PERFORMANCE HETEROGENEITY UNDER UNCERTAINTY:

SIX EMPIRICAL STUDIES EXAMINING THE CHARACTERISTICS AND CONSEQUENCES OF STRATEGIC COGNITION, DIRECTION, AND EXECUTION

Doctor of Philosophy (Business Studies)

August 2022

Kerry Louise Hudson

SUMMARY

This thesis explores the strategy process in the context of heightened levels of uncertainty present in the contemporary business environment. This is an underexplored phenomenon in strategic management research, which raises questions about the scope and applicability of established theoretical frameworks. Focusing on two dominant perspectives—resource-based theory (RBT) and upper echelons theory (UET) —this thesis presents six studies that aim to explicate the nature and effects of uncertainty.

These studies are used to address three core research questions that cover the strategy process from direction-setting to execution, specifically: (1) how boards with the ability to deal with uncertainty are formed; (2) how heterogeneity in board characteristics affects strategic direction under uncertainty; and (3) how heterogeneity in the execution of strategy under uncertainty affects firm performance. Key empirical phenomena under investigation include the cognitive characteristics of directors, the network of connections between boards, the strategic emphasis of firms, the proclivity of firms to deviate from strategic norms, and the deployment and development of resources via firm capabilities. Uncertainty at multiple levels is analysed, including the global regulatory environment, national macroeconomic conditions, persistent features of industries and sectors, and the dynamics of product-markets in which firms operate. The effects of these phenomena and their interactions with uncertainty are examined with respect to various firm-level outcomes, including financial performance, firm value, and the sustainment of competitive advantage.

Each study is presented as a self-contained chapter with detailed recommendations for future research and business practice pertaining to the specific phenomena under investigation. This is followed by an integrative and summative review of key substantive, theoretical, and practical implications. Taken together, this body of work offers contributions to the development and continued relevance of RBT and UET as interrelated frameworks for researchers, directors, and managers understanding and acting within a novel era of uncertainty.

TABLE OF CONTENTS

LIST OF TABLES AND FIGURES

1 INTRODUCTION

1.1 STRATEGIC DIRECTION AND EXECUTION UNDER UNCERTAINTY

The fundamental importance and difficulty of strategic management derives from the uncertainty of the future (Wernerfelt and Karnani 1987; Packard and Clark 2020). Business decisions are made in contexts where environmental conditions, inter-firm relationships, and internal resources are never precisely comparable to the past (Townsend et al. 2018). Consequently, strategy can rarely be formulated and implemented on the basis of probabilistic calculations of risk, instead requiring dynamic decision logics that account for the limitations of predictive modelling and the inherent immitigability of many forms of uncertainty (Dequech 2011; Packard et al. 2017; Ehrig and Schmidt 2022).

Uncertainty in the strategy process can arise from various sources. Many cases of uncertainty are mitigable; for example, through developing specialised skills within decision-making teams (Dosi and Egidi 1991) or acquiring additional relevant information (Camerer and Weber 1992). Generally, these forms of uncertainty are associated with factors within the immediate operating environment of the firm, such as consumer demand, supply markets, and competitive actions (Milliken 1987; Walker and Weber 1987; Anupindi and Jiang 2008). However, firms now face increasing uncertainty arising from sources that are further removed and thus less susceptible to influence or complete understanding. This encompasses uncertainty related to the macroeconomic, regulatory, and political environment (Smith and Grimm 1987; Baker et al. 2016), often collectively referred to as institutional uncertainty (Bylund and McCaffrey 2017).

Historically, institutional change has been incremental (North 1990), enabling strategic decision-makers to understand and adapt to sources of institutional uncertainty. However, recent economic, technological, and socio-political changes have resulted in a contemporary business environment in which institutional change is increasingly discontinuous and thus uncertainty more difficult to manage (Bloom 2014; Baker et al. 2016; Ahlstrom et al. 2020). While the global financial crisis of 2008 has often been recognised as a turning point in this regard (Bamiatzi et al. 2016; Bansal et al. 2018), institutional reactions to the Covid-19 pandemic provide the most striking illustration of the implications of discontinuous institutional change for strategic uncertainty (Howard-Grenville 2020; Rouleau et al. 2020). The majority of national governments implemented recurrent and often unexpected restrictions on economic activity, with associated shifts in monetary policy, leading to ongoing disruptions to supply chains including critical factor markets in labour, energy, and capital (Wenzel et al. 2021). These changes have strengthened recent calls for stakeholder-oriented management, in which firms are expected to operate in the interest of various constituents beyond their shareholders (Freeman et al. 2021; Lazzarini 2021; McGahan 2021). Contemporaneously, political instability and activism has been increasing (Rouleau et al. 2020). As a result, firms are expected to take public stances on, and often demonstrate tangible support for, increasingly polarizing socio-political issues (Bhagwat et al. 2020; Moorman 2020). These factors combine in a situation of heightened uncertainty in both the appropriate response to external crises and the likely material and reputational costs of strategic decisions (Wenzel et al. 2021).

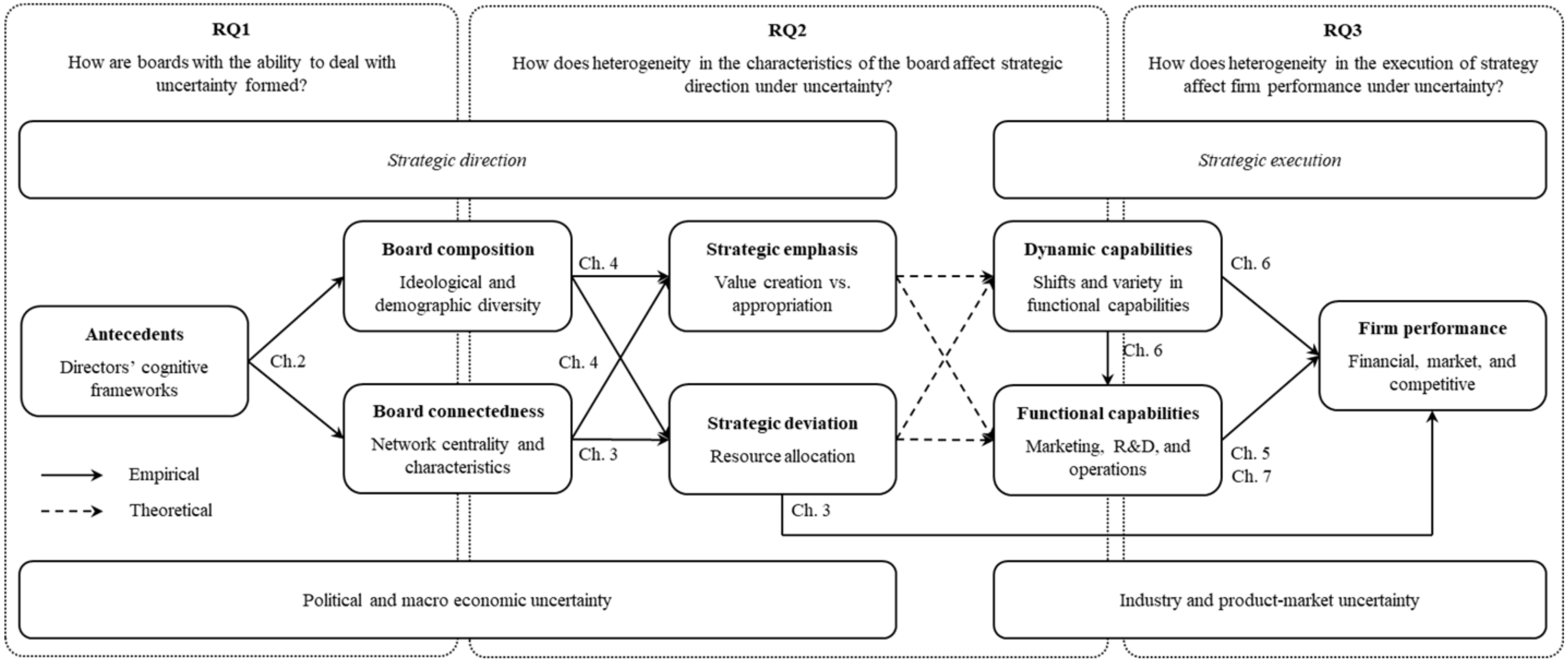
This unprecedented level of largely immitigable uncertainty raises fundamental questions about the scope and applicability of prominent theories in strategic management (c.f. George et al. 2016a). Such theories must be able to account for heightened variation under uncertainty – not only in the volatility of firms' operating environments, but in the heterogeneity of decision-makers' interpretations of the environment and the consequences of these varied responses for firm performance. Accordingly, uncertainty presents challenges to the current understanding of how firms set strategic direction and execute upon a chosen strategy (Meyer et al. 1990; Hitt et al. 2020).

Two of the most influential perspectives in the field concern these factors: *resource-based theory* (RBT), which seeks to explain firm performance as a consequence of strategically valuable, rare, inimitable, and properly deployed internal resources (Barney 1991; Barney et al. 2011) and *upper echelons theory* (UET), which posits that strategic decisions are informed by the backgrounds, experience, and values of key decision-makers (Hambrick and Mason 1984; Hambrick 2007). Contemporary levels of uncertainty raise questions about whether the characteristics of decision-makers and resources of firms that have previously been theorised and empirically corroborated as strategically important will continue to be so in the future (Hitt et al. 2020).

This thesis aims to explicate emerging issues in these areas, examining three core research questions that consider the strategic decision-making process from direction to execution. These questions consider the key sources of heightened variation under uncertainty in multiple levels of the operating environment, decision-makers' interpretations, and firm performance. Six empirical studies are presented to address these questions, distinct in their conceptual models, methodology, and implications but connected via this key theme. Taken together, this body of work is intended as a contribution to the development of RBT and UET as relevant and interrelated theoretical frameworks for a new era of uncertainty, with implications for future research, corporate governance, and management at various levels.

The following sections present the research questions, an overview of the empirical studies, and a summary of the implications of this work. The next six chapters present each empirical study in detail, followed by an integrative and summative review of key conclusions and contributions. Figure 1.1 presents a framework illustrating the links between chapters. This is not intended as a conceptual model – moderation and mediation relationships are introduced and examined in each study – but captures the key constructs examined in this body of work, the relationships between them, and their relevance to the three core research questions, diagrammatically represented by each 'RQ' box. The foci of each chapter are shown in the denotation 'Ch. X', with empirical relationships represented by solid links between constructs and theoretical relationships by dashed lines. Focal themes are represented as overarching constructs in the relevant areas of the framework.

FIGURE 1.1 Conceptual Framework.



Notes: This is not intended to represent a full conceptual model for the work presented in this thesis. Moderating and mediating relationships are discussed and examined in each chapter. 'RQ' denotes the conceptual span of each core research question; 'Ch. [X]' denotes the specific focus of each chapter. Solid lines represent the relationships that are empirically examined in the chapters; dashed lines represent the theoretical links that are established in the literature that has informed this body of work.

1.2 RESEARCH QUESTIONS

To examine how firms formulate and execute strategy under uncertainty, it is first necessary to explore how decision-makers come to perceive and understand uncertainty in the operating environment. A primary consideration here is the board of directors, which serves a boundary-spanning role at the interface between the firm and its environment (Finkelstein et al. 2009). This enables directors to bring external knowledge, experience, and cognitive models to the decision-making process (Rindova 1999; Hambrick et al. 2015) and positions the board as a critical source of information and deliberation about environmental conditions (Hillman et al. 2000; Kor and Sundaramurthy 2009). For this reason, the strategic involvement of boards is greatest during times of uncertainty and strategic change (Carpenter and Westphal 2001; Morais et al. 2020) when there is ambiguity regarding the appropriate goals of the firm and the best way to achieve these goals (Duplat et al. 2020). Directors now cite collaboration with top management in this function as a priority among their duties (Boivie et al. 2021).

Much research has examined the factors underlying the role and value of the board in strategic direction-setting (e.g., Finkelstein et al. 2009; Withers et al. 2012; Westphal and Zajac 2013). Two broad categories can be delineated within this literature stream, approximately reflecting the two roles of the board as a source of external information and a deliberative body.

First are factors related to the *connectedness* between the board and the external environment, which determine the nature of extent of information that the board can bring to the decision-making process (Westphal et al. 2001; Tuggle et al. 2010). Of particular importance here are the connections between boards, commonly referred to as the interlock network (Mizruchi 2013). These connections have been the subject of many empirical analyses, substantiating their role as a key facilitator of informational flows between firms (e.g., Haunschild and Beckman 1998; Carpenter and Westphal 2001; Beckman and Haunschild 2002; Srinivasan et al. 2018). Interlocks may be particularly important under uncertainty: as the informational requirements of the firm are greater, data about the external environment and strategic decisions of other firms may be more consequential for strategic decision-making (c.f. Geletkanycz and Hambrick 1997; Li 2019).

Second are factors related to the *composition* of the board, comprising those characteristics of directors that affect the consideration and interpretation of information (Milliken and Vollrath 1991; Withers et al. 2012). Given the same information, boards will form differing interpretations of the environment and appropriate strategic actions based on the values, experience, and cognitive biases of individual directors. This is a key insight of UET that has been widely corroborated by empirical studies (Hambrick 2007; Whitler et al. 2020). Research on the effects of directors' professional experience (e.g., Kroll et al. 2008; Kor and Sundaramurthy 2009; Whitler et al. 2018) and broader regulatory and political expertise (e.g., Hillman 2005; Lester et al. 2008) demonstrates that boards comprised of directors from varied backgrounds can formulate more effective responses to uncertainty at the micro- and macro-environmental level.

Though evidence regarding demographic diversity is mixed, this literature also suggests that boards function more effectively under uncertainty when a variety of director characteristics are represented (Miller and Triana 2009; Triana et al. 2021). These effects are due to the heterogeneous cognitive frameworks that directors may bring to the board's decision-making processes: when conditions are uncertain, appropriate strategies are ambiguous and multiple, informed perspectives can improve the quality of decision-making (Rindova 1999; Finkelstein et al. 2009; Duarte et al. 2015).

Despite substantial evidence for the importance of board connectedness and composition, knowledge of the antecedents to well-connected and cognitively diverse boards is presently limited. Specifically, much research has examined the situational factors affecting board connectedness and composition, with relatively little examination of the social and psychological factors underlying these phenomena (Shropshire 2010; Gupta and Wowak 2017). Under uncertainty, situational factors are inherently difficult to understand and manipulate and are subject to change rapidly (Townsend et al. 2018), whereas interpersonal dynamics and individual biases play a more consistent role across changing environments (Gerber et al. 2011; Withers et al. 2020). Analysis of these influences is therefore pertinent to understanding how boards with the ability to deal with uncertainty are formed, leading to the first research question of this thesis:

> ***Research Question 1 (RQ1):*** *How are boards with the ability to deal with uncertainty formed?*

The logical extension of RQ1 is to posit that the characteristics of the board will affect the strategic direction of the firm during times of uncertainty. In terms of both composition and connectedness, the relationship between board characteristics and firm-level outcomes is an area of continuing research (Whitler et al. 2020; Boivie et al. 2021), and current debate in this literature indicates a need to further examine the role of uncertainty. Specifically, an increasingly complex business environment necessitates a focus on the complexities of directors' cognition and boards' relational dynamics within the interlock network, paying greater attention to heterogeneity among firms (Tasselli and Kilduff 2021; Triana et al. 2021). Two key issues, related to board composition and connectedness respectively, illustrate this.

Regarding board composition, most research has focused on readily identifiable attributes of directors, such as demography and professional experience, to inform understanding of board diversity within UET (Hambrick 2007; Whitler et al. 2018). However, it is arguable whether this approach adequately captures the differences in board composition that are likely to affect strategic decision-making, leading to calls for further examination of the "deep-level" diversity – variation in directors' values, beliefs, and attitudes – that directly impact cognition (Mathieu et al. 2008; Post et al. 2021). Demographic and professional attributes are intended to approximate this (c.f. McPherson et al. 2001), but equivocal and often conflicting findings suggest opportunities for improving conceptualisation and measurement of attributes that are most impactful for firm-level outcomes (Holmes et al. 2021; Triana et al. 2021). Recent studies have responded to this gap in the literature by examining the effect of directors' ideology on strategic decisions (Di Giuli and Kostovetsky 2014; Gupta and

Wowak 2017; Park et al. 2020) yet there remains a lack of research on the strategic implications of ideological diversity. Considering that perceptions of uncertainty are a key delineating factor between individuals of differing ideological positions (Jost 2006; Gerber et al. 2011), the present status of this literature exemplifies the need for future research regarding heterogeneity in board composition.

Similarly, the literature on board connectedness has increasingly contained calls for further examination of heterogeneity among firms (Srinivasan et al. 2018; Tasselli and Kilduff 2021). Substantial evidence exists for the relationship between a board's position within the interlock network and a variety of strategic decisions, such as new technology development (Li 2019), acquisitions (Beckman and Haunschild 2002), and adoption of best practices (Westphal et al. 2001). However, little attention has been paid to how various forms of connectedness interact and how the agency of network actors alters the implications of their relationship with others (Burt 2012; Tasselli et al. 2015). Open questions in this research stream include how the nature of connected firms affect the implications of a focal firm's network position (Srinivasan et al. 2018), and how the characteristics of directors affects how boards capitalise upon the informational benefits of connectedness (Tasselli and Kilduff 2021), demonstrating the need for further consideration of heterogeneity in this literature. These questions are particularly pertinent to understanding the effects of board connectedness under uncertainty, when firms are likely to have multiple interpretations of the information gained via board interlocks dependent upon these factors (c.f. Packard et al. 2017; Townsend et al. 2018), leading to the second research question of this thesis:

> ***Research Question 2 (RQ2):*** *How does heterogeneity in the characteristics of the board affect strategic direction under uncertainty?*

A further source of variation in responses to uncertainty – and the evident corollary of RQ2 – is in the way that firms execute upon the strategic direction set by the board. RBT has become the dominant theory in strategic management in approaching questions of strategic execution (Barney et al. 2011; Freeman et al. 2021), as this fundamentally relies upon the acquisition, development, and effective deployment of firm resources (Barney 1991; Peteraf 1993). In the RBT literature, firm capabilities have emerged as the key concept, referring to the internal configurations of knowledge, skills, and processes that enable firms to transform resource inputs into strategically valuable outputs (Dutta et al. 2005; Helfat and Winter 2011). Empirical investigation has widely substantiated the importance of capabilities, documenting positive effect of "ordinary capabilities" in key functional areas and "dynamic capabilities" that enable flexibility and responsiveness in resource deployment (Krasnikov and Jayachandran 2008; Karna et al. 2016).

Recent work in RBT has highlighted a similar issue in the study of capabilities as explicated above regarding UET: limited understanding of the differences in the nature and performance effects of capabilities across firms (Mackey et al. 2017; Arunachalam et al. 2018). This is evident in examinations of both ordinary capabilities, which have tended to aggregate the reporting of effects across disparate industries and environments (Krasnikov and Jayachandran 2008; Feng et al. 2017), and dynamic capabilities, in which studies have largely been small-scale and qualitative and thus obscure comparisons across different conditions (Schilke et al. 2018; Fainshmidt et al. 2019). While firm heterogeneity has been a point of discussion in RBT for some time (see Powell 2001; Hansen et al. 2004; Hahn and Doh 2006), empirical examinations remain limited.

This is a central issue when interpretating research on firm capabilities in the context of uncertainty. As external conditions change in novel and unpredictable ways, capabilities are susceptible to becoming "strategic liabilities" whereby well-established routines – critical for the development of capabilities – inhibit the shifts in resource deployment that are necessary for a shift in strategic direction (Arend 2004). Conversely, overly responsive execution that shifts resource deployment according to environmental factors risks preventing the investment of time and resources necessary for developing the strong capabilities that can provide competitive advantage (Zahra et al. 2006; Fainshmidt et al. 2019). Understanding the effects of strategic direction under uncertainty therefore requires further examination of inter-firm differences in strategic execution, leading to the third research question of this thesis:

> ***Research Question 3 (RQ3):*** *How does heterogeneity in the execution of strategy affect firm performance under uncertainty?*

The next section explicates the issues involved in addressing RQ1-3 through a summary of the six empirical studies comprising this body of work.

1.3 OVERVIEW OF EMPIRICAL STUDIES

The following chapters comprise six empirical studies, distinct in their conceptual models, methodology, and implications but connected via the key themes of uncertainty and heterogeneity. Collectively, the studies encompass the strategy process from direction-setting, employing the theoretical lens of UET and focusing on the board of directors, to execution, grounded in RBT and focusing on the deployment firm resources and capabilities. These themes, and the correspondence between the empirical analyses and each RQ, are summarised in Figure 1.1 above.

1.3.1 Chapter 2: Ideological Homophily in Board Composition and Interlock Networks: Do Liberal Directors Inhibit Viewpoint Diversity?

Chapter 2 seeks to address RQ1, examining the dispositional antecedents of boards that are (a) cognitively diverse and (b) exposed to a broad range of information via the interlock network, thus developing the preconditions for dealing with environmental uncertainty. The study focuses on political ideology, for two reasons. First, individuals' political orientations reflect internally consistent systems of beliefs and values that are stable over time and manifest in behavioural patterns (Jost 2006; Gerber et al. 2011; Chin et al. 2013). Accordingly, political ideology has increasingly been employed in management research as an operationalisation of decision-makers' cognitive frameworks, with results that predictably align with common traits and behaviours of liberals and conservatives (e.g., Gupta and Wowak 2017; Park et al. 2020). Second, political ideology has broader relevance to this research due to the importance of political factors in the growing immitigable uncertainty faced by firms. A major source of unpredictability in the operating environment is changes in policies and regulations enacted by new governments (Bloom 2014; Amore and Corina 2021). Beyond being an indicator of cognitive diversity, heterogeneity in decision-makers' ideologies thus facilitates a broader understanding of the political shifts that a firm is likely to face (Benton et al. 2021).

Theoretically, the study focuses on *homophily*, a consistent feature of social networks in which individuals show a propensity to associate with similar others, particularly along ideological lines (McPherson et al. 2001). Analysing a panel of 408 large U.S. firms over the period 2000 to 2020, the study demonstrates the relationship between the ideology of incumbent directors and the board's propensity to (a) appoint ideologically diverse directors and (b) connect with ideologically diverse firms. Specifically, boards with a majority of liberal directors show greater levels of ideological homophily in both regards, being more likely to appoint liberal directors and connect with liberal boards. While homophily has decreased over time within the panel, this trend is driven by conservative boards, which are increasingly likely to make ideologically incongruent appointments and connections.

These results conflict with long-held stereotypes of liberal open-mindedness (Jost et al. 2003), rather reflecting a trend in psychological research that finds increasing ideological intolerance and in-group preference among liberals (e.g., Brandt et al. 2014; Duarte et al. 2015; Crawford et al. 2017). The study establishes incumbent directors' political orientations as a key antecedent of board composition and connectedness, addressing current research gaps in relation to RQ1 by demonstrating dispositional influences on the formation of boards with the ability to deal with uncertainty (c.f. Shropshire 2010; Gupta and Wowak 2017).

1.3.2 Chapter 3: The Wisdom and Madness of Crowds: Board Interlocks, Strategic Deviation, and Firm Performance

Chapter 3 addresses RQ2 and the next stage of the strategy process, examining how board composition and connectedness affect strategic direction. Focusing on the empirical context of recessions – a key source of macroenvironmental uncertainty (Dekimpe and Deleersnyder 2018) – this study pays particular attention to heterogeneity among firms in the effects of board characteristics on strategic outcomes. This study employs the theoretical lens of institutional isomorphism, which posits that uncertainty may induce homogeneous strategic responses via a process of "collective rationality" among firms (DiMaggio and Powell 1983). Board composition is theorised to influence this process via normative pressures arising from shared cognitive biases among directors, whereas board connectedness may induce isomorphism through mimetic processes. The study aims to identify the characteristics of boards that deviate from strategic norms and outperform competitors during recessions.

A Bayesian analysis of 1,615 U.S. firms covering the period 1999 to 2020 corroborates institutional isomorphism as an explanation for widespread poor performance during recessions, demonstrates hitherto overlooked nuances to the strategic consequences of board connectedness, and highlights the importance of firm heterogeneity in the study of uncertainty. Specifically, homogeneity in director characteristics is associated with poor performance, supporting the importance of board cognitive diversity for effective strategic direction. Board interlocks have differing effects depending upon the nature of connected firms and the strategic outcome of interest: generally, better-connected firms fare better than competitors during expansions and perform worse during recessions, indicating that information exposure during uncertainty may be both positive and negative. A Bayesian approach elucidates substantial inter-firm heterogeneity and provides probabilistic estimates of the effects of both board composition and connectedness across the business cycle.

These findings pertain to advancement of both UET, providing evidence of the underexamined board-level antecedents of strategic decisions during recessions (Bamiatzi et al. 2016; Dekimpe and Deleersnyder 2018) and RBT, contributing to the nascent stream of Bayesian research on resource deployment (Mackey et al. 2017).

1.3.3 Chapter 4: Board Ideological Diversity and Information Exposure as Antecedents to Value Creation and Value Appropriation

This study complements the preceding chapter in answering RQ2, addressing the effects of board composition and connectedness on a distinct form of uncertainty. While Chapter 3 focuses on macroeconomic uncertainty, Chapter 4 examines the firm's internal inclination toward uncertainty, operationalised in the value creation—value appropriation trade-off (Mizik and Jacobson 2003). This represents a key strategic decision that is significantly influenced by the board (Heyden et al. 2015) and has important implications for resource allocation (Kim et al. 2018), thus spanning the considerations of both UET and RBT. This study also directly follows Chapter 2 in its examination of the strategy process, positing ideological diversity as a major influence on firms' relative proclivity toward value creation or appropriation.

In a panel of 584 large U.S. firms over the period 2000 to 2018, the study demonstrates the interactive effects of board composition and connectedness on strategic direction. Ideological diversity on the board is associated with a value creation focus, and this effect is strengthened when the firm occupies a central position within the interlock network. However, in the absence of cognitive heterogeneity among directors, information exposure via board interlocks increases the firm's focus on value appropriation. Like the results presented in Chapter 3, this further demonstrates the nuanced effects of board connectedness and the importance of considering firm heterogeneity in understanding its implications uncertainty.

Taken together, Chapters 2 and 3 suggest that the ability to deal with uncertainty is a key benefit of cognitive diversity within the board: firms with ideologically heterogeneous directors fare better under macroeconomic pressures and are also better able to pursue internal policies that expose the firm to greater uncertainty at the microeconomic, product-market level. These findings inform the analyses conducted in Chapters 5 to 7, where the focus of this research shifts to RQ3 and the performance implications of such effects.

1.3.4 Chapter 5: Internationalisation and Mitigating Intellectual Property Risk Exposure: Leveraging Service Transition and Firm Capabilities

Chapter 5 is the first of three studies addressing RQ3, concerning the performance implications of strategic execution under uncertainty. As discussed above, the theoretical focus of this study and the following two chapters is RBT and the deployment of firm resources via capabilities. Chapters 3 and 4 implicate some key areas of capability development and types of uncertainty that inform the research conducted in these chapters. Specifically, analyses of both strategic deviation during recessions (Chapter 2) and strategic emphasis (Chapter 3) highlight the importance of capabilities in the key functional areas of marketing and R&D and the role of macroeconomic and product-market uncertainty in strategic direction-setting. The following studies thus adopt these foci in establishing the scope of empirical analysis.

This chapter examines one significant and increasing form of institutional uncertainty that spans both macro- and micro-environmental considerations: the regulation of intellectual property (IP) across international markets (e.g., Brander et al. 2017; Berry 2019). IP represents an ideal strategic resource in RBT: by definition, it is inherently heterogeneous across firms and inimitable by competitors, providing a buffer against competitive uncertainty and source of sustainable advantage (Peteraf 1993; Srivastava et al. 2001). However, these benefits are greatly undermined when firms operate in markets with weak legal protection of IP, posing considerable uncertainty in an era of increasing globalisation (Shinkle and McCann 2014; Berry 2017). Studying threats to the value of IP thus provides an opportunity to develop understanding of the interaction between uncertainty and strategic execution within the framework of RBT.

In a panel of 5,622 U.S. firms over the period 2007 to 2019, this study finds that firms can mitigate threats to the value of IP and improve performance in international markets via two key strategies: shifting the resource base towards service provision, or redeploying extant resources using functional capabilities in marketing and R&D. The effectiveness of each strategy is contingent upon both the regulatory environment and the starting resource position of the firm. Notably, strategic changes that prior research predicts to be advantageous are shown to be detrimental under certain combinations of these conditions, indicating important resource—environment contingencies that have previously not been explicated in the study of uncertainty (c.f. Feng et al. 2017; Fainshmidt et al. 2019) and further supporting the importance of considering firm heterogeneity in this regard.

1.3.5 Chapter 6: Dynamic Capabilities, Ordinary Capabilities, and Competitive Advantage: The Moderating Role of Product-Market Fluidity

Chapter 6 builds upon the key insight of Chapter 5 – specifically, that different levels of uncertainty in the operating environment require different configurations of firm capabilities – and endeavours to explicate how firms can achieve this. Accordingly, the study adopts the dynamic capabilities perspective, an extension of RBT which examines how firms can shift the development and deployment of functional capabilities such as marketing and R&D to better respond to changing environmental conditions (Teece 2014).

Research on dynamic capabilities has long invited criticism over theoretical disputes, inconsistent operationalisation of key constructs, and lack of generalisability arising from a reliance on small-scale and qualitative designs (Peteraf et al. 2013; Schilke et al. 2018; Suddaby et al. 2019). This chapter presents an attempt to clarify inconsistencies and derive broadly practicable conclusions about the role of dynamic capabilities in strategic execution under uncertainty, addressing two key issues: (1) developing measures of dynamic capabilities based on their relationship to functional capabilities and applicability in large, multi-industry datasets, and (2) operationalizing uncertainty in a way that captures the environmental dynamism that is integral to this perspective.

Results from a panel of 771 U.S. firms over the period 1997 to 2017 provide new insights into the role of dynamic capabilities as a critical factor in strategic execution under uncertainty. By focusing on the product-market as the appropriate level of analysis (Teece 2014), this analysis helps to clarify debate within the dynamic capabilities perspective and demonstrate the role of firm heterogeneity in capability development and deployment.

1.3.6 Chapter 7: Disaggregating the Characteristics and Contribution of Marketing Capabilities: Rarity, Persistence, and Development in Resource Deployment

Chapter 7 presents the final empirical study of this thesis, complementing Chapter 6 in its methodological and theoretical implications for the examination of firm capabilities as key element of strategic execution. Building upon the key insights of the preceding study, this chapter presents a series of Bayesian analyses that aim to decompose the elements of effective functional capabilities and explicate the degree of firm heterogeneity in their performance implications.

As in the dynamic capabilities literature, prior research on functional capabilities has received criticism regarding the operationalisation of key constructs (Barney 2014) and the lack of examination of inter-firm differences in nature and effects of capabilities (Feng et al. 2017), particularly under differing environmental conditions (Arunachalam et al. 2018). This study aims to address these issues, extending current best practice in the measurement of functional capabilities to develop measures of rarity, persistence, and development that capture the nature of capabilities within RBT (c.f. Sirmon et al. 2010; Helfat and Winter 2011).

Examining the performance effects of these measures in a panel of 706 U.S. firms over the period 1988 to 2019 using Bayesian hierarchical modelling provides new insights into the heterogenous nature of capabilities across firms and explicates the role of uncertainty via the analysis of industry-specific effects and variation. Concluding the empirical section of this thesis, Chapter 6 therefore offers answers to RQ3 at the most granular and managerially practicable level of strategic execution: the development and deployment of functionally specific routines within environments of varying levels of uncertainty.

1.4 OVERVIEW OF IMPLICATIONS

Chapters 2 to 7 are presented as self-contained empirical studies, including discussions of contributions to the relevant areas of research and practice. However, central to addressing RQ1 to 3 are the broader implications that can be drawn from a synthesis of these individual contributions. Following the six empirical studies, this thesis therefore concludes with a detailed exposition of the implications of this research in Chapter 8, which are briefly summarised in the subsections below.

1.4.1 Chapter 8.1: Implications for Research

In examining both strategic direction and execution, the studies in this thesis offer implications for research in both UET and RBT. These are among the most established theories in management research; however, uncertainty and heterogeneity remain underexplored in both (e.g., Hahn and Doh 2006; Barney 2014; Boivie et al. 2016; Boivie et al. 2021). To address this and offer contributions to these fields, these studies focus on underexamined phenomenon, unique data sources, and new methodological approaches that can inform future empirical research and theoretical development.

Among the key contributions to UET, Chapters 2 to 4 present evidence of the role of director ideology and social pressures as key influences on board composition, connectedness, and decision-making. This addresses the lack of research on dispositional antecedents in this research stream (Shropshire 2010; Gupta and Wowak 2017) and corroborates some central tenets of UET that have remained largely theoretical due to the historical difficultly of measuring these factors (see Hambrick and Mason 1984; Bromiley and Rau 2016). These studies also explicate, justify, and demonstrate the use of novel data sources on decision-makers' ideology as an important component of addressing current issues in diversity research, a prominent area of application for UET. This research typically uses demographic and professional characteristics as proxies for individuals' cognitive frameworks, which arguably fail to capture the "deep-level" diversity that appears to be most consequential for firms (Post et al. 2021; Triana et al. 2021) and can be better represented by measurement of ideological factors (c.f. Gerber et al. 2011).

The major contributions of Chapters 5 to 7 derive from the development of new methodologies for measuring firm capabilities and capturing heterogeneity in their effects across firms and environments. The theory—practice gap is an ongoing issue in RBT research, and recommendations for addressing this often focus on developing measures that better capture the realities of capability development and execution within firms (e.g., Barney 2014; Fainshmidt et al. 2019). Focusing on operationalisation of capabilities and environmental uncertainty at the appropriate level of analysis (see Feng et al. 2017; Arunachalam et al. 2018) and incorporating Bayesian approaches to modelling heterogeneity (see Hahn and Doh 2006; Mackey et al. 2017), the methodologies presented in these studies thus provide direction for future research to clarify the effects of both functional and dynamic capabilities beyond the empirical contexts examined in this thesis.

1.4.2 Chapter 8.2: Implications for Practice

Better alignment between theory and measurement in UET and RBT is a key research contribution of this thesis. Consequently, the studies presented herein also offer actionable implications for firms. Reflecting the dual theoretical and empirical foci, these contributions are primarily in the areas of (1) board formation and operation, and (2) resource allocation.

In explicating the role of dispositional and social factors in the composition of boards and board networks and the strategic decisions of firms, these studies develop new insights into director selection that may inform the nomination process and the actions of directors once appointed to the board. Providing the first empirical evidence for ideological antecedents to board characteristics, Chapter 2 shows why directors, managers, and others involved in director nomination need to be aware of how personal political biases shape their decisions. Subsequently linking this to strategic direction and firm outcomes in Chapters 3 and 4 demonstrates the material and financial implications of this. Accordingly, these chapters discuss the growing importance of awareness of these effects within firms and suggest strategies to mitigate ideological biases.

Chapters 3 and 4 also address resource allocation decisions, providing recommendations for managers advocating for investments in key functional areas when faced with boards of differing characteristics and under differing conditions of environmental uncertainty. This theme becomes the central focus of Chapters 5 to 7, which each provide nuanced managerial guidance regarding resource allocation decisions in different environments. These studies span multiple levels of analysis, extending the practical implications of extant research on firm capabilities by explicating the attributes of effective strategic execution at both the firm-level, concerning the development of appropriate capabilities under uncertainty, and the function-level, demonstrating the aspects of functional capabilities that provide the greatest performance benefit across heterogeneous firms and environments.

Taken together, these practical contributions provide novel guidance for firms regarding the interplay between external conditions, corporate networks, and the individual agency of managers and directors in managing uncertainty. Focusing on firms heterogeneity provides realistic expectations about the likely benefits that firms can derive from board operations and resource allocation in differing and changing environments, highlighting new contingencies that affect the direction and magnitude of effects of strategic direction and execution decisions.

2 IDEOLOGICAL HOMOPHILY IN BOARD COMPOSITION AND INTERLOCK NETWORKS: DO LIBERAL DIRECTORS INHIBIT VIEWPOINT DIVERSITY?

2.1 INTRODUCTION

The board of directors is the “apex of decision control” (Fama and Jensen 1983, p. 311), setting the strategic direction and objectives of the firm (Bailey and Peck 2013). Board interlocks—formed when a director serves on the board of two firms (Mizruchi 1996)—are a key conduit of information for boards’ decision-making, providing access to market intelligence (Yoshikawa et al. 2019), aiding in the diffusion of new and best practices (Beckman and Haunschild 2002), and opening access to critical resources (Withers et al. 2012). Consequently, the composition of the board and the firm’s position within interlock networks are pertinent topics in organisational research for two reasons: (1) interlocks affect the volume and content of interfirm information flows (Li 2019; Yoshikawa et al. 2019); and, (2) the cognitive frameworks of directors influences how this information is used in decisions (Van Ees et al. 2009; Bailey and Peck 2013).

Both board composition (Withers et al. 2012) and interlock formation (Bazerman and Schoorman 1983) are consequences of the social embeddedness of corporate boards, being substantially influenced by social and individual factors beyond the economic considerations of the firm and its shareholders (Westphal and Zajac 1995; Van Ees et al. 2009).

Specifically, the appointment of new directors—and thus the formation of board interlocks—is necessarily limited by extant social connections and dependent upon interpersonal political factors and individual biases (Bazerman and Schoorman 1983; Withers et al. 2020). Antecedents to the composition of boards and interlock networks are therefore both *situational*, pertaining to the operating environment of firms or social context of interpersonal interactions, and *dispositional*, related to the cognitive and affective biases of individuals (c.f. Kelley 1973).

Most research to date has examined situational factors, leading to a theoretical understanding of board composition and network formation that may understate the role of directors' cognitive and affective frames (Shropshire 2010; Gupta and Wowak 2017), despite longstanding recognition that the values, beliefs, and attitudes of decision-makers affect firm-level outcomes (Chin et al. 2013). Research on TMTs, and some notable exceptions to the situational focus in board research (Di Giuli and Kostovetsky 2014; Gupta and Wowak 2017; Park et al. 2020), highlight a key dispositional factor: *ideology*. This refers to an individual's internally consistent belief system, comprising the attitudes and values that underlie thought and behaviour (Tedin 1987; Jost 2006), and is observable and measurable by political orientations (Erikson and Tedin 2003; Jost et al. 2009; Chin et al. 2013). The liberal-conservative spectrum is most commonly applied, as the distinction has remained stable over time (Jost 2006), predictably correlates with personality traits (Gerber et al. 2011), cognitive biases (Fatke 2017), and values (Carney et al. 2008), and provides a framework for action across a range of domains (Jost et al. 2009).

Accordingly, there is evidence for effects of decision-makers' ideologies on a range of firm outcomes. Liberal CEOs are more likely to engage in corporate social responsibility (CSR) (Chin et al. 2013) and appoint CSR executives (Gupta et al. 2020), and have a higher rate of new product introductions (Kashmiri and Mahajan 2017). Firms with conservative managers have lower levels of debt, higher profitability, and less risky investments (Hutton et al. 2014), greater pay dispersion within the TMT (Chin and Semadeni 2017) and lower rates of tax avoidance (Christensen et al. 2015). At the board level, conservativism is associated with higher CEO compensation and a stronger correlation between compensation and performance (Gupta and Wowak 2017), higher rates of CEO dismissal following financial misconduct (Park et al. 2020), and lower adoption of CSR policies (Di Giuli and Kostovetsky 2014). These outcomes are predictability aligned with the personality characteristics typically associated with each pole of the political spectrum, such as differences in risk tolerance and perceptions of fairness (c.f. Haidt 2001; Gerber et al. 2010). To date, however, there have been no studies of the influence of ideology on the structure of board interlock networks and the position of the firm within these (Gupta and Wowak 2017), despite evidence that the ideologies of peer firms are salient to decision-makers at the TMT level (Gupta et al. 2020). Similarly, the relationship between ideology and board composition has only been studied tangentially to the monitoring effectiveness of inside and outside directors (Kim et al. 2013).

This study posits that director ideology is an overlooked dispositional antecedent to board composition and interlocks. This assertion is based in the psychological literature on *homophily*, a “remarkably consistent structural feature” of social connections whereby individuals demonstrate a preference for forming ties to similar others (McPherson et al. 2001, p. 429). Thus, director appointments may preferentially select for ideologically similarity to incumbent board members. As this process also determines the structure of the board interlock network, this study examines two outcomes: *board ideological homophily,* the degree of homogeneity in political orientations among directors, and *network ideological homophily,* the degree of homogeneity in political orientations of the boards to which a focal firm connects.

This author makes an ostensibly counterintuitive prediction: *liberalism will increase ideological homophily*, such that boards with more liberal directors will exhibit less viewpoint diversity within the board and establish fewer ideologically incongruent interlocks. This conflicts with the stereotype of the ‘open-minded liberal’ (Jost et al. 2003), but aligns with studies of social and professional networks (Inbar and Lammers 2012, p. e.g. ; Yoo et al. 2018), and psychological evidence (e.g. Brandt et al. 2014; Crawford et al. 2017) that indicates greater ideological intolerance among liberals. This study examines why these discrepancies have emerged and posit that the social context of the board is likely to induce the latter effect, with liberals’ beliefs about the social purpose of business encouraging the maintenance of ideological homogeneity.

Analysis of data on board composition and interlocks from 408 large U.S. firms between 2000 and 2020 demonstrates that board liberalism increases homophily at both the intra- and inter-organisational level.

Furthermore, despite overall levels of ideological homophily decreasing over the 20 years of the sample, the effect of liberalism on board and network homophily has increased. This suggests that increases in the ideological diversity of boards and interlock networks have been primarily driven by conservative directors.

This study provides the first theoretical rationale and empirical evidence for an ideological component in the composition of boards and the structure of interlock networks, with implications for understanding the dispositional antecedents to director selection. Notably, the findings run counter to the long-held assumption in political psychology of the 'rigidity of the right', i.e. the attribution of ideological intolerance as primarily a conservative trait (Jost et al. 2003). This has recently been challenged on the grounds of methodological limitations in survey studies and potentially biased assumptions in the field, with mounting evidence for ideological intolerance among liberals (Malka et al. 2014; Conway et al. 2016; Malka et al. 2017). By utilising an objective assessment of political ideology and examining the actual formation of network ties rather than stated preferences, this analysis thus provides a complement to these recent studies that further substantiates this more nuanced perspective. Specifically, these findings align with recent research demonstrating that differences in ideological homophily across the political spectrum may be issue- or context-specific (e.g. Brandt et al. 2014; Crawford et al. 2017), suggesting that liberal and conservative views on the role of firms in society may differentially induce homophily in the organisational setting.

Accordingly, while these findings ostensibly conflict with the behavioural differences between liberals and conservatives that have thus far been substantiated in management research (e.g. Gupta et al. 2020; Park et al. 2020), these may be explained by the well-documented tendency for conservatives to manage primarily according to the profit motive (Chin et al. 2013) compared with the increasing propensity for liberal ideologies to influence the strategic actions of firms (Bhagwat et al. 2020; Moorman 2020). The internal manifestations of this trend towards corporate sociopolitical activism have not yet been explored. These findings thus have practical significance in bringing attention to the issue of ideological homogeneity in firms, as has recently been highlighted in other organisational settings (Duarte et al. 2015; Haidt and Lukianoff 2018). Ideological diversity within teams can lead to more creative and novel problem-solving (Mannix and Neale 2005; Page 2008) whereas a lack of viewpoint diversity can prevent the recognition and correction of errors (Duarte et al. 2015). Similarly, network ties to dissimilar firms constitutes a form of board social capital that facilitates access to heterogenous knowledge resources (Withers et al. 2012). Ideological homophily within boards and interlock networks thus has clear implications for strategic decision-making , and understanding the factors that contribute to ideological homogeneity is pertinent to firms. Considering the temporal variation documented here in the homophilic effects of board liberalism, it may be increasingly important for directors to become aware, and mitigate the effects of, their ideological biases.

2.2 THEORY AND HYPOTHESES

2.2.1 The 'Rigidity of the Right' Versus 'Repressive Tolerance'

Homophily involves the selective and preferential formation of social connections to similar others. This effect is stronger for certain dimensions of similarity. For example, groups exhibit stronger homophily along the lines of race and ethnicity than gender or age (see McPherson et al. 2001 for a review). The most significant attribute upon which homophilic ties are formed is ideology: similarity in values, beliefs, and attitudes (Lazarsfeld and Merton 1954). This is the "arena where most people spontaneously recognise that similarity breeds fellowship" (McPherson et al. 2001, p. 428) and experimental evidence has long substantiated the tendency for preferential association along ideological lines (Huston and Levinger 1978). Ideological homophily may occur intentionally, as individuals learn about the beliefs of others and consciously choose to associate with similar others (Kossinets and Watts 2009). However, homophily may also occur on the basis of behaviour and thus unintentionally result in ideological homophily, as similar behavioural patterns are likely to reflect similar underlying belief structures (Jost et al. 2009; Gerber et al. 2011). Accordingly, much of what appears as demographic homophily can be explained by 'hidden' value congruence and/or the inclination to assume that demographically similar individuals hold similar ideological positions (Huckfeldt and Sprague 1995; McPherson et al. 2001).

