary Statistics						
Variable	N	Mean	p50	SD	Min	Max
Firm_Size (mln \$)	16,596	7,000	1,107	25,237	2	551,669
Firm_Age	16,596	25	21	20	1	98
Business_Segments	16,596	2.863	3	2.104	1	29
Capital_Expenditures	16,596	0.079	0.031	0.180	0.001	1.366
ROA	16,596	0.085	0.112	0.166	-0.709	0.398
Volatility	16,596	0.028	0.025	0.013	0.010	0.078
Leverage	16,596	0.249	0.202	0.248	0	1.203
CEO_Age	16,596	59	58	8	28	97
Board_Size	16,596	8.557	8	2.132	3	17
Board_Committees	16,596	3.680	3	1.006	1	10
Board_Independence	16,596	0.847	0.857	0.102	0	1
Board_Meetings	16,596	7.647	7	3.853	0	56
Classified_Board	16,596	0.445	0	0.497	0	1
Board_Skills	16,596	11.872	12	3.142	2	20
Monitoring_Skills	16,596	5.800	6	1.959	1	10
Advising_Skills	16,596	6.072	6	1.676	1	10
Panel B: Director-level Summary Statistics						
Variable	N	Mean	p50	SD	Min	Max
Female	122,538	0.171	0	0.376	0	1
Director_Age	122,538	62	62	9	20	98
Retiring_Director	122,538	0.143	0	0.350	0	1
Director_Tenure	122,538	8.408	6.200	7.675	0	65
Audit	122,538	0.600	0.571	0.179	0.167	1
Director_Skills	122,538	3.809	4	2.224	0	17
Monitoring_Skills	122,538	1.965	2	1.481	0	10
Advising_Skills	122,538	2.094	2	1.448	0	9

Table 4. Averages by Skill Category.

The table below reports the means of 20 firm-level skill categories at the director and board levels. The first column is the percentage of directors who possess the particular skill. The second and third columns present the percentages of outside and inside directors who have the particular skill. The last column is the percentage of boards that have the particular skill. *Monitoring (Advising)_Share* is the sum of Monitoring (Advising) related skills as a percentage of the total number of skills.

Skill Category	All Directors (%)	Outside Directors (%)	Inside Directors (%)	Boards (%)
Academic	19.48	20.3	14.63	64.85
Company Business	23.67	10.76	100	100.00
Compensation	18.4	20.39	6.63	54.98
Entrepreneurial	3.04	3.12	2.57	17.82
Finance/Accounting	41.02	44.27	21.85	100.00
Governance	24.54	26.89	10.65	64.29
Government Policy	10.84	11.57	6.52	43.85
International	44.13	45.69	34.92	88.06
Leadership	30.04	29.04	35.91	73.85
Legal	5.9	6.2	4.13	32.61
Management	46.93	47.5	43.55	93.94
Manufacturing	14.17	14.33	13.22	51.41
Marketing	15.39	14.83	18.7	59.61
Outside Board	24.86	26.3	16.33	70.71
Outside Executive	19.17	19.94	14.58	66.67
Risk Management	7.71	8.4	3.62	30.21
Scientific	2.37	2.3	2.75	12.73
Strategic Planning	22.36	21.79	25.72	69.86
Sustainability	4.77	4.88	4.15	22.00
Technology	26.33	27	22.39	70.03
Monitoring_Share	47.71	51.2	28.06	48.38
Advising_Share	52.29	48.8	71.94	51.62

Table 5. Board Skill Sets and Firm Value.

This table reports the results of OLS regressions on the total number of skills. The dependent variable in all model specifications is *Tobin's Q*, defined as the sum of total assets and market value of equity less book equity, divided by total assets. The independent variable of interest is *Board_Skills*, computed as the count of skills represented on a board of company *i* in year *t*. In Columns (1) - (2), I report the results of the Adams et al. (2018) model replications for the years 2010-2013. Columns (3) - (6) present the results of hierarchical OLS regressions for the full sample period of 2010 - 2022, starting from the parsimonious specification (Column (3)), then with firm-level control variables (Column (4)), board-related control variables (Column (5)), and additional robustness control variables in Column (6). All model specifications include industry and year fixed effects and robust firm-clustered standard errors. Variable definitions are provided in Appendix A1.