Political orientation has been established as a key measure of ideology in the study of homophily (Knoke 1990; Huckfeldt and Sprague 1995), with the liberal-conservative spectrum considered the most parsimonious and practical classification for over 200 years (Jost 2006). Regarding social beliefs, conservatives prefer gradual change and respect existing norms and institutions (Carney et al. 2008), whereas liberals show greater tolerance of revolutionary change, risk, novelty, and complexity (Thórisdóttir and Jost 2011). In economic terms, conservatives' emphasis on individual agency and proportionality in rewards leads to a preference for free markets, property rights, and capitalism (Tetlock 2000) whereas liberals' focus on collective agency and social justice leads to an emphasis on egalitarianism and social safety nets (Gerber et al. 2010). This spectrum is a valid proxy for individuals' belief systems due to a strong and persistent association with underlying personality traits and values (Carney et al. 2008; Gerber et al. 2011,2012), stability over time (Jost 2006), and evidence for behavioural implication across multiple domains (Jost et al. 2009).

Evidence of the close correspondence between political ideology and personality predisposition appears to offer a clear prediction: conservatives will exhibit higher levels of homophily. Conservatives tend to view risk and novelty in more negative terms, feel a greater need to maintain safety and order, and are more likely to adopt rigid solutions to minimise perceived threats (Jost et al. 2008; Gerber et al. 2011). Conversely, liberals score higher on measures of openness to experience (Carney et al. 2008; Mondak and Halperin 2008) and exhibit greater tolerance for opposing points of view (Jost et al. 2003; Thórisdóttir and Jost 2011). However, findings from experimental psychology and survey studies challenge the assumption of conservative closed-mindedness, popularised in the 'rigidity of the right' model (Jost et al. 2003), finding that liberals and conservatives are equally intolerant against those with opposing views (Chambers et al. 2013; Brandt et al. 2014; Brandt and Van Tongeren 2017). Furthermore, intolerance is greater among liberals on economic issues, suggesting that prior results may arise from a conflation of social and economic aspects of political beliefs (Malka et al. 2014; Crawford et al. 2017). Similarly, liberals are more intolerant than conservatives when questionnaires are phrased in opposition to the respondents' ideology (for example, assessing intolerance to 'religious groups' or 'environmental groups' for liberals and conservatives, respectively) (Conway et al. 2016). Moreover, conservatives' emphasis on constitutionalism and thus the individual's right to freedom of speech and association may lessen the willingness to exclude others as a result of ideological intolerance (Wetherell et al. 2013) and, paradoxically, liberal open-mindedness increases intolerance of people who do not share this trait (Brandt et al. 2015).

Overall, experimental and survey evidence points to similar levels of ideological intolerance across the political spectrum. However, evidence from online and professional social networks shows revealed preferences among liberals that demonstrate *less* tolerance of opposing views (see also Haidt 2012; Haidt and Lukianoff 2018). For example, liberalism increases 'unfriending' behaviour on social media, with conservatives playing a lesser role in the dissolution of network ties (Yoo et al. 2018). This is reflected in liberals' social graphs: Colleoni et al. (2014) found that 88 percent of connections from liberal social media accounts are to other liberal accounts, whereas only 24 percent of connections from conservative accounts are ideologically congruent. This homophily also appears in offline networks. In a study of hiring and grant application decisions among social psychologists, Inbar and Lammers (2012) found that 82 percent of liberals admit to discriminating against those with opposing political beliefs, in comparison to 33 percent of moderates and 17 percent of conservatives. While this remains an understudied phenomenon (c.f. Duarte et al. 2015), the available evidence suggests that liberalism may increase homophily in certain social and professional contexts.

This raises the question of why recent studies diverge from common expectations about liberals' and conservatives' behaviour. Two interrelated causes have been identified. First, research has highlighted methodological issues in the surveys used to demonstrate the 'rigidity of the right', where early surveys conflate cognitive rigidity with attributes that are more common among conservatives, such as religiosity (Malka et al. 2017). In addition, measures of threat sensitivity were constructed around issues that are salient to conservatives, such as crime and terrorism, whilst omitting salient liberal issues such as climate change and police violence (Duarte et al. 2015). Later studies, which modified questions according to the ideologies of subjects, report significantly higher rates of intolerance among liberals (Conway et al. 2016, and see above). Notably, these studies find little difference in conservative intolerance between the original and modified scales, substantiating the claim that earlier instruments were biased towards capturing conservative intolerance (Malka et al. 2017). Second, these methodological issues may be partly explained by the ideological composition of psychology as an academic field (Haidt and Lukianoff 2018), where some of the most stark differences in intolerance have been observed. The acceptance of open discrimination along ideological lines documented by Inbar and Lammers (2012) has been attributed to the tendency for social groups, such as occupational fields, to serve as moral communities from which their members derive a shared sense of acceptable beliefs and behaviour (Hardin and Higgins 1996). This normalises intolerance against the ideological ‘outgroup’, who are seen to violate the shared morality of the community, and thus perpetuates homogeneity (Haidt 2012). The resultant composition of the field, which is dominated by liberals in a ratio of 14-to-1 in some areas (Duarte et al. 2015) and has become increasingly homogenous in recent years (Haidt and Lukianoff 2018), constrains the identification and correction of limitations when researching politicised topics (Baumeister 2015). The above methodological issues may thus be the unintentional consequence of ideologically influenced propensities to view certain issues as more worthy of examination (Duarte et al. 2015).

2.2.2 Homophily in Intra- and Inter-Organisational Networks

The trend towards ideological homogeneity in organisational settings is noteworthy due to the well-documented benefits of ideological diversity for the functioning of decision-making groups (Page 2008). When members of a team approach a problem with divergent mental models, the process of reconciling disagreements requires individuals to justify and re-evaluate their assumptions, surfaces potential blind spots, and consequently improves the quality of resultant decisions (Rindova 1999). Accordingly, ideologically heterogenous teams have consistently been shown to produce more creative and novel solutions to problems (Triandis et al. 1965; Mannix and Neale 2005). Conversely, ideological homogeneity discourages the exploration of ideas that conflict with the dominant assumptions of the group (Westphal and Zajac 1995), preventing the recognition of important questions and errors, which are then amplified by the commitment of the majority (Frey and van de Rijt 2020). A lack of consensus can therefore be critical to effective decision-making (Klarner et al. 2021). The appropriate setting to study ideological homophily in organisations is thus the level at which innovative solutions and erroneous decisions are most consequential. The board of directors, as the body that sets the strategic direction and objectives of the firm and must consider the impact of decisions on multiple stakeholders (Bailey and Peck 2013), meets this condition.

Ideological diversity is also pertinent at the level of the board interlock network due to the importance of shared directors in the process of information dissemination (Yoshikawa et al. 2019; Withers et al. 2020). Interlocks with dissimilar firms, which have primarily been studied in terms of industry membership, provide access to novel sources of information that may otherwise be outside of the focal firm's attention (Geletkanycz and Hambrick 1997; Srinivasan et al. 2018; Li 2019). Heterogeneity in board interlocks therefore constitutes a form of board social capital which facilitates access to varied knowledge resources (c.f. Withers et al. 2012). In the inter-organisational setting, cognitive differences between ideologically dissimilar boards may therefore confer a benefit to firms that form connections across the liberal—conservative spectrum, increasing exposure to divergent perceptions and interpretations of information.

Ideological homophily may therefore be consequential at two levels: within the intra-organisational group of directors and the inter-organisational network between firms. Despite recent calls for research into the dispositional antecedents of board and network composition (Gupta and Wowak 2017), the literature is silent on the effects of directors' ideologies on the structure of organisational networks and the position of the firm within these.

This author proposes that ideological homophily in the intra- and inter-organisational setting is a likely outcome of the two-sided matching problem that underlies the director selection process. New directors are generally proposed by the nominating committee and voted on by shareholders. While there is debate regarding the degree to which director selection is influenced by either rational economic concerns or sociological considerations (Withers et al. 2012) these two perspectives share a recognition that the personal attributes of directors and their alignment with incumbent board members are major factors in the nomination process (Hillman and Dalziel 2003). Furthermore, the appointment of new directors is not solely determined by the choices of the firm, but depends also on the preferences of potential directors. On this side of the matching problem, congruence of values is a key motivation for the acceptance or rejection of board appointments (Finkelstein et al. 2009; Withers et al. 2012). Board interlocks are also an outcome of this process, as an interlock is formed when an incumbent director at one firm is appointed to serve on the board of another firm. However, this is not merely a by-product of new director appointments, but often an intentional choice driven by the sociological and psychological consequences of network ties (Mizruchi 2013; Withers et al. 2020); for example, seeking connections with prestigious firms as a means of increasing perceived legitimacy within the corporate ecosystem (Mizruchi 1996; Connelly et al. 2011).

In sum, director appointments – and the resultant interlock network – are influenced by the desire of incumbent and potential board members to affiliate with peers that are deemed similar or favourable (Koenig et al. 1979). Considering the strong tendency for ideological homophily in interpersonal relationships (McPherson et al. 2001), it is reasonable to expect that ideology will play a critical role in these evaluations. Expressions of personal political values are becoming increasingly common among firm leaders (e.g. Moorman 2020), and the political activity of high-profile individuals is more visible than ever due to the widespread use of social media and public availability of campaign finance data. Consequently, directors have ample opportunities to learn about the ideology of their peers both within and across firms, even if such issues are not explicitly discussed in the director selection process. Furthermore, political ideology is highly correlated with a number of behaviours, including directors' decision-making on firm-level issues that are easily observable across companies and directly relevant to evaluations of whether a potential board member is compatible with a firm's governance approach (e.g. Di Giuli and Kostovetsky 2014; Gupta and Wowak 2017; Park et al. 2020). Homophily may therefore also include an ideological component as directors preferentially form connections with those that behave in similar ways, rather than because they explicitly seek peers of similar political orientations (c.f. McPherson et al. 2001).

Accordingly, ideological homophily in board composition and network ties may occur in two ways. First, given the socially embedded nature of the board, the nomination of new directors will be constrained by the attentional scope, social connections, and personal biases of incumbent directors (Bazerman and Schoorman 1983; Withers et al. 2020), encouraging both a conscious and unintentional preference for ideologically similar individuals (Koenig et al. 1979). Second, potential directors may accept or refuse board nominations based on alignment of values and behaviours with the incumbent board, whether or not these are explicitly recognised as arising from ideological similarity (c.f. McPherson et al. 2001; Withers et al. 2012). On both the supply and demand sides of this process, the ideology of the incumbent board is a hitherto unexamined criterion for matching.

Given the lack of previous research on ideological homophily in firms, the below hypotheses are derived from both organisational and psychological research. Following the reasons for the discrepancy between emerging psychological research and the 'rigidity of the right' model, and drawing upon recent research in organisations, three factors are observed that suggest greater ideological homophily among liberals in the board context: (1) *the relative importance of shared versus individual identity*; (2) *differences in the diversity of beliefs within political ideologies*; and (3) *differing perceptions of the relevance of ideology in firm decisions.*

First, liberal politics has recently shifted from the traditional focus on economic disparities toward cultural and social issues that are based in notions of group identity (Fukuyama 2018), placing increasing emphasis on the creation and maintenance of shared values and behaviours (see Bernstein 2005). The presence of ideologically divergent individuals within a social group threatens this cohesion and the 'shared reality' of members (Hardin and Higgins 1996). Furthermore, while liberalism has maintained a focus on addressing inequality and oppression, the philosophical foundation of this emerging form of 'identity politics' contrasts the materialist underpinnings of the traditional left-wing view, being substantially influenced by postmodernism (Horowitz et al. 2018). This has led to an increasing focus on the power of language to reinforce or disrupt social hierarchies (Bernstein 2005). Influenced by the concept of 'repressive tolerance' (Moore et al. 1965), there has been increasing acceptance of the notion that the liberation of historically oppressed groups necessitates the suppression of ideologies that are understood to support this oppression (Haidt and Lukianoff 2018; Pluckrose and Lindsay 2020). As conservatives are seen to uphold the status quo and thus the perceived oppression, intolerance of their presence within institutions becomes justified in the new liberal worldview (Horowitz et al. 2018; Epstein 2020). The implications of this for homophily are evident in the academy (Haidt and Lukianoff 2018) and media (Pluckrose and Lindsay 2020), the ideological composition of which has increasingly shifted towards liberalism as a result of organic homophilic processes and active attempts to exclude conservative viewpoints (Epstein 2020). This tendency conflicts with the conservative emphasis on freedom of association (Lister 2013), which attenuates conservatives' propensity to actively exclude ideologically incongruent others from social settings (Wetherell et al. 2013), and thus may be expected to induce greater homophily among liberals.

Second, the liberal focus on shared identity is juxtaposed by contemporary conservatism, which encompasses multiple distinct ideological groups (Klein and Stern 2005; Feldman and Johnston 2014). Many conservatives identify (and vote) as such because of a strong preference for free market economics (Iyer et al. 2012) without sharing the social and religious views traditionally associated with both conservatism and ideological intolerance (Keckler and Rozell 2015). Conversely, social and economic values are more closely correlated among liberals (Duarte et al. 2015). Social attitudes are more likely to form the basis of a shared group ideology as these tend to be more personally meaningful and emotive (Crawford 2017), which has been shown to contribute to higher levels of ideological intolerance among liberals on such issues (Malka et al. 2014; Crawford et al. 2017; Johnston et al. 2017). Furthermore, social issues have increasingly replaced economics in the landscape of political debate (Fukuyama 2018). Consequently, greater ideological homophily may be expected among liberals, as conservativism as a political affiliation lacks the shared social values that are (a) most relevant to formation of an in-group identity and (b) most salient in contemporary politics.

Third, two streams of research suggest that liberals and conservatives hold divergent views regarding the relevance of ideological considerations in the business context. A growing literature in strategic management examining the influence of decision-makers' ideologies on firm outcomes shows that while conservatives view their responsibility towards shareholders as primary, liberals consider a broader range of stakeholder needs as relevant to the goals of the firm (Chin et al. 2013). Accordingly, there is a robust relationship between liberalism and CSR activities at both the top management and board level (Chin et al. 2013; Di Giuli and Kostovetsky 2014; Gupta et al. 2020), while conservative managers have been associated with higher financial performance (Hutton et al. 2014). More recently, the marketing literature has begun to explore the antecedents and consequences of corporate socio-political activism, where firms take a public stance on divisive political or social issues (Bhagwat et al. 2020). While decision-makers' ideologies have not been examined as a contributing factor in the decision to undertake such actions, these studies consistently report higher levels of activism regarding liberal social causes (e.g. Bhagwat et al. 2020; Hydock et al. 2020). Furthermore, the temporal increase in corporate socio-political activism has been attributed to the growing perception that firms have a social responsibility to use their positions of power to promote societal change (Moorman 2020), reflecting the progressive worldview and focus on power dynamics that are central to contemporary liberal perspectives (Jost et al. 2009; Fukuyama 2018).

These findings concur with studies of ideology in academia, which find that liberals are more likely to view the promotion of ideological aims as relevant to their professional role (Haidt and Lukianoff 2018; Horowitz et al. 2018). If a certain progressive aim is viewed as desirable, and promotion of this aim seen as a central responsibility of the firm, liberal directors may be more likely to seek ideological congruence as a means of generating consensus and thus facilitating achievement of these aims (c.f. Rindova 1999). Conversely, the lower salience of ideological aims among conservatives in relation to firm decisions suggests that such considerations will not influence intra- and inter-firm relationship formation to the same extent.

Taken together, these three factors suggest that liberals will exhibit greater homophily than conservatives in both the relations between directors and the network of connections between boards. This leads to the hypothesis that *board liberalism*, the extent to which incumbent directors hold liberal rather than conservative political affiliations, will lead to higher levels of *board ideological homophily,* manifest as less ensuing diversity in directors' political views:

> ***Hypothesis 1 (H1):*** *Board liberalism is positively related to board ideological homophily, such that higher liberalism among directors leads to lower ideological diversity within the board*

Similarly, it logically follows to predict that board liberalism will lead to higher levels of *network ideological homophily,* i.e., preferential connections to other ideologically congruent boards:

> ***Hypothesis 2 (H2):*** *Board liberalism is positively related to network ideological homophily, such that higher liberalism among directors leads to lower ideological diversity within the board interlock network*

As suggested at multiple points in the preceding discussion, many reasons to expect greater ideological homophily among liberals have emerged or accelerated in recent years (Haidt and Lukianoff 2018). This leads to the hypothesis that these effects exhibit temporal variation, with liberalism exhibiting a stronger relationship with ideological homophily over time.

> ***Hypothesis 3 (H3):*** *The positive effect of board liberalism on (i) board homophily, (ii) network homophily has increased over time.*

2.3 METHOD

2.3.1 Data and Sample

Following common practice in board research (Withers et al. 2020) and due to the availability of data (Zhu et al. 2014), this study was conducted on large U.S. firms. Data from BoardEx was used to derive measures of board composition, director characteristics, and to identify board interlocks. Corresponding firm-year data from Compustat was used for firm- and industry-level variables. Measurement of political ideology was based on data on the campaign contributions of individuals from the U.S. Federal Election Committee (FEC), the regulatory agency that records campaign financing for all donations over 200 USD. Per the coverage of these databases, the sample covers publicly traded firms that have at least one establishment and one director in the U.S. Firms operating in highly regulated or noneconomic sectors (SIC codes 60-69 and 91-99) and those with less than 100 million USD in total assets were removed to ensure that the sample excludes firms in which incumbent directors have little influence over board composition and smaller firms in which the board has relatively little influence over strategy formulation (Finkelstein and Hambrick 1996; Withers et al. 2020). The final sample comprises 2,172 observations of 408 firms between 2000 and 2020. Table 2.3.1.1 summarises all measures and data sources. Table 2.3.1.2 provides descriptive statistics and correlations.

TABLE 2.3.1.1 Variable Operationalisations and Sources

Variable	Definition	Source
Board liberalism	Average of directors' political ideology, where director ideology is calculated as the average of four measures over the previous 10 years: (1) number of donations to Democrat campaigns divided by total number of contributions (to Republican and Democrat campaigns), (2) dollar amount of donations to Democrat campaigns divided by total dollar amount of donations, (3) number of years in which a donation is made to Democrat campaigns divided by the total number of years in which a donation is made, (4) number of unique Democrat recipients of donations divided by total number of donation recipients.	U.S. FEC, BoardEx
Board ideological homophily	Inverse of the coefficient of variation in directors' personal political ideologies (standard deviation divided by mean)	U.S. FEC, BoardEx
Network ideological homophily	Ratio of ideologically congruent director interlocks to total number of interlocks, where ideologically congruent interlocks are defined as a director serving on a liberal (conservative) focal board and a liberal (conservative) connected board	U.S. FEC, BoardEx
Board tenure	Average number of years that directors have served on the board	BoardEx
Board size	Number of directors	BoardEx
Board independence	Proportion of outside directors	BoardEx
Director gender diversity	Female directors as a percentage of all directors	BoardEx
Director nationality diversity	Non-U.S. directors as a percentage of all directors	BoardEx
Director age diversity	Standard deviation in directors' age	BoardEx
CEO duality	Indicator that takes the value of 1 if the CEO is also the board Chair; zero otherwise	BoardEx
Firm size	Natural log of total assets	Compustat
Firm performance	Tobin's Q, calculated as the market value of the firm plus liabilities divided by the book value of assets	Compustat

Variables are standardised in all models to aid interpretation of coefficients.

TABLE 2.3.1.2 Descriptive Statistics and Correlations

Variable	Mean	SD	1	2	3	4	5
1 Board liberalism	.526	.335					
2 Board ideological homophily	.925	.177	.162				
3 Network ideological homophily	.530	.358	.139	.064			
4 Board tenure	8.775	4.138	-.038	-.044	.005		
5 Board size	8.969	2.269	-.018	-.081	.005	-.037	
6 Board independence	8.190	2.334	-.017	-.076	.005	-.042	.984
7 Director gender diversity	.118	.107	.084	-.055	.017	-.057	.320
8 Director nationality diversity	.093	.167	.037	.025	.023	-.126	.134
9 Director age diversity	7.550	2.392	.007	.008	-.011	.132	-.039
10 CEO duality	.553	.497	-.044	-.025	-.014	.024	.004
11 Firm size	7.396	1.560	-.008	-.086	-.017	-.108	.571
12 Firm performance	1.402	1.313	-.002	-.044	-.028	.002	-.050

Variable	6	7	8	9	10	11
7 Director gender diversity	.317					
8 Director nationality diversity	.140	.058				
9 Director age diversity	-.035	-.146	-.026			
10 CEO duality	-.101	.018	-.016	-.051		
11 Firm size	.565	.311	.173	-.180	.076	
12 Firm performance	-.050	.023	.054	.033	.009	-.062

Variables are standardised in all models to aid interpretation of coefficients.

2.3.2 Measures

Independent variable. Following prior research (e.g., Chin et al. 2013; Chin and Semadeni 2017; Gupta et al. 2020), political ideology was measured using political campaign contributions recorded by the U.S. FEC. This measure focuses on donations to the two major parties, as third party contributions are rare (200,000, compared to over 32 million donations to major parties, in this dataset) and support for Democrats and Republicans is strongly related to ideological liberalism and conservatism, respectively (Jost 2006). This measure is based on individual directors' donations, as corporate contributions tend to be motivated by non-ideological aims (i.e., lobbying), whereas directors will use their personal contributions to express ideological preferences (Ansolabehere et al. 2003; Fremeth et al. 2013). U.S. FEC donations were matched to the director data in BoardEx based on correspondence between individuals' names, organisations, and occupations, employing automated matching and manual cross-verification to avoid false negatives/positives.

Individual directors' yearly campaign contributions were coded as either Democrat or Republican and calculated four measures of ideology for each director-year in the sample, using a rolling window of the previous 10 years of donation data. This window encompasses five congressional and two presidential election cycles, enabling meaningful inference about an individual's stable ideology (Chin et al. 2013). The four measures are: (1) the number of donations to Democrats divided by the total number of donations to both parties; (2) the number of years in which a donation is made to a Democrat divided by the total number of years in which a donation is made to either party; (3) the number of unique Democrat recipients divided by the total number of unique recipients across both parties; and, (4) the dollar amount of donations to Democrats divided by the total dollar amount of donations to both parties. In line with previous usage, means and distributions are similar across these measures and they exhibit high internal reliability (Cronbach's $\alpha = .99$), enabling the computation of a composite measure of liberalism by calculating the mean. As each measure is a ratio, director ideology is thus measured on a zero to one scale, with higher values representing liberalism. A value of .5 was imputed for directors who made zero donations, thus assuming these individuals to be ideologically moderate. This is justified and validated by Chin et al. (2013), who combine donation-based measures of ideology with executive surveys and find close correspondence, including for moderates and non-donors.

Board liberalism is then computed as the average liberalism across directors in each firm-year, i.e. the sum of the ideology scores of individual directors divided by the number of directors on the board. This measure of board liberalism is thus time-varying for two reasons. First, the ideology of individual directors may change over time as the rolling 10-year window of donations changes. Accordingly, the ideology score assigned to each director is primarily driven by the long-run trend in donation behaviour while also accounting for recent changes. Second, board liberalism will vary over time as directors enter and leave a firm's board. As ideology tends to remain fairly consistent within individuals (Jost 2006; Chin et al. 2013), most temporal variation will arise from these changes in board composition.

Dependent variables. The above hypotheses state that board liberalism will affect the structure of intra- and inter-organisational networks, respectively termed board and network homophily. These variables were computed from a combination of FEC and BoardEx data for each firm-year in the sample, allowing network structure and position to vary over time. To construct a network of board interlocks, a bimodal network was first created representing (i) the connections between directors and the boards on which they serve and (ii) the connections between boards, defined by the presence of a shared director. From this, a unimodal network of inter-firm connections was derived, enabling computation of network variables (Borgatti and Everett 2006).

Board homophily. Using the composite measure of board liberalism defined above and the corresponding director-level measures of ideology, board homophily is measured by first computing the coefficient of variation in board ideology*:* the standard deviation in liberalism across directors scaled by the mean liberalism of the board (Narayan et al. 2020). This captures the variation in political ideology among the firm's directors independent of the overall level of liberalism or conservatism on the board (c.f. Harrison and Klein 2007). To measure homophily, the inverse of this measure is therefore used, such that higher values represent lower variation in ideology among directors.

Network homophily. The measure of network homophily was similarly derived from the composite board liberalism score calculated above. First, the number of interlocks between the focal firm and other firms in the network was counted, assigning indicators for ideologically congruent interlocks (i.e., liberal-to-liberal or conservative-to-conservative boards) based on whether board liberalism is above or below moderate (.5) for the focal and connected board. Moderate-to-moderate interlocks were not counted as ideologically congruent, per the argument that moderates' lack of ideological commitment attenuates any ideologically motivated behaviours (Ansolabehere et al. 2003; Gupta and Wowak 2017). Network homophily was then calculated as the ratio of ideologically congruent interlocks to the total number of interlocks.

Using donation-based measures of individual ideology overcomes a key issue in the study of homophily: disentangling the effects of real ideological similarity from the effects of (mis)perceived similarity that arises from cognitive biases (Huckfeldt and Sprague 1995; McPherson et al. 2001). In previous studies of political ideology homophily, it has been unclear whether individuals form ties based on actual ideological similarity or on demographic characteristics that tend to be correlated with political beliefs (McPherson et al. 2001). Using donation data addresses this confounding effect, as it avoids the subjectivity inherent in self-reported measures of one’s own and others political beliefs. Controlling for key demographic characteristics (see below) further mitigates this issue.

Controls. The various controls used in this study were selected for their effects on the implications of director ideology (e.g. Gupta and Wowak 2017; Park et al. 2020), the composition of boards and interlock networks (Withers et al. 2020), and the extent to which homophily is ideologically driven (McPherson et al. 2001). At the board-level, these are: *board tenure,* measured as the average number of years that directors have served on the board; *board size,* the number of directors; *board independence,* the proportion of outside directors; *director gender diversity,* the proportion of female directors; *director nationality diversity,* the proportion of non-U.S. directors; *director age diversity,* the standard deviation in directors’ ages; and *CEO duality,* an indicator that takes the value of 1 if the CEO also serves as board Chair. At the firm-level, these are: *firm size,* measured as the natural log of total assets, and *firm performance,* for which Tobin’s Q is used to capture future and present market and financial aspects. All models also include controls for *peer firm outcome,* calculated as the average of the dependent variable across other firms (excluding the focal firm) in the same 2-digit SIC code. As network structure is necessarily dependent on other firms, this serves to isolate the focal firm's outcomes from broader changes in the network.

All models were also estimated with industry and year dummies. Controlling for year effects serves two main purposes in these analyses. First, directors' contributions to political campaigns are likely to differ based on the presidential and congressional candidates in each election. Second, directors may alter their contributions according to the macroeconomic environment; for example, reducing their donations during recession years. Including year fixed effects mitigates these issues (c.f. Fremeth et al. 2013).

2.3.3 Model Specification and Estimation

Hypotheses 1 and 2 were tested using generalised estimating equations (GEE) to deal with multiple observations of the dependent variables, non-independent observations, and unobserved firm heterogeneity. A Gaussian distribution was specified, as the dependent variables are normally distributed, an identity link function, and an exchangeable correlation structure (tests of the correlation structure assumptions are provided in the robustness checks). All variables were standardised to aid interpretation of coefficients.

Several methods were implemented for addressing endogeneity, which may arise from unobserved heterogeneity or reverse causality. As in prior research utilising variables based on political ideology (Chin et al. 2013; Chin and Semadeni 2017; Gupta and Wowak 2017), fixed effects estimation is inappropriate to address firm heterogeneity as the dependent variables exhibited moderate intertemporal correlation within firms (board homophily = .397; network homophily = .271). Instead, a comprehensive list of control variables was included to account for alternative explanations of network structure and position at the board-, firm-, industry-, and year-level. Including the average dependent variable among peer firms as a control is critical here, as this helps to capture current and historical influences on the focal firm's network (Wooldridge 2013). Additional tests, detailed below, examined the impact threshold for a confounding variable (ITCV) (c.f. Harmon 2019; Hill et al. 2020) and found that the results are unlikely to be driven by the effects of a correlated omitted variable.

A further concern related to omitted variables is that homophily may be largely driven by a baseline component, reflecting opportunity constraints rather than active selection (McPherson et al. 2001; Borgatti and Foster 2003). For example, women show greater heterophily in male-dominated professions: despite a preference for demographic homophily, these ties are inevitable given the baseline availability of network ties (Ibarra 1993). A similar concern may be present in this data if liberal directors are more prevalent than conservatives. However, the mean and standard deviation of board ideology in the sample indicated a platykurtic normal distribution centred on moderate positions (mean = .526, SD = .335), suggesting that homophily in inter-firm networks is not significantly driven by a baseline component. The distribution of individual directors' liberalism (mean = .513, SD = .436) also suggested that baseline homophily in intra-firm networks is not an issue, in line with prior research (Kleinbaum et al. 2013).

Reverse causality may also be a concern in these models: individuals have a propensity to form ties with similar others, but are ideologically influenced by those with whom they interact, which may induce ideological homogeneity as a result, rather than antecedent, of network proximity (Carley 1991; Kilduff and Corley 2000). This was addressed in four ways. First, all independent variables were measured one period prior to the dependent variables, thus predicting future network structure from current ideology to mitigate concerns of simultaneity. Second, to address intertemporal correlation in the dependent variables, the average of the dependent variable among peer firms was included as a control to isolate the changes in network structure within the focal firm. Third, two-stage least squares (2SLS) instrumental variables regression was used to test for endogeneity. This requires an instrument that is theoretically relevant (i.e., a strong predictor of the potentially endogenous variable of board ideology) and exogenous (i.e., uncorrelated with the error term in the main model) (Bascle 2008). Following prior research (Gupta and Wowak 2017), peer firm liberalism was used as the instrumental variable, which is a significant predictor of the focal firm's board liberalism ($F = 1474.380$; $p < .001$). 2SLS analyses indicated that there are no endogeneity concerns for the key independent variable: a Durbin-Wu-Hausman test did not reject the null hypothesis that board liberalism was exogenous (board homophily: $F = .340$, $p = 0.560$; network homophily: $F = .100$, $p = 0.752$). It can therefore be concluded that the instrumental variables approach is unnecessary (Wooldridge 2013). Accordingly, the results estimated with GEE are presented below. Finally, a panel instruments approach (Arellano and Bond 1991) was employed, where lagged values of the focal variables are employed as instrumental variables. Results are in accordance with the main models and reported in the robustness checks.

Hypothesis 3 was examined with a mixed effects model with time as a linear random component, enabling the examination of time as a focal predictor of homophily. This model assumed a Gaussian distribution for the overall error structure and independence of the variance parameters for the firm-level and temporal random effects (Raudenbush and Bryk 2002). All control variables listed above were included.

2.4 RESULTS

Table 2.4.1 presents the results of the GEE models corresponding to tests of Hypotheses 1 and 2. Table 2.4.2 presents the results of two mixed effects models corresponding to tests of Hypothesis 3 regarding temporal shifts in homophilic behaviour at the board- and network-level.

TABLE 2.4.1 Effects of Board Liberalism on Network Structure and Position

Dependent variable	(1) Board ideological homophily		(2) Network ideological homophily	
Effects of interest				
Board liberalism	0.062	(.000)***	0.094	(.001)***
Controls				
Board tenure	-0.042	(.453)	-0.002	(.988)
Board size	-0.311	(.367)	1.203	(.065)*
Board independence	0.208	(.541)	-1.010	(.113)
Director gender diversity	-0.023	(.470)	0.054	(.369)
Director nationality diversity	0.025	(.364)	0.035	(.490)
Director age diversity	-0.066	(.222)	-0.151	(.139)
CEO duality	-0.004	(.785)	-0.061	(.018)**
Firm size	-0.012	(.794)	0.004	(.955)
Firm performance	-0.058	(.528)	0.137	(.415)
Peer firm board ideological homophily	0.197	(.038)**		
Peer firm network ideological homophily			0.071	(.292)
Year dummies	Included		Included	
Industry dummies	Included		Included	
Constant	0.674	(.000)***	0.411	(.051)*
Wald χ^2	260.180	(.000)***	136.180	(.000)***

* $p \leq 0.1$, ** $p \leq 0.05$,*** $p \leq 0.01$

TABLE 2.4.2 Temporal Change in Effects of Board Liberalism on Network Structure

Dependent variable	(1) Board ideological homophily		(2) Network ideological homophily	
Effects of interest				
Board liberalism	-0.010	(.752)	-0.111	(.103)
Time	-0.157	(.000)***	-0.231	(.001)***
Board liberalism x Time	0.125	(.023)**	0.392	(.000)***
Controls				
Board tenure	-0.037	(.509)	-0.016	(.880)
Board size	-0.165	(.646)	0.727	(.272)
Board independence	0.071	(.839)	-0.565	(.382)
Director gender diversity	0.007	(.831)	0.076	(.209)
Director nationality diversity	0.025	(.361)	0.010	(.839)
Director age diversity	-0.013	(.808)	-0.129	(.202)
CEO duality	-0.007	(.639)	-0.043	(.109)
Firm size	-0.011	(.787)	-0.062	(.363)
Firm performance	0.087	(.313)	0.184	(.237)
Peer firm board ideological homophily	-0.148	(.052)*		
Peer firm network ideological homophily			0.136	(.022)**
Industry dummies	Included		Included	
Constant	1.062	(.000)***	0.427	(.002)***
Wald χ^2	44.040	(.000)***	42.010	(.000)***

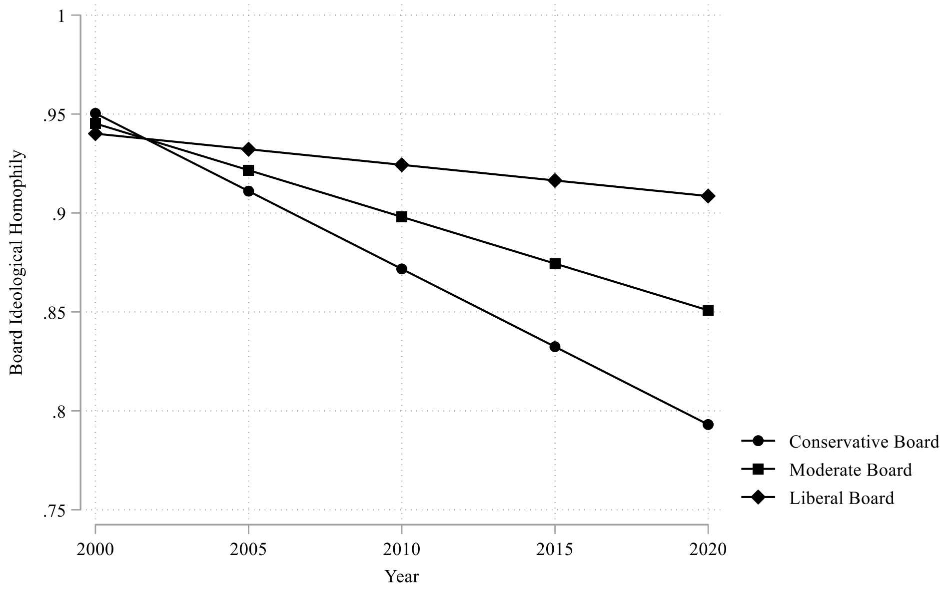
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

H1 predicted that board liberalism would lead to greater ideological homophily within the board. This is supported: the effect of board liberalism is positive and significant at the 1% level (0.062, $p < .001$). H2 likewise predicted that board liberalism would lead to greater homophily within the board interlock network. This is also supported by a positive and highly significant effect (0.094, $p = .001$). These results therefore provide strong support for the notion that board liberalism increases ideological homophily in both intra- and inter-firm networks.

In terms of temporal variation (H3), it is first observable that both board and network ideological homophily have decreased between the years of 2000 and 2020, as indicated by the negative effect of time in both models (board: -0.157, $p < .001$; network: -0.231, $p = .001$). The results also show that the interaction of board liberalism and time has a positive and significant effect on both dependent variables. In the case of board ideological homophily (0.125, $p = .023$), this effect is lesser in absolute magnitude than the negative temporal change. From these results it can be concluded that (1) while overall homophily among directors has decreased in recent years, this effect is less pronounced among liberals and (2) the positive effect of liberalism on board ideological homophily has increased over time. Figure 2.4.1 illustrates these effects.

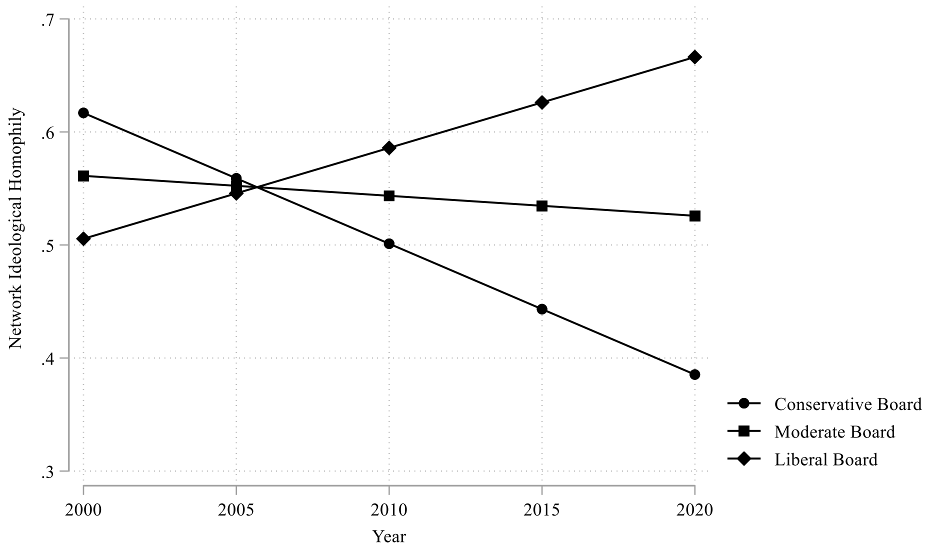
A different temporal trend is evident for the effect of board liberalism on network ideological homophily. Again, the contingent effect is positive (.392, $p < .001$). However, this is substantially larger than the negative effect of time, resulting in a positive marginal effect. As shown in Figure 2.4.2, these results indicate that the general decrease in network ideological homophily is absent among liberal boards; instead, there has been a decrease in homophilic ties among conservative boards, stability among moderates, and an increase among liberals. In both models, the main effect of board liberalism becomes nonsignificant when the interaction with time is included, further validating a temporal shift in homophilic behaviour among liberal boards.

FIGURE 2.4.1 Temporal Effects of Board Liberalism on Board Ideological Homophily



Conservative, moderate, and liberal boards indicate linear predictions at board liberalism values of 0, 0.5, and 1, respectively.

FIGURE 2.4.2 Temporal Effects of Board Liberalism on Network Ideological Homophily



Conservative, moderate, and liberal boards indicate linear predictions at board liberalism values of 0, 0.5, and 1, respectively.

Overall, H1 and H2 are supported, indicating positive effects of board liberalism on board- and network-level ideological homophily. H3 is also supported, though the nature of temporal change differs between the outcomes of board and network ideological homophily.

2.4.1 Robustness Checks

Several methods were used to assess the robustness of these results. First, the correlation structure assumptions of the GEE models were assessed using the quasi-likelihood under the independence model criterion (QIC) test (Cui and Qian 2007). Table 2.4.1.1 displays the results for three common correlation structures across the two models. With the assumption of unstructured correlation, model convergence was not achieved. From the remaining correlation structures, the results of this test show a lower QIC for the exchangeable structure in each of the models, thus indicating that this is the most appropriate assumption for estimation.

TABLE 2.4.1.1 Tests of Correlation Structure Assumptions for GEE Models

Dependent variable	Correlation	QIC
(1) Board ideological homophily	Unstructured	Convergence not achieved
	Independent	143.302
	Exchangeable	**134.162**
(2) Network ideological homophily	Unstructured	Convergence not achieved
	Independent	175.940
	Exchangeable	**174.673**

Second, tests were conducted for the impact threshold for a confounding variable (ICTV) (Frank 2000; Pan and Frank 2003). The ICTV estimates the size of the effect of an omitted variable that would be required to invalidate the results of a model. As shown in Table 2.4.1.2, the required impact is substantially greater than the impact of all other control variables. Under the assumption that the included control variables are appropriate, the ICTV test therefore suggests that the above results are unlikely to be driven by the effects of a correlated omitted variable.

TABLE 2.4.1.2 Tests of Impact Threshold of a Confounding Variable for GEE Models

Dependent variable	(1) Board ideological homophily	(2) Network ideological homophily
ICTV	0.053	0.031
Observed impact		
Board tenure	0.000	-0.000
Board size	0.003	-0.002
Board independence	0.003	-0.002
Director gender diversity	-0.001	0.001
Director nationality diversity	0.001	0.002
Director age diversity	-0.000	-0.000
CEO duality	-0.000	0.006
Firm size	0.004	0.003
Firm performance	-0.001	-0.001
Peer firm board ideological homophily	-0.004	
Peer firm network ideological homophily		0.003

Third, as a further check against potential endogeneity all models were estimated using the panel instruments approach of Arellano and Bond (1991). As reported above, 2SLS was determined unnecessary as a Durbin-Wu-Hausman test did not reject the null hypothesis that board liberalism was exogenous for each model. However, this test relies on the assumption that the instrumental variables used in 2SLS are valid, which cannot be directly tested (Semadeni et al. 2014). Given this concern and the intertemporal correlation of the dependent variables, the Arellano and Bond estimator was nevertheless employed as an alternative method of accounting for endogeneity without requiring the introduction of additional instruments. Table 2.4.1.3 reports the results. In each model, the effects of board liberalism correspond to the main results reported above.

TABLE 2.4.1.3 Panel Instruments Estimation of Effects of Board Liberalism

Dependent variable	(1) Board ideological homophily		(2) Network ideological homophily	
Effects of interest				
Board liberalism	0.148	(.000)***	0.171	(.000)***
Controls				
Board tenure	0.020	(.833)	0.329	(.118)
Board size	0.459	(.374)	0.398	(.712)
Board independence	-0.512	(.314)	-0.337	(.747)
Director gender diversity	0.022	(.617)	0.049	(.615)
Director nationality diversity	0.013	(.754)	0.005	(.954)
Director age diversity	0.046	(.601)	-0.371	(.056)*
CEO duality	-0.034	(.090)*	0.011	(.789)
Firm size	-0.260	(.026)**	-0.118	(.678)
Firm performance	-0.011	(.934)	-0.807	(.006)***
Peer firm board ideological homophily	1.124	(.000)***		
Peer firm network ideological homophily			0.764	(.000)***
Lagged dependent variable	0.034	(.123)	-0.029	(.305)
Constant	-0.136	(.364)	0.682	(.009)***
Wald χ^2	261.720	(.000)***	165.290	(.000)***

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

2.5 DISCUSSION

This study addresses the lack of research examining how the dispositional characteristics of directors influence both board- and network-level outcomes (Shropshire 2010; Gupta and Wowak 2017), providing new evidence for the role of ideology in the composition of board and the formation of interlocks. Ostensibly, these findings diverge from the present body of evidence on director ideology, which supports the stereotypical view of the liberal—conservative behavioural divide (e.g. Gupta and Wowak 2017; Park et al. 2020). These results instead echo recent evidence that challenges traditional assumptions and demonstrates that the values and behaviour of liberals and conservatives may be issue- or context-specific (Brandt et al. 2014; Crawford et al. 2017; Malka et al. 2017). Specifically, this author suggests that the higher levels of ideological homophily observed among liberal boards may be due to the differing salience of ideology in the business setting, with liberal directors increasingly viewing the role of the firm in social and political terms whereas conservatives uphold the primacy of shareholder responsibility (c.f. Bhagwat et al. 2020; Moorman 2020). Manifestations of this trend within the firm have not yet been examined; thus, this study highlights the need for greater recognition of these factors in the firm setting. This is important given the recent and ongoing rise in political polarisation in the U.S. and other major economies – developing an understanding of the characteristics and behavioural tendencies of those with opposing views that transcends established stereotypes may be imperative for managing intra-organisational tensions in the contemporary political environment.

These findings mirror those of recent investigations into the structure of academic fields, where there have been concerns regarding the effect of (liberal) ideological homogeneity within research domains due to the documented benefits of ideological diversity (Duarte et al. 2015). Politically heterogenous teams have consistently been shown to produce more creative and novel solutions to a variety of problems (Page 2008). Conversely, lack of ideological diversity can prevent the recognition of important questions and new ideas (Westphal and Zajac 1995) and correction of errors (Duarte et al. 2015), leading to poorer group decision-making when there is a clear ideological majority as mistakes becomes self-perpetuating (Frey and van de Rijt 2020). The absence of consensus among key decision-makers can therefore improve strategic decisions (Rindova 1999; Klarner et al. 2021). Similarly, heterogeneity in network ties increases the likelihood that a firm will be exposed to novel sources of information , constituting a form of board social capital that enables access to knowledge resources (Withers et al. 2012).

Considering the key differences between liberals and conservatives, homogeneity in political ideologies may be particularly consequential for these two benefits. At the board-level, for example, the tension between novelty- or risk-seeking behaviours (liberal) and maintenance of order and routine (conservative) reflects the need to balance managerial discretion with preventing agency problems in corporate governance (Fama and Jensen 1983) and exploration versus exploitation in developing and utilizing firm capabilities (Kang and Kim 2020). Similarly, competing emphases on egalitarianism (liberal) and proportionality (conservative) may be beneficial in creating compensation policies that mitigate the problems of pay disparities while effectively incentivising performance (Gupta and Wowak 2017). At the network-level, homophily may limit the information that firms choose to share, limiting the diffusion of relevant knowledge. For example, if conservative boards are more likely to encourage adoption of governance practices, and liberal boards of CSR, among interlocked firms (as postulated by Gupta & Wowak, 2017), network homophily may inhibit the spread of best practices – a key benefit of interlock networks (Yoshikawa et al. 2019).

Accordingly, while ideological homogeneity may facilitate the pursuit of certain progressive aims, this could hinder the adoption of other beneficial policies and practices. The observed temporal variation in the homophilic tendencies of liberal boards indicates that it may be more important than ever for directors to be aware, and mitigate the effects, of their personal ideological biases; for example, by seeking to appoint directors with differing political views, establishing interlocks with ideologically incongruent firms, or simply actively challenging their own assumptions (c.f. Baumeister 2015). A fruitful avenue for further research may be to examine the performance implications of this, particularly under the presently increasing focus on stakeholder-oriented governance practices that are typically associated with liberal ideologies (c.f. McGahan 2021).

On a broader level, this study contributes to the growing literature demonstrating that ideological intolerance is prevalent on both sides of the liberal—conservative spectrum and greater among liberals under certain circumstances (e.g. Inbar and Lammers 2012; Brandt et al. 2015; Crawford et al. 2017). The approach employed here is particularly pertinent, as these recent contributions have developed from methodological criticisms of earlier work: specifically, the use of survey instruments that are arguably biased toward capturing ideological intolerance among conservatives and measure opinion rather than behaviour (Malka et al. 2017). This study presents an alternative method that circumvents the issues inherent in questionnaire design by utilising a secondary measure of ideology and capturing revealed preferences for homophily by examining network ties. The results complement recent studies in political psychology that further corroborates a more nuanced perspective of intolerance across the ideological spectrum.

2.5.1 Limitations and Directions for Future Research

The author recognises several limitations of this study that present opportunities for further research. While the use of secondary data provides some advantages over previous methodologies, this also limits the ability to examine the motivations for ideological homophily. Survey-based research may therefore offer a path toward elucidating whether board and network homophily along ideological lines is deliberate or unintentional. Furthermore, the main data source (BoardEx) does not provide information on the source of board appointments or interlocks, i.e., whether a director is appointed to a second board following nomination by shareholders, the CEO/top management team, or incumbent directors. It is assumed that the extant board has considerable influence in both composition and network formation (see Mizruchi 2013; Withers et al. 2020), however, more in-depth information gathered from firms' archival sources may elucidate how the appointment of new directors influences the extent of ideological homophily. As a preliminary hypothesis, higher levels of homophily may be expected when directors have greater control over this process, due to their involvement in the resultant social networks and thus greater motivation to influence these towards ideological congruence. If this is the case, increased involvement of shareholders and managers in the appointment of new directors may be an effective method of mitigating ideological homophily.

Using data from the U.S. FEC also necessarily limits this investigation (as in prior research on directors' and executives' ideologies) to the U.S. context. However, the effects of personal politic ideologies on tolerance and homophily have been found to differ across national contexts, where the liberal—conservative distinction is not reflected in a clear left—right party divide (Malka et al. 2014; Malka et al. 2017). Furthermore, as in prior research, this study does not consider the political ideologies of directors who donate to third parties – yet psychological research suggests a more nuanced classification of political affiliation may provide valuable information about the beliefs and behaviours of individuals. For example, while libertarians are often economically aligned with conservatives in the U.S. due to a shared focus on free market capitalism and individualism, these groups exhibit stark differences in their openness to new ideas and deference to established norms (Iyer et al. 2012): traits that may be consequential for strategic decisions due to their effects on innovation and risk-taking (Christensen et al. 2015; Kashmiri and Mahajan 2017). The idiosyncrasies of the U.S. political spectrum may therefore contribute to this ostensibly counterintuitive finding of greater tolerance among conservatives. Research in other political contexts with a variety of potential party affiliations (such as European countries) could therefore clarify these results, as well as providing insight into whether the effects observed here are present under differing national systems of corporate governance.

2.5.2 Conclusion

This study presents the first examination of ideological homophily in two key organisational networks: the intra-firm connections among directors on a firm's board and the inter-firm network of interlocks between boards with shared directors. The author hypothesises and demonstrates that board liberalism increases the propensity towards ideologically congruent ties at both levels. Further, this effect is shown to have increased in recent years: while both the composition of boards and the connections between boards have become more ideologically diverse in recent years, this effect has been driven by conservatives while liberal directors have reduced their ties to those with opposing political views, particularly at the inter-firm level. A review of the psychological and management literature highlights three primary reasons for these findings: (1) the increasing emphasis placed on shared identity among liberals; (2) the trend towards convergence of ideological positions within the liberal end of the political spectrum, as opposed to growing differences among social and economic conservatives; and, (3) the greater tendency among liberals to view ideological considerations as relevant to firm-level decisions.

In providing the first evidence for an ideological component in the composition of boards and board networks, this study advances present understanding of the dispositional antecedents to director selection and network formation, with theoretical and practical implications for corporate governance and broader conversations regarding homophilic tendencies across the political spectrum. For researchers, these findings contribute to the development of a more holistic theoretical framework of direction selection and interlock formation that accounts for individual dispositional factors in addition to the more commonly studied situational and dispositional antecedents. For directors, these results bring attention to the presence and growth of homophilic tendencies within firms, suggesting that it may be increasingly important to be aware, and mitigate the effects of, one's own ideological biases in order to maintain cognitive diversity in information networks and decision-making.

3 THE WISDOM AND MADNESS OF CROWDS: BOARD INTERLOCKS, STRATEGIC DEVIATION, AND FIRM PERFORMANCE

3.1 INTRODUCTION

During recessions, most firms reduce investment in marketing and R&D and instigate job and wage cuts to conserve resources (Fan et al. 2020), despite evidence that this exacerbates the impact of declining demand and environmental uncertainty (Dekimpe and Deleersnyder 2018). A small minority of firms counter this trend: following the recessions of 1980, 1990, and 2000, 80% of U.S. firms struggled to restore profitability, while 9% outperformed competitors by 10% or more in terms of both revenue and profit growth (Gulati et al. 2010). These high-performers appear to view recessions as an opportunity to improve long-term performance, investing in areas that their peers neglect (Steenkamp and Fang 2011). However, this conclusion is based on inferring strategic motives from patterns of investment—little is known about *why* specific firms deviate from strategic norms (Dekimpe and Deleersnyder 2018). What leads the majority of firms to respond to recessions in homogenous ways, and what this can tell us about the minority that succeed despite this trend, thus remain open questions.

To address these questions, this study draws on the theory of institutional isomorphism, which posits that environmental uncertainty leads to ‘collective rationality’ among firms and thus to homogeneous strategic responses (DiMaggio and Powell 1983). This occurs through *mimetic* *processes*, where firms search for satisfactory strategies by imitating others, and *normative pressures*, which produce common cognitive biases among decision-makers. The rarity of strong performance during recessions suggests that this may be due to an ability to avoid isomorphism, either by maintaining independence from peer firms (avoiding mimetic processes) or widening the cognitive scope of decision-making teams (avoiding normative pressure).

This author proposes that mimetic processes and normative pressures operate at the level of the board of directors—the key decision-making unit in times of strategic change (Carpenter and Westphal 2001; Morais et al. 2020)—to affect firm performance. This study assesses mimetic processes by examining board interlock networks, utilising three network-level measures of the degree to which a firm's board is *connected or isolated* from others in the network. Two director-level measures of normative pressures are developed based on the *diversity or homogeneity* of directors' educational and professional experience. The findings support institutional isomorphism as an explanation for widespread poor performance. Specifically, profitability, firm value, and investments in marketing and R&D during recessions are negatively related to the board's network centrality and ties to other industries, whereas intra-industry ties have a positive effect on performance and negative effects on investment, indicating benefits to isolation from the information environment and suggesting the presence of mimetic processes. These results also provide evidence for normative pressures arising from homogeneity in director characteristics, with stronger effects on long-term value than near-term financial outcomes. In sum, firms perform better during recessions when their boards are less connected to others and appoint directors from a range of backgrounds.

These results offer several contributions to understanding how board-level factors influence firm-level outcomes. First, the findings highlight the nuanced effects of board interlock networks, providing evidence of negative effects of connectedness contingent on environmental conditions: better-connected boards fare worse in recessions, whilst their relatively isolated peers exhibit stronger financial performance and higher stock valuations. Furthermore, additional analyses demonstrate that firm failure is highest among moderately well-connected boards, indicating benefits to both isolation and connectedness. These findings challenge the notion that such networks are generally valuable (Aalbers 2020; see Withers et al. 2020), suggesting a need for greater attention to the liabilities of board interlocks. The results also validate institutional isomorphism as a theoretical lens in this context: previous research has tended to examine strategic imitation in a positive light (Westphal et al. 2001; e.g. Beckman and Haunschild 2002), leaving a gap in understanding of its negative effects. Second, this study shows that diversity in directors' functional and educational backgrounds differentially affects firm-level outcomes across the business cycle. This demonstrates the significance of individuals' characteristics for understanding strategic decision-making within networks, which has been neglected in network studies (Tasselli and Kilduff 2020). Third, this study clarifies the internal variables that influence performance across the business cycle. Empirical research has focused on which investment decisions are beneficial during recessions, notably marketing and R&D (Dekimpe and Deleersnyder 2018), whereas the antecedents of such decisions have been overlooked (Bamiatzi et al. 2016). The analyses presented here address this gap, demonstrating that directors' exposure to and interpretation of information are critical determinants of whether firms make such counter-cyclical investments. Using a Bayesian approach provides probabilistic estimates of the effects of these focal variables, offering actionable insights into how board-level decisions affect performance across the business cycle and across firms.

3.2 THEORY AND HYPOTHESES

3.2.1 Counter-Cyclical Investments and Firm Performance

Recessions threaten the performance and survival of all firms, narrowing the margin for error in strategic decisions and compelling managers to reconsider their strategic priorities (Garcia-Sanchez et al. 2014; Fan et al. 2020). Most firms respond accordingly: following the 2008 financial crisis, 96% of managers reported making significant changes to investment decisions (McKinsey & Company 2009). Paradoxically, these are largely counterproductive, amplifying the negative impact of economic conditions (Dekimpe and Deleersnyder 2018). Typical responses include reducing investment in marketing and R&D (Srinivasan et al. 2011) and implementing job and wages cuts (Bamiatzi et al. 2016) to conserve resources. Although intuitively compelling, these actions have unintended consequences: changes to the labour force exacerbate productivity declines, and cessation of demand-generating investments increases the difficulty of recovery once conditions normalise (Steenkamp and Fang 2011).

These actions are referred to as *pro-cyclical*: firms conserve resources during economic contraction and expend during expansion.[1] Conversely, evidence suggests that *counter-cyclical* strategies improve performance. Specifically, investments in advertising and R&D lead to higher profitability and stock returns both during recessions (Srinivasan et al. 2011; Özturan et al. 2014) and subsequent recovery (Steenkamp and Fang 2011). Researchers have thus recommended that firms refrain from "blindly following the herd in an attempt to adhere to the wisdom of the crowd" and instead view recessions as an opportunity to strengthen long-term performance by investing in areas that competitors neglect (Dekimpe and Deleersnyder 2018, p. 53). However, despite the prevailing evidence, few firms abide by this view (Gulati et al. 2010).

3.2.2 Institutional Isomorphism and Collective Rationality

To explain why most firms adopt counterproductive strategies during recessions, this study draws on the theory of institutional isomorphism, which posits that "individual [firms'] efforts to deal rationally with uncertainty and constraint often lead, in the aggregate, to homogeneity in structure, culture, and output" (DiMaggio and Powell 1983, p. 147). Faced with sudden environmental change, firms thus tend to converge around a standardised set of strategic actions. Two drivers of isomorphism are

[1] In line with previous research (Reyes et al. 2010; Steenkamp and Fang 2011; Dekimpe and Deleersnyder 2018) 'expansion' refers here to all non-contractionary periods of the business cycle, including periods of relatively low or stable economic growth.

particularly relevant in this context: mimetic processes and normative pressures.[2]

Environmental uncertainty creates ambiguity surrounding the appropriate goals of a firm and the best way to achieve these goals (Duplat et al. 2020; Morais et al. 2020). Under such circumstances, firms are more likely to seek a viable solution than attempt to optimise decision-making, looking to peer firms and imitating their strategic actions (Cyert and March 1963). These *mimetic processes* have been demonstrated in acquisitions (Haunschild 1993), technology adoption (Burt 1987), and the spread of organisational structures (Palmer et al. 1993). As imitation is facilitated by the formal and informal interorganisational ties between firms (Mizruchi 1996), mimetic pressures are greater for firms that are more well-connected to peers (Galaskiewicz 1985).

Similar strategic responses to environmental threats also occur at the individual level. *Normative pressures* arise when a field becomes professionalised, as occurred in management during the twentieth century (DiMaggio and Powell 1983). Greater requirements for formal education, with certain institutions being favoured, leads to homogenisation of the 'cognitive base' of managers. Professional associations further propagate a set of normative rules, creating "a pool of almost interchangeable individuals who occupy similar positions…and possess a similarity of orientation" (DiMaggio and Powell 1983, p. 152). Despite the recent focus

[2] DiMaggio and Powell (1983) also identify *coercive pressures* as a third driver. However, these represent constraints imposed by regulatory bodies, setting mandatory standards across industries or sectors, and are thus unlikely to explain why isomorphism differs across firms.

on increasing demographic diversity among managers and directors, educational and professional homogeneity remains pervasive: boards are dominated by directors with career paths in finance and operations, with fewer than 3% having experience in marketing or sales (Whitler et al. 2018). The backgrounds of a firm's leaders determine the lens through which information is interpreted and thus the strategic emphasis and goals of the firm (Hambrick and Mason 1984; Rindova and Fombrun 1999). Accordingly, lack of diversity in training and experience reduces the cognitive scope of decision-making teams, leading to a smaller set of options being considered and homogeneity in strategic choices (DiMaggio and Powell 1983).

Overall, the theory of institutional isomorphism indicates that strategies are more likely to converge when firms have greater exposure to interorganisational networks and when there is little cognitive diversity among directors. The combined influence of mimetic processes and normative pressures suggest that, when faced with environmental uncertainty, decision-makers may rely on other firms for guidance and fall back on mental models shaped by their cognitive biases, rather than "make decisions on the basis of systematic analyses of goals, since such analyses would prove painful or disruptive" (DiMaggio and Powell 1983, p. 155). Recessions, as a source of environmental uncertainty, may instigate this isomorphic process and thus explain the homogeneity of strategic responses.

The following sections examine how certain firms may avoid isomorphism and its negative consequences. The author argues that mimetic processes are encouraged by a firm's *exposure* to information whereas normative pressures affect the *interpretation* of this information. Typically, these processes are difficult to study, as measurement of the cognitive processes of boards requires data that is internal to the firm (Kaplan 2011; Mohammed et al. 2021). However, the empirical setting of recessions can be used to infer these mechanisms from an examination of firm performance, for two reasons explicated above. First, the relationship between deviation from strategic norms during recessions and financial performance is well-substantiated (Dekimpe and Deleersnyder 2018; Frick 2019). Second, the heightened uncertainty induced by macroeconomic threats leads to greater influence of the board over strategic decisions (Carpenter and Westphal 2001; Morais et al. 2020). Accordingly, differences in factors that determine the degree of information exposure and cognitive scope of boards are likely to be related to firm performance during recessions. These are summarised in Figure 3.2.2.

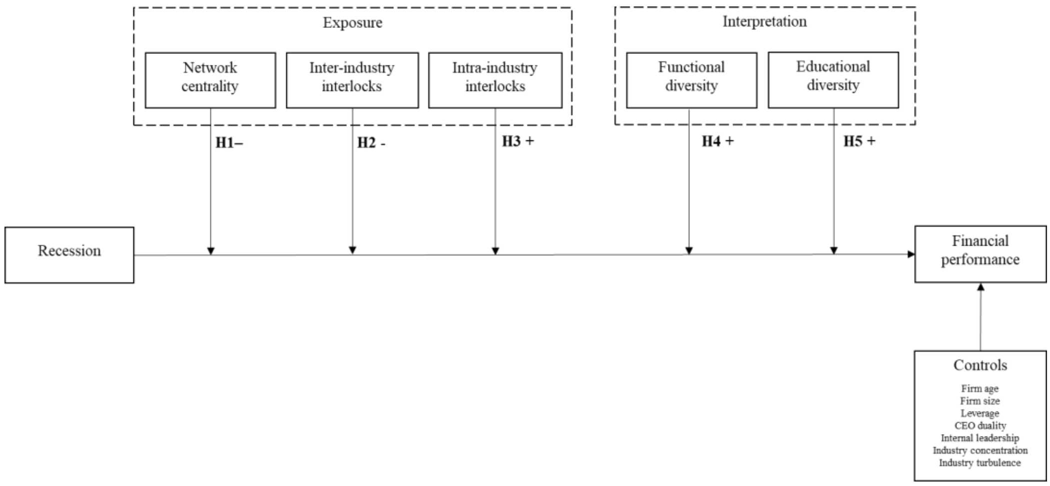


FIGURE 3.2.2 Hypothesised Relationships Between Information Exposure, Interpretation, and Firm Performance.

3.1.1 Exposure to Information: Board Interlock Networks

The primary conduit of mimetic processes is interorganisational networks (Galaskiewicz 1985). Because a firm's strategic objectives are set by its board of directors, the network of interest in the study of strategic imitation is the board interlock network, in which two firms are connected by a director who serves on the board of both firms (Mizruchi 1996). These *board interlocks* are key sources of information about external conditions (Westphal et al. 2001), and are thus highly relevant to board decision-making during recessions. While previous research has not directly examined the effect of board interlocks on strategic imitation across the business cycle, related literature suggests that a firm's position in the interlock network may be consequential for promoting or resisting isomorphic pressures.

The most common operationalisation of a firm's network position is *network centrality,* where a large proportion of directors are connected to other boards which are, in turn, highly connected to others, leading to greater access to information within the network (Tuggle et al. 2010). Occupying a central position in the network facilitates the flow of environmental intelligence between boards, influencing opportunity identification (Mizruchi 1996) and decision-making (Carpenter and Westphal 2001) for the focal firm, which can lead to improvements in business processes (Beckman and Haunschild 2002) and encourage adoption of best practices (Westphal et al. 2001). However, while these benefits may accrue to firms dependent on the *extent* of information to which they are exposed, evidence suggests that the informational *content* of board interlocks has differential consequences for firm-level outcomes (Srinivasan et al. 2018). For example, in terms of innovation outcomes, interlocks are not universally beneficial: when a focal firm's new product development is incremental, *intra-industry interlocks* are associated with positive outcomes as these provide relevant, context-specific market intelligence (Rowley et al. 2000; Srinivasan et al. 2018). Conversely, firms pursuing disruptive innovation do not benefit from access to industry information, but show performance improvements from *inter-industry interlocks* which provide less information on current market conditions but a broader range of intelligence that may stimulate novel insights (Geletkanycz and Hambrick 1997; Li 2019).

In sum, board interlocks are a form of social capital that can improve firm-level outcomes via broader, more relevant, or more timely exposure—and thus increased opportunity to respond—to market intelligence (Srinivasan et al. 2018). Prior research has documented differential effects of overall network centrality, intra-industry, and inter-industry interlocks, suggesting that benefits are dependent on the scope of exposure and the overlap between incoming information and the requirements of the focal firm's strategy (Geletkanycz and Hambrick 1997; Srinivasan et al. 2018). Isolation from board interlock networks therefore constrains strategic decision-making in two ways: *(1) decreased awareness of other firms' strategies* (the extent of information exposure) and *(2) increased reliance on context-specific market intelligence* (the informational content of board interlocks). However, when most firms' strategies are counterproductive and based on macroeconomic intelligence (i.e. during recessions) this may be advantageous, as the social process of isomorphism will exert less pressure on the isolated firm (Galaskiewicz 1985).

Exposure to the strategic decisions of others will be lowest, and the salience of context-specific information highest, when a firm’s overall position in a board interlock network is one of isolation, i.e., a firm has *low network centrality*. Mirroring beneficial effects under normal operating conditions, the role of board interlocks in diffusion of best practices during a recession may be deleterious, encouraging widely adopted but detrimental resource allocation strategies. In support of this, firms with greater exposure to market intelligence are more likely to perform poorly during recessions (Özturan et al. 2014). When a firm’s board is isolated from the network, decisions are likely to rely to a greater extent on internal information and be less influenced by the strategic decisions of others. Accordingly, directors will face fewer isomorphic pressures, providing greater opportunity to pursue the counter-cyclical strategies that have been shown to improve firm performance (Dekimpe and Deleersnyder 2018).

This leads to the hypothesis that the positive effects of network centrality under normal operation conditions will be diminished during recessions. Given the lack of previous comparison of the effects of board interlocks in expansions and contractions, this diminishment may be expected to result in either net negative effect of network centrality on financial performance during recessions, or an attenuation of the predicted positive effects during expansions. For the purposes of this study, this is consequently treated as an empirical issue, leading to the following hypotheses:

> ***Hypothesis 1a (H1a)****: Firms with higher network centrality will exhibit stronger financial performance during expansions.*
>
> ***Hypothesis 1b (H1b)****: The positive effect of network centrality on financial performance will be attenuated or reversed during recessions.*

Inter- and intra-industry interlocks may also differentially affect isomorphic pressures, as the effects of these ties depend on the informational requirements of a firm's strategy (Rowley et al. 2000; Srinivasan et al. 2018; Li 2019). The nature of environmental information upon which strategic decisions are based in a recession differs from prior empirical settings. Generally, industry-specific market intelligence is likely to be more salient than trends that affect all sectors (Srinivasan et al. 2018). In contrast, macroeconomic shocks shift the strategic focus of firms to formulating responses to the threat, with a consequent broad tendency towards pro-cyclical resource allocation decisions across all industries (Dekimpe and Deleersnyder 2018). This suggests that collective rationality in recessions occurs at the *inter*-industry level, as firms shift their attention away from immediate competitive conditions. The salient market intelligence thus becomes the adoption of pro-cyclical strategies across industries, which suggests the existence of a context-independent 'best practice' in responding to recessions (c.f. Porter and Siggelkow 2008). Thus, inter-industry interlocks may negatively affect performance, as pressure to conform to cross-industry norms dominates other strategic concerns:

> ***Hypothesis 2a (H2a)****: Firms with a greater number of inter-industry interlocks will exhibit stronger financial performance during expansions.*
>
> ***Hypothesis 2b (H2b):*** *The positive effect of inter-industry interlocks on financial performance will be attenuated or reversed during recessions.*

In contrast, intra-industry interlocks do not broaden the scope of environmental intelligence beyond a firm's immediate competitive environment (Geletkanycz and Hambrick 1997). Furthermore, intra-industry interlocks are formed through directors with a fiduciary duty to indirect competitors of the focal firm, discouraging the sharing of industry-specific intelligence across firms (Srinivasan et al. 2018). This has previously been shown to be detrimental to innovation due to a lack of information on both broad and particular market trends (Rowley et al. 2000). However, when this information may drive imitation of counterproductive strategies, context specificity in the information environment may protect against isomorphism as it necessitates a reliance on internal information. Given the equivocal findings discussed above, heterogeneous effects of intra-industry interlocks under normal operating conditions may be expected, which does not support the prediction of a directional relationship during expansions. The above arguments thus suggest that firm-specific effects during recessions will be increasingly uniform, with those that may normally gain no benefit from intra-industry interlocks realising an advantage:

> ***Hypothesis 3a (H3a)****: The effect of intra-industry interlocks on financial performance will be heterogenous across firms during expansions.*

> ***Hypothesis 3b (H3b)****: The effect of intra-industry interlocks will be more homogeneous and positive across firms during recessions***,** *such that firms with a greater number of intra-industry interlocks will exhibit stronger financial performance during recessions.*

Both prior research and these hypotheses do not therefore suggest that inter- and intra-industry interlocks act antagonistically, supporting the analysis of both variables (instead of a ratio, e.g., Li 2019). Rather, the author predicts opposing effects, but theorises that these arise from different mechanisms: increased pressure to mimic strategic decisions (inter-industry interlocks) versus limited information about peer firms and broad market trends (intra-industry interlocks).

To summarise, the information gained through board interlocks may cease to be beneficial when this encourages imitation of pro-cyclical strategies. As these are widespread, this negative effect is likely to be strongest when a firm's network is comprised of inter-industry interlocks. Conversely, when a board is isolated from the information environment by a network based on intra-industry interlocks or low network centrality, firm performance may improve as strategic decisions are more likely to rely on internal information.

3.2.3 Interpretation of Information: Director Diversity

Interlock networks affect the degree to which board members are exposed to environmental intelligence. How this is used in strategic decisions—and consequently, how this may affect firm-level outcomes—depends on the attention and interpretation of directors (Ocasio 1997). The board is the key decision-making body when dealing with complex and uncertain strategic problems (Rindova 1999; Carpenter and Westphal 2001), and the backgrounds and experience of directors determine the lens through which such problems are viewed and resolved (Hambrick and Mason 1984). Accordingly, firms respond differently to the same information based on the cognitive framework of the board (Forbes and Milliken 1999) which in turn depends on the characteristics of directors (Westphal and Zajac 2013; Kolev and McNamara 2020).

A key determinant of leaders' cognition is experience in different functional areas (McDonald et al. 2008; Gabaldon et al. 2018). Two broad categories can be delineated: output-oriented, with a focus on demand generation (e.g., marketing and sales), and throughput-oriented, with a focus on efficiency and risk management (e.g., finance, operations, and legal). Although both are essential for firm performance, boards are predominantly throughput-oriented (Whitler et al. 2020). This suggest the influence of normative pressure: the cognitive base from which directors approach strategic threats is relatively homogenous, encouraging an emphasis on risk mitigation over demand generation (Whitler et al. 2018).

This may explain the popularity of pro-cyclical strategies despite their demonstrated ineffectiveness. If boards are dominated by throughput-oriented directors, recessions are likely to be seen as a need to reduce costs and inefficiencies: investments in marketing or R&D may be outside of the cognitive scope of decision-makers despite their benefits for performance during recessions and subsequent recovery. Conversely, directors with output-oriented functional experience are more likely to prioritise these demand-generation activities, and may therefore improve performance by widening the cognitive scope through which environmental signals are perceived (Bettis and Prahalad 1995). However, even when output-oriented directors are present they typically remain a minority (Whitler et al. 2018). If other board members are biased towards efficiency and risk mitigation, in-group preferences may create resistance to alternative viewpoints (Westphal and Zajac 1995). In support of this, Whitler et al. (2018) find that the performance impact of output-oriented directors is weakened when a large proportion of board members have a background in finance. Thus, resistance to the normative pressures of throughput-oriented cognitive bias may require *diversity* in directors' functional experience, i.e., the extent to which directors' expertise indicates the existence of a lack of consensus, rather than the presence of an opposing view (c.f. Klarner et al. 2021).

As previous research has found equivocal effects of director diversity on firm performance (Boivie et al. 2011; Johnson et al. 2013), heterogenous effects of functional diversity under normal operating conditions may be expected, with a tendency towards more positive effects during recessions, as in H3 regarding intra-industry interlocks:

> ***Hypothesis 4a (H4a)****: The effect of functional diversity on financial performance will be heterogenous across firms during expansions.*
>
> ***Hypothesis 4b (H4b)****: The effect of functional diversity will be more homogeneous and positive across firms during recessions**,** such that firms with higher functional diversity will exhibit stronger financial performance during recessions.*

Similarly, cognitive scope is also determined by formal education. DiMaggio and Powell (1983) note that the preference for qualifications from selected educational institutions in recruitment leads to homogeneity in the cognitive frameworks of leaders. Supporting this, Pfeffer and Fong (2002) observe that business school education prepares executives for identifying the same set of problems and responding with a standard set of solutions (see also Bell et al. 2018). The evidence that effective strategies in recessions are counter-cyclical in nature indicates an advantage to avoiding standardised solutions. Diversity of educational backgrounds among directors may therefore present similar benefits as functional diversity, by broadening the cognitive scope of decision-making. This leads to the following hypotheses:

> ***Hypothesis 5a (H5a)****: The effect of educational diversity on financial performance will be heterogenous across firms during expansions.*
>
> ***Hypothesis 5b (H5b)****: The effect of educational diversity will be more homogeneous and positive across firms during recessions**, **such that firms with higher educational diversity will exhibit stronger financial performance during recessions.*

In sum, the preceding discussion explicates that an examination of the effects of information gained from interlock networks must also consider director attributes. Diversity of functional and educational experience widens the cognitive scope of decision-making teams, leading to differences in the interpretation of environmental intelligence and attention to strategic objectives. While previous research indicates equivocal effects of such diversity, this author therefore theorises that this may increase resistance to isomorphic processes and improve firm performance during recessions.

3.3 METHOD

3.3.1 Data and Sample

This investigation focuses on large U.S. firms—a common empirical setting for board research due to the availability of director- and firm-level data and the importance of interlock networks to the U.S. economy (Withers et al. 2020). The sample is based upon data from BoardEx, which provides details of (1) directors' employment and education history, (2) board interlocks, and (3) the composition of firms' boards and management. Data on the latter are provided from 1999 onwards, which defines the census date. Corresponding firm-year data was collected from Compustat to measure firm characteristics and financial performance. The sample therefore includes all firms that have at least one establishment in the U.S. and are publicly traded in U.S. stock markets (the coverage of Compustat) and report director information in BoardEx. Firms with less than 10 million USD in total assets were excluded, as well as those operating in the financial (SIC codes 60-69) or non-classifiable/noneconomic sectors (SIC codes 91-99). The final sample comprises 10,569 firm-year observations of 1,615 firms operating between 1999 and 2019, with a mean of 6.5 years of data per firm. Table 3.3.1 summarises all variables and data sources.

TABLE 3.3.1 Variable Descriptions.

Variable	Description	Source
Profit	Net income in million USD	Compustat
Past performance	Net income in million USD in the previous year	Compustat
Centrality	Eigenvector centrality (EVC), calculated as the weighted centrality of the firm in the board interlock network where weights for each firm connected to the focal firm are determined by the EVC of the connected firm.	BoardEx
Inter-industry interlocks	Natural log of the number of connections between the focal firm and other firms in other 2-digit SIC codes.	BoardEx, Compustat
Intra-industry interlocks	Natural log of the number of connections between the focal firm and other firms in the same 2-digit SIC code.	BoardEx, Compustat
Functional diversity	Coefficient of variation of the number of functional areas represented in the employment history of directors, calculated as the standard deviation in the number of previous positions held by all directors across each area divided by the mean number of previous positions across directors	BoardEx
Educational diversity	Coefficient of variation of the number of qualifications (at undergraduate level or above) held by directors, calculated as the standard deviation in the number of qualifications across directors divided by the mean number of qualifications	BoardEx
Recession	Indicator taking the value of 1 if more than six of the months in the current year are classified as a recession, zero otherwise.	NBER
Firm age	Years elapsed since firm is first listed in database.	Compustat
Firm size	Natural log of total assets.	Compustat
Leverage	Debt to equity ratio.	Compustat
CEO duality	Indicator taking the value of 1 if the CEO also hold the position of board Chair, zero otherwise.	BoardEx
Internal leadership	Number of board members who also hold a position on the firm's top management team	BoardEx
Industry concentration	Hirschmann-Herfindahl Index (sum of squared market shares) in the focal firm's 2-digit SIC code	Compustat
Industry turbulence	Standard deviation of total industry revenues in the firm's 2-digit SIC code over the preceding three years, divided by mean industry revenues over those three years.	Compustat

3.3.2 Network-Level Variables

Testing the proposed mechanism through which a firm's connectedness affects strategic decisions during recessions required a measure that captures the overall exposure of a firm to environmental information via board interlock networks. There are four main approaches to quantifying centrality (Borgatti and Everett 2006). Degree centrality represents a firm's total number of interlocks but provides no estimate of the informational role of these connections, while closeness and betweenness centrality capture a firm's ability to disseminate information rather than the influence of incoming information on the focal firm. The measure best suited to this context is *eigenvector centrality (EVC)*, a weighted measure in which the weights are determined by the centralities of the firms connected to the focal firm (Mariolis and Jones 1982). This captures direct information flows between the focal firm and others as well as the extent of information transmission: firms connected to other well-connected firms are likely to be exposed to more of the information contained within the network (Owen-Smith and Powell 2004).

Board interlock centrality was therefore measured using EVC (Tuggle et al. 2010; Srinivasan et al. 2018). This first requires the construction of a bimodal network in which directors are connected to the boards on which they serve, and two boards are connected by a shared director. From this was derived a unimodal network of firms based on the number of shared directors. In a network of *N* firms, the EVC of firm *i* connected to *M(i)* other firms was then calculated as:

(3.1) $$C_i = \frac{1}{\lambda} \sum_{j \in M(i)} a_{ij} C_j$$

Where $a_{ij} = 1$ if firm *i* is connected to firm *j* and zero otherwise. In eigenvector notation;

(3.2) $$AC = \lambda C$$

Where *C* is the vector of centralities, λ the vector of eigenvalues, and *A* the adjacency matrix containing the relationships between firms. C_i was calculated for each year in the sample, to capture shifts in a firm's centrality arising from changes to board composition over time. The unimodal board interlock network also provided the basis for calculating the two measures of the informational content of board interlocks. *Intra-industry interlocks* were defined as the natural log of the number of connections between a focal firm and firms in the same 2-digit SIC code. *Inter-industry interlocks* were analogously defined as connections to firms in other 2-digit SIC codes.

3.3.3 Director-Level Variables

Diversity among directors was opreationalised using two measures based on the coefficient of variation. This has been used analogously to measure heterogeneity in firm strategies and resource investments (see Nadkarni and Narayanan 2007) as it provides an estimation of diversity that is independent of the value of the variable(s). This is well-suited to capture cognitive scope as it measures the variability, rather than the overall level, of functional or educational experience within the board.

The measure of functional diversity is derived from job descriptions provided in the employment histories of directors. Following recent research, computer-aided text analysis was used to categorise job descriptions (Srinivasan et al. 2018; Whitler et al. 2018). However, this study builds on prior approaches by using a probabilistic algorithm rather than word lists. This ensures that this measure captures changes in word usage across industries and time, which are not accounted for in deterministic classifiers. For example, a dictionary-based approach may use the words ‘marketing’ or ‘sales’ to classify a director with marketing experience (Whitler et al. 2018). However, firms are increasingly adopting a broader range of positions at the strategic level (Gupta et al. 2020), leading to a proliferation of executive roles with non-standard titles (e.g. Chief 'Branding' or 'Creative' Officers) that this dictionary would overlook.

To overcome this issue, job descriptions were classified using guided Latent Dirichlet Allocation (LDA), a probabilistic topic modelling technique that simulates the human production of language to identify the latent thematic content (topics) of a collection of documents and the words most strongly associated with each topic (Blei 2012). In basic LDA, no prior assumptions are made about the presence of topics or their associated words: the model aims to maximise the probability of observing the actual content of the documents. However, when certain words are common across all documents, the topics that dominate the model will not be semantically meaningful (Griffiths et al. 2007). For example, in this case, words such as 'chief', 'director' or 'manager' are highly prevalent in job descriptions but irrelevant to classification by functional area. Guided LDA circumvents this problem by biasing the identification of topics towards a set of 'seed words' (Blei and McAuliffe 2008). This improves the likelihood of detecting the topics of interest whilst retaining the probabilistic nature of LDA and thus ensuring that relevant words omitted from the seed lists are included in the final model.

Appendix A provides details of the guided LDA procedure. The final model identified six functional areas, to which each job description was assigned based on its highest topic probability. Next, the sum of the total number of previous positions in each functional area for each director-year was calculated. These were then matched to firm-year observations, after which the average experience in each functional area across all directors was computed. *Functional diversity* was calculated as the standard deviation in experience across functional areas divided by the mean experience across all areas, such that higher values reflect greater variability in the experience of a firm's directors and lower values reflect a relatively even distribution of experience across the six areas.

Educational diversity was analogously measured as the coefficient of variation of the number of qualifications held by directors, i.e., the standard deviation in the number of qualifications across directors divided by the mean number of qualifications. Higher values thus indicate firms in which directors have varying levels of formal education, while low values indicate that the educational backgrounds of directors are relatively homogenous.

3.3.4 Recession and Financial Performance

Following the methodology of previous studies of strategic decisions across the business cycle (e.g., Graham and Frankenberger 2011; Srinivasan et al. 2011; Reyes et al. 2020) recession years were identified using classifications of peaks and troughs in economic activity from the National Bureau of Economic Research (NBER). As the data sources used in this study (BoardEx and Compustat) are provided on an annual basis, a calendar year was identified as a recession when more than six months (i.e., two quarters) of that year are classified as such, leading to three recession years in the sample: 2001, 2008, and 2009.

Few studies of strategic decisions across the business cycle examine the implications for overall firm financial performance, often using industry-specific or subjective measures or proximal outcomes such as sales volume (see review in Dekimpe and Deleersnyder 2018), Consequently, this study follows Steenkamp and Fang (2011) in measuring financial performance as profitability, defined as a firm's net income in million USD.

3.3.5 Controls

Key control variables were included that may affect firm performance across the business cycle and the formation and/or effects of network ties. At the firm-level, these were: *firm size,* defined as the natural log of total assets*; firm age;* and, *leverage,* measured as the firm's debt-to-equity ratio (Srinivasan et al. 2011; Steenkamp and Fang 2011). A lagged dependent variable was also included to control for the effects of previous financial performance.

The included controls were also intended to account for the fact that the impact of board-level decisions on performance is contingent on implementation (Lee and Puranam 2016). Board members who also hold executive positions in the firm are more likely to generate consensus around decisions and ensure the utilisation of market intelligence gained through board interlocks (Nyberg et al. 2010; Nguyen 2012). CEO duality is a specific form of internal leadership where the CEO also serves as board Chair, which may be particularly effective in aligning responsibility for strategic actions across decision-making levels (Dalton et al. 2007). Consequently, this variables was disaggregated into *internal leadership*, measured as the total number of directors who also hold a position in the firm's top management team, and *CEO duality*, an indicator taking a value of 1 if the CEO also serves as board chair and zero otherwise, for the purposes of this analysis.

Further controls at the industry level include *industry concentration,* measured using the Hirschmann-Herfindahl Index (sum of squared market shares) in the focal firm's 2-digit SIC code, and *industry turbulence,* calculated as the standard deviation of total industry revenues in the firm's 2-digit SIC code over the preceding three years divided by mean industry revenues over those years. These variables were included because competition and growth may affect the salience of economic trends (Steenkamp and Fang 2011) and importance of board interlock networks (Li 2019) for firms in different industries. The model also includes industry dummies at the 2-digit SIC code level, to account for other industry-level differences such as variations in levels of profitability. Instead of controlling for other aspects of firm-specific heterogeneity, these effects were estimated in the model. Table 3.3.5 presents descriptive statistics and correlations for all variables.

TABLE 3.3.5 Descriptive Statistics and Correlations.

		Mean	SD	1	2	3	4	5	6	7	8	9	10	11
1	Profit	246.886	1482.350	1.000										
2	Centrality	-23.057	4.463	.209	1.000									
3	Inter-industry interlocks	2.315	0.899	.206	.541	1.000								
4	Intra-industry interlocks	0.873	0.030	.046	.113	.123	1.000							
5	Functional diversity	-0.903	0.538	-.138	-.237	-.320	-.018	1.000						
6	Educational diversity	-0.760	0.340	.053	.027	.023	-.103	-.009	1.000					
7	Firm age	57.178	8.811	.056	.076	.001	-.115	-.084	.005	1.000				
8	Firm size	6.875	1.934	.315	.470	.565	.021	-.353	.091	.170	1.000			
9	Leverage	1.721	54.431	-.005	.008	.004	-.012	.001	.010	.001	.015	1.000		
10	Internal leadership	4.667	3.036	.104	.144	.114	-.043	-.112	.043	.111	.203	-.004	1.000	
11	Industry concentration	0.044	0.039	.005	-.014	.058	-.141	-.022	.074	.022	.085	.001	.009	1.000
12	Industry turbulence	0.055	0.037	-.034	-.090	.052	.019	.035	.015	-.102	.051	.001	-.039	.250

3.3.6 Model Specification and Estimation

Three of the above hypotheses (H3, H4 and H5) predict heterogenous effects of focal variables across firms during expansions, with a shift towards positive effects during recessions. This requires an approach that appropriately captures shifts in the distribution of firm-specific effects whilst enabling examination of sample-level effects. However, firm-level heterogeneity poses issues for isolating the effects of variables of interest. Standard approaches to panel data analysis address heterogeneity by including an individual intercept (fixed effects) or error term (random effects) for each firm. Whilst this improves the accuracy of estimates of *average* effects, the relevance of these is debatable: they represent effects for the "mythical average firm" rather than the *actual* effects for any real firm in the sample (Mackey et al. 2017, p. 339). This is insufficient when seeking to understand firms that diverge from sample-level trends (Hansen et al. 2004) as this study does in aiming to determine the factors that distinguish which firms deviate from the strategic consensus during recessions. Consequently, the analyses conducted here account for firm heterogeneity via an alternative approach, explicitly incorporating this information to estimate firm-specific coefficients for each relationship of interest.

This is typically achieved using mixed-effects models, which estimate both an average effect and firm-specific deviation. However, with panel data, where there are many firm-specific coefficients and few observations per firm, deviations are estimated with weak confidence (Rossi et al. 2005). This study addressed this issue with a Bayesian hierarchical model. As with all Bayesian models, this approach estimates probability distributions rather than point estimates for each coefficient, explicitly incorporating uncertainty into the model. The hierarchical structure allows the estimation of firm-specific coefficients, as in mixed effects models. Estimation of firm-specific coefficients 'borrows strength' from information contained within the distributions for other units of analysis, allowing these to be estimated with greater confidence (Hahn and Doh 2006). Thus, Bayesian estimation addresses the concerns with mixed effects models in the context of panel data and facilitates examination of firm-specific effects.