	1	2	3	4	5	6
Board_Skills	-0.044*** -0.016	-0.018* (0.009)	0.004 (0.009)	-0.042*** (0.009)	-0.013 (0.009)	-0.014 (0.009)
Size		-0.060*** (0.019)		0.390*** (0.020)	0.501*** (0.024)	0.504*** (0.024)
Firm_Age		-0.009 (0.03)		-0.124*** (0.036)	-0.086** (0.035)	-0.081** (0.035)
ROA		7.618*** (0.471)		-1.001*** (0.314)	-1.159*** (0.296)	-1.160*** (0.298)
Capital_Expenditures		-0.174 (0.323)		0.014 (0.023)	0.013 (0.023)	0.013 (0.023)
Business_Segments		-0.067*** (0.009)		-0.189*** (0.015)	-0.165*** (0.014)	-0.164*** (0.014)
Volatility		-6.346 (4.116)		13.273*** (2.592)	14.735*** (2.585)	15.067*** (2.657)
Board_Size		0.019 (0.013)			-0.162*** (0.017)	-0.160*** (0.018)
Board_Committees		-0.039** (0.018)			-0.091*** (0.027)	-0.091*** (0.027)
Board_Independence		-0.571*** (0.202)			-0.775*** (0.241)	-0.771*** (0.241)
CEO_Age		-0.011*** (0.003)			-0.003 (0.003)	-0.003 (0.003)
Board_Meetings		-0.023*** (0.006)			-0.037*** (0.005)	-0.036*** (0.005)
Leverage						-0.166 (0.253)
Classified_Board						0.058 (0.058)
_cons	3.410*** (0.23)	3.790*** (0.376)	2.237*** (0.116)	-2.070*** (0.312)	-1.322*** (0.395)	-1.394*** (0.399)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	2,199	2,199	16,596	16,596	16,596	16,596
Adjusted R-squared	0.178	0.437	0.111	0.233	0.264	0.264

*** p<.01, ** p<.05, * p<.1

Table 6. Monitoring- and Advising-Related Skill Sets and Firm Value.

This table reports the results of hierarchical OLS regressions on the monitoring and advising-related skill sets. The dependent variable in all model specifications is *Tobin's Q*, defined as the sum of total assets and market value of equity less book equity, divided by total assets. The independent variables of interest are *Monitoring_Skills*, computed as the count of board monitoring-related skills, and *Advising_Skills*, computed as the count of board advising-related skills. Column (1) presents the parsimonious specification, Column (2) includes firm-level control variables, Column (3) adds board-related control variables, and Column (4) includes additional robustness control variables. All model specifications include industry and year fixed effects and robust firm-clustered standard errors. Variable definitions are provided in Appendix A1.

	1	2	3	4
Monitoring_Skills	-0.030*	-0.073***	-0.040***	-0.040***
	(0.017)	(0.016)	(0.016)	(0.015)
Advising_Skills	0.047**	-0.010	0.018	0.016
	(0.022)	(0.019)	(0.019)	(0.019)
Size		0.390***	0.501***	0.503***
		(0.020)	(0.024)	(0.024)
Firm_Age		-0.124***	-0.087**	-0.082**
		(0.035)	(0.034)	(0.035)
ROA		-0.985***	-1.142***	-1.144***
		(0.314)	(0.296)	(0.298)
Capital_Expenditures		0.014	0.013	0.013
		(0.023)	(0.023)	(0.023)
Business_Segments		-0.188***	-0.165***	-0.164***
		(0.015)	(0.014)	(0.014)
Volatility		13.248***	14.711***	15.026***
		(2.586)	(2.578)	(2.650)
Board_Size			-0.162***	-0.160***
			(0.017)	(0.018)
Board_Committees			-0.090***	-0.090***
			(0.027)	(0.027)
Board_Independence			-0.771***	-0.767***
			(0.240)	(0.241)
CEO_Age			-0.003	-0.003
			(0.003)	(0.003)
Board_Meetings			-0.037***	-0.036***
			(0.005)	(0.005)
Leverage				-0.156
				(0.253)
Classified_Board				0.056
				(0.058)
_cons	2.224***	-2.121***	-1.350***	-1.420***
	(0.109)	(0.311)	(0.395)	(0.398)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Number of observations	16,596	16,596	16,596	16,596
Adjusted R-squared	0.112	0.234	0.264	0.265

*** p<.01, ** p<.05, * p<.1

Table 7. Board Skill Sets, Firm Value, and Firm Complexity.

This table reports the results of hierarchical OLS regressions on the total count of board skills and firm complexity. The dependent variable in all model specifications is *Tobin's Q*, defined as the sum of total assets and market value of equity less book equity, divided by total assets. The independent variables of interest are *Board_Skills*, computed as the sum of skills represented on board, and *Complexity* as per Loughran & McDonald (2024). Column (1) presents the parsimonious specification, Column (2) includes firm-level control variables, Column (3) adds board-related control variables, and Column (4) includes additional robustness control variables. All model specifications include industry and year fixed effects and robust firm-clustered standard errors. Variable definitions are provided in Appendix A1.

	1	2	3	4
Board_Skills	0.006 (0.022)	-0.067*** (0.019)	-0.044** (0.019)	-0.045** (0.019)
Complexity	-1.126** (0.516)	-2.528*** (0.461)	-2.324*** (0.466)	-2.347*** (0.470)
Complexity_Skills	0.014 (0.041)	0.069* (0.036)	0.072** (0.036)	0.074** (0.036)
Size		0.438*** (0.021)	0.529*** (0.025)	0.531*** (0.025)
Firm_Age		-0.121*** (0.035)	-0.087** (0.035)	-0.077** (0.035)
ROA		-1.021*** (0.319)	-1.158*** (0.303)	-1.160*** (0.304)
Capital_Expenditures		0.015 (0.028)	0.017 (0.028)	0.017 (0.028)
Business_Segments		-0.162*** (0.014)	-0.145*** (0.014)	-0.144*** (0.014)
Volatility		14.288*** (2.680)	15.495*** (2.681)	15.631*** (2.740)
Board_Size			-0.144*** (0.017)	-0.144*** (0.018)
Board_Committees			-0.077*** (0.027)	-0.077*** (0.027)
Board_Independence			-0.732*** (0.245)	-0.737*** (0.245)
CEO_Age			-0.004 (0.003)	-0.005 (0.003)
Board_Meetings			-0.035*** (0.005)	-0.034*** (0.005)
Leverage				-0.005 (0.263)
Classified_Board				0.065 (0.058)
_cons	2.644*** (0.271)	-1.781*** (0.370)	-0.958** (0.433)	-1.012** (0.435)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Number of observations	15,334	15,334	15,334	15,334
Adjusted R-squared	0.120	0.253	0.277	0.277

*** p<.01, ** p<.05, * p<.1

Table 8. Subsample Analysis for High vs. Low Complexity Firms, More vs. Less Innovative Firms, and Young vs. Mature Firms

This table reports the results of OLS regressions on the board skill sets for sample splits based on firm complexity (columns 1 and 2), firms operating in less or more innovative industries (columns 3 and 4), and mature or young firms based on the firm life cycle stage (columns 5 and 6). The dependent variable in all model specifications is *Tobin's Q*, defined as the sum of total assets and market value of equity less book equity, divided by total assets. The independent variables of interest are *Monitoring_Skills*, computed as the count of board monitoring-related skills, and *Advising_Skills*, computed as the count of board advising-related skills. Low complexity firms (column 1) are the ones with the value of *Complexity* below the industry-year median, and High complexity firms (column 2) are the ones with the value of *Complexity* equal to or higher than the industry-year median. Less and more innovative firms (columns 3 and 4) are those operating in industries with respectively low or high levels of average R&D and digital intensity, as defined by the OECD Taxonomy of Economic Activities (Galindo-Rueda & Verger, 2016). Mature firms (Column 5) are those in the maturity, stagnation, or decline stages as per Dickinson's (2018) life cycle stage methodology. Young firms (Column 6) are those in the introduction or growth stages as per Dickinson's (2018) life cycle stage methodology. All model specifications include industry and year fixed effects and robust firm-clustered standard errors. Variable definitions are provided in Appendix A1.

	low complexity 1	high complexity 2	less innovative 3	more innovative 4	mature 5	young 6
Monitoring_Skills	-0.044** (0.020)	-0.051*** (0.017)	-0.028* (0.016)	-0.036* (0.021)	-0.027* (0.016)	-0.062*** (0.018)
Advising_Skills	-0.012 (0.022)	0.083*** (0.026)	-0.016 (0.017)	0.064** (0.027)	0.021 (0.021)	0.050** (0.021)
Size	0.576*** (0.031)	0.458*** (0.032)	0.316*** (0.029)	0.630*** (0.035)	0.481*** (0.031)	0.492*** (0.030)
LN_Age	-0.080* (0.047)	-0.063 (0.045)	-0.071 (0.043)	-0.055 (0.054)	-0.043 (0.042)	-0.104** (0.043)
ROA	-1.341*** (0.304)	-0.588 (0.613)	0.035 (1.054)	-1.287*** (0.254)	0.493 (0.493)	-2.344*** (0.242)
Capital_Expenditures	0.019 (0.030)	0.003 (0.054)	0.020 (0.044)	0.020 (0.031)	0.222** (0.108)	-0.029** (0.011)
Business_Segments	-0.164*** (0.018)	-0.140*** (0.017)	-0.108*** (0.018)	-0.192*** (0.021)	-0.146*** (0.015)	-0.178*** (0.016)
Volatility	0.977*** (0.229)	0.941*** (0.216)	0.364* (0.218)	1.388*** (0.268)	1.445*** (0.366)	0.562*** (0.157)
Board_Size	-0.164*** (0.024)	-0.132*** (0.022)	-0.081*** (0.019)	-0.222*** (0.029)	-0.146*** (0.021)	-0.150*** (0.021)
Board_Committees	-0.052 (0.039)	-0.107*** (0.032)	-0.004 (0.032)	-0.178*** (0.043)	-0.097*** (0.030)	-0.063* (0.034)
Board_Independence	-0.628** (0.298)	-0.999*** (0.331)	-0.314 (0.331)	-1.003*** (0.355)	-0.621** (0.281)	-0.758** (0.321)
CEO_age	-0.002 (0.004)	-0.010** (0.004)	-0.004 (0.004)	0.002 (0.005)	-0.003 (0.004)	-0.003 (0.005)
Board_Meetings	-0.037*** (0.007)	-0.032*** (0.007)	-0.031*** (0.007)	-0.035*** (0.007)	-0.036*** (0.007)	-0.030*** (0.007)
Leverage	-0.354 (0.352)	0.386 (0.273)	0.040 (0.295)	-0.211 (0.191)	0.047 (0.403)	-0.178 (0.133)
Classified_Board	-0.017	0.134*	0.046	0.090	0.133*	0.013