The hierarchical model has two levels. In the first level, the effects of the independent variables on performance were estimated as:

(3.3) $$Y_{it} = \beta_{0_i} + \beta_{1_i} R_t + \sum_b \beta_i B_{bit-1} + \sum_b \beta_i R_t B_{bit-1} + \gamma_i X_{it-1} + \varepsilon_{it}$$

Where Y_{it} represents firm performance in year t, R_t is the dummy variable indicating whether year t is a recession year (and thus β_{1i} is the firm-specific estimate of the effects of recession on performance), B_{bit-1} is a vector of independent variables capturing board characteristics (network- and director-level variables), X_{it-1} of control variables, measured one period prior to the observation of firm performance and macroeconomic conditions, and $\varepsilon_{it} \sim N(0, \sigma_i^2)$. Performance is thus modelled as a function of economic conditions, board characteristics, the interaction between economic conditions and board characteristics, and controls:

(3.4) $$\Theta_i = f(\beta_i, \gamma_i)$$

While a comprehensive vector of control variables were included, differences between industries must also be accounted for, both in terms of the economic consequences of the identified recession years of 2001, 2008, and 2009 and persistent inter-industry differences in the dependent variable of profitability. A second-level equation for each β and γ was therefore introduced. This level models each parameter Θ_{ij} as a function of firm-specific variation around the hypermean $\overline{\Theta}$ and industry-specific mean Θ_j. This second level was also used to address potential issues of endogeneity arising from the likely relationships between firm age and size, network- and director-level variables, and response to recessions. Larger, more mature firms tend to be more sensitive to macroeconomic changes and may be less able to quickly shift their strategies in response, due to the complexity of their value chains (Bamiatzi et al. 2016). Firm size and age also tend to be associated with more established interlock networks (Mizruchi 2013, and see Table 3.3.5). Accordingly, these control variables may influence both the focal independent variables and dependent variable. To resolve this issue, the impact of firm age and size was modelled in the second level, estimating the effects of the board- and network-level independent variables on firm performance as a function of the potentially endogenous control variables (Dotson and Allenby 2010; Nandialath et al. 2014; Mackey et al. 2017). Prior beliefs on Θ_i in Equation 3.4 therefore come from the average and industry-specific parameters, plus firm-specific variation coefficients for the influence of age and size:

(3.5) $$\Theta_{ij} = \overline{\Theta} + \Theta_j + \delta_i X_i + \eta_{ij}$$

Where industry j is identified by a firm's 2-digit SIC code and $\eta_i \sim N(0, \sigma^2)$. Diffuse normal priors were specified for the mean and variance of all parameters, of 0 and 10,000, respectively. The shape and scale parameters of the inverse gamma distributions used to sample the variance are given diffuse priors of 0.01. The model was estimated using Markov Chain Monte Carlo (MCMC) methods, using Gibbs sampling. After 2,500 burn-in draws, 10,000 MCMC iterations were retained for inference. Efficiencies for all parameters are higher than .95, representing an effective sample size (ESS) > 9,500. The close correspondence between the ESS and total iterations indicates that draws are independent (i.e., no autocorrelation) and thus that the model has converged. A high acceptance rate (81%) for sampling iterations provides further evidence of model convergence (see Appendix B).

3.4 RESULTS

As this model provides firm-specific coefficients for each parameter, each hypotheses is technically tested for each of the 1,615 firms in the sample. Presenting these results individually is clearly impracticable. This section therefore presents the posterior distributions only, which is sufficient for examination of the hypotheses pertaining to changes in the distribution of firm-specific effects across the business cycle for network-level (Figure 3.4.1) and director level (Figure 3.4.2) variables. These distributions correspond to the main and interaction effects reported in Table 3.4, which details the mean, SD, Monte Carlo standard error (MCSE), and highest posterior density 95 percent credible intervals (HPD 95% CI). The percentage of firm-specific effects greater than zero represents the proportion of firms that show increased profitability as a result of higher values for each variable, enabling inference about the actual probability that a firm will derive benefit from a given variable. Support for the directional hypotheses thus comes from observation of the predicted effects across a majority of firms.

TABLE 3.4 Distribution of Firm-Specific Coefficients: Profitability.

Dependent variable: Profit	Mean	SD	MCSE	HPD 95% CI		% > 0
Main effects						
Centrality	14.633	2.378	0.024	10.072	19.263	100
Inter-industry interlocks	114.056	14.246	0.142	86.260	141.775	100
Intra-industry interlocks	-3.070	14.278	0.147	-31.284	24.420	42
Functional diversity	-89.021	22.212	0.219	-132.409	-45.130	0
Educational diversity	47.031	27.622	0.276	-7.030	100.681	96
Recession	-26.350	92.076	0.921	-208.841	155.291	38
Interactions						
Centrality x recession	-7.705	3.898	0.039	-15.420	-0.153	2
Inter-industry interlocks x recession	-140.395	28.135	0.281	-195.659	-84.958	0
Intra-industry interlocks x recession	65.229	32.615	0.326	1.137	128.456	97
Functional diversity x recession	34.677	48.081	0.481	-59.576	129.474	76
Educational diversity x recession	4.612	57.296	0.573	-106.152	116.927	53
Controls						
Past performance	0.635	0.010	0.002	0.610	0.651	100
Leverage	-0.088	0.197	0.002	-0.473	0.297	67
CEO duality	19.069	31.365	0.317	-43.137	79.824	72
Internal leadership	11.828	3.857	0.039	4.245	19.336	100
Industry concentration	-16.513	93.952	0.939	-198.718	170.544	43
Industry turbulence	99.338	94.910	0.949	-83.266	284.297	85
Constant	87.590	70.470	0.705	-48.973	224.396	88
Firm-specific variation effects						
Firm age	0.396	1.066	0.256	0.005	4.456	64
Firm size	0.017	0.009	0.002	0.005	0.044	97
Industry dummies			Included			

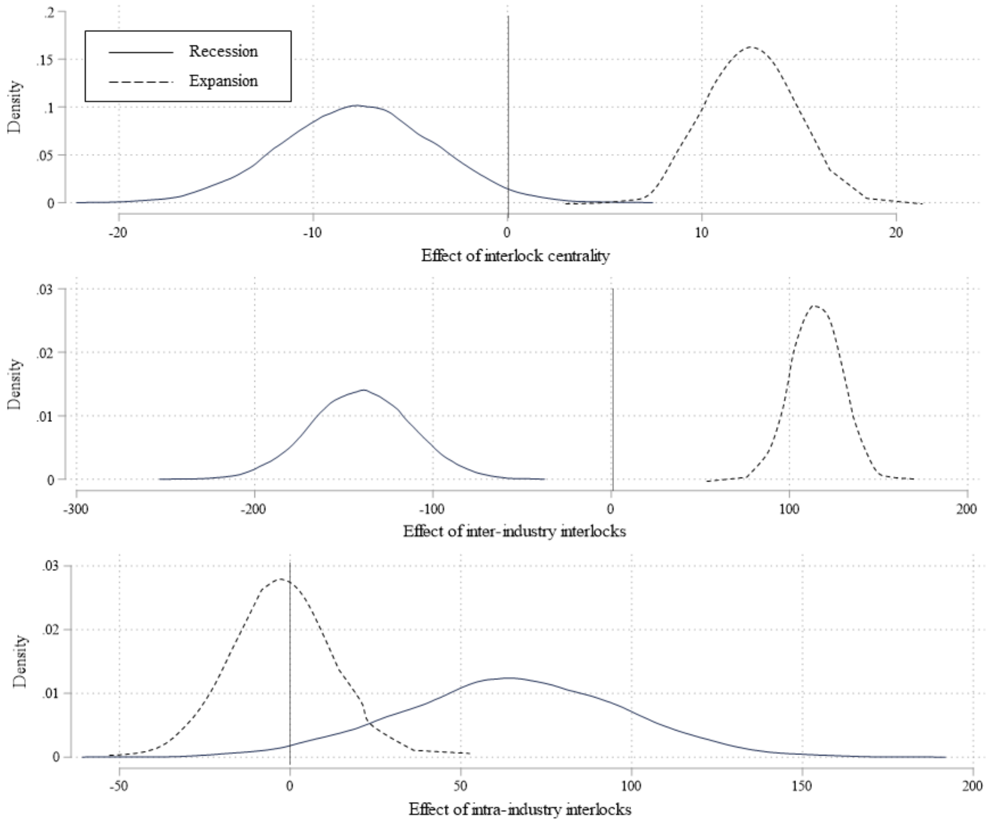


FIGURE 3.4.1 Distribution of Effects in Expansion and Recession: Network Variables.

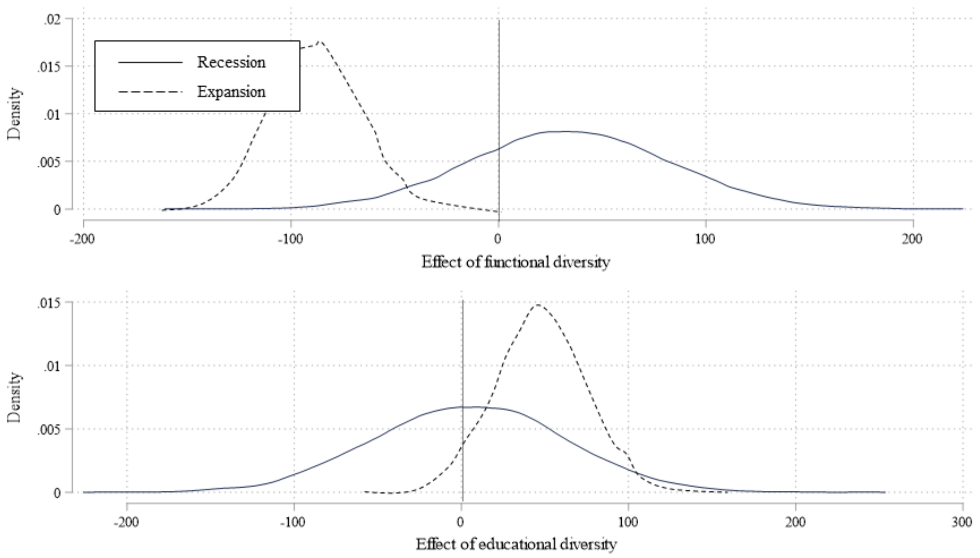


FIGURE 3.4.2 Distribution of Effects in Expansion and Recession: Director Variables.

H1a predicted that firms with higher board interlock centrality would exhibit stronger financial performance during expansions. H1b predicted that this effect would be attenuated during recessions. The results support both hypotheses. During expansions, 100 percent of firms derive economic benefit from occupying a more central position in networks. In contrast, during recessions the contingent effect on profitability is negative for 98 percent of firms. This lack of overlap in the posterior distributions (shown in Figure 3.4.1 and by the HPD 95% CI in Table 3.4) indicates a consistent difference in effects across the business cycle and strongly supports H1.

H2 similarly stated that the positive effect of inter-industry interlocks on financial performance (H2a) would be attenuated during recessions (H2b). The results indicate a large difference in the distributions that both supports these hypotheses and corroborates prior research. During expansions, 100 percent of firms benefit from inter-industry interlocks, whereas the effect is negative for 100 percent of firms during recessions. Again, a lack of overlap in the HPD 95% CI for the recession and non-recession distributions indicates that the business cycle has substantial and consistent effects. Furthermore, the mean marginal effect (114.056 + -140.395 = -26.339) shows that on average, firms can expect a *reversal* (rather than attenuation) of the benefits gained from inter-industry interlocks; these become detrimental during recessions.

H3 concerned the effect of intra-industry interlocks, with H3a predicting heterogenous effects during expansion. The distribution of effects shown in Figure 2 supports this: 42 percent of firms experience increases in profitability from a higher level of intra-industry ties during non-recession years, suggesting that effects are highly contingent on firm-specific factors. However, during recessions, 97 percent of firms exhibit stronger financial performance when intra-industry interlocks are higher. This lends strong support to H3b, indicating that firm-level determinants of the effect of intra-industry interlocks become less influential during recessions, leading to more consistent effects across the sample. Furthermore, and similar to the findings related to inter-industry interlocks, the mean marginal effect (-3.070 + 65.229 = 62.159) reverses during recessions: whilst, on average, firms experience a detriment to performance during expansions, intra-industry interlocks are beneficial during recessions.

H4 and H5 pertain to the effect of director characteristics on financial performance, predicting heterogeneity in firm-specific effects of functional and educational diversity during expansions (H4a and H5a) and a shift towards positive effects in recessions (H4b and H5b). While non-recession year effects are not central to this investigation, it is notable that there is less heterogeneity in firm-specific coefficients than H4a and H5a predict, with functional diversity negatively affecting performance for 100 percent of firms and educational diversity improving performance in 96 percent of firms during expansions. Positive mean contingent effects during recessions suggest support for H4b and H5b. However, while there is a clear rightward shift in the posterior distribution for functional diversity (H4b; see Figure 3.4.2) this is unclear for educational diversity (H5b), as the spread of firm-specific coefficients also increases during recessions (see also the HPD 95% CI in Table 3.4). It can therefore be observed that the probability of a firm benefitting from functional diversity *increases* during recessions (0 versus 76 percent) whereas the likely benefit from educational diversity *decreases* during recessions (96 versus 53 percent). This provides support for H4b but no support for H5b: functional diversity is generally beneficial during recessions, but educational diversity has ambiguous effects at the sample level and is more likely to contribute to financial performance during expansions.

Interpreting the economic significance of these results requires some additional explanation. The mean effects in Table 3.4 (and the specific coefficients reported in this section) represent the expected value, in terms of profitability, that a firm is likely to gain (or lose) from a single-unit change in the independent variable. For example, there is an average decrease in net income of -89.021 million USD during expansions when functional diversity (the coefficient of variation in directors' background) increases by one. A negative firm-specific coefficient is observed in 100 percent of firms in the sample, lending high confidence in the prediction that firms can, on average, expect substantial and detrimental results from functional diversity during expansion. Intra-industry interlocks have an expected negative effect on profitability (-3.070). However, the magnitude of this effect is small and positive coefficients are observed in only 42 percent of the sample, indicating that firms should have low confidence in the expectation of a negative effect. Economically significant effects can therefore be inferred when (a) mean effects show a large increase or decrease in the dependent variable[3] and (b) the distribution of firm-specific

[3] The magnitude of effects that can be expected during a recession is given, as shown above, by taking the sum of the baseline and interaction mean coefficients. Thus, for

coefficients represents a consistent expectation of positive or negative effects.

3.4.1 Additional Analyses

The results reported in Table 3.4 support institutional isomorphism as an explanation for poor performance during recessions. These analyses followed prior research in defining performance as net income, as near-term financial viability is of primary concern during recessions (Steenkamp and Fang 2011). Given this choice of dependent variable, three issues warrant further attention to ensure the robustness of results and generalisability of implications.

First, profitability is distinct from the counter-cyclical investment decisions that are frequently the focus of the business cycle research. To examine how these findings relate to previous studies, additional analyses were therefore conducted to examine the effects of the focal network- and director-level variables on the two most widely studied beneficial investments during recessions: advertising and R&D (Dekimpe and Deleersnyder 2018). These analyses serve to investigate whether the mechanisms proposed by this author – resistance to normative and mimetic processes as an explanation for superior recessionary performance – may also contribute to explaining counter-cyclical investments. For example, if the positive effects on profitability during recessions observed here reflect a

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example, intra-industry interlocks have a small average effect that is inconsistent across firms in expansions, but a large and consistent positive expected value during recessions (-3.070 + 65.229 = 62.159).

decrease in investment, this would suggest that counter-cyclical investments are driven by an alternative mechanism.

Second, while financial performance may be the primary concern in the near-term during recessions, the above results cannot inform on the effects of board connectedness and diversity on longer-term or market outcomes. Consequently, additional analyses were also conducted to examine the effects of network- and director-level variables on firm value as a proxy for the long-term earnings potential of a firm (Deleersnyder et al. 2009; Dekimpe and Deleersnyder 2018).

Third, the benefits observed for board isolation during recessions may be affected by survivorship bias. For example, as interlocks provide access to resources (Hillman and Dalziel 2003), isolated firms may be less likely to survive recessions when resource constraints are generally more severe (Bamiatzi et al. 2016). If this effect is present, the benefits of isolation may reflect the presence of an omitted variable that increases the chance of survival for isolated firms and also contribute to their success during recessions, raising potential issues of endogeneity (Hill et al. 2020). Furthermore, an examination of firm survival can provide additional insights into the long-term implications of board connectedness and diversity. The following analyses therefore investigate whether connectedness and diversity affect firm failure rates.

3.4.1.1 Counter-Cyclical Investments

The effects of board interlocks and director characteristics on counter-cyclical investments were estimated using the same model as specified in

Equation 3.3, in which Y_{it} is now specified as (1) *advertising expenditure* and (2) *R&D expenditure*. Table 3.4.1.1 presents the results.

TABLE 3.4.1.1 Distribution of Firm-Specific Coefficients: Counter-Cyclical Investments.

Dependent variable	Advertising expenditure						R&D expenditure					
	Mean	SD	MCSE	HPD 95% CI		% > 0	Mean	SD	MCSE	HPD 95% CI		% > 0
Main effects												
Centrality	4.683	1.492	0.253	2.257	7.919	100	5.645	1.042	0.030	3.648	7.694	100
Inter-industry interlocks	15.523	8.903	0.778	0.501	32.645	95	31.494	6.787	0.341	17.945	44.900	100
Intra-industry interlocks	14.532	6.795	0.439	1.320	27.820	98	20.756	5.606	0.197	9.938	32.036	100
Functional diversity	-84.418	38.381	9.139	-177.576	-29.882	1	-106.335	21.186	2.914	-146.539	-61.392	0
Educational diversity	-49.552	13.783	0.859	-76.850	-22.751	0	13.253	12.189	0.590	-10.514	37.268	86
Recession	14.418	63.461	1.275	-108.987	138.808	59	-66.014	58.465	0.775	-180.245	48.130	13
Interactions												
Centrality x recession	-0.641	1.996	0.042	-4.640	3.288	38	-3.831	1.791	0.022	-7.385	-0.329	1
Inter-industry interlocks x recession	-15.298	10.945	0.287	-37.045	5.973	10	-7.632	9.866	0.126	-26.747	11.831	21
Intra-industry interlocks x recession	-7.357	10.840	0.211	-28.380	13.884	25	-40.925	9.629	0.127	-59.469	-21.797	0
Functional diversity x recession	4.604	16.204	0.380	-26.781	36.356	62	9.193	14.742	0.193	-20.178	37.991	73
Educational diversity x recession	-9.647	21.077	0.594	-51.169	31.417	33	-20.890	18.613	0.253	-56.888	15.339	13
Controls												
Past performance	0.032	0.007	0.002	0.025	0.047	100	0.066	0.003	0.000	0.161	0.072	100
Leverage	-0.169	0.141	0.003	-0.448	0.098	12	0.037	0.050	0.001	-0.059	0.135	77
CEO duality	-44.105	38.668	5.394	-112.596	32.786	13	-18.846	32.452	3.671	-77.504	47.359	27
Internal leadership	25.231	11.020	2.457	13.773	45.560	98	11.920	4.823	0.824	2.646	20.909	100
Industry concentration	20.089	90.751	7.657	-160.111	200.715	58	-25.065	90.607	2.960	-203.952	155.147	39
Industry turbulence	-58.970	79.346	1.969	-214.618	96.373	23	-153.724	77.290	1.247	-304.948	-2.801	2
Constant	-45.292	50.814	6.222	-146.379	46.008	18	18.072	41.889	2.490	-62.947	101.014	66
Firm-specific variation effects												
Firm age	31.837	13.154	3.840	0.063	42.169	100	51.939	2.631	0.208	47.048	57.301	100
Firm size	0.051	0.064	0.018	0.003	0.240	78	0.038	0.045	0.012	0.005	0.181	79
Industry dummies			Included						Included			
Observations			4,145						7,636			
Average ESS			9,522						9,484			
Average $\hat{R}$			.952						.948			
Acceptance rate			.873						.895			

In line with the main results reported above, there is a clear change in effects between expansions and recessions in most firms. Network centrality has a positive effect on both investments in 100 percent of firms during expansions, but a negative contingent effect during recessions for the majority of firms, with only 38 percent of firm-specific effects above zero for advertising expenditure and 1 percent for R&D expenditure. Similarly, inter-industry interlocks lead to increased advertising and R&D expenditure during expansions (in 95 and 100 percent of firms, respectively), but this effect is attenuated in recessions, with negative contingent effects for 90 and 79 percent of firms, respectively. Functional diversity consistently decreases advertising and R&D expenditures during expansions but has a positive contingent effect in most firms (62 and 73 percent, respectively) during recessions. The direction of these effects is aligned with the main model, suggesting that the effects of these variables in the above analysis is related to a higher propensity to engage in counter-cyclical strategies. However, intra-industry interlocks have a positive effect on both investments during expansions and a negative contingent effect during recessions. Thus, while similar patterns of effects on profitability and investments for centrality, inter-industry interlocks, and functional diversity support the proposed mechanism, the attenuated effect of intra-industry interlocks during recessions suggests that this variable also positively affects recessionary performance via a different route.

Reflecting equivocal results for educational diversity in the main model, the distribution of firm-specific effects of this variable on counter-cyclical investments is mixed. On average, educational diversity reduces advertising and R&D expenditure during recessions, with negative mean contingent and marginal effects. However, Table 3.4.1.1 shows consistent negative effects on advertising expenditure, and positive effects on R&D expenditure, during expansions. As for the main results, this suggests the need for further research on the firm-specific factors and performance metrics that determine the implications of director diversity.

Overall, these analyses suggest that the main results are partly explicable by the role of mimetic and normative pressures in discouraging counter-cyclical investments. Variables that have the most consistent effects on profitability—centrality, inter-industry interlocks and functional diversity—exhibit similar changes in the magnitude and direction of effects on counter-cyclical investments during recessions. Reflecting differential outcomes across firms in the main model, these analyses show equivocal effects of educational diversity. Finally, the effects of intra-industry interlocks on R&D expenditure are inconsistent with this mechanism, suggesting an additional mechanism through which firms benefit from intra-industry ties during recessions.

3.4.1.2 Market Performance

To gain additional insights into the effect of connectedness and director characteristics on long-term performance indicators, Equation 3.3 was estimated with Y_{it} specified as *firm value,* which was measured using the year's closing stock price. Results are presented in Table 3.4.1.2

TABLE 3.4.1.2 Distribution of Firm-Specific Coefficients: Long-Term Performance.

Dependent variable: Firm value	Mean	SD	MCSE	HPD 95% CI		% > 0
Main effects						
Centrality	0.100	0.076	0.002	-0.049	0.249	90
Inter-industry interlocks	-0.287	0.416	0.013	-1.099	0.529	25
Intra-industry interlocks	-0.579	0.370	0.010	-1.292	0.150	6
Functional diversity	-1.013	0.724	0.028	-2.459	0.386	10
Educational diversity	-1.037	0.754	0.023	-2.526	0.423	10
Recession	-12.717	5.309	0.071	-23.157	-2.314	0
Interactions						
Centrality x recession	-0.285	0.161	0.002	-0.605	0.029	4
Inter-industry interlocks x recession	-1.129	0.806	0.010	-2.703	0.445	8
Intra-industry interlocks x recession	1.021	0.730	0.009	-0.384	2.456	91
Functional diversity x recession	3.367	1.154	0.014	-1.064	5.654	99
Educational diversity x recession	2.660	1.495	0.018	-0.307	5.576	96
Controls						
Past performance	0.936	0.017	0.004	0.915	0.982	100
Leverage	0.003	0.004	0.000	-0.005	0.011	77
CEO duality	0.111	1.051	0.045	-1.886	2.192	54
Internal leadership	0.036	0.130	0.005	-0.216	0.291	60
Industry concentration	16.738	8.377	0.295	-0.454	33.037	97
Industry turbulence	-17.135	7.186	0.190	-31.116	-3.113	0
Constant	7.136	2.659	0.074	1.939	12.420	100
Firm-specific variation effects						
Firm age	0.004	0.006	0.002	0.001	0.020	74
Firm size	2.074	0.743	0.209	0.018	2.664	100
Industry dummies			Included			

Providing further support for H1, 78 percent of firms benefit from network centrality during expansions, with a negative contingent effect for 87 percent during recessions. However, in contrast to the main results, the mean marginal effect is also negative (0.100 + -0.285 = -0.185); thus, the positive effect of centrality on firm value is not only attenuated but *reversed* during recessions. There is also a negative contingent effect of inter-industry interlocks, corroborating H2b. However, the baseline effect is negative, with only one-quarter of firm-specific coefficients being positive during expansions. Thus, while the effect of inter-industry interlocks during recessions remains consistent with the main results, H2a is unsupported in this model and the contingent effect represents an exacerbation, rather than an inversion, of non-recession year effects. The effect of intra-industry interlocks, while demonstrating lower baseline heterogeneity than H3a predicts, also conform to H3b: 91 percent of firm-specific coefficients are positive during recessions, with a reversal in the marginal effect analogous to the main results (-0.579 + 1.021 = 0.442). Taken together, these results suggest that mimetic processes have similar or greater consequences for long-term firm value than near-term profitability.

These results also suggest that normative pressures may be *more* consequential for long-term performance. The mean contingent effect of functional diversity is positive, consistent with the main model (and thus with H4b) but is also positive for 100 percent of firms (versus 76 percent; see Table 3.4). Furthermore, while the marginal effect of functional diversity remains negative in the main analysis, these results show a reversal (-1.013 + 3.367 = 2.354). Similarly, while the main results are equivocal for educational diversity, here there is a clear shift in the posterior distributions: 10 percent of firm-specific coefficients are positive during expansions, 96 percent during recessions, and again the marginal effect is reversed (-1.037 + 2.660 = 1.623).

Overall, these results provide further support for the hypotheses of this study, corroborating some findings of the main analysis and highlighting other notable differences. These are in line with the theoretical mechanisms of isomorphism and suggest potentially greater consequences from mimetic and normative processes for long-term, rather than near-term, performance.

3.4.1.3 Firm Survival

A proportional hazards model (Cox 1972) was specified to examine how board connectedness affects firm failure in expansions and recessions. A failure event is identified as the last year a firm is present in the sample (excluding the final year). Table 3.4.1.3 presents the results. This shows a significant increase in firm failure for intra-industry interlocks and functional diversity only and no significant effects for the focal variables during recession years, suggesting that the above analysis is not affected by survivorship bias.

TABLE 3.4.1.3 Cox Proportional Hazards Model: Firm Survival

Dependent variable	Firm failure[a]		
	Hazard ratio	Coefficient	*p*
Main effects			
Centrality	0.993	-0.007	.526
Inter-industry interlocks	0.925	-0.078	.135
Intra-industry interlocks	1.114	0.108	.016
Functional diversity	1.301	0.263	.000
Educational diversity	0.908	-0.096	.264
Recession	1.225	0.203	.863
Interactions			
Centrality x recession	0.996	-0.004	.891
Inter-industry interlocks x recession	0.951	-0.051	.758
Intra-industry interlocks x recession	0.808	-0.214	.189
Functional diversity x recession	1.207	0.188	.440
Educational diversity x recession	0.815	-0.204	.487
X^2	90.69		.000

[a]As this study relies on Compustat data, which draws primarily from SEC filings, these failure events may represent actual failure (i.e., a firm ceasing to exist) or delisting from public markets. This distinction is inconsequential for determining whether the main findings are affected by survivorship bias but should be considered in interpreting these results.

To further explore these effects, Figure 3.4.1.3 displays the survival curves, splitting the sample by quartile on each of the network- and director-level measures. For functional diversity, survival curves are similar across all quartiles, corroborating the significant linear effect reported in Table 3.4.1.3. However, for all measures of connectedness, firm failure is greatest in the middle two quartiles, with the most isolated and most connected firms – in terms of network centrality, intra- and inter-industry interlocks – exhibiting higher survival rates. This further suggests that the above results are not biased in one direction by survivorship bias and indicates that both isolation and connectedness can confer benefits in terms of firm survival: *moderately* well-connected firms are at the highest risk of failure. Though there is no significant effect for educational diversity, Figure 3.4.1.3 also illustrates a trend toward higher survival among firms with less diverse boards. This is in line with the equivocal effects of educational diversity in the main analyses.

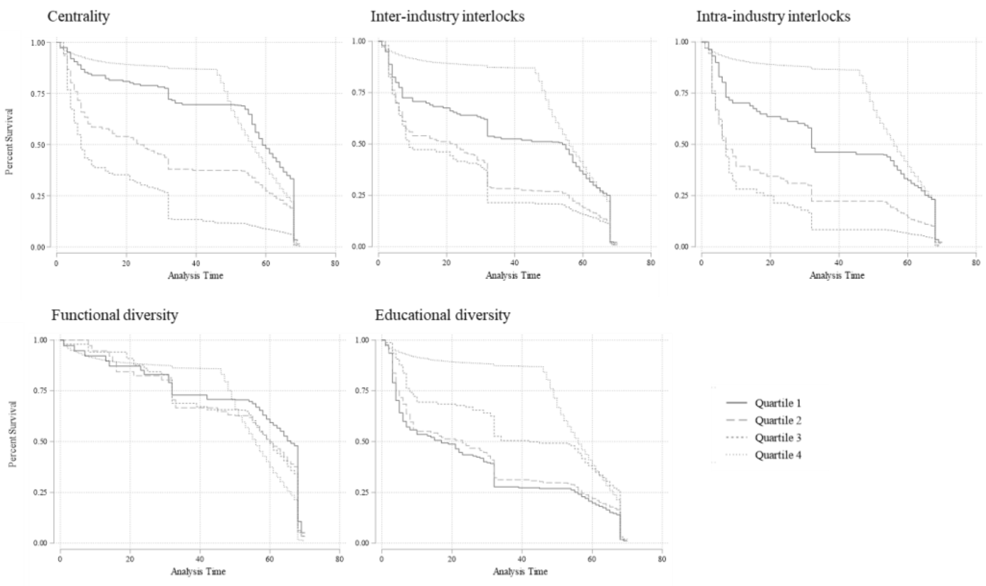

FIGURE 3.4.1.3 Kaplan-Meier Survival Curves.

3.5 DISCUSSION

This study sought to examine the characteristics of boards that contribute to widespread poor performance among firms during recessions. Based on the theory of institutional isomorphism (DiMaggio and Powell 1983), the author identified five network- and director-level variables as probable determinants of a firm's ability to resist mimetic and normative pressures and thus avoid this trend. Overall, the results lend support to institutional isomorphism as an explanation for the prevalence of counterproductive, pro-cyclical strategies during recessions by demonstrating that factors which reduce isomorphic forces are associated with increased investment in advertising and R&D, greater profitability, and higher stock valuations. The analyses reported above provide strong support for mimetic processes, operating via social networks between firms, as an explanation for widespread poor performance during recessions: firms that are more isolated from peers and reliant to a greater extent on context-specific information exhibit stronger performance. In further support of the long-term implications of these effects, the additional analysis of firm failure indicates benefits to both isolation and connectedness, with failure rates highest among moderately well-connected firms. These results also provide evidence for the influence of normative pressures arising from directors' professional and educational experiences, with stronger effects on firm value than near-term financial performance. Using a Bayesian approach, this study presents probabilistic inference about the effects of these variables that offers actionable insights for strategic decision-making.

3.5.1 Contributions

These results offer several contributions to research and practice on corporate governance and strategic investments. First, the findings highlight a negative effect of connectedness contingent on environmental conditions: *better-connected boards fare worse in recessions, whilst their relatively isolated peers exhibit stronger financial performance*. Current evidence suggests that board interlocks improve access to market intelligence, with benefits for strategic decision-making (Withers et al. 2020). However, this study shows that connectedness negatively affects both near-term profitability—critical for firm survival during a recession – and long-run estimates of firm value. The findings suggest that inter-industry interlocks, which provide access to broad environmental intelligence, are most detrimental for both aspects of performance. Conversely, an interlock network based on intra-industry ties, which has heterogeneous but generally negative effects on performance during economic expansion, appears to offer protection against isomorphic pressures and thus improve profitability and firm value during recessions. Consistent with prior research, these analyses show that network centrality, capturing the overall degree to which a firm is exposed to information within board interlock networks, improves performance during expansions. In recessions, this effect is attenuated but remains positive for profitability; however, the marginal effect on firm value is negative. This is notable, as it implies that the near-term effects of connectedness (lack of benefit) may underestimate the long-term implications (causing harm). Furthermore, the highest rates of firm failure occur among moderately well-connected firms, corroborating the perspective that both connectedness and isolation can be beneficial. This suggests the need for additional nuance in the study of interlock networks, with greater attention to the downsides of collective rationality in relation to common performance metrics. This study demonstrates the validity of isomorphism as a theoretical lens in this context: previous research has tended to examine strategic imitation in a positive light (e.g., Westphal et al. 2001; Beckman and Haunschild 2002), and this approach may facilitate further understanding of its negative effects.

Second, this study provides a substantive contribution to understanding how the backgrounds and experience of directors contribute to firm-level outcomes. *Firms with directors from multiple professional and educational backgrounds show improvements in firm value during recessions*, demonstrating that both forms of diversity are beneficial in the face of macroeconomic threats. Additionally, while educational diversity has equivocal effects on profitability during recessions, three quarters of firms experience a positive contingent effect of functional diversity. This extends recent research into the role of output-oriented board members, which has found effects on strategic outcomes related to demand generation and innovation (Whitler et al. 2020). However, limited evidence for their contribution to firm performance means that such directors are overlooked in recruitment, and thus remain a minority (Whitler et al. 2018). This study presents evidence for the role of output-oriented board experience in driving both proximal and financial outcomes. This finding therefore also provides insights for governance, highlighting a clear advantage from which shareholders and recruiters may advocate for appointment of directors with varied professional backgrounds: firms can increase cognitive scope in strategic decision-making and thus better prepare for recessions by buffering against isomorphic pressures.

Furthermore, this study shows that there is wide variation in the firm-specific effects of educational diversity on profitability, and differences in the contingent and marginal effects of both functional and educational diversity between models of near- and long-term performance. This indicates a complex relationship between directors' experience and firm outcomes that is contingent on firm-level factors. These findings present a challenge to widespread calls for greater diversity (see Zhu and Shen 2016), in accordance with the literature demonstrating equivocal financial outcomes (Boivie et al. 2011; Johnson et al. 2013), suggesting the need for future research into the forms of diversity that are most consequential for performance, the relevant metrics and time horizon for measuring their effects, and the firm-specific factors that affect this relationship (c.f. Almor et al. 2019). This examination of the cognitive attributes of directors also represents a contribution to the study of board interlock networks, which has focused on the structure of networks and the positions of firms within them at the expense of consideration of firm-level attributes, leading to an incomplete analysis of how agency operates within networks (Aalbers 2020; Tasselli and Kilduff 2020). This has clear implications for the understanding of strategic-decision making: as these results demonstrate, both network- and director-level variables have significant effects.

Third, this study provides a substantive contribution to knowledge of the firm-specific factors that influence performance during recessions; an issue that has been overlooked in the empirical literature (Bamiatzi et al. 2016). *Whilst previous research has shown investments in marketing and R&D to be beneficial, these findings indicate that the decision to make such investments is influenced by the connectedness and diversity of directors,* with effects aligned with the main analysis of financial performance. This suggests that the degree to which a firms' leaders are exposed to external intelligence and the lens through which this information is interpreted are both critical factors to understanding how firms come to resist the trend towards counter-cyclical investment and poor performance during recessions. These results provide probabilistic estimates of the likely benefits firms can derive from board-level factors, providing guidance for corporate governance decisions during recessions and opening an avenue for further research into why most firms suffer whilst their "deviant peers" (DiMaggio and Powell 1983, p. 154) survive and thrive.

This has important practical implications for corporate governance in terms of the relative reliance on internal versus external information in different macroeconomic environments when considering investments marketing and R&D, for which the extant literature provides little guidance. No research to date has examined board-level influences on marketing resource allocation, instead focusing on the role of the CEO and other executives (Whitler et al. 2020). Given the documented importance of counter-cyclical investments during recessions (Dekimpe and Deleersnyder 2018) and current attention to understanding effective strategic responses to crises (Wenzel et al. 2021), these results thus offer a novel contribution to understanding board-level influences on such decisions.

3.5.2 Limitations and Directions for Future Research

The implications of these findings point to one overarching direction for future research—the adoption of Bayesian methods to examine firm-specific variation in the effects of strategic variables—and two specific areas in which this may be beneficial: (1) clarifying the forms of director diversity that are most beneficial for different performance objectives and (2) further examination of how a minority of firms avoid collective rationality in adverse conditions.

A key limitation of this study suggests one way these issues could be examined. Specifically, the analyses presented herein focus on *detecting* rather than *explaining* the role of firm-specific factors in determining the impact of board-level variables. However, the model used in this study can be extended to incorporate explanatory variables in estimating firm-specific effects, enabling future research to examine *why* the distributions presented here occur. This would increase the managerial relevance of these results, providing additional insight into the variables that determine a firm's position in the distribution and thus facilitate understanding of the characteristics present at the tails – i.e., those firms likely to realise the largest gains (or most severe detriment) from changes to board composition or connectedness (c.f. Hahn and Doh 2006).

A second limitation of this study provides further guidance on how this may be pursued. In line with prior research on board interlocks and director characteristics, this study relies on secondary data. This provides advantages of scale and objectivity, but precludes study of the internal, firm-specific factors that may be most relevant to explaining differences between firms, such as organisational culture or the role of the CEO. The above questions may therefore be addressed by combining network and director data with surveys, observation, or interviews; for example, to elucidate the degree to which educational background is an important consideration in board composition. Utilising data internal to the firm may also facilitate greater understanding of the role of board cognition in the effects observed here. While this approach of using secondary data and performance outcomes is common in this research stream and allows inferences about cognitive processes, a direct examination of the theoretical mechanisms proposed in this study would require further in-depth, qualitative research (Kaplan, 2011; Mohammed et al., 2021).

Using secondary data also restricts observations to large U.S. firms. This is often justified as interlock networks are arguably most important in the U.S. corporate context (Withers et al. 2020). However, recessions affect the performance and survival of all firms and often have global impacts. Future research utilising primary data could therefore also examine the international generalisability of these findings, improving applicability across a range of contexts. Relatedly, in-depth data from a smaller number of firms may also provide greater temporal coverage than the databases from which this data was obtained, allowing investigation of the generalisability of these effects across a larger number of business cycles.

4 BOARD IDEOLOGICAL DIVERSITY AND INFORMATION EXPOSURE AS ANTECEDENTS TO VALUE CREATION AND VALUE APPROPRIATION

4.1 INTRODUCTION

Strategic emphasis, reflecting a firm's relative proclivity toward value creation versus value appropriation, is a core strategic decision (Mizik and Jacobson 2003). *Value creation* is fundamentally driven by the R&D function and involves innovating, commercializing, and delivering products and services that provide new value to customers. *Value appropriation* is typically associated with advertising, which communicates these offerings to customers in order to capture value for the firm in the form of profits (Mizik and Jacobson 2003). These competing foci are essential for firm growth and profitability respectively (Kim et al. 2018). Consequently, appropriate allocation of attention and resources between R&D and advertising is central to balancing risk and returns for long-term performance (Josephson et al. 2016a; Han et al. 2017).

Despite longstanding recognition of the importance of the value creation—value appropriation trade-off, there has been no research to date examining the role of the board of directors. Extant literature provides evidence of firm-, market-, and top management team- (TMT) level antecedents (e.g., Currim et al. 2012; Kim et al. 2018). However, managerial articles indicate a role for corporate governance (O'Conner 2019), likening the balance between R&D and marketing to the left and right lobes of the “corporate brain” (O'Connell 2014). Boards are increasingly influential in setting the strategic direction of firms (Withers et al. 2012) with directors in recent years coming to view strategic collaboration with top management as central to their duties (Boivie et al. 2021). Serving a boundary-spanning role at the intersection of the firm and its environment, boards are a unique and valuable source of external and tacit knowledge in formulating strategy (Finkelstein et al. 2009). This information processing function is particularly important with regard to complex and uncertain decisions, as it shapes the scope and interpretation of information used in strategy formulation (Rindova 1999). Given the complexity and trade-offs inherent in the value creation—value appropriation decision (Mizik and Jacobson 2003), board-level influences are a pertinent omission from this literature.

To address this gap, this study draws on the cognitive perspective of corporate governance, which posits that boards’ scanning of the information environment, interpretation of information, and choice among alternatives solutions determine the nature and quality of strategic decisions (Rindova 1999). Accordingly, the author examines how exposure to external information and the cognitive framework of the board interact to affect a firm’s focus on value creation versus value appropriation. These constructs are operationalised via an integration of two literature streams. Information exposure is measured by examining a firm’s *network centrality* within the board interlock network: a key source of external intelligence (Mizruchi 1996; Withers et al. 2020). As network centrality has been shown to promote both innovation (Srinivasan et al. 2018; Li 2019) and imitation

(Westphal et al. 2001; Beckman and Haunschild 2002), the author hypothesises competing effects on a firm’s strategic emphasis. The cognitive framework of the board is examined using the political affiliations of directors, based on the close correspondence between political ideology and underlying cognitive and behavioural patterns (e.g., Jost et al. 2009; Gerber et al. 2011), and the consequent role of decision-makers’ ideologies in various strategic decisions (e.g., Gupta et al. 2020; Park et al. 2020). Validated measures of individuals’ ideological leanings are used to create an index of *board ideological diversity* that captures the range of cognitive frameworks present among a firm’s directors. Based on the established benefits of ideological diversity for creative problem-solving (Page 2008; Duarte et al. 2015), the author predicts that ideologically heterogenous boards will exhibit an increased focus on value creation.

An investigation of 584 large U.S. firms between 2000 and 2018 shows that network centrality increases value appropriation focus, in line with evidence for the role of board interlocks in diffusion of established strategies (Geletkanycz and Hambrick 1997; Westphal et al. 2001), whereas board ideological diversity increases value creation focus, supporting the hypothesis. Furthermore, the interaction between network centrality and ideological diversity leads to an increased focus on value creation. This suggests that strategic emphasis is influenced via the interplay between environmental scanning, information interpretation, and negotiating consensus around strategic decisions.

These results offer several contributions to research and practice. First, this study identifies board cognition and information exposure as novel drivers of the value creation—value appropriation trade-off. This has implications for executives, providing insight into situations where they are likely to encounter support or resistance to R&D and marketing budget decisions, and thus strengthening the case for increased functional discretion and board-level representation in this process (Kim et al. 2018; Whitler et al. 2018). Second, in examining the interaction of board- and network-level influences on decision outcomes, this study contributes to the ongoing debate regarding the problem of "overembeddedness" in network research (Srinivasan et al. 2018), demonstrating that the agency and cognition of actors affects the implications of their position within information networks (Tasselli and Kilduff 2020). Third, while diversity in directors' demographic and professional characteristics has received much attention in the management literature (Holmes et al. 2020), ideological diversity remains underexplored. Given the breadth of psychological and behavioural factors associated with ideology, the methodological approach employed here answers recent calls for examination of the effects of "deep level" diversity (Mohammadi et al. 2017; Triana et al. 2021) among board members on strategic decisions (Gupta and Wowak 2017). Findings demonstrate the importance of this factor, highlighting opportunities for future research into board cognition and implications for the appointment of directors.

4.2 THEORY AND HYPOTHESES

4.2.1 Antecedents of Value Creation and Value Appropriation

Prior research has identified numerous antecedents to strategic emphasis that can be broadly categorised as market-, firm- and TMT-level factors.

While many studies have examined R&D and advertising investments independently rather than the relative emphasis between the two, this literature nevertheless provides insight into many important drivers of value creation and value appropriation. At the market-level, industry concentration, competitiveness (Josephson et al. 2016a), and the technological environment (Mizik and Jacobson 2003) have been found to be key antecedents. Firm-level influences include financial performance (Mizik and Jacobson 2003), organisational maturity (Kim et al. 2018), and slack resources (Josephson et al. 2016a). TMT-level antecedents include CEOs' psychological characteristics (Kim et al. 2018; Scoresby et al. 2021) and compensation (Currim et al. 2012; Chakravarty and Grewal 2016), as well as the discretion afforded to the TMT by governance provisions (Kim et al. 2018).

The literature on board-level antecedents is limited, primarily focusing on R&D expenditure in isolation and the effects of board monitoring effectiveness (e.g., Kor 2006; Zona 2016). There has been only one study to date that provides insight into the effect of board *cognition* on value creation activities (Heyden et al. 2015). This does not examine advertising or R&D expenditure (c.f. Josephson et al. 2016a) and focuses on the influence of national differences in governance, rather than factors that are manipulable within or between firms. Nonetheless, it provides preliminary support for the role of board cognition in the value creation—value appropriation decision, finding that heterogeneity in directors' professional experience across functional areas leads to an increase in exploratory innovation. However, functional diversity—and diversity in other director characteristics such as demography—has been argued to provide only a surface-level approximation of the "deep-level" diversity in values, attitudes, and beliefs (Mathieu et al. 2008) that shape individuals' cognition and contribution to firm decisions (Triana et al. 2021).

The importance of deep-level diversity is reflected in the cognitive perspective on corporate governance, which views directors' professional experience as antecedent to their role in strategic decision-making, rather than an influence on the outcome of this participation (Daft and Weick 1984; Milliken and Vollrath 1991; Forbes and Milliken 1999). Instead, board-level effects on the nature of strategic decisions are seen to arise from three interrelated factors: *scanning*, which determines the information collected by the board; *interpretation,* resulting from the influence of directors' cognitive frameworks on categorising, understanding, and extrapolating from this information; and, *choice* among the alternatives generated in the interpretation stage (Rindova 1999). Viewed through this theoretical framework, two key omissions from the literature on the antecedents of value creation and appropriation can be identified: (1) the board's information environment and (2) the information processing capability created by the combination of directors' cognitive frameworks.

4.2.2 Network Centrality

Preceding the scanning, interpretation, and choice activities of the board is the information environment to which directors are exposed (Hillman et al. 2000). Exposure to external information has been widely studied as an antecedent of activities linked to both value creation and value appropriation. Information exposure has been shown to improve outcomes from exploratory innovation efforts, a value creation activity (e.g., Li et al. 2013; Kiss et al. 2020). Conversely, complementarities between internal and external knowledge increase firms' ability to improve current products and processes (Rosenkopf and Nerkar 2001; Bierly et al. 2009), enabling better appropriation of value from existing activities (Zhou and Li 2012; Chatterji and Fabrizio 2014).

The source of heterogeneity in information exposure that has received the most attention is board interlock networks (Withers et al. 2020): the connections between firms formed by directors who serve on the boards of two or more 'interlocked' firms (Mizruchi 1996). When a focal firm occupies a central position in a densely connected network, i.e., it is well-connected to firms that are, in turn, well-connected to others, directors have greater access to the information contained within the network (Borgatti and Everett 2006). Board interlocks are thus a key source of information about external conditions (Westphal et al. 2001).

The board interlocks literature reflects the conflicting effects of external information, documenting effects of network centrality that can broadly be seen to act via two mechanisms. This author consequently proposes competing hypotheses for the effect of network centrality on strategic emphasis. On the one hand, by providing access to market intelligence that facilitates the recognition of opportunities for strategic change (Mizruchi 1996), board interlocks can stimulate new product development (Srinivasan et al. 2018) and innovation (Li 2019), suggesting that the information exposure gained from interlocks may promote a focus on value creation:

> ***Hypothesis 1a (H1a):*** *Network centrality increases value creation focus.*

As noted above, the majority of prior research has examined either value creation- or value appropriation-related outcomes in isolation. Accordingly, evidence that board interlocks promote a value creation focus does not preclude positive effects on value appropriation, which may occur via an alternative mechanism. Specifically, the increased visibility and knowledge of other firms' activities gained through interlocks promotes reliance on their actions for guidance in strategic decision-making (DiMaggio and Powell 1983). Accordingly, interlocks have also been shown to facilitate the diffusion of best practices (Westphal et al. 2001), lead to improvements in existing processes (Beckman and Haunschild 2002), and encourage the imitation of strategies (Geletkanycz and Hambrick 1997), with the likelihood of imitation increasing the more well-connected a firm is to its peers (Galaskiewicz 1985). A value creation focus requires that the firm develop products or services that offer new value to customers, either through significant improvement or new innovations (Mizik and Jacobson 2003). A reliance on the actions of other firms in strategic decision-making increases the difficulty of achieving this, as it is less likely that imitative decisions will provide new value from the customer's perspective (Srinivasan et al. 2018). Network centrality may therefore promote a focus on value appropriation by increasing awareness of, and opportunities to imitate, established strategies:

> ***Hypothesis 1b (H1b):*** *Network centrality increases value appropriation focus.*

4.2.3 Board Ideological Diversity

Given the same information environment, boards will utilise external information in different ways depending on three sequential cognitive tasks: scanning, interpretation, and choice (Milliken and Vollrath 1991). Scanning involves filtering information that is perceived as relevant from that which is considered noise (Daft et al. 1988). This occurs at the individual-level, with the function of the board being the aggregation of directors' scanning activities (Rindova 1999). Cognitive diversity among directors is thus a key determinant of scanning effectiveness: this maximises the likelihood that a variety of information will be aggregated by the board, as individuals differ in the types of environmental stimuli that are perceived as relevant to decision-making (Forbes and Milliken 1999).

Following scanning, individuals attempt to make sense of the new information within their existing cognitive frameworks (Weick 1995). Cognitive diversity leads to differences in how new and existing knowledge is combined, the problems that are identified, the potential solutions that are generated, and the perceived consequences of these alternatives (Forbes and Milliken 1999). This interpretation process involves "assembling conceptual schemas"—mental representations of the key concepts in the information environment and the relationships between them (Daft and Weick 1984, p. 286). The nature of the board's conceptual schemas will differ based on the forms of heterogeneity that directors bring to the interpretation process. Three key forms of cognitive diversity are relevant here (Rindova 1999).

External variety refers to the diversity among directors relative to the firm and industry. Lack of external variety promotes similar interpretations, leading to fewer strategic options being considered (DiMaggio and Powell 1983). Diversity can therefore assist in identifying competitive blind spots and developing innovative strategic responses (Zajac and Bazerman 1991)—a prerequisite for value creation. *Requisite variety* refers to the diversity among directors relative to the causal complexity in the firm's environment. This compensates for individual cognitive biases, which tend to oversimplify environmental complexity (Miller 1993) and may erroneously attribute causality to events based on entrenched decision biases (Weick 1995). Cognitive diversity can thus help to overcome organisational inertia, ensuring the preservation of interpretations that will identify the need for adaptation in times of environment change (Talke et al. 2011) and thus encourage value creation. Finally, *representative variety* refers to the diversity among directors relative to the firm's stakeholders. The pertinent forms of diversity are those that increase the social representativeness of the board and ensure that the interests of stakeholder groups are considered (Rindova 1999). This is important to preserving the firm's reputation (Fombrun 1996), which can reduce the risk associated with value creation and create relational assets that allow firms to capture value in the market (Srivastava et al. 2001).

These three forms of director diversity interact to prevent the convergence of board decision-making on a narrow range of considerations (Rindova 1999): external variety ensures competitive blind spots are addressed; requisite variety encourages recognition of causal complexity;

and, representative variety ensures that strategic decisions safeguard the long-term interests of the firm. The choice of strategic decisions is evidently contingent on the effects of diversity during interpretation, as this determines the breadth of alternatives that are generated. However, director diversity further influences choice via its effects on selection among options. Strategic decisions where no ‘best’ choice exists, such as the value creation—value appropriation trade-off (Mizik and Jacobson 2003), are a negotiation process (Milliken and Vollrath 1991). Unlike homogenous groups, where there is little need for compromise, diversity requires individuals to justify and re-evaluate their preferred solutions during this process (Rindova 1999), meaning that erroneous reasoning is more likely to be surfaced (Frey and van de Rijt 2020). The need to build consensus in diverse boards can therefore improve decision quality and lead to more novel solutions (Page 2008).

The importance of director diversity in scanning, interpretation, and choice activities suggests that heterogeneity in board cognition will produce more innovative decision outcomes, and therefore that board diversity may increase a firm’s focus on value creation. However, the form of diversity that meaningfully affects board cognition is less clear. While diversity in professional experience has been studied as an aspect of board heterogeneity (Heyden et al. 2015; Whitler et al. 2018), it is unlikely to capture differences in cognition per se (Mathieu et al. 2008; Triana et al. 2021). Despite diversity in demographic characteristics being of interest, the relationship between demography and cognition is tenuous (Duarte et al. 2015) and equivocal in its effects on firm-level outcomes (Zhu and Shen 2016; Holmes et al. 2020).

This author proposes that a more meaningful dimension of diversity for firm decision-making is *ideological diversity*. Ideology refers to an individual's internally consistent belief system, comprising the attitudes and values that underlie thought and behaviour (Jost 2006). Ideology therefore captures the key concepts discussed in the cognitive view of the board, reflecting the "perceptual filters" (Starbuck and Milliken 1988), "cognitive frameworks" (Weick 1995), or "conceptual schemas" (Daft and Weick 1984) that determine directors' attention to and interpretation of information. Furthermore, ideology is reliably associated with personality dimensions that directly affect individuals' work and problem-solving styles (e.g., Jost et al. 2009; Gerber et al. 2011), attributions of salience and causality to events (Fatke 2017), and group decision-making (Haidt 2012; Duarte et al. 2015). These aspects of personality have been posited as the pathways through which ideology affects board cognition (e.g., Park et al. 2020).

Ideology is pertinent to each aspect of board cognition described above. At the scanning stage, ideology affects which aspects of the information environment individuals attend to (Fatke 2017). Thus, ideological diversity among directors may result in a greater breadth of information being brought to the board's attention. At the interpretation stage, ideology is relevant to each form of director variety. Ideology has been shown to influence firm-level decisions, such as tax avoidance (Christensen et al. 2015), compensation (Chin and Semadeni 2017), and

CSR activity (Chin et al. 2013). Accordingly, ideological diversity may increase external variety by broadening the range of strategic options that are considered relative to firm and industry norms. Ideology also affects individuals' causal attributions and consequently their interpretation of environmental complexity (Skitka and Tetlock 1992). This implies that ideological diversity will increase requisite variety, buffering against simplification biases and ensuring that alternative options are considered. In terms of representative variety, ideology is often viewed as the most salient dividing factor among societal groups (McPherson et al. 2001; Jost 2006). Therefore, ideological diversity of the board reflects an improved ability to recognise and attend to divergent stakeholder interests. Finally, ideology is a key source of individual disagreements (Haidt 2012) and the basis of negotiation and consensus-building in varied organisational settings (Page 2008; Duarte et al. 2015), suggesting that ideological diversity will stimulate the processes that lead to more creative and effective strategic choices.

The theoretical relevance of ideological diversity to board cognition and the value creation—value appropriation decision is empirically supported in the psychology literature. Ideological diversity is consistently associated with more creative and novel problem-solving within teams (Triandis et al. 1965; Mannix and Neale 2005; Page 2008). Equally, a lack of viewpoint diversity prevents recognition of important but unaddressed questions, leading to the perpetuation of entrenched decision biases and errors (Haidt 2012; Duarte et al. 2015). Group decision-making consequently suffers when there is a clear majority, as prior mistakes are left unchallenged, amplifying their consequences (Haidt and Lukianoff 2018; Frey and van de Rijt 2020). Accordingly, homogeneity in directors' ideologies may inhibit the breaking of entrenched organisational routines and exploration of alternative strategic options—a key aspect of value creation (Kang and Kim 2020). The author therefore predicts an increased focus on value creation when boards are ideologically diverse:

> ***Hypothesis 2 (H2):*** *Board ideological diversity increases value creation focus.*

4.2.4 Interaction Between Network Centrality and Board Ideological Diversity

As the scanning (and subsequent interpretation and choice) activities of the board are contingent on the availability of external information, it is also likely that there exists an interaction between network centrality and board ideological diversity. Based on the notion that information availability stimulates information processing (Starbuck and Milliken 1988; Rindova 1999), this author predicts that the effects of ideological diversity on value creation will be augmented in well-connected boards, as the range of available informational inputs to the board's cognitive processes will increase the potential for director heterogeneity to surface different attentional patterns, generate alterative interpretations, and stimulate negotiation in the choice process. Attentional effects suggest that ideological diversity will increase boards' ability to utilise the information gained through interlocks for opportunity identification and innovation (c.f. Mizruchi 1996), while a breadth of interpretations suggests that ideological diversity will afford protection against the mimetic effects of network centrality (c.f. DiMaggio and Powell 1983). While competing hypotheses are proposed for the main effect of network centrality, a shift toward value creation when boards are ideologically diverse may therefore be expected:

> ***Hypothesis 3 (H3):*** *Board ideological diversity positively moderates the relationship between network centrality and value creation focus.*

As value creation and appropriation are measured on a continuum, it can equally be predicted that board ideological diversity negatively moderates the relationship between network centrality and value appropriation focus. H3 thus states a moderation hypothesis for both H1a and H1b.

4.3 METHOD

4.3.1 Data and Sample

Three data sources were combined to conduct this investigation. Board ideological diversity was measured following prior research (e.g., Gupta and Wowak 2017; Park et al. 2020) utilising data on directors' political campaign contributions obtained from the U.S. Federal Election Committee (FEC), the regulatory agency that records campaign financing for all donations over 200 USD in presidential and congressional elections. This was combined with director information from BoardEx, from which data on board interlocks was also obtained to construct the measure of network centrality and other board-level controls. Corresponding firm-level data was obtained from Compustat for calculating firm- and industry-level variables. Table 4.3.1.1 details the data sources and operationalisation of variables. Table 4.3.1.2 provides descriptive statistics and correlations.

TABLE 4.3.1.1 Variable Operationalisations and Sources.

Variable	Definition	Source
Strategic emphasis	Advertising expenditures minus R&D expenditures, scaled by total assets. Positive scores represent value appropriation-focused strategies and negative scores value creation-focused strategies	Compustat
Board ideological diversity	Coefficient of variation in directors' political ideologies (standard deviation divided by mean), where director ideology is calculated as below	US FEC
Network centrality	Eigenvector centrality (EVC), calculated as the weighted centrality of the firm in the board interlock network where weights for each firm connected to the focal firm are determined by the EVC of the connected firm[a]	BoardEx
Board liberalism	Average of directors' political ideology, where director ideology is calculated as the average of four measures over the previous 10 years: (1) number of donations to Democrat campaigns divided by total number of contributions (to Republican and Democrat campaigns), (2) dollar amount of donations to Democrat campaigns divided by total dollar amount of donations, (3) number of years in which a donation is made to Democrat campaigns divided by the total number of years in which a donation is made, (4) number of unique Democrat recipients of donations divided by total number of donation recipients.	US FEC
Board tenure	Average number of years that directors have served on the board	BoardEx
Board size	Number of directors	BoardEx
Board independence	Number of outside directors	BoardEx
Director gender diversity	Female directors as a percentage of all directors	BoardEx
Director age diversity	Standard deviation in directors' age	BoardEx
Director functional diversity	Coefficient of variation of the number of functional areas represented in the employment history of directors	BoardEx
Director educational diversity	Coefficient of variation of the number of qualifications held by directors	BoardEx
CEO duality	Indicator that takes the value of 1 if the CEO is also the board Chair; zero otherwise	BoardEx
Firm performance	Tobin's Q, calculated as the market value of the firm plus liabilities divided by the book value of assets	Compustat
Firm age	Number of years since firm first appeared in Compustat database	Compustat
Firm size	Natural log of number of employees	Compustat
Advertising expenditure	Absolute value of advertising expenditure	Compustat
R&D expenditure	Absolute value R&D expenditure	Compustat
Absorbed slack	Working capital minus cash and cash equivalents, scaled by total assets (Kim and Bettis 2014)	Compustat
Unabsorbed slack	Cash and cash equivalents scaled by total assets (Kim and Bettis 2014)	Compustat
Industry concentration	Hirschmann-Herfindahl Index (sum of squared market shares) in the firm's 4-digit SIC code	Compustat

Industry turbulence	Standard deviation of total industry revenues in the firm's 4-digit SIC code over the preceding three years, divided by mean industry revenues over those three years.	Compustat
Industry growth	Revenue growth in a firm's 4-digit SIC code over four years, scaled by industry size. Calculated as the slope coefficient of total industry revenues regressed over the preceding four years, divided by mean industry revenues over those four years (Fang et al. 2008).	Compustat
Industry strategic emphasis	Average strategic emphasis across all firms in the focal firm's 2-digit SIC code, excluding the focal firm (Kim et al. 2018).	Compustat

[a] Eigenvector centrality is scaled by a factor of 100 to aid interpretation.

TABLE 4.3.1.2 Descriptive Statistics and Correlations

Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10
1 Strategic emphasis	0.316	0.229										
2 Board ideological diversity	0.281	0.469	-.029									
3 Network centrality	-0.217	0.045	-.017	.062*								
4 Board liberalism	0.568	0.335	.017	-.197*	-.019							
5 Board tenure	8.324	3.238	.085*	.035	-.135*	.034						
6 Board size	9.890	2.010	.038	.075*	.402*	-.113*	.051*					
7 Board independence	9.117	2.019	.048*	.084*	.381*	-.103*	.061*	.978*				
8 Director gender diversity	0.189	0.087	.213*	-.011	.141*	.073*	-.016*	.071*	.063*			
9 Director age diversity	7.302	2.181	.052*	-.019	-.152*	.047*	.107*	.040	.040	-.099*		
10 Director functional diversity	0.418	0.234	-.010*	-.066*	-.232*	.024	.158*	-.208*	-.194*	-.126*	-.019	
11 Director educational diversity	0.538	0.217	-.019	.023	-.067*	-.022	.086*	.090*	.082*	-.071*	.083*	-.015
12 CEO duality	0.561	0.469	-.069*	-.014	.126*	-.060*	-.015	.116	-.012	.034	-.035	.009
13 Firm performance	0.252	0.775	.036	-.080*	.056*	.029	.058*	.034	.039	.097*	.056*	-.076*
14 Firm age	61.343	4.738	-.085*	.094*	.013	.153*	.145*	-.036	-.015	.282*	-.051*	.043*
15 Firm size	2.345	1.585	.114*	.053*	.409*	-.058*	.037	.489*	.464*	.125*	-.157*	-.278*
16 Advertising expenditure	218.725	558.355	.099*	.002	.301*	.005	-.130	.315*	.309*	.137*	-.033	-.227*
17 R&D expenditure	258.976	785.921	-.194*	-.029	.247*	-.055*	-.064*	.179*	.176*	.052*	-.099*	-.219*
18 Absorbed slack	0.043	0.136	.134*	.047*	-.167*	-.047*	.173	-.068*	-.070*	-.103*	.048*	.327*
19 Unabsorbed slack	0.158	0.152	.000	-.113*	-.165*	.102*	-.093*	-.294*	-.262*	-.056*	.021	-.027
20 Industry concentration	0.090	0.103	.241*	.030	.047*	-.032	.094*	.082*	.068*	.000	--.014	-.009
21 Industry turbulence	0.048	0.034	-.031	-.021	.004	-.039	-.055*	.002	.003	-.058*	-.017	-.003
22 Industry growth	0.059	0.201	.029	-.031	.007	.012	.036	.007	-.000	.007	.013	-.020

23 Industry strategic emphasis	0.277	0.157	.591*	-.013	-.055*	.020	.143*	-.008	-.015	.059*	-.014	-.030

Variable	11	12	13	14	15	16	17	18	19	20	21	22
12 CEO duality	.032											
13 Firm performance	-.054*	-.045*										
14 Firm age	-.077*	-.142*	.076*									
15 Firm size	.120*	.136*	.046*	-.033								
16 Advertising expenditure	-.025	.058*	.087*	.001	.418*							
17 R&D expenditure	.020	.039	.117*	.046*	.273*	.356*						
18 Absorbed slack	.100*	.017	-.352*	.062*	-.151*	-.155*	-.179*					
19 Unabsorbed slack	-.091*	-.127*	.139*	-.029	-.351*	-.122*	.048*	-.238*				
20 Industry concentration	.180*	.006	-.135*	.021	.289*	.016	-.119*	.159*	-.224*			
21 Industry turbulence	.030	-.031	-.031	-.172*	-.029	-.026	-.029	.041	-.046*	.200*		
22 Industry growth	.039	.006	-.045*	-.158*	.025	-.031	-.044*	.080*	-.040	.138*	.142*	
23 Industry strategic emphasis	.146*	-.003	-.164*	-.088*	.296*	.009	-.162*	.244*	-.013	.458*	-.034	.073*

* = $p < .05$. 4,161 observations of 584 firms.

Prior to removing any observations from the dataset, the board interlock network was constructed and all network-level variables were calculated. This ensures that the measure of centrality captures all network ties for the focal firm, regardless of whether the connected firms are included in the final analysis. The sample was then refined to firms with over 100 million USD in total assets to ensure that this study only includes large firms. There are three main reasons for this. First. the influence of directors on strategic decision-making relative to the TMT is greater within large firms (Finkelstein et al. 2009; Kiss et al. 2020). Second, the board interlock network in the U.S. economy largely consists of directors who serve on the boards of the largest, most important firms and accordingly confers the greatest informational benefit to these firms (Mizruchi 2013; Withers et al. 2020). Consequently, board research typically focuses on this empirical context. In fact, the sampling frame used here is broader than is typical in this stream of research, which often focuses on the Fortune 500 or a subset of this group (e.g., Howard et al. 2016; Withers et al. 2020). Broadening the sample in this way enables a test of the above hypotheses in a wider, and thus more generalisable, context, while remaining focused on the "corporate elite" for which board interlock networks are most consequential in terms of firm-level outcomes (Mizruchi 2013). Third, a focus on large publicly listed firms in the U.S. means that this sample does not include firms with alternative ownership structures (such as family-owned or governmental enterprises), which may influence R&D activity (Kim et al. 2008) and thus strategic emphasis. This analysis therefore follows precedent (e.g., Chakravarty and Grewal 2016; Josephson et al.

2016a; Kim et al. 2018) in focusing on this commonly examined empirical setting.

Next, firms operating in highly regulated sectors (SIC codes 60-69 and 91-99) were removed, to ensure this sample excludes firms in which directors have little discretion (c.f. Heyden et al. 2015) and political donations are more likely to be driven by tactical rather than ideological motivations (Ansolabehere et al. 2003). The final sample comprises 4,161 observations of 584 firms operating in 44 industries by 2-digit SIC code between the years 2000 and 2018.

4.3.2 Measures

Dependent Variable: Strategic Emphasis. This study employed the established ratio measure of strategic emphasis that has been used consistently in prior research (e.g., Mizik and Jacobson 2003; Josephson et al. 2016a; Kim et al. 2018) to assess a firm's relative focus on value creation or value appropriation. While no single organisational factor can completely represent strategic emphasis, this operationalisation provides a suitable proxy as it is based upon the two key functional areas representing each end of the value creation—value appropriation trade-off (Mizik and Jacobson 2003). This is calculated at the firm-year level as advertising expenditures minus R&D expenditures, scaled by total assets. Positive values represent a focus on value appropriation and negative values indicate a focus on value creation.

Independent Variables: Ideological Diversity and Network Centrality. Individual directors' political ideology was measured using the procedure developed by Chin et al. (2013), after which an index of board ideological diversity was calculated. This measure is derived from data on individuals' contributions to the campaigns of the two major U.S. political parties, recorded by the U.S. FEC. Financial support for Democrats and Republicans is strongly correlated with self-reported ideological liberalism and conservatism respectively (Hetherington 2009; Chin et al. 2013), providing a valid indicator of individuals' beliefs and attitudes (Gupta and Wowak 2017). Donations to third parties were excluded from this analysis as the U.S. FEC data does not differentiate between smaller parties of widely differing ideological positions (such as the Libertarian and Green parties), thus prohibiting inference of directors' ideology from these donations. Third party donations are also rare in the FEC dataset, with approximately 200,000 recorded donations to third parties and over 32 million donations to the Republican and Democratic Parties in this sample. By constructing ideological measures from personal, rather than corporate, donation data, this approach also avoid the misattribution of ideological motivations to contributions that are made as attempts to influence policy (Ansolabehere et al. 2003). U.S. FEC donation data was matched to directors' identifying information in BoardEx based on correspondence between individuals' names, organisations, and occupations, using automated matching and manual cross-verification to ensure accuracy.

To calculate individual director ideology, each donation was first coded as either Democrat or Republican. Four measures were then calculated for each director-year, based on the individual's donations over the preceding ten years. This window enables meaningful inference about stable ideological preferences (c.f. Jost et al. 2009; Chin et al. 2013) as it encompasses two presidential and five congressional election cycles. The four measures are ratios, calculated as: (1) the number of donations to Democrats divided by the total number of donations to Democrats and Republicans; (2) the number of years in which a donation is made to a Democrat divided by the total number of years in which a donation is made to either Democrats or Republicans; (3) the number of unique Democrat recipients divided by the total number of unique Democrat and Republican recipients; and, (4) the dollar amount of donations to Democrats divided by the total dollar amount of donations to both Democrats and Republicans. Each measure has a zero to one scale, with higher values representing liberalism. As in prior usage, these measures exhibited high internal reliability (Cronbach's $\alpha = .99$) and similar means and distributions. The average (mean) was thus computed as a composite index of director liberalism. This study also followed prior research and imputed values of .5 for directors who made zero donations during the coverage of this sample, thus assuming these directors to be ideological moderates. This approach was validated by Chin et al. (2013), who report close correspondence between donation-based and self-report measures of executives' ideology for both donors and non-donors.

From the director-year level index of liberalism, *board ideological diversity* was calculated as the coefficient of variation: the standard deviation of directors' ideologies divided by the mean. This captures ideological differences around the average political orientation within the board. This measure was calculated for each firm-year in the sample. Thus, while individuals' ideologies are relatively stable (c.f. Christensen et al. 2015), ideological diversity varies over time as directors enter and leave the board, exhibiting an intertemporal correlation of .397.

To measure *network centrality*, a bimodal network was first constructed for each year in the sample, which comprises (1) the connections between directors and the boards on which they serve and (2) the connections between firms created by the presence of a shared director. This was then reduced this to a unimodal network of board-to-board connections, which is treated as a map of firms' information environment (Srinivasan et al. 2018). Several methods exist for assessing a focal firm's position within this network (Borgatti and Everett 2006). Degree centrality represents the total number of direct connections to other firms but provides no information about the likely information flows from these connections. Betweenness and closeness centrality capture the number of times that any firm in the network must pass through the focal firm to reach any other firm in the network, thus representing the focal firm's gatekeeping capacity in the flow of information (Freeman 1980). However, this provides no estimate of incoming information flows. The measure best suited to capturing information exposure is eigenvector centrality, which accounts for the amount of information to which a firm is likely exposed (Mariolis and Jones 1982). This is a weighted measure, where the weight assigned to each of the focal firm's connections is determined by the centrality scores of the connected firm. Eigenvector centrality therefore accounts for the density of the information network surrounding the focal firm, capturing the notion that connections to other well-connected firms are likely to provide access to more of the information contained within the network (Borgatti and Everett 2006). The eigenvector centrality of a focal firm *i* (C_i), connected to *M(i)* other firms within a network of *N* possible firms was computed as:

$$C_i = \frac{1}{\lambda} \sum_{j \in M(i)} a_{ij} C_j \tag{4.1}$$

Where a_{ij} = 1 if firm *i* is connected to firm *j* and zero otherwise. In eigenvector notation;

$$AC = \lambda C \tag{4.2}$$

Where *C* is the vector of centralities, *λ* the vector of eigenvalues, and *A* the adjacency matrix containing the relationships between firms. As for ideological diversity, eigenvector centrality was measured at the firm-year level, allowing for temporal variation.

Controls. The following analyses control for *board liberalism*, calculated as the average ideology across directors, to account for potential effects of liberalism or conservatism on strategic emphasis. While previous research on boards and TMTs treats this measure as the main ideological variable of interest, predicting and finding directional effects on firm outcomes (e.g., Christensen et al. 2015; Park et al. 2020), it is treated as a control variable in this context as neither liberalism or conservatism is expected to be consistently associated with either value creation or value appropriation. Considering value creation, the higher risk tolerance and open-mindedness of liberals (Carney et al. 2008; Gerber et al. 2011) may lead to greater emphasis on innovative and uncertain investments. However, conservatives show a stronger ability to delay gratification and pursue long-term projects (Gerber et al. 2011), which suggests a preference for the longer time horizons and greater rewards of R&D versus advertising investments. Conversely, conservatives also tend to be loss averse (Gerber et al. 2011), suggesting a tendency against risky value creation strategies (c.f. Christensen et al. 2015). Liberals are also less likely to have an internal locus of control (Skitka and Tetlock 1992), leading to lower confidence and assertiveness in decision-making (Carney et al. 2008), which has been identified as an antecedent to value creation focus (Kim et al. 2018). Given these equivocal findings and consequent ambiguous predictions, this study includes board liberalism as a control but does not hypothesise directional effects on strategic emphasis.

A comprehensive set of controls was also included to account for other antecedents of strategic emphasis and board participation in strategic decisions. At the board-level, these are: *board tenure*—the average number of years that directors have served on the board; *board independence*—the proportion of outside directors; and *CEO duality*—an indicator that takes the value of 1 if the CEO also serves as board Chair and zero otherwise. These variables capture the effects of other characteristics that may affect the board's involvement in strategic decisions (e.g., Zona 2016). *Board size,* defined as the number of directors on the board, was also included to account for the fact that larger boards, by definition, will have greater scope for different perspectives and more opportunities for board interlocks. Inclusion of these board-level variables also ensures that these analyses account for influences on the formation and structure of board interlock networks and thus a firm's information exposure (Srinivasan et al. 2018).

Four board-level controls were also included to capture other aspects of board diversity that may affect group cognitive processes. Two key dimensions are relevant: demographic diversity and job-related diversity (Holmes et al. 2020; Triana et al. 2021). To account for demographic influences, *director gender diversity*, measured as the proportion of female directors, and *director age diversity*, measured as the standard deviation in directors' ages, were included. Job-related diversity was controlled for using two measures. *Director educational diversity* was calculated as the coefficient of variation in the number of qualifications (at undergraduate level of above) obtained by directors within a firm's board. *Director functional diversity* was similarly calculated as the coefficient of variation in the number of functional areas in which directors have professional experience. Higher values on these measures thus represent boards in which directors have varying levels of formal education or heterogenous professional experience, whereas low values indicate that the educational and functional backgrounds of directors are relatively homogeneous.

While data on directors' qualifications is readily obtainable from BoardEx, functional experience must be inferred from job titles. Recent research has achieved this by utilising dictionary-based computerised text classification (e.g., Srinivasan et al. 2018; Whitler et al. 2018). However, as firms are increasingly adopting non-standard executive titles (Gupta et al. 2020), this may not accurately capture directors' experience: for example, identifying marketing-experienced directors by prior job titles including the words 'marketing' and 'sales' would fail to identify a 'Chief Brand Officer'. To address this limitation, this study extends the dictionary-based approach by employing a probabilistic algorithm to capture differences in word usage within job titles across industries and time. This was achieved using Guided Latent Dirichlet Allocation (Guided LDA), a topic modelling technique that identifies the latent themes in a collection of documents (i.e., job titles) and the words most strongly associated with each topic (Blei and McAuliffe 2008). While basic LDA is often used for this purpose, this is unsuitable for the aims of this study as there is a collection of words that are common across all documents (e.g., 'manager', 'director', and 'chief'), meaning that the topics identified by a basic LDA algorithm would be unlikely to differentiate between functional areas. Guided LDA mitigates this issue by introducing lexical priors or 'seed words' – here, words representing functional areas – greatly improving the identification of semantically meaningful topics while retaining the probabilistic nature of the LDA process (Jagarlamudi et al. 2012). Details of the guided LDA procedure are provided in Appendix A. The final model identifies six functional areas, to which each job title was assigned based on its highest topic probability. The sum of the number of previous positions in each functional area was then calculated for each director-year in the sample. Matching these to board-year observations, the average experience on the board in each functional area was then computed. The coefficient of variation was then calculated as the standard deviation scaled by the mean experience across all functional areas for each firm-year.

At the firm-level, *firm performance* was included as a control, using Tobin's Q to capture both market and financial aspects (Chung and Pruitt 1994). *Firm size,* measured as the natural log of the number of employees, and *firm age* were also included to control for the effects of organisational maturity and inertia on a firm's relative focus on value creation and value appropriation (Kim et al. 2018; Kiss et al. 2020). Additional controls were included for *unabsorbed slack*—cash and cash equivalents scaled by total assets, and *absorbed slack*—working capital minus cash and cash equivalents scaled by total assets (Kim and Bettis 2014), as both forms of slack affect firms' strategic emphasis (Josephson et al. 2016a; Kiss et al. 2020). Lastly, *advertising expenditure* and *R&D expenditure* were included as controls such that the measurement of strategic emphasis is not distorted by absolute levels of investment. Accounting for this factor is important, as similar strategic emphasis ratios may represent firms where the magnitude of investment differs greatly. Including these measures therefore avoids treating firms that heavily invest in both advertising and R&D in the same way as those that invest in neither.

At the industry-level, controls for *industry concentration*, *industry turbulence,* and *industry growth*, measured as detailed in Table 4.3.1, were used to account for effects of the competitive environment on strategic emphasis (Josephson et al. 2016a; Kim et al. 2018; Kang and Kim 2020). *Industry strategic emphasis,* measured as the average strategic emphasis across all firms in an industry excluding the focal firm, was included to account for competitive pressure on advertising and R&D expenditures (Kim et al. 2018). As detailed below, the use of firm, industry, and year fixed effects was also used to account for omitted variables. These firm- and industry-level variables also ensure that this analysis controls for internal and external factors that affect both the complexity and uncertainty of board decision-making (Rindova 1999) and the likely suitability of value creation or value appropriation strategies (Josephson et al. 2016a; Kang and Kim 2020).

4.3.3 Model Estimation

The following basic model was specified to test the hypothesised relationships between board ideological diversity, network centrality, and strategic emphasis:

(4.3) $SE_{it+1} = \beta_0 + \beta_1 NC_{it} + \beta_2 ID_{it} + \beta_3 NC_{it} \times ID_{it} + \beta_k Controls_{it} + \varepsilon_{it}$

Where i indexes the focal firm, and t the year. SE_{it+1} represents the strategic emphasis of the firm measured one year following the measurement of all independent variables, NC_{it} represents network centrality, ID_{it} ideological diversity, and ε_{it} unexplained variance in SE_{it+1}. $\beta_1, \beta_1,$ and β_3 correspond to hypotheses H1, H2, and H3.

This model evidently raises endogeneity concerns arising from both omitted variables and simultaneity. While the extensive list of control variables detailed above were chosen to ensure a stringent test of the predictions of this study, there is likely to exist unobserved heterogeneity that is not captured by these measures. The model was thus estimated with fixed effects at the firm, industry, and year level:

(4.4) $SE_{it+1} = \beta_0 + \beta_1 NC_{it} + \beta_2 ID_{it} + \beta_3 NC_{it} \times ID_{it} + \beta_k Controls_{it} + \mu_i + \upsilon_t + \eta_j + \varepsilon_{it}$

Where j indexes the focal firm's industry, μ_i represents firm-specific effects, υ_t year-specific effects, η_j industry-specific effects, and ε_{it} i.i.d. errors.

The fixed effects approach is typically precluded in research examining decision-makers' ideologies, as measures at the individual-level tend to be temporally stable and therefore require an estimation method that accounts for intertemporal correlation in predictor variables, such as generalised estimating equations (GEE) (Chin et al. 2013; Chin and Semadeni 2017; Gupta and Wowak 2017). However, as this study focuses on ideology measures at the board-level that vary over time (compare with the individual-level focus of Chapter 2), it is possible to exploit the panel structure of the data and temporal independence of predictor variables to control for omitted variables using fixed effects (Hill et al. 2020).

While fixed effects can mitigate concerns arising from unobserved heterogeneity, this leaves the potential for reverse causality, which is pertinent to both predictor variables. Strategic emphasis might affect board ideological diversity if the relative focus on value creation or value appropriation is perceived as more attractive to potential directors with liberal or conservative leanings. While the equivocal evidence for the effects of ideology on strategic emphasis discussed above suggests this is unlikely, it must nevertheless be noted as a concern. Similarly, strategic emphasis might affect the motivation to connect to other boards in an attempt to gather external information; for example, a value creation-focused firm might seek to establish more interlocks to gain access to new market intelligence (c.f. Srinivasan et al. 2018; Li 2019). This may introduce simultaneity in network centrality and strategic emphasis.

To empirically test whether endogeneity arising from reverse causality is an issue, two stage least squares (2SLS) estimation was used (Hill et al. 2020). The instrumental variables employed were *peer firm board ideological diversity* and *peer firm network centrality*, calculated as the average across firms in the focal firm's 4-digit SIC code (excluding the focal firm). These instruments meet the criteria of relevance in that they are sufficiently strong predictors of the potentially exogenous variables, as indicated by a highly significant F-statistic (ideological diversity: F = 2146.86, $p < .001$; network centrality: F = 351.06, $p < .001$). These instruments are also theoretically exogenous, i.e., uncorrelated with the error term of the outcome in the primary model (Bascle 2008): peer firm levels of the variables of interest have been justified as suitable instruments in prior research on both political ideology and the value creation—value appropriation decision (Gupta and Wowak 2017; Kim et al. 2018).

Results of 2SLS estimation indicated that the original firm-level measure of ideological diversity is not endogenous. Both the Durbin (χ^2 = 0.14, p = .709) and Wu-Hausman (F = 0.14, p = .710) tests did not reject the null hypotheses that ideological diversity is exogenous, thus indicating that 2SLS is not required and fixed effects estimation is sufficient to account for endogeneity concerns arising from unobserved heterogeneity (Wooldridge 2013). However, both the Durbin (χ^2 = 3.79, p = 0.052) and Wu-Hausman (F = 3.75, p = 0.053) tests were marginally significant (at the 10% level) for network centrality. To ensure a prudent and robust test of the hypotheses, the model was also estimated with the instrumental variable of peer firm network centrality, introducing a second equation in addition to Equation 4.3, where Z_{it} represents the instrumental variable that is excluded from Equation 4.3:

(4.5) $$IE_{it} = \gamma_0 + \gamma_1 Z_{it} + \gamma_2 X_{it} + \vartheta_{it}$$

The above tests can determine whether 2SLS is required based on the assumption that the instruments are valid. Though theoretical justification is provided above, this cannot be tested directly (Bascle 2008). It is therefore prudent to account for endogeneity via an alternative approach that does not require the introduction and justification of additional instruments (Hill et al. 2020). Consequently, the model was also estimated using the panel instruments approach proposed by Arellano and Bond (1991), a generalised method of moments (GMM) estimator in which first differences are used as instrumental variables to remove unobserved heterogeneity and serial correlation in residuals. This is represented by a system of the levels equation including the lagged dependent variable and firm-specific error (4.6) and differences equation (4.7):

(4.6) $$SE_{it+1} = \beta_0 + \beta_1 NC_{it} + \beta_2 ID_{it} + \beta_3 NC_{it} \times ID_{it} + \beta_k Controls_{it} + \gamma SE_{it-1} + \mu_i + \varepsilon_{it}$$

(4.7) $$SE_{it+1} - SE_{it-1} = \beta_1(NC_{it} - NC_{it-1}) + \beta_2(ID_{it} - ID_{it-1}) + \beta_3((NC \times ID)_{it} - (NC \times ID)_{it-1}) + \beta_4(SE_{it-1} - SE_{it-2}) + \beta_k(Controls_{it} - Controls_{it-1}) + (\varepsilon_{it} - \varepsilon_{it-1})$$

In sum, the hypotheses presented above were tested using the four most commonly recommended approaches to addressing endogeneity. Equation 4.4 utilises fixed effects to correct for unobserved heterogeneity; the 2SLS (Equation 4.3 and 4.5) and GMM (Equation 4.6 and 4.7) estimators address the potential for reverse causality; and all models include extensive controls to reduce the influence of endogeneity problems arising from omitted variables (c.f. Hill et al. 2020).

4.4 RESULTS

Table 4.4 presents the results of three models: (1) estimated with firm, industry and year fixed effects, (2) 2SLS estimation with network centrality instrumented with peer firm network centrality, and (3) using the Arellano and Bond (1991) GMM estimator. While there is considerable variation in the effects of control variables across the three models, the direction and significance of the independent variables remain consistent, suggesting that the effects of interest are robust to alternative model specifications. For parsimony, the following discussion of hypotheses focuses on the coefficients obtained in Model 1.

TABLE 4.4 Effects of Ideological Diversity and Network Centrality on Strategic Emphasis[a]

	(1) Fixed Effects				(2) 2SLS[b]				(3) Arrelano—Bond GMM			
	Estimate	S.E.	*t*	*p*	Estimate	S.E.	*z*	*p*	Estimate	S.E.	*z*	*p*
Effects of interest												
Board ideological diversity	-0.044	0.017	-2.62	(.009)	-0.660	0.213	-3.09	(.002)	-0.035	0.01	-2.24	(.025)
Network centrality	0.254	0.064	3.98	(.000)	3.811	1.300	2.94	(.003)	0.168	0.05	3.02	(.003)
Board ideological diversity x network centrality	-0.174	0.078	-2.24	(.025)	-3.030	0.987	-3.07	(.002)	-0.153	0.06	-2.17	(.030)
Controls												
Board liberalism	0.004	0.007	0.59	(.555)	-0.024	0.015	-1.53	(.126)	0.007	0.006	1.11	(.265)
Board tenure	-0.011	0.029	-0.36	(.717)	0.148	0.061	2.39	(.017)	0.040	0.031	1.27	(.203)
Board size	-0.074	0.179	-0.42	(.677)	-0.706	0.346	-2.04	(.042)	-0.192	0.163	-1.18	(.239)
Board independence	-0.011	0.174	-0.07	(.948)	0.529	0.310	1.70	(.088)	0.083	0.158	0.53	(.598)
Director gender diversity	-0.009	0.016	-0.54	(.586)	0.206	0.037	5.54	(.000)	0.005	0.016	0.34	(.736)
Director age diversity	0.010	0.026	0.39	(.699)	0.203	0.059	3.43	(.001)	0.001	0.026	0.02	(.983)
Director functional diversity	0.190	0.219	0.87	(.384)	0.180	0.066	2.71	(.007)	0.141	0.182	0.77	(.439)
Director educational diversity	-0.051	0.037	-1.39	(.166)	-0.124	0.081	-1.53	(.127)	-0.025	0.035	-0.73	(.467)
CEO duality	-0.001	0.006	-0.10	(.924)	-0.040	0.013	-3.07	(.002)	0.004	0.006	0.06	(.529)
Firm performance	-0.039	0.046	-0.85	(.393)	0.134	0.078	1.71	(.088)	-0.011	0.043	-0.25	(.801)
Firm age	-0.002	0.002	-1.16	(.247)	-0.005	0.001	-4.72	(.000)	-0.000	0.001	0.06	(.954)
Firm size	-.026	0.005	-4.97	(.000)	-0.033	0.007	-5.04	(.000)	-0.009	0.006	-1.72	(.086)
Advertising expenditure	0.450	0.095	4.74	(.000)	0.399	0.114	3.50	(.000)	0.205	0.093	2.19	(.029)
R&D expenditure	-0.061	0.091	-0.68	(.499)	-0.852	0.139	-6.14	(.000)	-0.107	0.081	-1.31	(.189)
Absorbed slack	-0.025	0.028	-0.90	(.369)	0.027	0.043	0.63	(.529)	0.065	0.028	2.35	(.019)
Unabsorbed slack	-0.070	0.022	-3.20	(.001)	0.032	0.041	0.80	(.423)	-0.081	0.021	-3.94	(.000)
Industry concentration	0.186	0.067	2.76	(.006)	-0.035	0.058	-0.60	(.550)	0.074	0.067	1.11	(.267)

Industry turbulence	0.128	0.056	2.26	(.024)	-0.156	0.145	-1.07	(.284)	0.049	0.043	1.13	(.258)
Industry growth	0.009	0.011	0.83	(.407)	-0.030	0.024	-1.28	(.199)	0.002	0.007	0.24	(.811)
Industry strategic emphasis	0.684	0.055	12.24	(.000)	0.953	0.046	20.93	(.000)	0.495	0.065	7.63	(.000)
Strategic emphasis									0.522	0.022	23.41	(.000)
Constant	0.388	0.140	2.870	(.004)	1.080	0.329	3.29	(.001)	0.728	0.060	1.20	(.228)
F / χ^2 [c]	7.46			(.000)	1111.12			(.000)	854.15			(.000)

[a] Positive coefficients represent an increase in value appropriation emphasis. Negative coefficients represent an increase in value creation emphasis. Variables are standardised in all models to aid interpretation of coefficients.

[b] In Model 2, network centrality is instrumented by peer firm network centrality.

[c] F statistic applies to Model 1; χ^2 to Models 2 and 3.

H1 posited two competing hypotheses for the effect of network centrality, which the author predicted would lead to increased value creation (H1a) or increased value appropriation (H1b). The positive and significant coefficient (0.254, $p < .001$) indicates that increased network centrality is positively associated with value appropriation, thereby supporting H1b. H2 predicted that board ideological diversity would be negatively associated with a firm's relative emphasis on value appropriation. Results provide support for this hypothesis in the negative main effect (-0.044, $p = .009$), which indicates increased value creation within ideologically diverse boards.

H3 predicted that board ideological diversity would negatively moderate the relationship between network centrality and value appropriation, such that the firm's relative strategic emphasis on value appropriation is lower when board ideological diversity is higher. Support for this hypothesis is found in a negative contingent effect (-.174, $p = .025$) indicative of an increased relative focus on value creation. Furthermore, there is a negative marginal effect, as shown in Figure 4.4. Thus, while the magnitude of the negative effect of network centrality is greater than the positive effect of ideological diversity across model specifications, high ideological diversity can invert the effects of network centrality on strategic emphasis. In line with theoretical formulations of board decision-making, these results therefore support the notion that the interaction between environmental and cognitive factors is most consequential for strategic decisions (DiMaggio and Powell 1983; Rindova 1999).

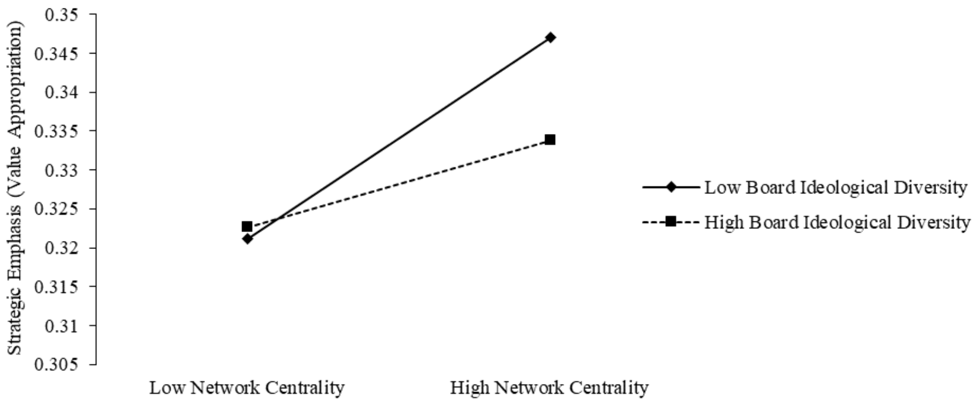

FIGURE 4.4 Interaction Effects of Board Ideological Diversity and Network Centrality

Coefficients for Model 1 are shown.