	(0.072)	(0.080)	(0.066)	(0.090)	(0.070)	(0.073)
_cons	-2.275***	-1.244**	-0.329	-2.180***	0.001	-0.015**
	(0.509)	(0.534)	(0.603)	(0.773)	(0.007)	(0.008)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Nr of obs	8,588	6,746	7,858	8,338	9,398	5,309
Adjusted R-squared	0.293	0.250	0.217	0.269	0.241	0.366
*** p<.01, ** p<.05, * p<.1						

Table 9. Robustness Tests.

This table reports the results of the robustness tests of board monitoring- and advising-related skills for high and low complexity subsamples. Panel A reports the results of the OLS regressions, where the dependent variable in Columns (1) and (2) is Tobin's Q for (t+1), defined as the sum of total assets and market value of equity less book equity, divided by total assets; in Columns (3) and (4) Fama-French Alpha, based on Fama-French four-factor model; in Columns (5) and (6) 3-year Buy-And-Hold-Abnormal Return; in Columns (7) and (8) industry-adjusted Tobin's Q; and in Columns (9) and (10) total q based on the Peters and Taylor (2017). In Panel B, the dependent variable in all columns is Tobin's Q; and the measure of firm complexity in Columns (1) and (2) the factor score based on the firm's sales, the number of business segments, and leverage (Coles et al., 2008; 2020); in Columns (3) and (4) the business complexity measure based on Hoitash and Hoitash (2018); and in Columns (5) and (6) the median number of business segments. In Panel C, the dependent variable is Tobin's Q, and the firm complexity measure is based on Loughran and McDonald (2024); *Monitoring_Skills* is the first principal component of the PCA based on the count of the board's monitoring-related skill sets, and *Advising_Skills* is the first principal component of the PCA based on the count of the board's advising-related skill sets. All model specifications include industry and year fixed effects and robust firm-clustered standard errors. Variable definitions are provided in Appendix A1.

PANEL A										
	Tobin's Q, t+1		Fama-French Alpha		Dependent Variable = BHAR, 3-year		Tobin's Q - industry adj.		Total q	
	Low Complexity	High Complexity	Low Complexity	High Complexity	Low Complexity	High Complexity	Low Complexity	High Complexity	Low Complexity	High Complexity
	1	2	3	4	5	6	7	8	9	10
Monitoring_Skills	-0.050**	-0.048**	-0.009**	-0.006	-0.030*	-0.028***	-0.043**	-0.042**	-0.051*	-0.042**
Advising_Skills	-0.003	0.093***	-0.003	0.014*	-0.006	0.026**	-0.003	0.074***	-0.040	0.070**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nr of obs	6,856	5,408	8,547	6,724	7,988	6,400	8,588	6,746	8,538	6,698

PANEL B						
	Alternative Complexity Measure =					
	1st factor as per CDN (2008; 2020)		Hoitash & Hoitash measure		Business Segments	
	Low Complexity	High Complexity	Low Complexity	High Complexity	Low Complexity	High Complexity
	1	2	3	4	5	6
Monitoring_Skills	-0.057***	-0.030**	-0.042**	-0.032**	-0.056***	-0.009
Advising_Skills	-0.002	0.053**	-0.005	0.054***	0.006	0.043**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Nr of obs	8,432	8,134	8,037	6,924	10,014	5,293

PANEL C	Low	High
	Complexity 1	Complexity 2
Monitoring_Skills	-0.103**	-0.117***
Advising_Skills	-0.094*	0.154***
Control variables	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Nr of obs	8,573	6,734

Table 10. Stacked Difference-in-Difference.

This table presents the results of the stacked DiD analysis based on a (-4;+4) event window. The treatment is the retirement or death event of a director in company *i* in year *t* and an increase in board monitoring-related number of skills in year *t*+1 (columns 1 - 3) or a decrease in board advising-related number of skills in year *t*+1 (columns 4 - 6). Heteroskedasticity-corrected standard errors are clustered at the firm level and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6
Post_Mon	-0.140** (-3.003)	-0.148*** (-3.666)	-0.146*** (-3.588)			
Post_Adv				-0.115** (-2.271)	-0.118** (-2.998)	-0.120** (-3.025)
Advising_Skills			-0.0127 (-1.463)			
Monitoring_Skills						-0.017** (-2.450)
Control variables	No	Yes	Yes	No	Yes	Yes
Firm-cohort Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-cohort Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	102,423	99,201	99,201	88,200	85,421	85,421
Adjusted R-squared	0.74	0.78	0.78	0.75	0.78	0.78

Table 11. Board Monitoring and Advising Skill Sets and Corporate Acquisitions.