It is also notable that the effect of board liberalism is consistently nonsignificant, in line with the author's expectation that the average ideology of the board exerts competing effects. This provides further evidence that it is diversity in directors' ideologies that matters for strategic emphasis, rather than the overall conservative or liberal leanings of the board. Furthermore, while there are some significant effects of other forms of diversity that may influence board cognition (e.g., demographic diversity in Model 2 and educational experience in Model 1), these are inconsistent across models. This suggests that the effects of ideological diversity, as a measure of heterogeneity in directors' cognitive frameworks, is most robust to alternative specifications.

4.5 DISCUSSION

The factors that determine a firm's prioritisation of R&D versus advertising investments are of considerable importance to research and practice (Chakravarty and Grewal 2016; Josephson et al. 2016a). However, these investigations are largely focused on the TMT (e.g., Currim et al. 2012; Kim et al. 2018), thus overlooking the increasingly central role of the board of directors in strategic decision-making and the importance of board cognition in this regard (Withers et al. 2012). Similarly, studies of strategic emphasis recognise the importance of information processing (Kim et al. 2018; Kiss et al. 2020) and yet none have explicitly addressed the information environment in which the value creation—value appropriation decision is made.

This study addresses these two critical omissions in the extant literature, presenting the first empirical examination of the effect of board cognition and information exposure on a firm's relative focus on value creation or value appropriation. Drawing on the cognitive perspective of corporate governance (Rindova 1999), the author contends that board cognition can be manifest as the ideological diversity among directors. Ideology, which is operationalised using established and validated measures derived from directors' political donations (e.g., Chin et al. 2013; Park et al. 2020), reflects multiple underlying personality traits, cognitive biases, and behavioural patterns, with consequent relevance for a variety of firm-level decisions (Gupta and Wowak 2017; Gupta et al. 2020). To measure information exposure, this study examined firms' centrality within the board interlock network—the primary conduit of external information between corporate boards (Srinivasan et al. 2018). Combining these measures allows an analysis of the impact of boards' information exposure and processing on strategic emphasis.

The author hypothesises and substantiates both direct and interaction effects of board ideological diversity and network centrality. Multiple models were specified to address endogeneity concerns and show that these results are robust across estimation methods. Specifically, board ideological diversity leads to an increased focus on value creation, in line with psychological evidence that ideologically heterogenous teams produce more novel and creative solutions in problem-solving tasks (e.g. Page 2008; Duarte et al. 2015). Conversely, network centrality leads to an increased focus on value appropriation; an ostensibly surprising finding given the documented benefits of board interlocks for new product development (Srinivasan et al. 2018; Li 2019) but in line with the evidence that network centrality also encourages imitation of strategies (Geletkanycz and Hambrick 1997; Westphal et al. 2001). The interaction of board ideological diversity and network centrality leads to an increased focus on value creation. Consistent with the cognitive perspective on corporate governance, this therefore suggests that board cognitive diversity and external information influence decision-making via the interplay between environmental scanning, information interpretation, and negotiating consensus around strategic choices. By offering additional insight beyond the previously studied firm-, TMT-, and market-level factors that affect strategic emphasis, these results have several implications for theory and practice.

4.5.1 Implications for Theory

The principal contribution of this study is the introduction of board-level cognition and information flows into the study of value creation and value appropriation. These factors are identified as novel drivers of the value creation—value appropriation trade-off, and the analyses presented herein demonstrates their interaction effects. In particular, these findings highlight director ideology as a fruitful avenue for future investigations. While diversity in other director characteristics, such as demography and professional experience, has long been recognised as consequential for decision-making (Holmes et al. 2020; Triana et al. 2021), ideological diversity has not been studied to date. Psychological evidence provides ample support for political ideology as a valid proxy for patterns of underlying beliefs, biases, and personality traits (e.g., Jost et al. 2009; Gerber et al. 2011). Accordingly, a growing literature has been motivated by the strong and consistent relationship between ideology and individuals' behaviour, identifying the political affiliations of decision-makers as a significant influence on many firm outcomes, including CSR (Chin et al. 2013; Gupta et al. 2020), compensation (Chin and Semadeni 2017), and tax avoidance (Christensen et al. 2015). However, diversity in these attributes has been overlooked, with most studies focused on the average ideology of the board or TMT or individual decision-makers such as the CEO. This study therefore also presents a methodological contribution to the development of composite measures of directors' cognitive heterogeneity. The approach employed here is based on existing and validated measures of personal ideology (Chin et al. 2013) and can inform future research on a unique form of director diversity that has long been theorised as central to board cognition and its effects on strategic decisions (Forbes and Milliken 1999; Rindova 1999).

This study also contributes to emerging research on the interactive effects of individual cognition and structural aspects of networks. Much prior research does not distinguish the opportunities provided by the information gained from interlock networks from the motivation for actors within the network to utilise these for their advantage (Srinivasan et al. 2018). This approach addresses this problem of "overembeddedness" (Granovetter 1985) and reveals the limitations of this approach: in demonstrating directionally opposing effects for network centrality in isolation and in interaction with board ideological diversity, these analyses provide evidence that the agency and cognition of network actors can alter the effects of network position on firm-level outcomes. This notion of "network agency" is presently a concern in the management literature (Tasselli and Kilduff 2020). This study contributes to this debate regarding the appropriate levels of analysis in information networks.

4.5.2 Implications for Practice

In furthering understanding of the board-level factors that shape a firm's strategic focus and investment decisions, these findings also have implications for directors (as well as shareholders, managers, and consultants involved in the appointment of new directors) and executives.

For directors and their appointment, the recommendations that can be derived from this study echo those that have recently emerged in academia as a response to increasing ideological homogeneity in many fields (e.g., Duarte et al. 2015; Haidt and Lukianoff 2018). Ideological diversity has long been recognised as beneficial for problem-solving (Triandis et al. 1965; Mannix and Neale 2005; Page 2008), whereas homogeneity in individuals' cognitive frameworks hinders the exploration of new ideas (Forbes and Milliken 1999; Heyden et al. 2015), discourages decision-making teams from addressing important questions (Haidt 2012), and prevents the correction of errors (Frey and van de Rijt 2020). Fundamentally, viewpoint diversity is critical to effective strategic decision-making (Milliken and Vollrath 1991; Rindova 1999), and these results support this, indicating that this can help firms utilise external information for value creation (c.f. Talke et al. 2011; Lin and McDonough 2014). This author therefore suggests that the hiring process of new directors considers this evidence and purposefully recruit from across the ideological spectrum. This likely requires conscious effort, as individuals tend to preferentially associate with others of similar political affiliations (McPherson et al. 2001). However, this is notably less challenging or invasive than previous recommendations for changing the "psychological architecture" of strategy-making environments (c.f. Powell et al. 2011), such as psychological assessment and training to mitigate decision biases (Kim et al. 2018). At the individual-level, directors can also help to reduce the potential adverse consequences of ideological homogeneity by being aware of how their political beliefs affect their attentional focus, interpretation of environmental information, and preference for certain solutions (Duarte et al. 2015). Challenges to the consensus can be a powerful driver of more effective strategic decisions (Whitler et al. 2018; Klarner et al. 2021).

For executives, these results provide insight into the likely support or resistance to R&D and marketing budget decisions and the situations in which the corresponding functions should negotiate for increased discretion in this process. Both value creation and value appropriation are essential to firm success and an excessive focus on either dimension can be detrimental (Mizik and Jacobson 2003; Josephson et al. 2016a). Consequently, while increased ideological diversity on the board can improve value creation, marketing managers should be aware that this may require greater advocacy for maintaining investments in advertising. Justifying such investments may be difficult unless the firm has strong marketing representation in the TMT or directors with marketing experience (Whitler et al. 2018). Conversely, R&D executives may face similar issues when advocating for value creation strategies in the face of ideologically homogeneous boards. Accordingly, these findings strengthen the growing case for representation of demand-generation functions in the upper echelons of the firm, as opposed to the present dominance of directors with financial, legal, and operational expertise (Whitler et al. 2018).

Even in the absence of R&D and marketing leadership, these findings add to the case for functional discretion in investment decisions. As in previous research (e.g., Kim et al. 2018), this study does not examine effects on firm performance. This is because cognitive processes—particularly at the board-level—are difficult to trace directly to financial or market outcomes (Hambrick 2007). However, executives may combine these results with studies of the consequences of a firm's relative focus on value creation or value appropriation in different competitive environments and for various firm objectives (see Han et al. 2017, for a summary). This body of evidence should enable executives to develop strong arguments for greater discretion in the allocation of funds to advertising or R&D, ensuring that the ideological biases of the board and external information environment do not lead the firm toward a counterproductive strategic emphasis.

4.5.3 Limitations and Directions for Future Research

The author acknowledges several limitations of this study, some of which are inherent to the literature of boards of directors and/or strategic emphasis and others that present opportunities for future research. First, relying on data from the U.S. FEC limits this investigation to the U.S. context. This is a limitation of other studies on the effect of decision-makers' political affiliation on firm outcomes (e.g., Gupta et al. 2020; Park et al. 2020) and most psychological research on ideology, limiting the inferences that can be drawn from this research stream. Specifically, many other national contexts do not have a two-party system that clearly reflects the liberal-conservative divide (Malka et al. 2014). Inferring ideology from political beliefs will therefore differ in such contexts, suggesting the need to develop generalisable methods of capturing ideological differences that can be applied on an international scale.

Second, this study relies on data from BoardEx and Compustat, limiting the generalisability of the results to public firms. Relatedly, the analysis was also limited to large firms due to the importance of board interlocks in this empirical setting (Mizruchi 2013; Withers et al. 2020). However, the effects of decision-makers' ideology, ideological diversity, and the information environment likely also applies to smaller and private companies. Recent research demonstrates that CEOs' cognition and information processing affects the emphasis on exploratory innovations in

SMEs (Kiss et al. 2020). This remains a fruitful area for future research examining board-level influences and ideological effects, particularly as private firm directors are often appointed by existing directors. Given that individuals tend to associate with politically similar others (McPherson et al. 2001), less ideological diversity may be expected in private firms. Thus, it is pertinent to examine whether these findings apply in such circumstances.

Third, this study focuses on the construct of strategic emphasis as it has been defined and measured in the literature to date (e.g., Mizik and Jacobson 2003; Josephson et al. 2016a; Kim et al. 2018). While this facilitates contribution to this research stream by demonstrating the importance of previously unexamined antecedents to an established dependent variable, there are opportunities for future research to address the limitations of this construct and thus extend its applicability in practice. For example, the operationalisation of variables in this study follows Mizik and Jacobson (2003) in defining value as created for customers and appropriated through sales; a conceptualisation that reflects the emergence of this construct in the marketing literature. Alternative conceptualisations that account for simultaneous pursuit of value creation and appropriation, potentially drawing on the literature on leadership, cognition and strategic ambidexterity (e.g. Kiss et al. 2020), could provide more nuanced insights into these effects.

Finally, the implications of this study may encourage future research that examines the effects of ideological diversity on a variety of decisions beyond strategic emphasis, such as acquisition behaviour or other strategic investments. As ideology accurately proxies a range of beliefs and behaviours, the potential for theorizing and testing relationships to firm-level decisions is great, and diversity on this measure remains largely unexplored. With the increasing focus on diversity in firm leadership largely focused on demographic and professional characteristics (e.g., Mohammadi et al. 2017; Holmes et al. 2020), these findings may assist scholars and practitioners in recognising and expounding the importance of ideological diversity for effective decision-making.

5 INTERNATIONALISATION AND MITIGATING INTELLECTUAL PROPERTY RISK EXPOSURE: LEVERAGING SERVICE TRANSITION AND FIRM CAPABILITIES

5.1 INTRODUCTION

Intangible assets have long been recognised as critical strategic resources that drive sustainable superior performance in firms (Srivastava et al. 2001). Being heterogenous and imperfectly mobile between firms, this typically protects them from competitive imitation (Barney 1991). However, despite recognition that the strategic value of resources is highly contextual, the resource-based view (RBV) literature has not fully addressed threats to the value of intangible assets in the globalised business environment. Operating in foreign markets requires firms to navigate complex institutional arrangements, creating significant uncertainty when deploying strategic resources (Vahlne and Johanson 2019; Donthu et al. 2021). A key source of risk in internationalisation, critical to the value of intangible assets, lies in the regulation of intellectual property (IP) across markets (Samiee 2020).

IP is a key intangible asset for many firms due to its inherent exclusivity and inimitability (Peteraf 1993). These characteristics rely on ownership and control of the asset (Magelssen 2019). Despite recent institutional improvements in the protection of IP in emerging markets, large differences persist between countries (Berry 2017,2019) and adherence to regulation is often limited (Brander et al. 2017). For U.S. firms in particular, internationalisation often requires entry into countries where

IP protection is weaker than in the domestic market (Sartor and Beamish 2014). This increases the risk of product imitation, leading to a loss of the value of intangible assets and erosion of competitive advantage (Shinkle and McCann 2014). Consequently, U.S. firms that leverage IP as a strategic asset domestically may be unable to do so overseas (Papanastassiou et al. 2019). These growing threats to the inimitability of IP exemplify the need to better understand complementarities between firm resources, capabilities, and the international environment (Schweiger et al. 2019).

This study examines strategies that international firms can use to mitigate risks to the value of intangible assets. The author posits that the inimitability of intangible assets created through product- (i.e., IP) and process- (i.e., service) based business models is contextually dependent. The hypotheses are based on evidence for both the performance benefits of service transition (Eggert et al. 2014; Josephson et al. 2016b) and defensibility of assets created through service offerings from competitive threat (Gremler et al. 2019). This is coupled with a recognition of the importance of institutional factors in developing service offerings (Vargo and Lusch 2016,2017) and firm capabilities (He et al. 2018). For product-based international firms, this study predicts that *developing process-based intangible assets through service transition will mitigate threats to IP in foreign markets, stabilizing revenues and thus improving profitability*. For process-based international firms in which service transition is not possible, this study predicts *performance gains from capabilities that foster either product-based or process-based intangible assets, contingent on the institutional risk faced by the firm*. Data from 5,622 U.S. firms over 12 years supports these hypotheses, showing that effective deployment of intangible assets is contingent on a firm's resource position and the institutional environment. Specifically, transition to knowledge-intensive services is detrimental under normal conditions but beneficial when international firms face threats to the protection of IP. For firms with an extant knowledge-based service offering, the results demonstrate contrary effects of marketing and R&D capabilities depending on the level of IP protection in the firm's foreign markets. These differential effects manifest in firm profitability via changes in revenue volatility, in line with the importance of intangible assets and service transition strategies for reducing revenue risk (Fang et al. 2008; Katsikeas et al. 2016).

This study offers several contributions to the international marketing literature regarding complementarities in the RBV (Schweiger et al. 2019) and the effect of institutional contexts on service strategies (Vargo and Lusch 2016,2017). First, the findings provide evidence that firm capabilities can have deleterious effects if misaligned with environmental conditions, highlighting the downsides to capability development as a possible signal of resource misallocation (c.f. Feng et al. 2017). Second, these analyses demonstrate that the firm-level complementarities required for effective service transition (Josephson et al. 2016b; Patel et al. 2019) may be *less* consequential when the institutional environment threatens the value of firm resources, offering a more nuanced perspective on the efficacy of service transition that incorporates critical internal and external contingencies. This is pertinent given the prevalence of service transition in internationalizing firms (Hennart 2019), as it challenges the assumption that firms can exploit assets developed in the home market (Gupta and Govindarajan 2000). These results show that this may not hold when assets cannot be protected or leveraged overseas. Given the dearth of literature on the protection of knowledge resources during internationalisation (Berry 2019), this study thus offers novel insight into *why* asset value differs across markets and *which* strategies are effective for mitigating these threats, with practical implications for the internationalisation and service transition processes.

5.2 THEORY AND HYPOTHESES

5.2.1 Intellectual Property Risk and the Value of Intangible Assets

The RBV conceptualises firm performance as the result of resources that possess four key characteristics: value, rarity, inimitability, and non-substitutability (Barney 1991; Peteraf 1993). Empirical research and meta-analyses support these central tenets (Crook et al. 2008; Karna et al. 2016). However, contingencies affecting the characteristics of resources are presently poorly understood, despite evidence that the performance effects of resources differ based on the strategic position of the firm and environmental context (Barney 2014; Schweiger et al. 2019), In particular, the institutional context as an environmental contingency has received little empirical inquiry (Sirmon and Hitt 2009). This is especially pertinent to understanding the effectiveness of strategies based upon intangible assets, as the strategic value of these resources differs widely across institutional environments due to differences in the protection of intellectual property (IP) (Berry 2017,2019).

The importance of intangible assets derives from the likelihood that they meet the RBV conditions for attaining competitive advantage (Kozlenkova et al. 2014). Intangible assets are more likely than tangible assets to be heterogenous and imperfectly mobile across firms, increasing inimitability and rarity and thus opportunities for strategic deployment (Barney 1991; Peteraf 1993). When legislative protection is sufficient, IP epitomises these characteristics: by definition, it is held exclusively by the creator and cannot be legally imitated by competitors, creating the conditions of ownership and control that are critical to generating value from strategic assets (Magelssen 2019). However, IP does not in itself indicate a *valuable* resource. To drive financial performance, IP must be commercialised (Baldwin and Von Hippel 2011). Yet, most IP generates little financial return (Trajtenberg 1990; Rubera and Kirca 2012).

Market characteristics that affect the commercial value of IP have only recently received empirical attention (Giannetti and Rubera 2019; Papanastassiou et al. 2019). A central notion in this growing research stream is that operating across foreign markets, where IP protection varies, raises the risk of competitive imitation (Berry 2019; Samiee 2020). Established firms from developed economies are natural targets of imitation, as this can reduce uncertainty, increase legitimacy, and thus improve performance for emerging market competitors (Giannetti and Rubera 2019). Broad foreign market coverage also increases information processing demands due to the need to navigate a more complex institutional environment, leading to greater difficulty in detecting competitive or regulatory threats and coordinating responses within the multinational firm (Vahlne and Johanson

2019; Donthu et al. 2021); factors that may contribute to the inconsistent effects of multinationality on firm performance (Berry and Kaul 2016). If these factors undermine control of IP it may cease to be a strategically valuable resource, as it cannot effectively be leveraged for financial gain. Empirically, the preference among U.S. firms to expand into markets with similar IP regulation (Berry 2017; Brandl et al. 2018) and develop IP domestically (Zhao 2006; Berry 2019) supports this.

As a baseline, adverse financial consequences may therefore be expected when firms operate in markets with weak IP protection. The mechanism through which this is likely to occur is that such environments, through increasing the likelihood of imitation and thus erosion of the strategic resource base, will undermine the ability of firms to predictably generate revenues (c.f. Palmer and Wiseman 1999). This is in line with evidence that the performance effects of intangible assets accrue through improved revenue stability (e.g., Srivastava et al. 2001; Fang et al. 2008; Rego et al. 2009; Katsikeas et al. 2016), i.e., a reduction in *revenue risk*:

> ***Hypothesis 1:*** *IP risk is positively related to revenue risk, such that threats to IP protection increase the volatility of revenues.*

Following this, negative effects on profitability would consequently be expected:

> ***Hypothesis 2:*** *Revenue risk is negatively related to profitability, such that more volatile revenues decrease firm profits.*

Figure 5.2.1 illustrates these relationships and the risk mitigation strategies discussed below.

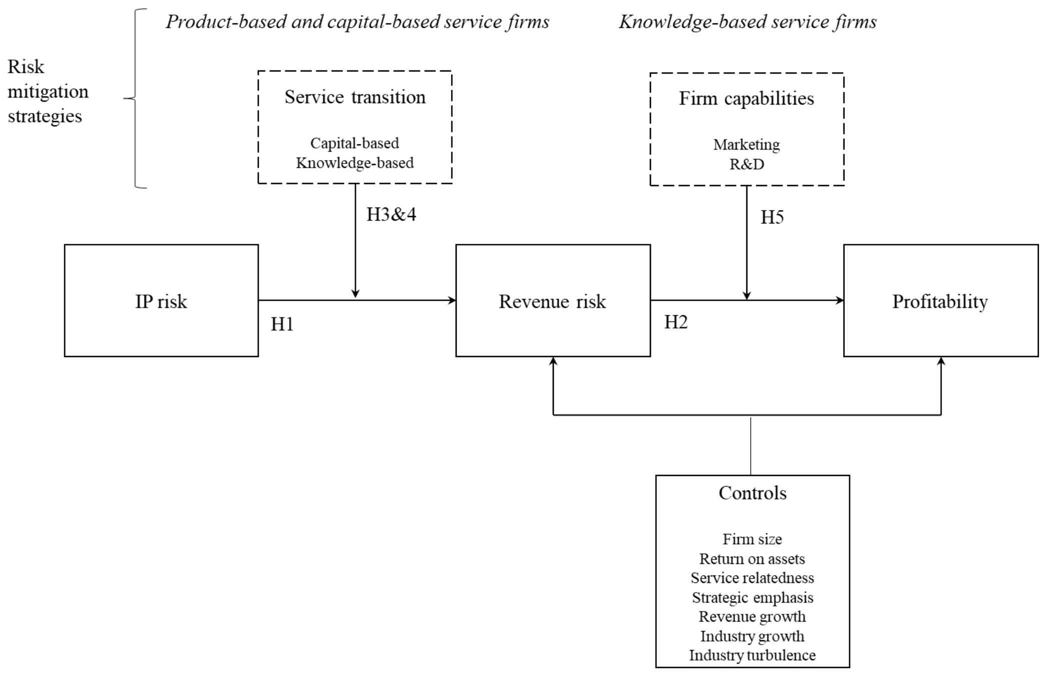

FIGURE 5.2.1 Service Transition and Firm Capabilities as Strategies to Mitigate IP Risk.

5.2.2 Product- Versus Process-Based Intangible Assets

Studies of how firms can mitigate IP risk in global markets have focused on efforts to protect the *existing* resource base (Zhao 2006; Berry 2017; Brandl et al. 2018). However, different environments may require different configurations of resources (Sirmon et al. 2011; Schweiger et al. 2019). Consequently, an alternative strategy may be to *shift* the resource base to a different form of intangible assets, of which ownership and control is more defensible when IP risk is high. To explicate this argument, this author proposes that a firm’s stock of intangible assets exists on a continuum that reflects the firm’s relative focus on products versus services. *Product-based intangible assets* can be defined as those that relate to a specific innovation, design, or product, and thus fall under the remit of IP protection. In contrast, *process-based intangible assets* refer to those that are not made inimitable through regulation but through tacit knowledge and internal processes, such as distribution agreements and customer subscriptions.[4]

Product-based intangible assets are key to competitive advantage in manufacturing firms, whereas process-based intangible assets are critical in services (Eggert et al. 2014). However, both forms can be valuable resources for all firms, the relative importance of each depending on how purely service- or product-based is a firm's business model. Faced with threats to IP protection, a purely product-based resource base will be most vulnerable to imitation and development of process-based intangible assets may be required to sustain performance.

5.2.3 Service Transition as a Risk Mitigation Strategy

The importance of process-based intangible assets is reflected in the trend towards service transition (Fang et al. 2008; Josephson et al. 2016b) where product-based business models are augmented with auxiliary services (Ulaga and Reinartz 2011). This affords protection against imitation due to the complex, unobservable processes involved in service delivery (Eggert et al. 2014) and reduces revenue risk through customer loyalty (Rego et al. 2009). Developing process-based intangible assets through services may thus create a more defensible resource base than product-based intangible assets (Gremler et al. 2019) when firms face threats to IP, mitigating environmental risk and improving stability of revenues. However, this strategic change poses a degree of risk in itself (Fang et al. 2008). The most competitively defensible service strategies tend to be *knowledge-based*

[4] This classification is based on the U.S. and Canadian GAAP definition of intangible assets.

(KB), i.e., sophisticated services that rely largely on human capital, rather than *capital-based* (CB), i.e., more standardised services that depend upon assets such as distribution networks or retail real estate (Contractor et al. 2003). The gap between the extant resources of *product-based* (PB) firms and those required for transition is greater for KB than for CB services, increasing the risks and costs of a transition strategy (Patel et al. 2019). It may therefore be expected that PB firms will typically realise greater returns from CB service transition, which can help to stabilise revenues without requiring overextension and investment that can outweigh these benefits:

> ***Hypothesis 3a:*** *In product-based firms, capital-based service transition is negatively related to revenue risk, such that increasing revenues from capital-based service segments leads to more stable revenues.*
>
> ***Hypothesis 3b:*** *In product-based firms, knowledge-based service transition is positively related to revenue risk, such that increasing revenues from knowledge-based service segments leads to more volatile revenues.*

However, CB services may not be sufficient to protect revenues when threats to IP are high. Conversely, the costs of KB service transition may be more than offset (c.f. Kraatz and Zajac 2001; Patel et al. 2019). For example, without IP protection, a manufacturer that vertically integrates into retail faces the same risk of imitation (perhaps more, if product visibility among competitors is increased), whereas the addition of a skilled sales force or repair service introduces process-based assets that competitors cannot easily replicate. For PB firms, the effects of service transition may therefore be expected to reverse when IP risk is high:

> ***Hypothesis 3c (H3c):*** *In product-based firms, IP risk negatively moderates the relationship between capital-based service transition and revenue risk, such that increasing revenues from capital-based services leads to more volatile revenues when threats to IP are high.*

> ***Hypothesis 3d (H3d):*** *In product-based firms, IP risk positively moderates the relationship between knowledge-based service transition and revenue risk, such that increasing revenues from knowledge-based services leads to more stable revenues when threats to IP are high.*

As explicated above, CB service firms also face IP risk and are also capable of service transition, despite having a process-based business model. These firms possess the service industry experience that PB firms lack, suggesting lesser risks and costs associated with developing the more complex intangible assets required for KB services (Contractor et al. 2003; Patel et al. 2019) and thus a greater likelihood of realizing benefits. Due to the defensibility of complex process-based intangible assets against imitation, these benefits are likely to be greater when IP risk is high:

> ***Hypothesis 4a:*** *In capital-based service firms, knowledge-based service transition is negatively related to revenue risk, such that increasing revenues from knowledge-based segments leads to more stable revenues.*

> ***Hypothesis 4b:*** *In capital-based service firms, IP negatively moderates the relationship between knowledge-based service transition and revenue risk, such that increasing revenues from knowledge-based services has a stronger effect on stabilizing revenues when threats to IP are high.*

In sum, these hypotheses invite an empirical test of the role resource-environment contingencies, positing that the performance effects of service transition will depend on the starting resource position of the firm and the degree to which the external environment enables product-based intangible assets (i.e., IP) to be deployed effectively.

5.2.4 Mitigating IP Risk in Service Firms

Shifting from product- to process-based intangible assets is only feasible when a firm's extant resource base is not oriented toward knowledge-intensive service provision. However, IP is a valuable resource across all sectors (Demmou et al. 2019) and thus threats to its protection remain pertinent. For example, many professional services firms offer both consulting services and intangible asset development, such as patents and industrial designs (Probert et al. 2013). Increasing the prevalence or complexity of process-based intangible assets is impractical here, as specialised processes and human capital are central to the extant business model (Von Nordenflycht 2010). Moreover, reducing revenue risk is unlikely to affect profits, as such firms already have low fixed costs and stable income from client relationships (Castaldi and Giarratana 2018). For KB services, it is therefore necessary to consider a different mechanism for mitigating IP risk: the deployment of intangible assets via capabilities (Sirmon et al. 2011).

By coordinating firm resources towards a desired outcome, capabilities act as complementary assets that facilitate the deployment—and therefore increase the strategic value —of intangible assets (Teece 1986). Importantly, the value of complementary assets is independent of the value of the resources with which they interact, affording protection against erosion of advantages built upon specific product-based assets (Tripsas

1997). Furthermore, complementarities between capabilities and resources increase the difficulty of competitive imitation (Rivkin 2000). Accordingly, strong capabilities may insulate firms against threats to IP: competitors can imitate products, but may be unable to fully emulate the activity systems that enable a firm to develop, and generate value from, intangible assets (Barney 2014).

For KB service firms which rely upon both product- and process-based intangible assets, complementarities may be leveraged with marketing and R&D capabilities. Marketing capabilities refer to a firm's ability to deploy customer-focused assets in line with market demand (Krasnikov and Jayachandran 2008), whereas R&D capabilities indicate a capacity to renew product offerings and leverage technologies (Dutta et al. 2005). Complementarities may thus be present between marketing capabilities and process-based assets, and between R&D capabilities and product-based assets. However, the independence between the value of capabilities and resources, inherent in the notion of complementary assets (Teece 1986), may be detrimental if a firm fails to leverage complementarities. In this case, strong capabilities can signify strategic inflexibility or redundant activities (Stieglitz and Heine 2007; Pham et al. 2017). This can occur when the bases of competition shift but the same combination of resources and capabilities is deployed in changed conditions (Sirmon et al. 2010). IP risk may induce this situation, as changes to the relative value of product- and process-based intangible assets may also change the value of the functional capabilities that develop and maintain these assets. As resources are inherently limited, developing the wrong capabilities—or too many—for a given situation creates both real and opportunity costs (Sirmon et al. 2011). With strong IP protection, firms may therefore benefit from focusing on R&D capabilities, as the resultant product-based assets will be fully protected. While marketing capabilities may also be beneficial, diverting resources to a less defensible asset class may create a substitutive relationship (Feng et al. 2017), where profit is negatively affected by a failure to capitalise upon a potential source of competitive advantage.[5]

> ***Hypothesis 5a:*** *In knowledge-based service firms, marketing capabilities negatively moderate the relationship between revenue risk and profitability, such that profitability is decreased in firms with volatile revenues when marketing capabilities are high.*

> ***Hypothesis 5b:*** *In knowledge-based service firms, R&D capabilities positively moderate the relationship between revenue risk and profitability, such that profitability is increased in firms with volatile revenues when R&D capabilities are high.*

In contrast, threats to IP suggest that a focus on R&D capabilities may be detrimental: even the most sophisticated R&D processes will not be valuable if the resultant innovations cannot be kept proprietary (Bellstam et al. 2020). Thus, specialisation in this area may lead to wastage of resources (Feng et al. 2017). Under IP risk, marketing capabilities may be expected to confer the greatest performance benefits as, in the absence of reliable protection of product-based intangible assets, process-based assets based on customer and partner relationships will be a more defensible source of competitive advantage (Saidi and Zaldokas 2020).

[5] There is less theoretical justification for H5a; accordingly, the effects of marketing capabilities under conditions of low IP risk are treated here as a largely empirical issue.

> ***Hypothesis 5c:*** *In knowledge-based service firms, marketing capabilities positively moderate the relationship between revenue risk, IP risk and profitability, such that profitability is increased in firms with volatile revenues and high threats to IP when marketing capabilities are high.*
>
> ***Hypothesis 5d:*** *In knowledge-based service firms, R&D capabilities negatively moderate the relationship between revenue risk, IP risk and profitability, such that profitability is decreased in firms with volatile revenues and high threats to IP when R&D capabilities are high.*

5.3 METHOD

5.3.1 Data and Sample

Financial and business segment data for publicly listed U.S. firms was obtained from the Compustat Fundamentals and Compustat Segments databases. To develop an index of firms' IP risk, two data sources were used. First, the International Property Rights Index (IPRI) has since 2007 published a score quantifying the protection of IP rights in 129 countries, representing 98% of world GDP (Property Rights Alliance 2019). Presently, this is the only dedicated index of IP protection. This country-level information was combined with the Offshoring Activity Index (OAI) developed by Hoberg and Moon (2017). The OAI uses text analysis of annual reports to identify the scope and intensity of a firm's foreign activity by identifying co-occurrences of country—activity word pairs. Activities are categorised as 'output' (identified by words such as *sales, customer* and *revenues*), 'external input' (e.g., *supplier, import*) and 'internal input' (e.g., *subsidiary, factory*) (see Hoberg and Moon 2017, Appendix A). This provides a more comprehensive measure of the forms of foreign market involvement that may contribute to firm risk than traditional metrics such as export sales. After removing firms with missing data, the sample covers the period 2007 to 2019, with 422 firm-year observations of 5,622 firms representing 234 industries by 4-digit SIC code.

5.3.2 Firm Risk and Performance

To measure firm risk, *revenue risk* was calculated as the standard deviation of a firm's revenues over the preceding four years, scaled by the mean of firm revenues over those four years (c.f. Rego et al. 2009). Controlling for revenue growth (see below) ensures that this measure does not capture increases in revenue during the period of interest. *Gross profit* was used to measure firm performance.

5.3.3 IP Risk

IP risk was measured by combining IPRI scores with data from the Hoberg and Moon (2017) OAI. The inverse of the IPRI score was used in these calculations, such that higher values represent high-risk markets. First. the average inverse IPRI score for each firm-year was calculated, weighted by the level of activity in each market (i.e., the number of country—activity word co-occurrences for that market in that firm's annual report). This weighted average IPRI score was then scaled by the total level of foreign activity for each firm-year (i.e., the total number of country-activity word co-occurrences)[6] to derive a measure of IP risk. This measure differs in important ways from IP-related variables utilised in prior research. First, it operationalises IP risk as a continuum. Unlike dichotomous measures based

[6] This is necessary to account for the full extent of foreign market activity, as some of the entries in the OAI do not specifically identify country or region markets but refer simply to 'foreign' sales, imports, ventures, etc.

on specific IP regulations (e.g., Brandl et al. 2018), this allows fine-grained differentiation between levels of protection. Second, the IPRI score accounts for multiple forms of IP regulation and, importantly, their enforcement. Other studies have focused on patent protection (e.g., Zhao 2006; Berry 2019). As patents represent only one form of potentially valuable IP (Demmou et al. 2019), the IPRI-based approach provides a more appropriate measure for the study of IP (for further discussion of patent-based measures, see section 5.3.5.1)

5.3.4 Service Transition

The degree of service transition was quantified as the year-on-year change in revenues from (1) CB and (2) KB service segments. Both apply to PB firms, whilst only the latter is applicable to CB service firms. Industries were identified as either PB, CB service, or KB service by two independent coders assigning these classifications to each 4-digit SIC code based on industry descriptions. From 1,207 SIC codes, 57 discrepancies (4.7%) were identified and reconciled, indicating .95 inter-rater reliability. The agreed classifications were then applied to the Compustat data based on the primary SIC code of each firm and business segment. Each coder then manually checked 100 randomly selected segments, ensuring that the classification accurately reflected the firm-assigned segment description. This closely follows prior research (Fang et al. 2008) but adds the distinction between KB and CB services based on the sector lists provided in Contractor et al. (2003). Of 30,422 firm-year observations, 16,360 are PB firms, 6,052 CB service firms and 8,010 KB service firms. Of 16,360 observations pertaining to PB firms, 12,536 contain revenues from CB service segments. Of the combined 22,412 firm-years for which the core industry was not classified as KB, 8,175 contain revenues from KB service segments.

5.3.5 Firm Capabilities

5.3.5.1 Operationalisation

As discussed in the formulation of the above hypotheses, this study posits firm capabilities – specifically, in marketing & R&D – as a mechanism for mitigating risk when service transition is not a strategic option (i.e., for knowledge-based service firms).

The measurement of capabilities followed prior research (Narasimhan et al. 2006; Bahadir et al. 2008; Feng et al. 2017) in defining the inputs and outputs of marketing capabilities. Inputs were defined as a firm's current and previous year's advertising expenses (Compustat item XAD) and sales, general, and administrative expenses (SG&A; Compustat item XSGA). Current year sales revenues (Compustat item SALE) were used as the output.

A common method of operationalising R&D capabilities is to use current and prior R&D expenses as input variables and the number of patents assigned to a firm in a given year as the output variable (Dutta et al. 1999,2005; Narasimhan et al. 2006; Feng et al. 2017). However, this patent-based measure of R&D capability has been widely criticised in that patent assignments are highly skewed: each patent is counted as equally as important to commercialised R&D output, yet the preponderance of patents generate little or no return for the firm (Trajtenberg 1990). Weighting patent numbers by citations is commonly argued to overcome this issue, based on the logic that highly cited patents reflect greater success in value-generating R&D activities (Dutta et al. 2005; Narasimhan et al. 2006). However, patents tend to be cited according to their novelty, which does not necessarily imply that they can be used in the development of a commercially viable product. Thus, while citation-weighted patent counts may serve as an accurate measure of innovative capacity, novelty *per se* does not imply R&D capability when commercial success is the ultimate objective.

Prior research on patenting behaviour among private firms supports this critical view of patent-based measures. Patenting requires that product details are made publicly available and therefore visible to competitors; consequently, many firms avoid patenting and instead rely on tacit production knowledge and confidentiality agreements to maintain propriety leading to patent counts providing an underestimate of R&D output (Chan et al. 2001; Bellstam et al. 2020). This is particularly true for more complex and innovative products, where the desire to avoid competitive imitation is greatest (Cohen et al. 2000; Zahra and George 2002; Saidi and Zaldokas 2020), and is further compounded by industry differences in patenting norms (Pakes 1985; Bilir 2014). As a result of this complexity in patenting practice, patent counts have been justified and used as a measure of both R&D input and capability, suggesting that they may more accurately reflect an intermediate output somewhere between the two (Coad and Rao 2008).

As a result, patent-based measures are increasingly seen as a questionable indicator of the contribution of innovation to firm value (Mann 2018; Cohen et al. 2019). Furthermore, recent OECD research highlights the growing importance of non-patentable R&D outputs as a driver of growth at both the firm- and country-level, suggesting that a narrow focus on patents underestimates the financial consequences of R&D capabilities (Demmou et al. 2019). Here, as in most studies of R&D in business and management, the outcome of interest is a firm's financial performance (Krasnikov and Jayachandran 2008; Steenkamp and Fang 2011). Consequently, it is the contribution of R&D to customers' willingness to pay that is of primary interest, as it is this variable (not innovativeness) that influences the capability—performance relationship (Baldwin and Von Hippel 2011). R&D capabilities were therefore measured using an output variable that includes both the value of patents and the additional contribution of R&D activity to customer value. Importantly, this measure retains the characteristics of a "conceptualisation and measurement of capabilities that is independent of their rent generation ability" (Dutta et al. 2005, p. 278).

This measure uses the total value of a firm's intangible assets and subtract goodwill and acquired intangibles. These adjustments serve two purposes. First, goodwill captures brand equity, which accrues from marketing activities (Srivastava et al. 1998) and cannot therefore be attributed to R&D. Second, acquisition of potentially valuable patents and other research-derived outputs may improve the ability to create commercially viable, innovative products, but does not reflect a firm's capability to generate these assets internally. After removing these items, the adjusted measure of intangible assets attributable to R&D includes the value of patents as well as unpatented designs, blueprints, software and licenses, in addition to non-compete covenants indicative of skilled employees with tacit knowledge. Consequently, this author suggests that this measure more comprehensively captures the commercial value of proprietary technology and technological know-how than patent-based measures.

In support of this, this data shows a correlation between this measure and R&D expense that far exceeds those found between patent-based measures used in prior research: .68, compared to -.002 with patent stock (Liu and Wong 2011) and .013 with patent count (Giarratana et al. 2018). This suggests that this measure is more conceptually aligned with the relationship between inputs and outputs in the estimation of other functional capabilities: for comparison, there is a correlation between marketing output (sales) and input of .96 for advertising expense and .86 for SG&A expense. Furthermore, this is closer than patent-based measures to the .40 correlation between R&D inputs and innovation found in the text-based measure developed by Bellstam et al. (2020), whilst relying on far simpler calculations and more accessible data sources.

In summary, R&D capabilities were measured using current and prior R&D expense as inputs (Compustat item XRD) and intangible assets minus goodwill and acquired intangibles (Compustat item INTAN minus GDWL and ACQINTAN) as the output.

5.3.5.2 Model specification

In line with current practice in marketing and strategic management (Dutta et al. 2005; Feng et al. 2017), firm capabilities were estimated using stochastic frontier analysis (SFA). SFA computes an efficient frontier for a specified production process whilst including a stochastic error component that accounts for random statistical noise (Aigner et al. 1977). This error component avoids attribution of efficiency estimates to events outside of the control of the firm, making it conceptually suited to the study of capabilities (Dutta et al. 2005). Estimates of firm capabilities are derived from the second error component of SFA, which represents the inefficiency of a given firm relative to the frontier in that firm's industry (Jondrow et al. 1982). This study used the true random effects (TRE) maximum likelihood procedure developed by Greene (2005) and recommended for panels of length *T* > *10* (Belotti et al. 2013), which allows for year-to-year variance in efficiency within firms and consequently enables the resultant measures to be used in both fixed and random effects estimation.

Firm capabilities were estimated using the following equations, in which SIC_i is an industry dummy representing the firm's 2-digit SIC code, μ_i is the firm-level unobserved random effects representing stochastic error and ε_{it} the firm- and time-specific effects representing relative inefficiency. The error components follow OLS distributional assumptions, i.e. $\mu_i \sim N(0, \sigma_\mu^2),\ \varepsilon_{it} \sim N(\varepsilon, \sigma_\varepsilon^2)$ with $\varepsilon > 0,\ E[\mu_i \varepsilon_{it}] = 0$ (Dutta et al. 2005). The relative efficiency (i.e. capability) for each firm is given by $Exp(-E(\upsilon_i | \varepsilon_{it})$, yielding a score from 0 to 1 with 1 being the efficient frontier (Jondrow et al. 1982).

To estimate marketing capabilities (*MKC)*:

(5.1) $\ln(SALE_u) = \alpha_0 + \alpha_1 \cdot \ln(XAD_{it}) + \alpha_2 \cdot \ln(XAD_{it-1}) + \alpha_3 \cdot \ln(XSGA_{it}) + \alpha_4 \cdot \ln(XSGA_{it-1}) + \alpha_5 \cdot SIC_i + \mu_i + \varepsilon_{it}$

Where $SALE_u$ is the firm's sales revenue in the current year, XAD_{it} is the current year's and XAD_{it-1} the previous year's advertising expense and $XSGA_{it}$ is the current year's and $XSGA_{it-1}$ the previous year's SG&A expense.

To estimate R&D capabilities (*RDC)*:

(5.2) $\ln(INTANRD_u) = \beta_0 + \beta_1 \cdot \ln(XRD_{it}) + \beta_2 \cdot \ln(XRD_{it-1}) + \beta_3 \cdot SIC_i + \mu_i + \varepsilon_{it}$

Where $INTANRD_u$ is the firm's intangible assets minus goodwill and acquired intangible assets in the current year, XRD_{it} the current and XRD_{it-1} the previous years' R&D expense.[7]

5.3.5.3 Diagnostic tests

Two diagnostic tests conducted following the SFA estimation indicated that variation in capability scores for both *MKC* and *RDC* are due to firm-specific variation rather than unobserved random events. These tests are used to demonstrate that SFA provides a valid measurement of firm capabilities as (i) results are not due to stochastic error and (ii) variation in capabilities accounts for a high proportion of variation in firm output.

First, the likelihood ratio test assesses the goodness of fit of an unrestricted model (SFA) compared to a restricted model (in this case, OLS based on a single error term). The test statistic is given by:

(5.3) $$-2[L(H_0) - L(H_1)]$$

[7] Lag structures of up to three years have been used in previous research on R&D expenditures (e.g. Steenkamp and Fang 2011); however, these lags are highly correlated (at least .96) suggesting that a one-year lag is sufficient to capture the effects of prior R&D expenditures.

Where H_0 is the log-likelihood of the restricted model and H_1 is the log-likelihood of the unrestricted SFA model, with 1 degree of freedom representing the imposed constraint. The likelihood is compared with a critical value to determine whether the null hypothesis of no technical inefficiency can be rejected. For *MKC* ($\chi^2_{(2)}$ = 350202, *p* <.001) and *RDC* ($\chi^2_{(2)}$ = 41558, *p* <.001) the likelihood ratio exceeded the critical value of 9.500, demonstrating significance at the 0.01% level (Kodde and Palm 1986).

Second, the proportion of output variation attributable to technical inefficiency was computed as:

$$\gamma = \frac{\sigma_\upsilon^2}{\sigma^2} \tag{5.4}$$

Where $\sigma^2 = \sigma_\upsilon^2 + \sigma_v^2$, i.e., the sum of the variance of the firm- and time-specific error component and the stochastic error component (Kumbhakar et al. 2015). $\gamma = 1$ indicates that 100% of variation in output is attributable to variation in efficiency. For *MKC,* $\gamma = 0.51$ and for *RDC,* $\gamma = 0.53$, indicating that approximately 50% of variation in output is due to differences in capabilities rather than unobserved factors or random events Kumbhakar et al. (2015).

5.3.6 Controls

In all models, controls were included for *firm size* and *return on assets* (ROA). *Revenue growth* was also included to ensure that the measure of revenue risk captures variability rather than increases in revenues. Following prior service transition research, additional controls were included for *industry growth* and *industry turbulence* (Fang et al. 2008). Together, these variables also serve as a proxy for the stage of the industry life cycle and therefore the intensity of competition (Stieglitz and Heine 2007). This is necessary as the relative importance of IP differs across each stage of an industry's development (Tripsas 1997).

Service relatedness was included in models examining service transition, following prior research demonstrating its moderating effects (Fang et al. 2008; Josephson et al. 2016b). *Strategic emphasis* represents a firm's investment in marketing versus R&D and is thus relevant to examination of these capabilities (Feng et al. 2017). This was included as a control in models examining firm capabilities in KB firms.

Table 5.3.6.1 provides procedures for calculating controls and summaries of other variables. Table 5.3.6.2 presents descriptive statistics and correlations.

TABLE 5.3.6.1 Variable Descriptions.

Variable	Description	Source
Profitability	Gross profit of firm in year t+2	Compustat Fundamentals
Revenue risk	Variability of revenues of firm in year t+1. Calculated as the standard deviation of total revenues over the preceding four years.	Compustat Fundamentals
Intellectual property risk	Average of the (inverse) IPRI score for each country market in which the firm operates weighted by the level of activity in each market, scaled by the firm's total level of foreign activity (includes sales and distribution, export, import and manufacturing).	Property Rights Alliance annual International Property Rights Index; Offshoring Activity Database (Hoberg and Moon, 2017, 2018).
Δ Capital-based service revenues	Year-on-year change in revenues from capital-based service business segments.	Compustat Segments
Δ Knowledge-based service revenues	Year-on-year change in revenues from knowledge-based service business segments.	Compustat Segments
Service relatedness	Difference between the primary 4-digit SIC code of a firm's core business and the primary 4-digit SIC code of each business segment. For firms with multiple segments, the average difference weighted by sales in each segment.	Compustat Fundamentals Compustat Segments
Marketing capabilities	Technical efficiency score obtained from stochastic frontier analysis of the efficiency with which a firm transforms advertising expenses and SG&A expenses to sales revenue, relative to other firms in the same 4-digit SIC code.	Compustat Fundamentals
R&D capabilities	Technical efficiency score obtained from stochastic frontier analysis of the efficiency with which a firm transforms R&D expenses to intangible assets (minus acquired intangibles and brand goodwill), relative to other firms in the same 4-digit SIC code.	Compustat Fundamentals
Strategic emphasis	A firm's emphasis towards marketing (high values) versus R&D (low values), calculated as the difference between marketing and R&D expenses scaled by total assets.	Compustat Fundamentals
Firm size	Natural log of a firm's total assets.	Compustat Fundamentals
ROA	Net income divided by total assets.	Compustat Fundamentals
Revenue growth	Year-on-year change in a firm's total revenues.	Compustat Fundamentals
Industry growth	Revenue growth in a firm's core industry (4-digit SIC code) over four years, scaled by industry size. Calculated as the slope coefficient of total industry revenues regressed over the preceding four years, divided by mean industry revenues over those four years.	Compustat Fundamentals
Industry turbulence	Variability in revenues in a firm's core industry (4-digit SIC code) over four years, scaled by industry size. Calculated as the standard deviation of total industry revenues over the preceding four years, divided by mean industry revenues over those four years.	Compustat Fundamentals

TABLE 5.3.6.2 Descriptive Statistics and Correlations.

		Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Profitability	3692.00	11072.74													
2	Revenue risk	8946466.00	7180000.00	.363*												
3	IP risk	14.91	24.14	.113*	.049*											
4	Δ CB service revenues	2549.34	15509.81	.271*	-.139*	.040*										
5	Δ KB service revenues	1951.16	11965.22	.234*	.033*	.033*	.909*									
6	Service relatedness	-1856.97	33012.93	.002	.002	.002	-.000	-.000								
7	Marketing capabilities	.75	.18	.067*	-.038*	.130*	.038*	-.004	-.003							
8	R&D capabilities	.48	.24	.061*	.007	-.011	-.040*	-.019	-.005	.117*						
9	Strategic emphasis	.31	.86	-.008	-.002	-.019*	-.001	-.001	-.001	-.089*	-.060*					
10	Firm size	6.84	2.64	.394*	.117*	.203*	.013	.007	.007	.186*	.157*	-.111*				
11	ROA	-0.14	1.68	.010	.002	.008	.001	.001	-.000	.010	.040*	-.604*	.055*			
12	Revenue growth	192.33	2937.41	.076*	-.128*	-.012*	.287*	.275*	-.000	.063*	.026*	-.001	.044*	.001		
13	Industry growth	0.04	1.20	-.002	-.000	-.033*	-.000	-.000	.001	-.007	-.005	-.001	-.016*	-.001	-.000	
14	Industry turbulence	0.08	0.08	-.037*	.012*	-.069*	-.004	-.009	<.001	-.138*	-.018*	-.004	-.049*	.004	-.035*	.104*

* $p \leq 0.05$ (two-tailed). All variables are standardised in analyses to aid interpretation of coefficients.

5.3.7 Model Estimation

Diagnostic tests indicated several econometric concerns with the panel data. For parsimony, results are reported here for models including all firms, for both dependent variables. The necessary corrections were applied to all models to ensure comparability.

First, a Hausman test showed covariance between firm-specific error and the independent variables (revenue risk (RR) model: $\chi^2_{(5)}$= 13.02, *p* = .023; gross profit (GP) model: $\chi^2_{(4)}$= 212.56, *p* < .001), and consequently that fixed effects estimation was required to ensure consistency (Greene 2008). Second, a significant Wald test indicated that inclusion of year dummies was necessary (RR: $F_{(8,27249)}$= 2.47, *p* = .011; GP: $F_{(9,23146)}$= 16.87, *p* < .001). Third, a modified Wald statistic indicated strong heteroskedasticity (RR: $\chi^2_{(5725)}$= 3.4e+43, *p* < .001; GP: $\chi^2_{(5163)}$= 3.0e+39, *p* < .001) requiring robust standard errors to correct for bias and allow accurate inference (Stock and Watson 2008). Fourth, as the dataset comprised an unbalanced panel (firms entering and leaving the dataset over time), a unit root test for heterogeneous panels was required to test for stationarity. A Fisher test using an augmented Dickey-Fuller statistic (Maddala and Wu 1999) indicated that variables were stationary across panels (RR: $\chi^2_{(4434)}$= 1520.00, *p* < .001; GP: $\chi^2_{(10706)}$= 1960.00, *p* < .001), requiring no further correction. Finally, a Wooldridge test for serially correlated errors (Wooldridge 2010) indicated first-order autocorrelation (RR: $F_{1,4519}$= 700.93, *p* < .001; GP: $F_{(1,4046)}$= 61.50, *p* < .001) and therefore the need for robust standard errors.

To address issues of reverse causality, gross profit was measured at time *t+2* and revenue risk at time *t+1*, ensuring that changes in firm risk were not attributable to contemporaneous or preceding changes in profitability. However, this does not address the possibility of self-selection, where service transition or capability development decisions may be influenced by *predicted* performance: if a firm's managers expect strong profits or stable revenues, they may be more likely to pursue uncertain (service transition) or expensive (capability development) activities. These omitted variables pertaining to managerial expectations may influence both the level of the independent variables and their performance effects. Including firm fixed effects removes between-firm variation in such unobserved factors, alleviating endogeneity concerns (c.f. Aral et al. 2012).

In sum, all models were estimated using fixed effects panel regression with robust standard errors and year dummies. For revenue risk the model in Equation 5.5 was used, where $\beta'$is a vector of coefficients of the independent variables, X'_{it} is a vector of the independent variables, μ_i represents firm-specific effects, υ_t year-specific effects and ε_{it} i.i.d. errors:

(5.5) $$RR_{it+1} = \alpha + \beta' X'_{it} + \mu_i + \upsilon_t + \varepsilon_{it}$$

For gross profit (Equation 5.6), the dependent variable was measured at time *t+2* and utilise revenue risk in period *t+1* as an independent variable. All other variables are measured at time *t*:

(5.6) $$GP_{it+2} = \alpha + \beta_0 RR_{it+1} + \beta' X'_{it} + \mu_i + \upsilon_t + \varepsilon_{it}$$

In estimating the effects of revenue risk on profitability, the vector X'_{it} comprises all other independent variables as controls. In examining the impact of firm capabilities for KB firms, X'_{it} includes the interaction terms and independent effects of interest.

5.4 RESULTS

Table 5.4.1 presents results for H1 pertaining to the effect of IP risk on revenue risk. To ensure robustness, the model was estimated for all firms (Model 1) and by service classification (2 to 4). Positive, significant results across models indicate that exposure to IP risk reliably increases the volatility of revenues for firms in all sectors, supporting H1 .

TABLE 5.4.1 Effects of IP Risk on Revenue Risk.

	All firms		PB firms		CB service firms		KB service firms	
	(1)		(2)		(3)		(4)	
Effects of interest								
IP risk	0.027	(.000)***	0.023	(.005)***	0.056	(.000)***	0.047	(.004)***
Controls								
Firm size	0.036	(.083)*	0.010	(.696)	0.053	(.393)	0.173	(.002)***
ROA	-0.001	(.853)	- 0.001	(.974)	-0.001	(.915)	-0.003	(.744)
Revenue growth	0.081	(.000)***	-0.105	(.000)***	0.322	(.000)***	0.162	(.000)***
Industry growth	- 0.001	(.979)	0.001	(.802)	-0.001	(.950)	-0.002	(.877)
Industry turbulence	-0.004	(.560)	-0.007	(.499)	0.019	(.307)	-0.064	(.001)***
Constant	-0.032	(.212)	-0.022	(.753)	-0.074	(.372)	-0.070	(.001)***
Year fixed effects	Included		Included		Included		Included	
Observations	32,987		17,924		6,432		8,631	
R^2	.036		.004		.282		.080	
F-value	42.980	(.000)***	40.320	(.000)***	73.930	(.000)***	24.800	(.000)***

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$ (two-tailed). PB = product-based, CB = capital-based, KB = knowledge-based.

Table 5.4.2 reports the results for H2, examining the effect of revenue risk on firm profit. For parsimony, models are presented for non-KB service firms (Models 5 and 6) and KB service firms (7 and 8), as the direction and significance of effects was comparable across models for PB and CB service firms. These models examine the effect of revenue risk in isolation and the interaction effect of revenue risk in the presence of IP risk. The results indicate support for H2 in non-KB service firms: revenue risk decreases profitability (-0.039, $p < .001$). The lack of a significant interaction effect with IP risk suggests that IP risk affects performance via its effect on revenue risk, as discussed in section 5.2 above. However, for KB service firms, revenue risk only exhibits a negative association with profit when combined with IP risk (-0.039, $p < .001$): in isolation, volatility of revenues increases profitability in KB service firms (0.141, $p < .001$).[8] Thus, while IP risk is shown to affect firm performance via its influence on revenue risk in non-KB service firms, an alternative mechanism appears to be present in KB service firms whereby the presence of *both* forms of risk is required to negatively affect profits.

[8] This may be because successful knowledge-intensive firms often derive a significant proportion of revenues from large, intermittent projects (Probert et al., 2013; Castaldi & Giarratana, 2018). Even if these revenue flows are predictable, measuring revenue risk annually may not capture this. This is a limitation inherent to this data source.

TABLE 5.4.2 Effects of Revenue Risk on Profitability.

	Non-KB service firms				KB service firms			
	(5)		(6)		(7)		(8)	
Effects of interest								
Revenue risk	-0.037	(.000)***	-0.039	(.000)***	0.100	(.000)***	0.141	(.000)***
Revenue risk x IP risk			-0.006	(.536)			-0.039	(.000)***
Controls								
Δ CB service revenues	-0.006	(.046)	-0.019	(.053)*				
Δ KB service revenues	-0.015	(.000)***	-0.025	(.000)***				
Service relatedness	- 0.001	(.762)	-0.001	(.761)				
IP risk	-0.002	(.756)	-0.002	(.852)	-0.043	(.000)***	-0.031	(.000)***
Firm size	0.016	(.590)	0.016	(.588)	0.139	(.000)***	0.132	(.000)***
ROA	-0.001	(.750)	-0.001	(.749)	-0.003	(.593)	-0.002	(.604)
Revenue growth	0.025	(.000)***	0.025	(.000)***	0.010	(.015)**	0.031	(.000)***
Industry growth	0.001	(.840)	0.001	(.839)	0.002	(.804)	0.002	(.790)
Industry turbulence	-0.005	(.339)	-0.005	(.339)	-0.002	(.534)	-0.005	(.515)
Constant	-0.004	(.000)***	-0.004	(.000)***	-0.023	(.833)	-0.020	(.915)
Year fixed effects	Included		Included		Included		Included	
Observations	1,845		1,845		7,165		7,165	
R^2	.040		.044		.207		.218	
F-value	11.43	(.000)***	10.73	(.000)***	36.43	(.000)***	52.40	(.000)***

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$ (two-tailed). KB = knowledge-based.

Table 5.4.3 presents tests of H3 and H4 related to the effects of service transition on revenue risk in PB and CB service firms. Results support H3: PB firms can reduce revenue risk by increasing revenues from service segments; however, the most effective form of service transition is contingent upon the level of IP risk, and changes to the revenue base may be detrimental if misaligned with the environment. Without threats to IP protection, KB service transition increases (0.509, $p < .001$) and CB service transition decreases (-0.580, $p < .001$) revenue risk. Interaction with IP risk reverses the direction of these effects: when IP risk is high, KB service transition decreases (-0.366, $p < .001$) and CB service transition increases (0.326, $p < .001$) revenue risk. Figure 5.4.1 illustrates these moderation relationships.

TABLE 5.4.3 Effects of IP Risk and Service Transition on Revenue Risk in Non-Knowledge-Based Service Firms.

	PB firms				CB service firms			
	IP risk		Service transition		IP risk		Service transition	
	(9)		(10)		(11)		(12)	
Effects of interest								
Δ CB service revenues			-0.580	(.000)***				
Δ KB service revenues			0.509	(.000)***			-0.027	(.295)
IP risk	0.023	(.005)***	0.018	(.543)	0.056	(.000)***	0.001	(.995)
Δ CB service revenues x IP risk			0.326	(.000)***				
Δ KB service revenues x IP risk			-0.366	(.000)***			-0.101	(.000)***
Controls								
Service relatedness			0.005	(.857)			0.005	(.834)
Firm size	0.010	(.696)	-0.008	(.954)	0.053	(.393)	0.093	(.677)
ROA	- 0.001	(.974)	0.001	(.959)	-0.001	(.915)	-0.001	(.985)
Revenue growth	-0.105	(.000)***	0.136	(.000)***	0.323	(.000)***	0.298	(.000)***
Industry growth	0.001	(.802)	0.002	(.895)	-0.001	(.950)	-0.002	(.918)
Industry turbulence	-0.007	(.499)	- 0.001	(.999)	0.019	(.307)	-0.018	(.672)
Constant	-0.022	(.753)	0.005	(.646)	-0.075	(.372)	-0.004	(.836)
Year fixed effects	Included		Included		Included		Included	
Observations	17,924		1,295		6,432		1,011	
R^2	.049		.028		.282		.291	
F-value	40.320	(.000)***	35.690	(.000)***	73.930	(.000)***	12.200	(.000)***

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$ (two-tailed). PB = product-based, CB = capital-based.

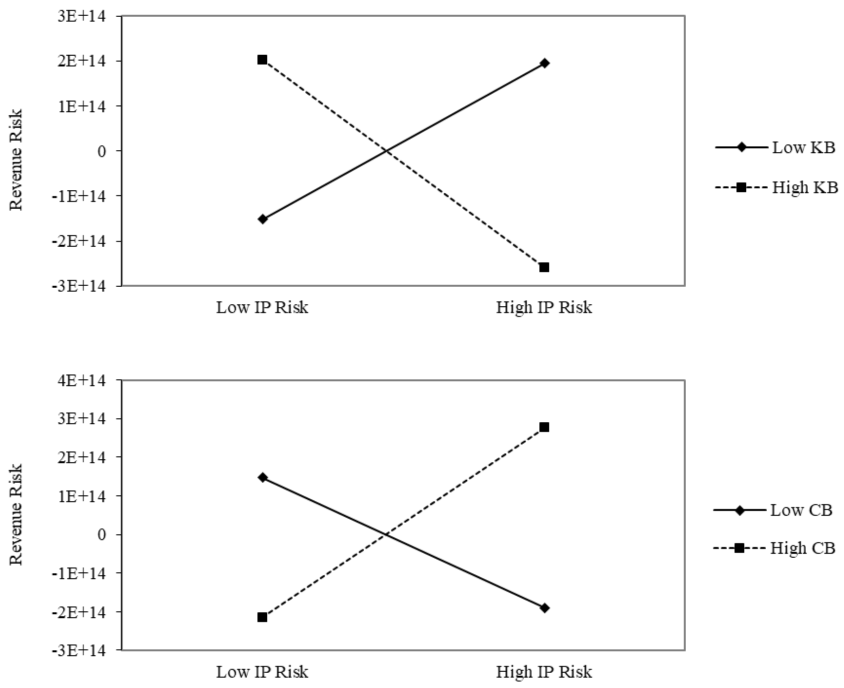

FIGURE 5.4.1 Effects of Service Transition on Revenue Risk for Product-Based Firms.

CB = change in revenues from capital-based services; KB = change in revenues from knowledge-based services.

These results support H4b pertaining to the effects of KB service transition in CB service firms: with threats to IP, increasing revenues from KB service segments decreases revenue risk (-0.101, $p < .001$). However, H4a is not supported, as indicated by the nonsignificant effect of KB service transition in the absence of IP risk. This suggests that increasing revenues from KB segments may only benefit CB firms when extant product-based assets are at risk. Figure 5.4.2 shows the moderating effect of IP risk.

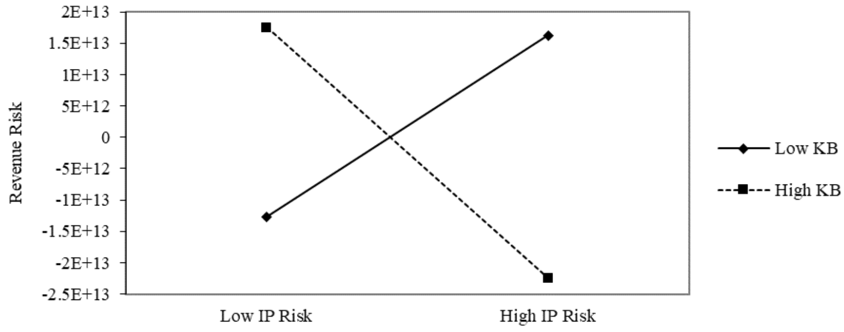

FIGURE 5.4.2 Effects of Knowledge-Based Service Transition on Revenue Risk for Capital-Based Service Firms.

KB = change in revenues from knowledge-based services.

Table 5.4.4 presents tests of H5 related to the effects of firm capabilities in KB service firms. H5a and H5b concern the situation of revenue risk but no IP risk (Model 15). The predicted effects capabilities are supported: when revenue risk is high, marketing capabilities have a negative effect (-1.118, $p < .001$) and R&D capabilities a positive effect (0.249, $p < .001$) on performance. Model 16 also shows full support for H5c and H5d: when both IP risk and revenue risk are high, the direction of effects of capabilities reverses such that marketing capabilities positively (0.478, $p = .029$) and R&D capabilities negatively (-0.380, $p < .001$) affect performance. Figures 5.4.3 and 5.4.4 illustrates the effects of capabilities.

TABLE 5.4.4 Effects of Firm Capabilities on Profitability in Knowledge-Based Service Firms.

	No risk		IP risk		Revenue risk		Revenue + IP risk	
	(13)		(14)		(15)		(16)	
Effects of interest								
Marketing capabilities	-0.042	(.000)***	-0.044	(.000)***	-0.008	(.394)	-0.018	(.000)***
R&D capabilities	-0.026	(.002)***	-0.035	(.001)***	-0.014	(.048)**	-0.014	(.000)***
IP risk			-0.039	(.479)				
Revenue risk					1.161	(.000)***		
Revenue risk x IP risk							-0.328	(.224)
Marketing capabilities x IP risk			-0.009	(.863)				
R&D capabilities x IP risk			0.019	(.333)				
Marketing capabilities x revenue risk					- 1.118	(.000)***		
R&D capabilities x revenue risk					0.249	(.000)***		
Marketing capabilities x revenue risk x IP risk							0.478	(.029)**
R&D capabilities x revenue risk x IP risk							-0.380	(.000)***
Controls								
Strategic emphasis	0.029	(.169)	0.031	(.155)	0.016	(.400)	0.015	(.469)
Firm size	0.273	(.000)***	0.302	(.000)***	0.205	(.000)***	0.238	(.000)***
ROA	0.014	(.370)	0.014	(.375)	0.005	(.691)	0.006	(.687)
Revenue growth	0.268	(.000)***	0.256	(.000)***	0.096	(.000)***	0.078	(.000)***
Industry growth	0.001	(.933)	- 0.001	(.984)	0.001	(.854)	0.001	(.937)
Industry turbulence	0.005	(.727)	0.001	(.926)	- 0.001	(.981)	-0.007	(.946)
Constant	-0.009	(.023)**	0.007	(.028)**	-0.124	(.291)	0.141	(.050)**
Year fixed effects	Included		Included		Included		Included	
Observations	2,085		2,070		1,674		1,659	
R^2	.405		.383		.452		.264	
F-value	58.280	(.000)***	44.560	(.000)***	134.440	(.000)***	47.94 0	(.000)***

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$ (two-tailed).

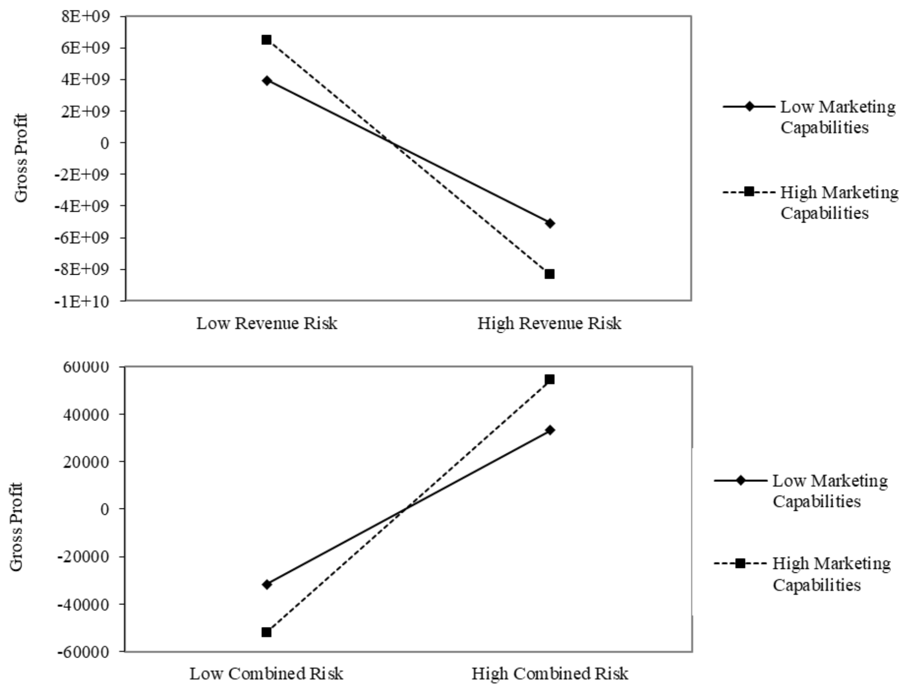

FIGURE 5.4.3 Effects of Marketing Capabilities on Profitability in Knowledge-Based Service Firms.

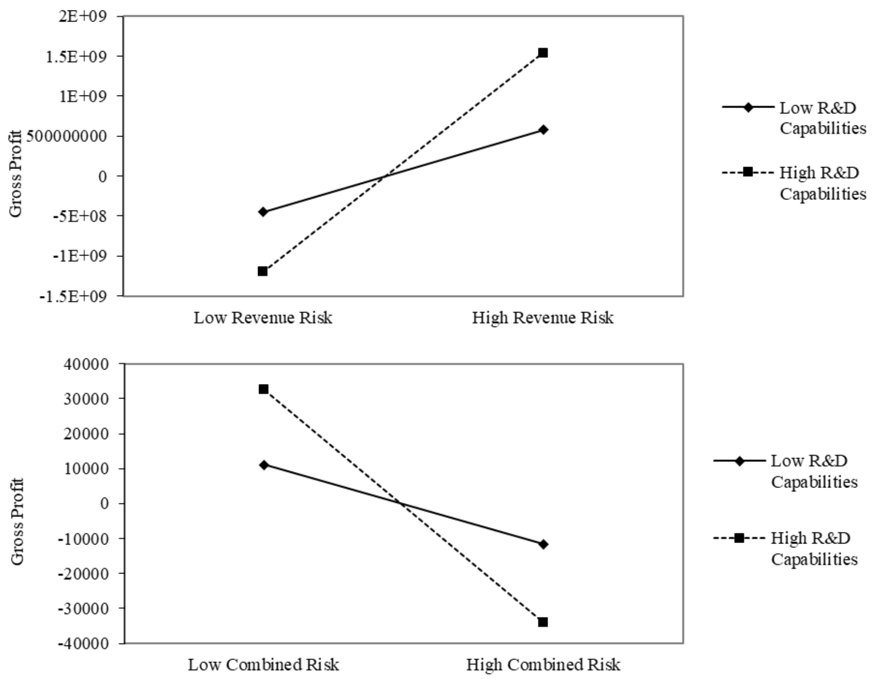

FIGURE 5.4.4 Effects of R&D Capabilities on Profitability in Knowledge-Based Service Firms.

5.5 DISCUSSION

The global trend towards increasing reliance on knowledge resources means that IP, like other intangible assets, is of growing strategic importance in both service and product-based firms (Probert et al. 2013; Papanastassiou et al. 2019). Contemporaneously, many firms face greater threats to IP due to expansion into markets where weak regulation undermines its inherent inimitability (Brander et al. 2017; Samiee 2020). This study tested two mechanisms for mitigating IP risk: (2) restructuring the resource base via service transition and (2) deploying existing resources differently via functional capabilities.

The first mechanism examined was service transition, as a means to afford greater defensibility against imitation. Prior research finds positive effects of service transition, as service offerings can protect firms against commoditisation of products and thus reduce firm risk (Josephson et al. 2016b). These results broadly support these findings and mechanism but suggest important caveats. For PB firms, this study finds that transition to CB services reduces risk, whilst transition to KB services increases risk, when threats to IP are low. This is in accordance with evidence that the risks of strategic change may outweigh the benefits if significant divergence from a firm's core business is required (e.g. Kraatz and Zajac 2001). However, the direction of effects reverses when IP protection is weak: revenues are stabilised by transitioning to KB services but exhibit greater volatility when CB service offerings increase. Thus, a firm's starting resource position may be secondary to environmental considerations when faced with threats that alter the relative value of different kinds of resources (Porter and Siggelkow

2008). Here, the risk of a drastic shift from product- to process-based business models is outweighed by the risk of *not* developing process-based assets when IP protection is weak.

Similar effects are observed for CB service firms, for which transition to a more knowledge-intensive business model remains a viable strategic option to enhance competitive defensibility. These results show that this improves the stability of revenues *only* when IP protection is weak. Thus, restructuring the resource base appears to only improve performance when it signifies an appropriate response to environmental threats.

The second mechanism posited in this study pertains to knowledge-intensive firms, where service transition is not feasible but IP risk remains a concern. Accordingly, the analyses focused on deployment of existing resources through firm capabilities as a risk mitigation strategy. Results indicate that the effects of capabilities are contingent upon external conditions. With IP risk, marketing capabilities improve profitability, whereas R&D capabilities exert a negative effect. Conversely, when IP is protected, R&D capabilities improve whilst marketing capabilities impair performance. As the foci of marketing and R&D capabilities are process- and product-based intangible assets, respectively, this indicates that firms benefit from deploying resources to develop the types of assets that are most defensible from competitors in each environment.

The environmentally contingent negative effects of high capabilities may reflect resource constraints: developing capabilities to produce outputs that are less inimitable in a specific environment suggests a misdirection of limited resources (Feng et al. 2017). Nonetheless, the large negative effect of marketing capabilities in the presence of revenue risk is ostensibly surprising. This may be explainable by the inclusion of revenue growth – a key marketing objective – as a control. Higher levels of marketing capabilities among firms with equivalent revenue growth suggests failure to achieve this objective, and thus resource misallocation. The positive effect under conditions of high IP risk substantiates this argument as in this case, beyond driving revenue growth, marketing contributes to competitive defense.[9]

Overall, these findings align with prior evidence of the benefits of service transition and capability development, whilst demonstrating that these seemingly beneficial strategies can be counterproductive if misaligned with environmental risks and/or the starting resource position of the firm; an important qualification in both theoretical and practical terms.

5.5.1 Implications for Theory

This study answers calls for further research considering institutional contingencies in service strategies and firm capabilities (Vargo and Lusch 2017; He et al. 2018), and addressing limitations of the RBV through examination of product-market considerations (Barney 2014), thus offering theoretical contributions to the interrelated domains of resource-based theory and service transition.

[9] It is also noteworthy that the baseline effects of both marketing and R&D capabilities on profit are negative or nonsignificant (Models 13 and 14) whereas, without moderation, extant research reports largely positive effects for both (Krasnikov & Jayachandran, 2008). However, the models presented here also control for strategic emphasis, which is a function of a firm's investment in marketing and R&D. The observed negative effects may therefore be due to the exclusion of positive effects via improvements in revenue generation and investment allocation and not indicative that firm capabilities in themselves are detrimental to profitability.

First, this study provides a theoretical contribution to the RBV literature by examining how the characteristics of resources are contingent on the level of regulatory threat to a firm's product or service offerings. Such dynamics have historically been overlooked in the RBV, resulting in an incomplete understanding of how resource-based and institutional factors interact to affect firm performance (Barney 2014). These findings highlight how key RBV considerations – inimitability and value – are influenced by both the characteristics of resources and the degree of environmental risk, integrating product-market considerations with the fundamentals of resource-based theory. Furthermore, the results presented here can be used to augment extant evidence of substitutive interactions between multiple capabilities (Sirmon et al. 2010; Feng et al. 2017) by showing that *individual* capabilities may also have negative consequences if the outcomes towards which they direct firm resources are misaligned with the competitive environment. This challenges the notion that capabilities are inherently positive, prevalent in the RBV, by highlighting their potential as a signal of resource misallocation (c.f. Stieglitz and Heine 2007; Pham et al. 2017).

Similarly, service transition has been framed as necessary for competitiveness in an increasingly customer-centric business environment (Vargo and Lusch 2017), supported by evidence of positive performance effects (Ulaga and Reinartz 2011; Eggert et al. 2014). Whilst these effects are contingent on complementarities with existing resources (Fang et al. 2008; Josephson et al. 2016b) this study shows that this is *less* consequential when environmental threats affect the potential value of these resources.

Moreover, strategies that extant research considers high-risk may in fact mitigate risk under different conditions. As service transition becomes increasingly common (Patel et al. 2019), these findings suggest the need for further contingency-theoretic perspectives.

The prevalence of service transition in internationalizing firms (Hennart 2019) further exemplifies the relevance of these results, which challenge two key assumptions of internationalisation research: (1) that firms transfer and exploit domestically developed assets when expanding overseas (Gupta and Govindarajan 2000) and (2) superior performance results from increased breadth of international experience (Vahlne and Johanson 2017). This study demonstrates that these assumptions may not hold when assets cannot be leveraged in the foreign market (c.f. Brandl et al. 2018) and explains *why* the strategic value of resources differs across markets. The results offer a nuanced perspective on the efficacy of service transition in mitigating these risks.

5.5.2 Implications for Practice

This study substantiates recent claims that examining resources in isolation from contextual factors may misattribute the direction and/or magnitude of performance effects (Schweiger et al. 2019), offering contributions to management practice by clarifying the likely implications of service transition strategies and capability deployment in different contexts.

Firms seeking to increase their revenues from services should be aware that CB and KB service transition strategies may have very different consequences depending on the regulatory environment. Specifically, both

PB and CB service firms may not benefit from increasing their knowledge intensity unless faced with threats to IP protection. Service transition is often seen as a prerequisite for competitiveness, but the results presented here challenge this. Managers should consider whether their extant stock of strategic resources is competitively defensible and if not, consider multiple routes of strategic change.

KB service firms also need to align resource deployment with the environment, using functional capabilities to enrich and extend those intangible assets that are most defensible and avoiding over-investment in those that are not. A key consideration is whether the relative emphasis on marketing versus R&D is concordant with regulatory conditions, as misdirection of resources towards the development of product-based intangible assets when IP protection is lacking, or process-based intangible assets when IP could offer a rarer and more inimitable strategic resource, can harm performance.

5.5.3 Limitations and Directions for Future Research

The theoretical implications of this study point to further investigation of resource-environment contingencies in relation to service transition, firm capabilities, and strategy in international markets. Some limitations of the analysis provide fruitful avenues for research in this stream. First, the classification of firms as product-based, CB services or KB services was used as a proxy for the likely significance of product-based intangible assets and thus the importance of IP protection to each firm. A deeper understanding of the strategic importance of IP may be gained by direct measurement of these factors; for example, through surveys of key decision-makers.

Similar methods may also explicate the role of managerial agency. As in previous research, this study infers alignment between resources, strategy, and environment from firm performance (Sirmon and Hitt 2009; Aral et al. 2012). Further examination of the strategy process would aid understanding of *how* effective resource orchestration and service transition is achieved. Surveys, interviews, or analyses of a firms' communications with stakeholders during strategy-making and implementation activities may provide valuable insight. This author therefore encourages further research to seek novel data sources to examine the role of decision-making in developing optimal configurations of strategic assets, and explore a broader range of contingencies that may challenge and refine established wisdom about the value of firm capabilities and service transition strategies.

6 DYNAMIC CAPABILITIES, ORDINARY CAPABILITIES, AND COMPETITIVE ADVANTAGE: THE MODERATING ROLE OF PRODUCT-MARKET FLUIDITY

6.1 INTRODUCTION

Although the dynamic capabilities (DCs) perspective has become one of the most widely adopted approaches in strategic management research, it continues to invite criticism due to disputes over central elements of the theory (Easterby-Smith et al. 2009; Suddaby et al. 2019). Specifically, both the concept of DCs and the notion of environmental dynamism which is theorised to moderate their effects on competitive advantage vary widely in conceptualisation and operationalisation (Peteraf et al. 2013). These disputes are compounded by the fragmented nature of empirical DC research, which largely comprises context-specific case studies, qualitative investigations, and survey research (see Schilke et al. 2018, for a review). DCs may therefore be seen as a 'reified' construct, being increasingly applied to a variety of problems and contexts but lacking conceptual and methodological rigor in addressing underlying assumptions (Giudici and Reinmoeller 2012).

Accordingly, extant evidence provides no clear consensus on DCs: the interaction between DCs and environmental dynamism is equivocal (Fainshmidt et al. 2019) and meta-analyses report effects that are indistinguishable from OCs in direction or magnitude, suggesting that the concept lacks discriminant validity (Karna et al. 2016). This author posits that greater clarity can be brought to the construct, mechanisms, and effects of DCs by developing measures that (a) capture the core constructs in the DCs perspective, to improve conceptual consistency, and (b) can be applied in large datasets, to test the core propositions of the theory across a broad range of contexts.

In this study, the author first defines DCs in terms of their functional relationship to ordinary capabilities (OCs); a notable strand of consistency across divergent conceptualisations (e.g., Eisenhardt and Martin 2000; Teece 2014). Measures of DCs are then developed to capture the two key aspects of this relationship: the ability to maintain a *variety* of OCs and *shift* their deployment in response to the environment (Di Stefano et al. 2014). To address measurement issues regarding environmental dynamism, the following analyses employ an index developed using textual analysis of annual 10-K filings (Hoberg et al. 2014), which quantifies changes in competitive threats at the product-market level and thus provides a more conceptually appropriate moderator of DCs than static, industry-level measures or subjective self-assessments. In a sample of 771 firms across 41 industries and 20 years, this provides support for the central tenets of the theory: DCs are beneficial in dynamic environments and redundant or detrimental in stable environments. Furthermore, the effects of DCs differ based on whether internal contingencies enable firms to recoup the costs of with their development and maintenance. In addition to corroborating the theorised roles of DCs and OCs across external conditions, this study therefore evinces the understudied firm- and market-level factors that raise the costs of DCs beyond their benefit (see Wang et al. 2015; Schilke et al. 2018).

These results offer several contributions. First, by defining DCs in objective terms and based on their functional relationship to OCs, the methodology employed in this study directly captures the mechanisms of change that are central to theorizing in the DCs perspective but remain underexplored empirically (Schilke et al. 2018). Results indicate that both DCs and OCs can negatively affect performance contingent upon environmental conditions. This suggests that refining the measurement of DCs and their moderators can clarify knowledge of their effects, and demonstrates the benefits of DCs research that "make[s] greater use of empirical methodologies beyond qualitative case analyses and analysis of survey data" (Schilke et al. 2018, p. 392) in this regard. Second, by utilising a measure of environmental dynamism at the appropriate level of analysis this study finds effects consistent with the DCs perspective, indicating that methodological issues may contribute to debates regarding the contingencies associated with DCs, where the importance of environmental dynamism has been questioned (Wang et al. 2015; Schilke et al. 2018; Fainshmidt et al. 2019). Third, in contrast to extant research, these results span multiple industries and years and utilise a broadly applicable measure of DCs. This allows for generalisable conclusions about the effective deployment of DCs, thus extending the managerial relevance of the DCs perspective (c.f. Easterby-Smith et al. 2009).

6.2 THEORY AND HYPOTHESES

6.2.1 Conceptual and Methodological Issues in The Dynamic Capabilities Perspective

While the DCs perspective has gained significant attention in strategic management, it has been widely criticised for lacking consistent definitions (Zahra et al. 2006; Wilden and Gudergan 2015), disputes about the basic elements and predictions of the theory (Wilden et al. 2016; Suddaby et al. 2019), lack of empirical progress (Easterby-Smith et al. 2009), and questionable discriminant validity (Karna et al. 2016). These issues have been attributed to a bifurcation of the research stream (Peteraf et al. 2013; Di Stefano et al. 2014; Teece 2014), where one view sees DCs as complex, embedded activities that are dependent on firm- and individual-specific knowledge and experience (Teece et al. 1997) while the other views DCs as simple rules based on iterative, adaptive processes (Eisenhardt and Martin 2000). In the former, DCs drive competitive advantage via inimitable, non-routine managerial coordination of resources (Helfat and Peteraf 2015). In the latter, advantage "lies in the resource configurations [DCs] create, not in the capabilities themselves" (Eisenhardt and Martin 2000, p. 1118).

These theoretical differences have led to an increasingly fragmented base of empirical research employing a range of assumptions, construct definitions, and methodologies (see Schilke et al. 2018), limiting the development of substantive knowledge (Schilke 2014b). Theoretical development is further constrained by a heavy reliance on industry- or firm-specific case studies that preclude generalisations about the effects of DCs; cross-sectional designs that limit causal inference about the role of DCs, and survey measures that raise concerns about tautological measures arising from self-assessments of success (see Table 6.2.1 for a representative overview). The few studies of large-scale secondary datasets employ context-specific definitions of DCs (Girod and Whittington 2017; Ringov 2017) that may not be applicable to firms outside of the empirical setting. Consequently, many questions regarding the nature and effects of DCs remain open, particularly in terms of the mechanisms of change that are central to the DCs perspective (Wilden et al. 2016; Schilke et al. 2018).

TABLE 6.2.1 Representative Empirical Studies of Dynamic Capabilities.

Study	Context	Data	Dynamic capability (DC) measure		Environmental dynamism (ED) measure		Key findings
Tripsas and Gavetti (2000)	Focal case study: one digital imaging firm	Company archives, interviews	Perceptual	Search activities	No direct measure	Technological change	Importance of managers' cognitive representations in adaptation to environmental change.
Danneels (2008)	77 U.S. manufacturing firms (SIC 20-39)	Surveys at two time points (2000 and 2004)	Perceptual	Market and technology exploration	None		Identifies five antecedents of DCs.
Danneels (2011)	Focal case study: one manufacturing firm (typewriters)	Company archives, interviews	Perceptual	Leveraging, creating, accessing, releasing resources	No direct measure	Decline of main product category	Importance of managerial cognition in DC theory.
Drnevich and Kriauciunas (2011)	48 Chilean firms	Survey (cross-sectional)	Perceptual	Use of IT	Perceptual	Country context	ED positively (negatively) affects relationship between DC (OCs) and performance.
Protogerou et al. (2012)	271 Greek manufacturing firms	Survey (cross-sectional)	Perceptual	Coordination, learning, competitive response	Perceptual	Technological and market change	DCs impinge on OCs effects on performance in both high and low ED
Schilke (2014a)	279 German firms in three industries	Surveys at two time points (2006 and 2009)	Perceptual	R&D alliance management, new product development	Perceptual	Product, marketing, and business model change, uncertainty	ED moderates DC-performance relationship (inverse U-shaped moderation).
Su et al. (2014)	Comparative case study: six cases from three firms in three industries	Interviews	Perceptual	Meta-learning; sensing weak signals; resilience	None		Level of quality performance is related to level of DCs.
Vanpoucke et al. (2014)	719 firms in 20 countries	Survey (cross-sectional)	Perceptual	Supplier integrative capability	Perceptual	Market and technological dynamism	DCs increase process flexibility and cost efficiency; effect is strengthened by ED.
Wilden and Gudergan (2015)	228 Australian firms	Survey (cross-sectional)	Perceptual	Marketing and technological capabilities	Perceptual	Market, competitor and technological turbulence	DC-performance relationship is contingent on form of ED and functional area of DCs.
Girod and Whittington (2017)	Top 50 U.S. industrial firms by size	19-year panel (1985-2004)	Objective	Change in business unit configuration	Objective	Volatility in industry sales	ED positively (negatively) affects relationship between DC (OCs) and performance.
Ringov (2017)	2119 U.S. mutual funds	10-year panel (1999-2009)	Objective	Asset portfolio reconfiguration process	Objective	Volatility index	ED—DC interaction effect is contingent on environmental

Fainshmidt et al. (2018)	162 Israeli firms in 15 industries	Survey (cross-sectional)	Perceptual	Sensing, seizing, reconfiguring	Perceptual	Environmental dynamism	DCs support different strategic orientations depending on ED.
This study	771 U.S. firms in 41 industries	20-year panel (1997-2017)	Objective	Capability shifts; capability variety	Objective	Product-market fluidity	DC/OC effects reverse based on dynamism. Nature of DCs differs based on strategic positioning.

This study aims to present a path towards addressing these questions by drawing upon a core commonality across these varied approaches to DCs: *the functional relationship between OCs and DCs.* This is consistent across otherwise divergent definitions. For example, DCs have been defined as "tools that manipulate resource configurations" (Eisenhardt and Martin 2000, p. 1118), "routinized activities directed to the development and adaptation of operating routines." (Zollo and Winter 2002, p. 339), and "higher-level activities that can enable an enterprise to direct its ordinary activities toward high-payoff endeavors" (Teece 2014, p. 328). This notable area of consistency stems from the centrality of the OC—DC relationship to the distinction between the DCs perspective and resource-based view (RBV): "Whereas the RBV emphasises the firm's current resource base, defined as the firm's resources… and operational capabilities, the dynamic capabilities perspective primarily addresses purposeful modifications of this resource base" (Schilke et al. 2018, p. 392). Accordingly, this author proposes that focusing on this relationship is critical to bringing conceptual cohesion to the DCs perspective (c.f. Bowman and Ambrosini 2003).

The following sections first examine theoretical assumptions relevant to the operationalisation of DCs and the conditions under which their effects should be examined. Second, hypotheses are presented based on the central predictions of the theory, summarised in Figure 6.2.1. Measures are then developed in line with the theoretical assumptions to test these hypotheses.