This table presents the results of the tests of the two-stage Heckman selection models on corporate acquisitions and monitoring and advising skill sets. Column (1) shows the results of a first-stage model predicting the decision to attempt an acquisition. Columns (2) – (6) present results of the second stage, explaining time to deal completion (2), cumulative number of acquisitions (3), probability of large loss (more than \$ 500 mln in MVE) (4), change in total factor productivity (5), final-offer premium computed based on the target stock price 42 days prior to the announcement date (4), final-offer premium computed based on the target stock price 42 days prior to the announcement date (5), premium CAR based on the percentage of shares acquired times the target CAR. All model specifications include industry and year fixed effects. Heteroskedasticity-corrected standard errors are clustered at the firm level and reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Acquirer 1	Time_Compl 2	Cum_Deals 3	Large_Loss 4	TFP_Gain 5	Premium_28 6	Premium_42 7
Monitoring_Skills	-0.002 (0.011)	0.043 (0.027)	-0.013 (0.019)	0.057* (0.030)	-0.798* (0.416)	0.002 (0.015)	0.006 (0.015)
Advising_Skills	0.027* (0.014)	-0.061** (0.030)	-0.055** (0.026)	-0.090** (0.039)	0.010 (0.645)	0.049** (0.020)	0.043* (0.023)
Ln_Assets	0.136*** (0.018)						
Cash_Holdings	-0.066* (0.040)						
ROA_lag	0.500** (0.216)						
Growth_Opportunities	0.000 (0.000)						
Board_Ownership	-0.624 (0.383)						
CEO_Duality	-0.049 (0.037)	-0.016 (0.088)	0.154** (0.069)	0.325*** (0.102)	-0.243 (1.198)	0.033 (0.059)	0.033 (0.061)
Leverage	0.534*** (0.083)	-1.605*** (0.235)	-1.408*** (0.194)	-2.067*** (0.315)	-9.367 (11.693)	0.044 (0.185)	-0.001 (0.192)
Percent_Cash		0.009*** (0.001)	-0.001 (0.001)	0.000 (0.001)	0.004 (0.011)	0.001 (0.001)	0.001 (0.001)
Private_Target		-1.067*** (0.088)	0.124** (0.057)	-0.028 (0.102)	-0.276 (0.765)		
Relative_Size		2.135***	-0.270***	0.410**	-0.473	0.004	0.013

		(0.212)	(0.104)	(0.189)	(1.249)	(0.096)	(0.095)
Intra_Industry		0.317***	-0.170***	-0.007	-0.389	-0.087	-0.099
		(0.087)	(0.060)	(0.102)	(1.482)	(0.070)	(0.079)
Board_Size		0.026	0.008	0.018	-0.871	-0.002	-0.006
		(0.030)	(0.022)	(0.030)	(1.233)	(0.018)	(0.017)
Busy_Board		-0.181	-0.305	0.267	-0.302	0.071	0.002
		(0.297)	(0.223)	(0.370)	(3.687)	(0.200)	(0.215)
Board_Independence		0.942	-0.047	-0.831	1.956	0.419	0.670
		(0.668)	(0.521)	(0.709)	(6.660)	(0.576)	(0.500)
CEO_directors		-0.539	0.103	1.210	29.244	-0.606	-0.533
		(0.849)	(0.614)	(1.016)	(30.614)	(0.622)	(0.609)
CEO_age		-0.001	-0.006	0.000	-0.024	0.002	0.002
		(0.006)	(0.005)	(0.007)	(0.074)	(0.004)	(0.004)
E_Index		-0.027	-0.100**	-0.148*	0.127	-0.056	-0.058
		(0.057)	(0.050)	(0.082)	(0.962)	(0.043)	(0.046)
Inverse_Mills_Ratio		6.959***	8.103***	9.934***	51.805	-0.313	0.148
		(0.817)	(0.699)	(0.909)	(47.847)	(0.521)	(0.526)
_cons	-2.049***	0.955	1.068*	-5.613***	11.366	-0.074	-0.193
	(0.213)	(0.759)	(0.599)	(1.075)	(11.961)	(0.390)	(0.422)
Number of observations	8909	2115	2115	1757	1923	218	215
R-squared		0.370	0.499		0.065	0.294	0.342
Pseudo R-squared	0.070			0.312			

*** p<.01, ** p<.05, * p<.1

Figures

Figure 1. Correlation Matrix for Firm-Level Variables.

This figure presents Pearson's pairwise correlations. Variable definitions are provided in Appendix A1.

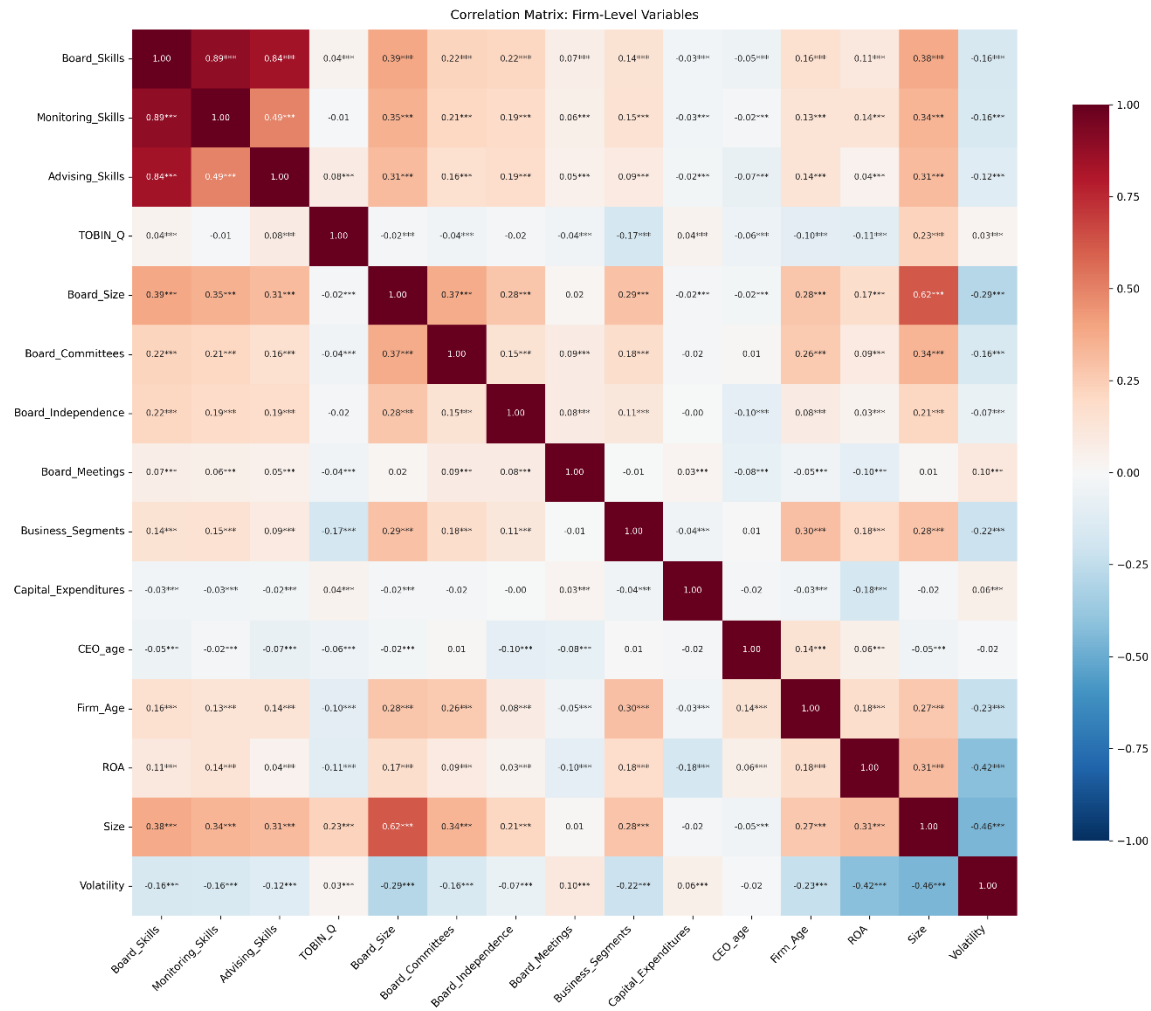


Figure 2. Distribution of Board Skill Sets.

The plots represent the frequency distribution for the average number of board skills in 2010-2022. Variable definitions are provided in Appendix A1.

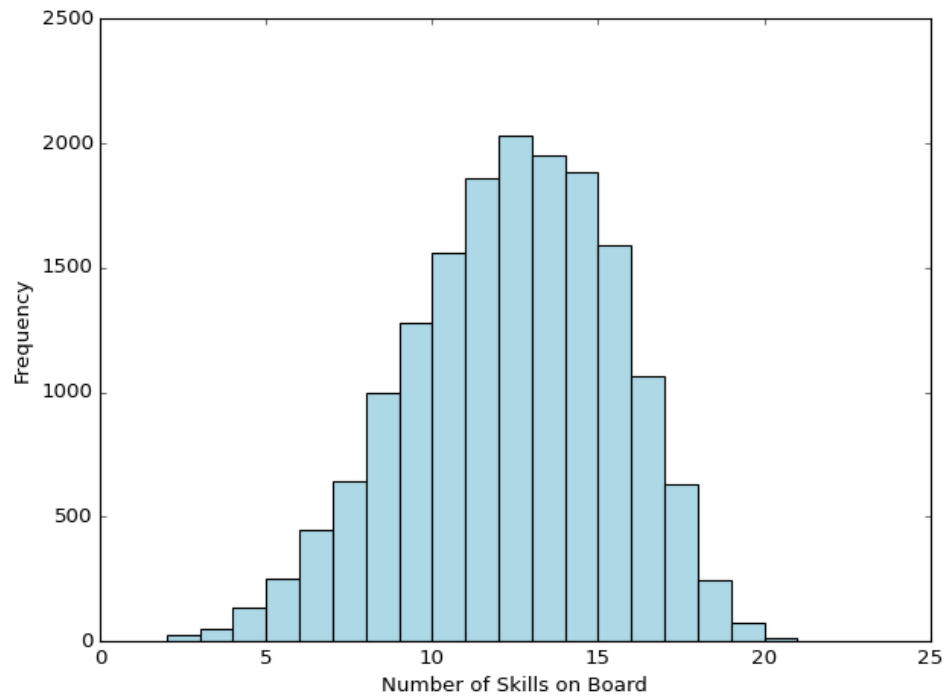
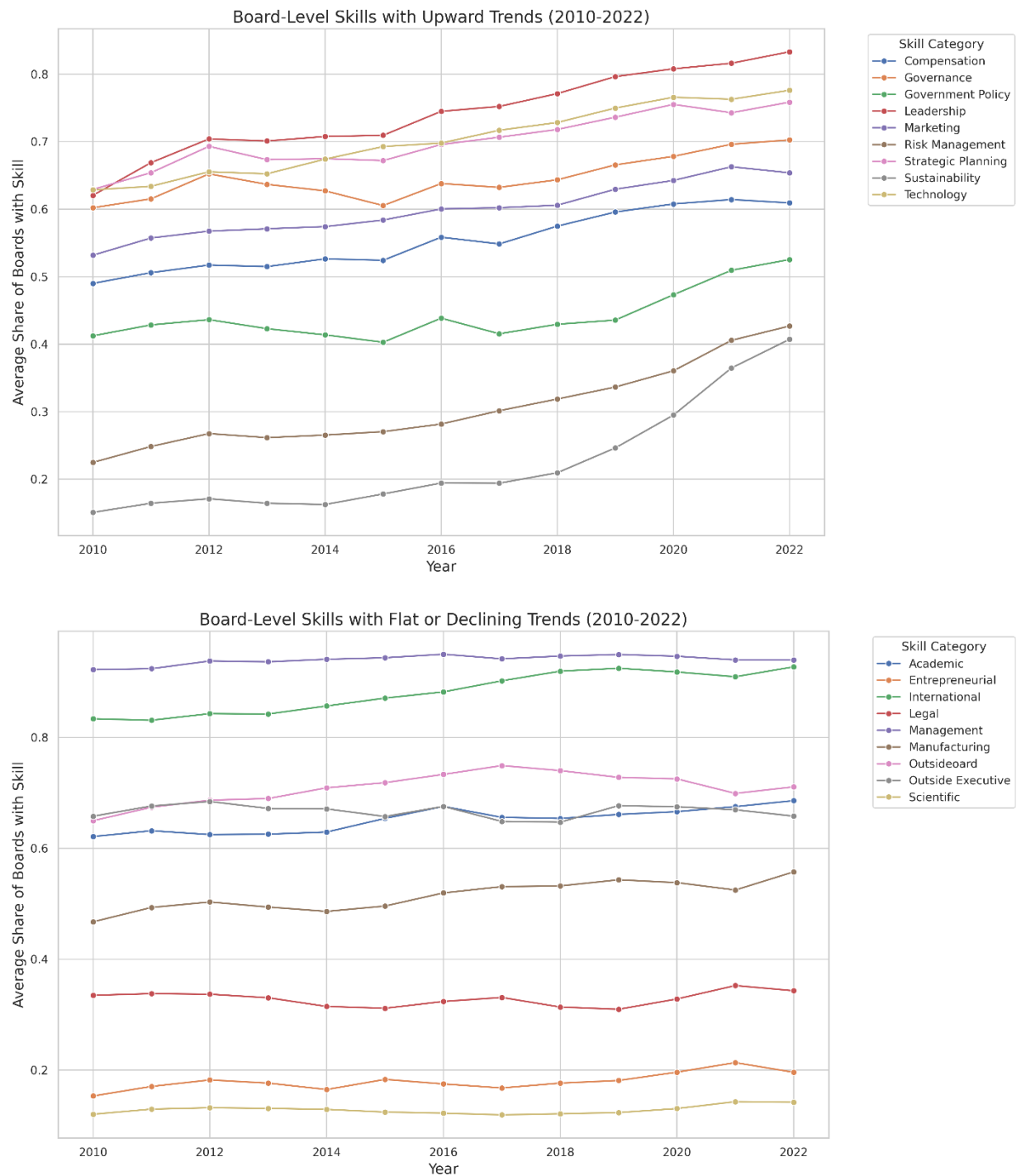


Figure 3. Skill Category Averages over Sample Period.

The figures represent the time trends in the means across 20 skill categories. Panel A shows the means for upward-trending skill categories; Panel B presents the means for flat or downward-trending skill categories. Variable definitions are provided in Appendix A1.



Appendix

A1. List of Variables and Definitions

Variable	Definition	Data Source
Board Skills Sets		
Board_Skills	The count of skill categories represented on the board of company i in year t	DEF 14A forms; author calculations
Monitoring_Skills	The count of monitoring-related skill categories represented on the board of company i in year t	DEF 14A forms; author calculations
Advising_Skills	The count of advising-related skill categories represented on the board of company i in year t	DEF 14A forms; author calculations
Firm-Level Variables		
Tobin_Q	The sum of total assets (#at) and market value of equity less book equity (#ceq), divided by total assets (#at). Market value of equity is the number of shares outstanding (#shrout) multiplied by the share price (#prc), adjusted for stock split factors	Compustat, CRSP
Size	Natural log of firm's total assets (#at)	Compustat
Firm_Age	Natural log of the number of years since each firm's CRSP listing date	CRSP
ROA	Operating income before depreciation (#oibdp) divided by total assets	Compustat
Capital_Expenditures	Capital expenditures over sales (#capx / #sale)	Compustat
Business_Segments	The number of business segments that the firm has	Compustat
Volatility	The standard deviation of the firm's daily stock returns during the year	CRSP
CEO_Age	The CEO's age	Execucomp, Boardex
Leverage	Long-term debt over firm's total assets (#dltt / # at)	Compustat
Complexity	The count of words representing firm business operations complexity, divided by the total number of words appearing in the Form 10-K filing, times 100	Loughran & McDonald (2024) dataset
Board-Level Variables		
Board_Independence	Percentage of independent directors on the board	BoardEx
Board_Size	Total number of directors on the board	BoardEx, DEF 14A
Board_Committees	Total number of committees on the board	BoardEx
Board_Meetings	The number of annual board meetings	DEF 14A

Classified_Board	A dummy variable equal to one if directors on the board are elected on a staggered basis and serve a term of two or three years before coming up for election again, and zero otherwise	ISS Governance, M. Serfling dataset
Director-Level Variables		
Audit	A dummy variable equal to one if the director is a member of the audit committee	Boardex
Female_Director	A dummy variable equal to one if the director is female, and zero otherwise	Boardex
Director_Age	Director's age at the time of the DEF 14A proxy statement	Boardex
Director_Tenure	The number of years the director has served on the board	Boardex
Retiring_Director	A dummy variable equal to one if the director is 72 or over and zero otherwise	Boardex

A2. Definitions of skills (Adams et al., 2018)

Academic	Academia, academic, dean, doctorate, education, faculty, graduate, masters, Ph.D., Ph.D., professor, school environment
Company Business	All aspects of our industry, chief executive officer of our, chief executive officer of the company, company's business, executive of our, executive of the company, experience with the company, historical insight, historical knowledge, history of the operation, history with our company, in-depth knowledge of, industry-specific perspective, industry experience, industry knowledge, inner workings, insider's perspective, internal operation, knowledge of all aspects of the company, knowledge of the, knowledge of the history, officer of our, officer of the company, president of our, president of the company, the company's chief, understanding of our business, working with the company
Compensation	Compensation
Entrepreneurial	Entrepreneur, entrepreneurial, entrepreneurship, evaluating business, innovative idea
Finance and accounting	Accountant, accounting and, accounting experience, accounting principles, and accounting, auditing, banking, capital markets, capital structure, corporate finance, experience in accounting, experience in finance, expertise in finance, finance experience, finance industry, finance matters, financial accounting, financial acumen, financial background, financial experience, financial expert, financial expertise, financial field, financial foundation, financial management, financial matters, financial reporting, financial services, investment, securities, understanding of finance
Governance	Governance
Government and policy	Government, policy, politics, regulatory
International	Global, international, multinational, worldwide
Leadership	Leadership
Legal	Attorney, lawyer, legal
Management	Experience in leading, experience in managing, management
Manufacturing	Industrial, manufactured, manufacturing
Marketing	Marketing
Outside board	Board experience, board of other, board practices of other, boards of companies, boards of other, boards of several other, boards of various, director of other, director of several other, member of the board of, numerous boards, on the boards of, other company boards, prior service as a director, several corporate boards, several other corporate boards, varied boards
Outside executive	As the chairman of a, business career, chief executive officer of a, executive experience, experience as a chief, experience as an executive officer of, experience as a senior, former executive of a, officer of a public, officer of other, officer of several companies, officer of numerous companies, president of a, senior-level executive, senior executive, senior management positions, serving as the CEO of a
Risk management	Risk
Scientific	Research and development, scientific expertise
Strategic planning	Business planning, decision-making, problem-solving, strategic, strategies
Sustainability	Environmental, safety, sustainability, sustainable
Technology	Technological, technology