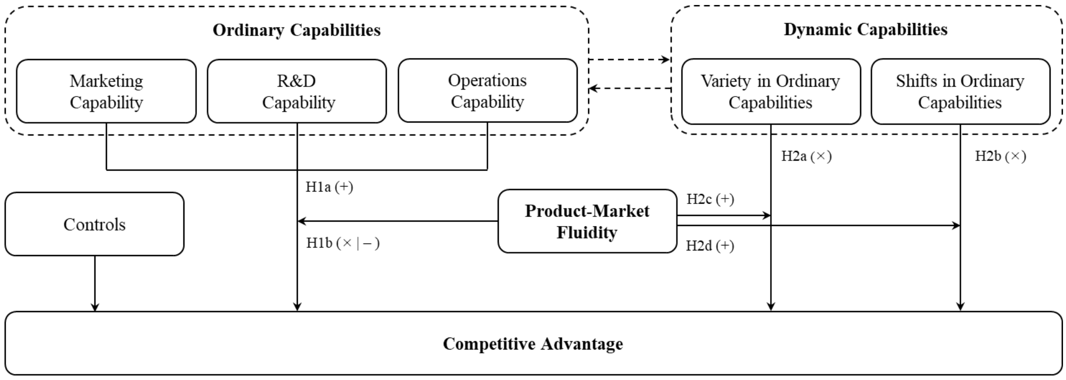

FIGURE 6.2.1 Hypothesised Relationships Between Ordinary Capabilities, Dynamic Capabilities, Product-Market Fluidity, and Competitive Advantage.

+ indicates a hypothesised positive effect, – a negative effect, and × no positive effect.

6.2.2 The Functional Relationship Between Ordinary and Dynamic Capabilities

OCs are the administrative and technical activities required in the everyday functions of a business, whereas DCs effect change in the firm's base of OCs (Newey and Zahra 2009). DCs are therefore most pertinent when environmental change demands frequent renewal of the processes, knowledge, and skills that comprise a firm's OCs (Teece 2014). The role of DCs in a theory of competitive advantage is thus to explain how and why some firms maintain or gain leadership in environments where the bases of competition frequently change (Zahra et al. 2006; Helfat and Winter 2011). Fundamentally, OCs involve "doing things right" and DCs "doing the right things, at the right time" (Teece 2014, p. 331). The propositions of the DCs perspective are therefore only explicable in reference to OCs: to do the right things at the right time first requires definition of the 'things'. Furthermore, falsifiable hypotheses can only be derived by defining DCs in terms of their relationship to the OCs upon which they act, as the alternative—defining them in terms of their outcomes, or what is 'right' – is innately tautological (Eisenhardt and Martin 2000; Powell 2001).

In an integration of theoretical perspectives on DCs, Di Stefano et al. (2014) identify two critical aspects of the OC-DC relationship. First, DCs require the presence of a variety of complex routines, developed through firm-level actions, which enable the pursuit of multiple strategic options. Second, these routines are leveraged, integrated, or uncoupled as conditions change, according to simple decision rules and intuition at the level of individual managers. The result is a "socially complex and hard-to-imitate dynamic bundle" (p. 320) of OCs and linking mechanisms, the complexity and causal ambiguity of which underlies the contribution of DCs to competitive advantage. In essence, "doing the right things, at the right time" requires that a firm is (1) technically proficient in a multitude of 'things' (or OCs)—hereafter referred to as *capability variety*—and is (2) able to shift the deployment of OCs to those that are 'right' given a new set of environmental conditions— hereafter referred to as *capability shifts*.

6.2.3 Dynamic Capabilities and Dynamic Environments

Another key element of the DCs perspective that has been criticised for lacking conceptual clarity is environmental dynamism (Fainshmidt et al. 2019). Clarifying this construct is essential to analysis of the functional relationships explicated above, as the proposed necessity of DCs relies on the argument that OCs "enable the production and sale of a defined (but static) set of products and services… When the firm's output is tuned to what the market desires, strong OCs may be sufficient for a fleeting competitive advantage but are insufficient to undergird sustainable competitive advantage as the business environment changes.” (Teece 2014, p. 343). This implies that the appropriate level of analysis for measuring environmental dynamism is the *product-market*, as changes to OCs are necessitated by shifts in demand (Drnevich and Kriauciunas 2011). However, measures of environmental dynamism employed in DCs research typically rely either on industry-level (e.g. SIC code) measures (e.g. Girod and Whittington 2017) or on respondents’ or researchers’ judgements of market conditions (e.g. Schilke 2014a)

The issues of subjective measurement are discussed above. However, industry-based measures also pose conceptual issues as such classifications are static across a firm’s lifecycle. If a firm’s products and services change significantly, defining its competitive environment based on industry membership will fail to capture dynamics among its current set of competitors (Hoberg and Phillips 2016). Furthermore, measures typically rely on metrics related to firm objectives such as revenues or market share, reflecting firms’ success or failure in adapting to change rather than the degree of change itself (Hoberg et al. 2014). These measures are thus incongruent with theoretical assumptions about the nature of dynamic environments within the DCs perspective, which can more accurately be conceptualised as shifts in a firm’s *product-market*, exogenous of the firm’s assessment of, or success in responding to, such shifts.

6.2.4 Ordinary Capabilities and Competitive Advantage

Typically, OCs have positive effects on firm performance (see Karna et al. 2016, for a recent meta-analysis) including firm growth, profitability (Feng et al. 2017), and firm value relative to competitors (Dutta et al. 1999). This is recognised in the DCs perspective, where OCs are seen as insufficient for long-term advantage *except* under stable environmental conditions. This view spans theoretical divides. Where DCs are viewed as directly contributing to competitive advantage, this is attributed to the static and activity-specific nature of OCs and the necessity of change to achieve growth and maintain leadership (Drnevich and Kriauciunas 2011; Teece 2014). Where competitive advantage is seen to ultimately derive from the underlying OCs, DCs remain necessary to bring about the right configuration of these activities (Eisenhardt and Martin 2000). Thus, the DCs perspective hypothesises OCs to contribute to superior performance when environmental conditions are stable:

> ***Hypothesis 1a (H1a):*** *Ordinary capabilities have a positive effect on competitive advantage in stable product-markets.*

The unique predictions of the DCs perspective lie in the effects of OCs in dynamic environments, where it is assumed that firms must reconfigure OCs to maintain leadership (Teece 2014). New environments require new knowledge, while the competitive advantage a firm can derive from OCs relies upon accumulated knowledge and experience (Helfat and Peteraf 2003). Consequently, OCs may cease to be useful, and potentially become harmful, if these activities are no longer aligned with market conditions (Leonard-Barton 1992; Newey and Zahra 2009). Research on DCs in IT (Drnevich and Kriauciunas 2011) and organisational restructuring (Girod and Whittington 2017) supports this notion, demonstrating that the relationship between OCs and relative performance becomes nonsignificant or negative in dynamic environments. OCs research similarly finds that positive effects of key functional capabilities diminish or reverse when environmental dynamism is high (Feng et al. 2017). This leads to the following hypothesis:

> ***Hypothesis 1b (H1b):*** *The positive effects of ordinary capabilities on competitive advantage are diminished or reversed in dynamic product-markets.*

For empirical tests of H1a and H1b, this study focuses on the three OCs that have been most widely studied: marketing, R&D, and operations (Krasnikov and Jayachandran 2008; Feng et al. 2017). Marketing capability refers to the ability to align products and services with knowledge of customer needs; R&D capability to the development and application of technological innovations; and operations capability to efficiency and flexibility in production that enables a firm to deliver quality whilst minimizing costs (Dutta et al. 1999). While each hypothesis is tested separately for these three OCs, the same directional effects are predicted in each functional area.

6.2.5 Dynamic Capabilities and Competitive Advantage

To effectively leverage OCs in dynamic environments, firms require DCs. This is the central proposition of the DCs perspective. However, debate continues as to whether DCs can also contribute to competitive advantage under stable conditions (Schilke et al. 2018; Fainshmidt et al. 2019; Suddaby et al. 2019). This author hypothesises that this is unlikely, based on the relative costs and benefits of the two central aspects of the relationship between OCs and DCs proposed above. Maintaining a variety of OCs is critical to the ability to pursue alternative strategies when conditions change (Di Stefano et al. 2014). However, the development and maintenance of OCs requires sustained investment (Winter 2003). When it is unlikely that OCs in specific functional activities will become important to competitive advantage, such investments may outweigh the benefits of maintaining optionality; firms may benefit more from focused investment in the areas most likely to contribute to sustained superior performance (Zahra et al. 2006). Furthermore, OCs in different functional areas often represent conflicting goals. For example, a focus on cost minimisation in operations versus demand generation in marketing can results in "negative synergies" when firms attempt to develop both OCs simultaneously (Feng et al. 2017, p. 83). When the environment is unlikely to require fundamental changes to strategic goals, balancing competing objectives may create tension and inefficiencies (King et al. 2008). In stable conditions, the potential benefits from maintaining a variety of OCs across different functional areas may therefore be outweighed by the costs of development and coordination (Wilhelm et al. 2015):

> ***Hypothesis 2a (H2a):*** *Maintaining a variety of ordinary capabilities does not have a positive effect on competitive advantage in stable product-markets.*

Developing the processes required for strategic shifts also incurs substantial costs (Zollo and Winter 2002; Kang and Kim 2020). In stable environments, this may impair performance by diverting resources from the OCs that are predictably associated with success (Zahra et al. 2006). Furthermore, altering the configuration of a firm's resource base may involve additional coordination or transaction costs (Karim 2006) and, if implemented frequently, can prevent the realisation of performance gains from any one OC (Schilke 2014a), as capability development requires a level of sustained commitment over time (Helfat and Winter 2011). Under stable conditions, shifts in the deployment of OCs may therefore be more disruptive than beneficial:

> ***Hypothesis 2b (H2b):*** *Shifts in ordinary capabilities do not have a positive effect on competitive advantage in stable product-markets.*

In dynamic environments, the direction of these relationships may be expected to reverse: both the variety of OCs a firm can maintain and the ability to shift between deployment of OCs will contribute positively to competitive advantage. A variety of OCs enables diversity of strategic response, as the firm possesses a broader base of knowledge and skills that is more likely to be applicable to changed conditions (Lant et al. 1992). A key constraint with OCs in dynamic environments is that embedded processes lock a firm in to a specific set of behaviours, creating inertial forces and path dependencies that inhibit necessary change (Arend 2004). Thus, the ability to maintain multiple behavioural options may prevent OCs from turning into rigidities (Leonard-Barton 1992), facilitating adaptation to dynamic environments:

> ***Hypothesis 2c (H2c):*** *Maintaining a variety of ordinary capabilities has a positive effect on competitive advantage in dynamic product-markets.*

Similarly, competitive advantage in dynamic markets requires the ability to rapidly shift the deployment of OCs (Di Stefano et al. 2014). This often involves parallel implementation of multiple strategic options, which is facilitated if a firm already possesses the OCs required for a diverse set of potentially viable strategies (Eisenhardt and Martin 2000). Moreover, maintaining leadership is unlikely unless a firm can quickly and iteratively shift its focus to the most profitable alternative, coupling and uncoupling aspects of its capability base as conditions change (Eisenhardt et al. 2010). Consequently, shifts in a firm's base of OCs are predicted to be positively associated with performance in dynamic environments:

> ***Hypothesis 2d (H2d):*** *Shifts in ordinary capabilities have a positive effect on competitive advantage in dynamic product-markets.*

6.3 METHOD

6.3.1 Data and Sample

This sample comprises U.S. firms operating between 1997 and 2017 (the coverage of the PMFI). Data for all other variables was obtained from Compustat. As the model for estimating capabilities requires panels of ten or more years (Belotti and Ilardi 2012), the sample was restricted to firms for which ten years of data is available on the inputs and outputs of OCs. This results in 8,805 firm-year observations of 771 firms in 41 2-digit SIC code industries (200 by 4-digit) which appear in both the Compustat and PMFI databases.

6.3.2 Ordinary Capabilities

As the measures of DCs used in this analysis are based on their relationship to OCs, valid operationalisation of the latter is critical. Stochastic frontier analysis (SFA) was used to model OCs as an intermediate variable between an input (resource base) and output (firm objective). This captures the concept of OCs as unobservable processes (Helfat and Winter 2011), avoiding misattribution of OC effects to either the resources upon which they act or the proximal outcome they generate (Dutta et al. 1999) and tautological problems of subjective measurement (Teece et al. 1997).

The SFA model for each OC is a production function that estimates a ‘frontier’ for a functional area’s input—output process based on the notion that no firm can exceed the optimal utilisation of inputs in the production of a specified output. The stochastic component accounts for exogenous shocks to a firm’s efficiency (Aigner et al. 1977), such that deviations from the frontier represent firm-specific inefficiencies arising from suboptimal resource deployment. The basic SFA model, as applied to panel data, can be expressed as:

$$y_{it} = a_i + x'_{it}\beta + \varepsilon_{it} \quad (6.1)$$

Where $\varepsilon_{it} = v_{it} \pm u_{it},\ v_{it} \sim N(0, \sigma_v^2),\ u_{it} \geq 0$ and $u_{it} \sim \mathcal{F}$. y_{it} is the natural log of the output of firm *i* in period *t*; x'_{it} is a vector of inputs and β of parameter estimates. The composite error ε_{it} is the sum of the symmetric, normally distributed stochastic error term v_{it} and the one-sided error u_{it} representing inefficiencies, which are assumed to be i.i.d. across observations.

Many specifications exist for SFA with best practice suggesting choice of model based on suitability to the specific research context (Andor et al. 2019). This study used the True Random Effects (TRE) specification (Greene 2005) as it addresses three key considerations in estimating OCs. First, TRE removes time-invariant unobserved heterogeneity from the inefficiency term u_{it}. This contrasts earlier models, which treat all time-invariant unobserved heterogeneity as inefficiency and thus may conflate estimates of OCs with other firm-specific, omitted variables. Second, TRE decomposes u_{it} into two components representing persistent and time-varying inefficiency.[10] This enables temporal shifts in OCs, which is critical to computing these measures of DCs. Third, the frontier is estimated at the industry-level via inclusion of exogenous variables that are outside of the control of the firm but influence efficiency. This is specified in the distribution of u_{it} in Equation 6.1:

(6.2) $$u_{it} \sim N^{+}(\mu_i, \sigma_u^2), \mu_i = z_i' \psi$$

Where u_{it} is a realisation from a truncated normal distribution, the mean of which is a function of the exogenous variables (z_i') and their associated parameters (ψ). In this case, the exogenous covariate is a dummy variable representing a firm's 2-digit SIC code. Thus, the distribution of firm-year inefficiencies is specific to each industry, accounting for differences in efficiency standards and capturing OCs relative to competitors. In this variation on the basic SFA model, the likelihood

[10] Recent models decompose the time-invariant error further into estimates of unobserved heterogeneity and persistent inefficiency; however, these models produce results in which only the time-variant *or* time-invariant estimates are accurate (Badunenko and Kumbhakar 2016). For accuracy and consistency with prior research, the three-component model is used here.

function does not have a closed-form solution, requiring estimation with simulated maximum likelihood (Train 2009). Briefly, the parameters in Equation 6.1 are given by;[11]

(6.3)

$$\log L_s$$
$$= \sum_{i=1}^{N} \frac{1}{R} \sum_{r=1}^{R} \left\{ \sum_{t=1}^{T} ln\Phi \left(\frac{[\mu_{ir}/(\sigma_{uir}/\sigma_v)] \pm [(y_{it} - \alpha_{ir} - \beta'_{ir} x_{it})((\sigma_{uir}/\sigma_v)]}{\sqrt{\sigma_{uir}^2 + \sigma_v^2}} \right) \right.$$
$$\left. - \frac{1}{2} \left(\frac{\mu_i \pm (y_{it-} \alpha_{ir} - \beta'_{ir} x_{it})}{\sqrt{\sigma_{uir}^2 + \sigma_v^2}} \right)^2 + ln \frac{1}{\sqrt{2\pi}} - ln\Phi \left[\frac{\mu_i}{\sigma_{uir}} \right] - ln \sqrt{\sigma_{uir}^2 + \sigma_v^2} \right\}$$
$$= \sum_{i=1}^{N} \frac{1}{R} \sum_{r=1}^{R} \sum_{t=1}^{T} \log P_{itr}$$

For the purposes of this study, the parameter estimates are of less relevance than the firm-specific estimates of inefficiency. These are derived during simulation (Greene 2012) using the commonly applied JLMS estimator (Jondrow et al. 1982) as follows:

(6.4) $$E[u_{it}|\varepsilon_{it}] = \frac{\sigma\lambda}{1+\lambda^2} \left[\frac{\varphi(a_{it})}{1-\phi(a_{it})} - a_{it} \right]$$

Where $\sigma = [\sigma_v^2 + \sigma_u^2]1/2$, $\lambda = \sigma_u/\sigma_v$, $a_{it} = \pm\varepsilon_{it}\lambda/\sigma$. $\varphi(a_{it})$ and $\phi(a_{it})$represent the standard normal density and cumulative density function evaluated a_{it}. The estimate of $\hat{u}_{it}$ is a score from 0 to 1, where 1 indicates "the best the firm could have done if it had used the resource level at its disposal efficiently", i.e. the frontier (Dutta et al. 2005, p. 278), and the firm-year score represents capability relative to this economically optimal level in a given functional area.

[11] Full details of the log likelihood function can be found in Greene (2005).

Focusing on the three key OCs of marketing, R&D, and operations (Krasnikov and Jayachandran 2008), this study followed precedent in defining the inputs and outputs of the SFA function (Dutta et al. 1999,2005; Feng et al. 2017). Marketing inputs are the current and previous year's advertising and sales, general, and administrative (SG&A) expense, with sales revenue as the output. Operations inputs are the current year's labor and capital costs, with the (inverse of) cost of goods sold (COGS) representing the minimisation of production costs. R&D inputs are the current and previous year's R&D expense, and R&D output is defined as the total value of intangible assets minus goodwill and acquired intangibles.[12] These adjustments remove the value of brand equity, thus avoiding overlap with marketing activities, and the value of acquired R&D outputs that are not the result of the firm's internal capabilities. This measure therefore includes the value of patents, blueprints, licenses, unpatented designs, and non-compete covenants that comprehensively captures the commercial value of proprietary technology and knowledge.[13]

[12] Prior studies use patent-based measures. However, these reflect technologically novel rather than commercially viable outcomes, and thus may not accurately represent the contribution of R&D to value creation (Kogan et al. 2017). This is particularly true when firms seek to avoid imitation: patenting requires disclosure of product details that many firms prefer to protect via tacit knowledge and confidentiality agreement (Saidi and Zaldokas 2020). Thus, patent-based measures lead to underestimation of the true commercial value of R&D output (Bellstam et al. 2020).

[13] Correlations between the inputs and outputs used in this study support this choice of R&D output. These data show correlations of .574 for labor expense and COGS; .384 and .734 for capital expense and COGS (for dividends and interest paid, respectively); .774 for SG&A expense and sales; .793 for advertising expense and sales, and .369 for R&D expense and the adjusted measure of intangible assets. Previous research reports correlations of -.002 between patent stock and R&D expense (Liu and Wong 2011) and .013 between patent count and R&D expense (Giarratana et al. 2018), suggesting that the functional relationship between this R&D measures is more comparable to other OCs than that of R&D expense and patent outcomes.

The production functions for marketing. R&D and operations were estimated as follows, with error terms defined as in Equation 6.1 and SIC_i representing the industry dummy that specifies the mean of the distribution of inefficiency estimates in Equation 6.2. For marketing capabilities:

(6.5) $\ln(SALE_{it}) = \alpha_0 + \alpha_1 \ln(XAD_{it}) + \alpha_2 \ln(XAD_{it-1}) +$

$\alpha_3 \ln(XSGA_{it}) + \alpha_4 \ln(XSGA_{it-1}) + \alpha_5 SIC_i + v_{it} - u_{it}$

Where $SALE_{it}$ is the firm's sales revenue in the current year, XAD_{it} is the current year's and XAD_{it-1} the previous year's advertising expense and $XSGA_{it}$ is the current year's and $XSGA_{it-1}$ the previous year's SG&A expense. For R&D capabilities:

(6.6) $\ln(INTAN_{it}) = \alpha_0 + \alpha_1 \ln(XRD_{it}) + \alpha_2 \ln(XRD_{it-1}) +$

$\alpha_3 SIC_i + v_{it} - u_{it}$

Where $INTAN_{it}$ is the firm's intangible assets minus goodwill and acquired intangible assets in the current year, XRD_{it} the current and XRD_{it-1} the previous years' R&D expense. For operations capabilities:

(6.7) $\ln(COGS_{it}) = \alpha_0 + \alpha_1 \ln(XCAP_{it}) + \alpha_2 \ln(XLAB_{it}) +$

$\alpha_3 SIC_i + v_{it} + u_{it}$

Where $COGS_u$ is the firm's cost of goods sold in the current year, $XCAP_{it}$ is the current year's cost of capital and $XLAB_{it}$ the current year's labor expense.

The suitability of these models was assessed using a likelihood ratio test (Kumbhakar et al. 2015), which compares the unrestricted SFA model to a restricted OLS model (i.e., based on a single error term), with the test statistic given by:

(6.8) $$-2[L(H_0) - L(H_1)]$$

Where H_0 is the log-likelihood of the OLS model and H_1 of the SFA model, with 1 degree of freedom representing the constraint. For marketing ($\chi^2_{(2)}$ = -395317.733, p < .001), R&D ($\chi^2_{(2)}$ = -45125.298, p < .001) and operations ($\chi^2_{(2)}$ = -226647.345, p < .001) the likelihood ratio exceeds the critical value of 9.500, indicating that SFA provides a suitable method of estimating inefficiencies.

6.3.3 Dynamic Capabilities

The objective of developing the following measures is to capture the functional relationship between OCs and DCs, which is identified above as comprising two key attributes: the ability to maintain a "dynamic bundle" of a variety of OCs and shift between parts of this system as conditions change (Di Stefano et al. 2014, p. 320). To measure the first of these attributes, *capability variety* was computed as the coefficient of variation in firm-year OC estimates, i.e., the standard deviation of marketing, R&D, and operations capabilities divided by the mean of these three OCs. The coefficient of variation is considered the most suitable operationalisation of variety among attributes with ratio scales (Harrison and Klein 2007)

The second attribute, *capability shifts*, was measured by first summing the OC scores across the three functions for each firm-year and dividing each OC score by the total to compute the proportion of OCs attributable to each functional area. For each OC, the previous year's proportion was then subtracted from the current year. The sum of the absolute differences across the three functional areas yields the aggregate measure of capability shift. Aggregating changes across marketing, R&D, and operations in this way is consistent with prior research on resource investments (Fombrun and Ginsberg 1990; Nadkarni and Narayanan 2007).

6.3.4 Product-Market Fluidity

Product-market fluidity was measured using the index developed by Hoberg et al. (2014) (PMFI hereafter), which provides firm-year scores for product-market fluidity derived from textual analysis of 10-K filings. The PMFI captures year-to-year changes in the product-market relative to the focal firm, based on changes in the business descriptions of competitors in the usage of words that are also used in the business description of the focal firm. For a given word *j* in year *t*, this is represented by $D_{t-1,t}$, the sum of the absolute differences in word usage:

(6.9) $$D_{t-1,t} \equiv \left| \sum_j \left(W_{j,t} - W_{j,t-1} \right) \right|$$

J_t is the number of unique words in the descriptions of all firms in a given year. W_{it} is an ordered Boolean vector of length J_t, where element *j* is equal to 1 if firm *i* uses word *j* in its description and zero otherwise. $N_{i,t}$ is the word vector for firm *i*, normalised for unit length. The PMFI is then calculated as the dot product between the firm-level vector $N_{i,t}$ and the product-market word vector $D_{t-1,t}$, which measures the cosine similarity between the two vectors:

(6.10) $$PMFI_{it} \equiv \langle N_{i,t} \cdot \frac{D_{t-1,t}}{\|D_{t-1,t}\|} \rangle \cdot$$

The PMFI of a firm thus increases with year-to-year changes in word usage and the degree of overlap between a firm's product descriptions and those of competitors. This ensures that the measure captures a higher level of competitive threat rather than reflecting the volatility of a firm's own product descriptions.[14] The PMFI offers several advantages over measures of market dynamism based on industry classification codes. First, the PMFI has an economically significant impact on firm financial decisions, suggesting that it captures product-market uncertainties that are pertinent to managers (Hoberg et al. 2014). Second, annual updates to business descriptions are legally required, whereas industry classification are fixed. Thus, the PMFI provides richer and more timely information about the state of product-markets. Third, product descriptions are created by management whereas industry classifications are externally imposed. As managerial cognition is central to the development and use of DCs (Di Stefano et al. 2014), using a measure that accounts for *perceptions* of product-market fluidity is thus conceptually better suited to the study of DCs. Finally, the PMFI addresses issues of endogeneity, reflecting the activity of rivals rather than the focal firm such that "changes [in the index] are likely to be exogenous from any one firm's perspective" (Hoberg et al. 2014, p. 305). Overall, the PMFI provides an advantage over industry-based measures, reflecting manager's perceptions while avoiding methodological concerns associated with modeling cognition.

[14] See Hoberg et al. (2014) for full details of the development and validation of the PMFI.

6.3.5 Dependent Variable and Controls

The DCs perspective fundamentally seeks to explain competitive advantage (Teece 2014). However, extant research on capabilities has been argued to suffer from a "theoretical and empirical misspecification of competitive advantage" resulting from the use of dependent variables that operationalise performance without reference to competitors (Sirmon et al. 2010, p. 1387). The DCs perspective posits profitability as the relevant measure of competitive advantage (see Teece 2014, Figure 1). Thus, this study used *relative gross profit* as the dependent variable, calculated as the natural log of a firm's gross profit scaled by the natural log of the median gross profit in the firm's 2-digit SIC code. As the DCs perspective focuses on temporary advantages (Eisenhardt and Martin 2000; Teece 2007), all models examine short-term performance, i.e., in the year following capability shifts and contemporaneous with capability variety.

Controls were included for *industry turbulence* and *concentration* as these factors may influence the effects of both OCs and DCs (Feng et al. 2017) and also assist in isolating the effects of environmental dynamism at the product-market level. The effects of capability shifts and variety are isolated from the effects of the underlying OCs by including these as independent variables in the model (c.f. Nadkarni and Narayanan 2007). Further controls for *firm age* and *firm size* were included to account for the fact that the resource deployment decisions of younger and smaller firms are more responsive to environmental conditions (Eisenhardt and Martin 2000). These controls, in addition to firm fixed effects, ensure that the effects of shifts and variety in capabilities reflect the intended operationalisation of

DCs rather than other firm-level factors. The dependent variable with a one-year lag was also included as a predictor, to account for the potential influence of past performance on resource deployment decisions. Table 6.3.5.1 provides a summary of all variables and the procedures for calculating controls. Table 6.3.5.2 presents descriptive statistics and correlations.

TABLE 6.3.5.1 Variable Descriptions.

Variable	Description
Relative profit	Natural log of gross profit of the focal firm scaled by the natural log of the median gross profit in the firm's 2-digit SIC code
Marketing capability	Estimates of technical efficiency computed with JLMS estimator following SFA using TRE specification, with inputs defined as the current and previous years' advertising and SG&A expense and output defined as the current year's sales revenue.
R&D capability	Estimates of technical efficiency computed with JLMS estimator following SFA using TRE specification, with inputs defined as the current and previous years' R&D expense and output defined as the current year's intangible assets minus goodwill and acquisitions.
Operations capability	Estimates of technical efficiency computed with JLMS estimator following SFA using TRE specification, with inputs defined as the current year's cost of capital (interest and dividends paid) and labor expense and output defined as the current year's cost of goods sold.
Capability shift	Sum of the absolute year-to-year differences in marketing, R&D, and operations capabilities as a proportion of a firm's total ordinary capabilities.
Capability variety	Coefficient of variation across functional capabilities, calculated as the standard deviation of marketing, R&D, and operations capabilities divided by the mean.
Product-market fluidity (PMF)	Cosine similarity between product descriptions used by the focal firm and competitors, using procedure and dataset provided by Hoberg et al. (2014)[1]
Industry turbulence	Standard deviation of total industry revenues in the firm's 2-digit SIC code over the preceding three years, divided by mean industry revenues over those three years.
Industry competition	Herfindahl-Hirschman Index (sum of squared market shares) in firm's 2-digit SIC code
Firm age	Natural log of years elapsed since firm first appears in Compustat database
Firm size	Natural log of total assets

[1] Updated (2017) dataset available at https://hobergphillips.tuck.dartmouth.edu/tnic_poweruser.htm

TABLE 6.3.5.2 Descriptive Statistics and Correlations.

		Mean	SD	1	2	3	4	5	6	7	8	9	10
1	Relative profit	1.996	0.306										
2	Marketing capability	.776	.141	.245*									
3	R&D capability	.457	.209	.081*	.094*								
4	Operations capability	.699	.169	.202*	.479*	.099*							
5	Capability shift	.136	.144	-.147*	-.125*	-.125*	-.155*						
6	Capability variety	-.487	.192	-.050*	-.308*	.610*	-.490*	-.002					
7	Product-market fluidity	5.719	2.919	-.013	-.149*	-.013*	-.183*	.115*	.067*				
8	Industry turbulence	.051	.033	-.014	-.038*	-.041*	-.010	.049*	-.017	.013			
9	Industry competition	.051	.042	-.002	-.032*	-.005	.091*	-.034*	-.040*	-.158*	.204*		
10	Firm age	28.380	17.981	.369*	.121*	.091*	.247*	-.150*	-.109*	-.284*	-.014*	.040*	
11	Firm size	6.991	2.027	.846*	.212*	.152*	.273*	-.167*	-.053*	-.069*	-.012	.082*	.481*

* $p \leq 0.05$ (two-tailed).

6.3.6 Model Estimation

The effects of OCs and DCs were estimated using panel regression with firm and year fixed effects. While the PMFI removes endogeneity issues related to managerial cognition in the calculation of this variable, the inclusion of firm fixed effects ensures that omitted variables are accounted for as they represent a key influence in the DCs framework (Helfat and Peteraf 2015). This approach therefore addresses a second source of endogeneity by utilising the panel structure of the data (Hill et al. 2020). A significant Hausman test ($\chi^2_{(16)}$= 1498.83, p < .001) for covariance between firm-specific error and independent variables also indicated that fixed effects are required to ensure consistency (Greene 2012). Year fixed effects were also included, as indicated by a Wald test ($F_{(18,8014)}$= 10.70, p < .001) and robust standard errors were used to correct for heteroskedasticity (modified Wald statistic: $\chi^2_{(757)}$= 4.3e+30, p < .001) and autoregressive error (Wooldridge test: $F_{1,732}$= 92.705, p < .001).

6.4 RESULTS

Table 6.4 reports the effects of OCs on relative performance (Model 1), the effects of DCs (Model 2) and the interaction between capabilities and product-market fluidity (Model 3). Across all three models, marketing and operations capabilities have positive effects, significant at the 1% level. R&D capabilities also show a positive and significant effect in Model 3, but effects are not significant across the other models. Overall, this supports H1a: OCs contribute to competitive advantage in stable product-markets, though results are equivocal for R&D.

TABLE 6.4 Effects of Capabilities on Relative Profit in Stable and Fluid Product-Markets.

	(1) Ordinary capabilities		(2) Ordinary and dynamic capabilities		(3) Interactions with product-market fluidity	
Main effects						
Marketing capability	0.101	(.000)***	0.106	(.000)***	0.051	(.001)***
R&D capability	0.002	(.632)	-0.006	(.259)	0.026	(.015)**
Operations capability	0.027	(.000)***	0.035	(.000)***	0.056	(.000)***
Capability shift			0.002	(.628)	-0.033	(.000)***
Capability variety			0.012	(.075)*	-0.013	(.367)
Product-market fluidity			0.001	(.170)	-0.001	(.898)
Interaction effects						
Marketing capability x product-market fluidity					0.009	(.000)***
R&D capability x product-market fluidity					-0.005	(.000)***
Operations capability x product-market fluidity					-0.003	(.079)*
Capability shift x product-market fluidity					0.006	(.000)***
Capability variety x product-market fluidity					0.004	(.040)**
Controls						
Industry turbulence	0.035	(.115)	0.034	(.130)	0.029	(.194)
Industry competition	-0.084	(.043)**	-0.085	(.041)**	-0.087	(.034)**
Firm age	-0.005	(.000)***	-0.005	(.000)***	-0.005	(.000)***
Firm size	0.035	(.000)***	0.035	(.000)***	0.035	(.000)***
Relative profit$_{t-1}$	0.584	(.000)***	0.584	(.000)***	0.582	(.000)***
Constant	0.231	(.000)***	0.228	(.000)***	0.234	(.000)***
Firm fixed effects	Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes	
Observations	8,805		8,805		8,805	
R^2	.609		.609		.612	
F-value	480.410	(.000)***	431.010	(.000)***	371.460	(.000)***

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$ (two-tailed).

The interactions between OCs and product-market fluidity in Model 3 test H1b. R&D capability follows this prediction, with a negative effect under conditions of high product-market fluidity (-0.005, p <.001). The effect of operations capability is nonsignificant at the 5% level, in line with this prediction (-0.003, p = .079). The effects of marketing capability remain positive (0.009, p = .001) but reduced in magnitude and significance compared to baseline (0.051, p <.001). Thus, these results provide support for H1b: the effects of OCs are diminished or reversed in highly fluid product-markets.

Models 2 and 3 report the baseline effects of the two measures of DCs, used to test H2a (variety) and H2b (shifts). Capability shifts affect relative performance in line with the predictions of this study, being nonsignificant in Model 2 (0.002, p = .628) and negative in Model 3 (-0.033, p < .001). The effects of capability variety are also nonsignificant in Model 3 (-0.013, p = .367). Although there is a positive effect of capability variety in Model 2 this is nonsignificant at the 5% level (0.012, p = .075). Thus, these results support H2a and H2b: DCs do not positively contribute to competitive advantage in stable product-markets. In the interactions between DCs and product-market fluidity (Model 3), both capability shifts (0.006, p < .001) and capability variety (0.004, p = .040) have positive effects on relative performance under conditions of high product-market fluidity, providing support for H2c and H2d. Figure 6.4 illustrates the differential effects of DCs in stable and fluid product-markets.

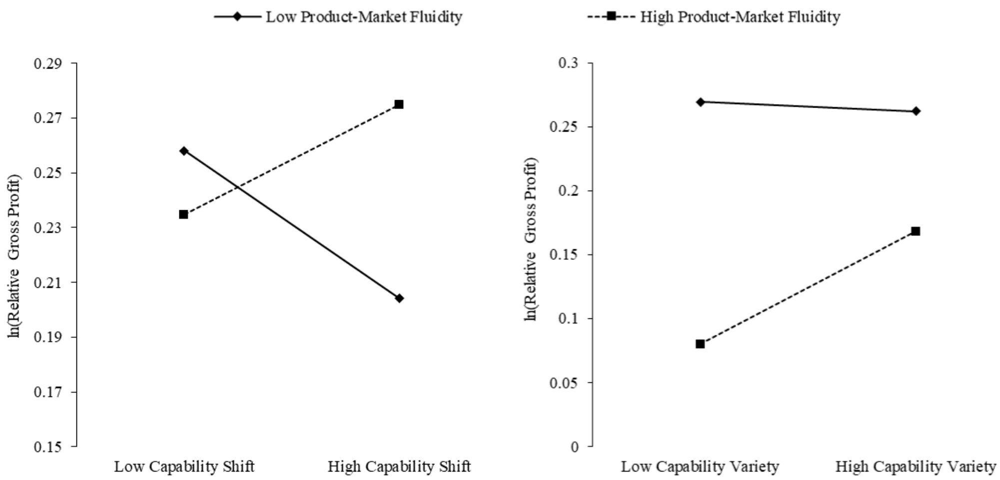

FIGURE 6.4 Moderating Effect of Product-Market Fluidity on Dynamic Capabilities.

Providing further evidence that DCs only contribute to competitive advantage when product-market fluidity is high, there is no change in the R^2 value between Models 1 and 2 ($R^2 = .609$) when DCs are added, but an increase between Models 2 and 3 ($R^2 = .612$) with the addition of interaction terms. This suggests that the incremental benefit of DCs is only apparent under conditions of high product-market fluidity, supporting the original conceptualisation of the DCs perspective as a theory of competitive advantage in dynamic markets.

6.4.1 Additional Analyses

Following the emphasis on environmental conditions in the DCs perspective, this study has so far focused on external contingencies. However, recent work has argued that DCs research should also consider factors internal to the firm (Wang et al. 2015; Wilden et al. 2016; Schilke et al. 2018). Accordingly, additional analyses were conducted to examine the effects of OCs and DCs under different conditions of strategic positioning, the most commonly theorised internal moderator (Karna et al. 2016; Fainshmidt et al. 2019).

Strategic positioning refers to the long-term managerial orientation that guides resource allocation decisions and thus determines responses to internal and external changes (Wilden et al. 2016). This is typically defined in terms of cost leadership versus differentiation, following Porter (1980). A firm's strategic positioning defines the activities, and thus the OCs, that are relevant to performance; for example, cost leadership is facilitated by strong operations capabilities whereas differentiation requires a greater emphasis on R&D. Consequently, strategic positioning influences resource deployment as environmental conditions shift, directing the use of DCs in bringing about alterations to OCs (Wilden et al. 2016).

Strategic positioning was operationalised using indicator variables (Nath and Bharadwaj 2020). The main model was then estimated in the sub-samples of firms following each strategy. *Differentiation* takes the value of 1 when a firm's advertising expenditure is greater than zero.[15] *Cost leadership* was measured by first calculating the ratio of sales to COGS such that a higher value indicates a focus on lower costs. The natural log of this variable was then taken as it is highly skewed, after which the industry mean was subtracted and the resultant number scaled by industry standard deviation (at the 2-digit SIC code level) to account for differences in production costs across industries. This was then converted to a dummy

[15] Following prior use, missing values of advertising expenditure are replaced with zero, as the decision to not report advertising can be interpreted as a signal that a firm does not prioritise differentiation-oriented investments (Nath and Bharadwaj 2020).

variable that takes the value of 1 if greater than zero (i.e., higher than the industry average).

Table 5 shows the results. Across all strategic positions, baseline effects are consistent with the main model presented above: capability shifts and variety have a negative or nonsignificant effect on performance, indicating the redundancy of DCs in stable product-markets. OCs are also generally positive, though specific effects vary across positions in a pattern that is concordant with theoretical predictions;[16] for example, OCs have larger effects in firms with a cost leadership position (Model 5). As cost leadership depends to a greater extent on efficiency than differentiation, this is consistent with the conceptualisation of OCs (Teece 2014). Furthermore, operations capabilities improve performance for undifferentiated firms (Model 6) but not differentiated firms (Model 7), whereas R&D capabilities only improve performance in differentiated firms, reflecting the requisite functional specialties for differentiation. Notably, in fluid product-markets, positive effects become negative and nonsignificant effects remain. This suggests that the OCs most pertinent to a firm's strategic position are also most likely to become liabilities or rigidities if they do not change in accordance with the environment.

[16] Regarding the nonsignificant effects of operations capabilities in firms with either strategic positioning, this may be due to the diminishing importance of operational efficiency among firms that have attained either strategic position, i.e., achieving a certain level of operational efficiency is a prerequisite for performance regardless of strategy, leading to lesser effects of this functional capability on competitive advantage among successful firms (Winter 2003).

TABLE 6.4.1 Effects of Capabilities Under Cost Leadership and Differentiation Strategies.

	(4)		(5)		(6)		(7)	
	Cost leadership = 0		Cost leadership = 1		Differentiation = 0		Differentiation = 1	
Main effects								
Marketing capability	0.036	(.063)*	0.077	(.003)***	0.049	(.029)**	0.063	(.002)***
R&D capability	0.037	(.012)**	0.036	(.026)**	0.011	(.477)	0.034	(.015)**
Operations capability	0.066	(.002)***	0.031	(.146)	0.093	(.000)***	0.019	(.318)
Capability shift	-0.025	(.040)**	-0.040	(.005)***	-0.034	(.008)***	-0.038	(.005)***
Capability variety	-0.060	(.004)***	0.012	(.611)	0.003	(.901)	-0.023	(.277)
PMF	0.002	(.468)	-0.001	(.902)	-0.001	(.563)	0.001	(.671)
Interaction effects								
Marketing capability x PMF	0.013	(.000)***	0.003	(.331)	0.012	(.000)***	0.005	(.050)**
R&D capability x PMF	-0.009	(.000)***	-0.005	(.006)***	-0.003	(.183)	-0.008	(.000)***
Operations capability x PMF	-0.001	(.922)	-0.001	(.660)	-0.009	(.002)***	0.003	(.282)
Capability shift x PMF	0.004	(.036)**	0.007	(.000)***	0.007	(.001)***	0.005	(.004)***
Capability variety x PMF	0.015	(.000)***	-0.001	(.572)	0.002	(.550)	0.007	(.011)**
Controls								
Industry turbulence	0.044	(.131)	0.019	(.580)	0.039	(.195)	0.027	(.432)
Industry competition	-0.140	(.008)***	0.010	(.887)	-0.093	(.138)	-0.102	(.062)*
Firm age	-0.005	(.000)***	-0.005	(.000)***	-0.005	(.000)***	-0.005	(.000)***
Firm size	0.035	(.000)***	0.032	(.000)***	0.039	(.000)***	0.032	(.000)***
Relative profit$_{t-1}$	0.562	(.000)***	0.568	(.000)***	0.543	(.000)***	0.617	(.000)***
Constant	0.218	(.000)***	0.270	(.000)***	0.250	(.000)***	0.234	(.000)***
Firm fixed effects	Yes		Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes		Yes	
Observations	5,201		3,604		4,998		3,807	
R^2	.604		.623		.563		.648	
F-value	206.42	(.000)***	153.27	(.000)***	169.15	(.000)***	183.76	(.000)***

* $p \le 0.1$, ** $p \le 0.05$, *** $p \le 0.01$ (two-tailed). PMF = product-market fluidity. Cost leadership and differentiation = 1 if greater than industry average, 0 otherwise.

In fluid product-markets, capability shifts consistently improve performance regardless of a firm's strategic position, in accordance with the main model. However, capability variety exhibits positive effects only for differentiated firms (Model 7) and those not pursuing a cost leadership strategy (Model 4), in which cases the magnitude of effect is greater than that of capability shifts. These results suggest that the nature of effective DCs varies based on a firm's strategic position: the ability to shift between OCs is important for all firms, whereas maintaining a variety of OCs has no benefit for some (undifferentiated) firms but is *more* important than shifts in other (differentiated) firms. This is in line with research suggesting significant costs associated with the DCs required for a differentiation strategy (Vergne and Depeyre 2016) and is theoretically aligned with the above results regarding the negative effects of DCs in stable product-markets: here, analogous reversals of the effects of DCs occur depending on whether *internal* conditions enable firms to recoup the costs of their development and maintenance. Overall, these additional analyses lend further support to the operationalisations of DCs employed in this study, being consistent with theoretical predictions (e.g. Wilden et al. 2016) and empirical evidence (e.g. Wang et al. 2015; Fainshmidt et al. 2019) regarding the role of DCs under internal contingencies.

6.5 DISCUSSION

The DCs perspective has become one of the most active and promising areas of strategic management research (Schilke et al. 2018). However, a lack of theoretical consensus has limited empirical progress (Easterby-Smith et al. 2009), with many attributing this to differences in conceptualisation and operationalisation of the central constructs of DCs (Di Stefano et al. 2014) and environmental dynamism (Fainshmidt et al. 2019). This study aimed to address these issues and improve the ability of DCs research to yield generalisable, practicable insights. Beginning with the proposition that DCs should be conceptualised in terms of their functional relationship to OCs (Eisenhardt and Martin 2000), two measures of DCs were derived to meet these criteria: *capability shift,* capturing the year-to-year change in the distribution of a firm's OCs, and *capability variety,* capturing the ability to simultaneously maintain multiple OCs. Combined, these measures represent the notion of DCs as mechanisms for linking and switching between a 'dynamic bundle' of OCs which enable a firm to create the capability configurations best suited to the environment (Di Stefano et al. 2014)

As the DCs perspective focuses on their role in dynamic environments, applying these measures required a suitable measure of this contingency – another area where previous operationalisations are problematic (Fainshmidt et al. 2019). This study employed a measure of product-market fluidity based on textual analysis of firms' business descriptions, updated annually and published in 10-K filings (Hoberg et al. 2014). This captures the degree of competitive threat faced by a focal firm based on changes in the descriptions of rivals' product mixes, providing a more objective, rich, and timely assessment of environmental dynamism.

Results support the central propositions of the DCs perspective in a sample of 771 U.S. firms across 41 industries, offering empirical substantiation of the theory across industry contexts. The DCs of shifting between, and maintaining variety in, OCs are key in dynamic product-markets, whereas efficiencies in key functional areas drive superior performance under stable conditions and DCs have no significant effect. Further analyses illustrate analogous reversals of effects contingent on whether internal conditions enable firms to recoup the costs of developing and maintaining DCs, lending further credence to the measured developed in this study as a valid operationalisation of DCs and corroborating research adopting a configurational approach (Wang et al. 2015; Wilden et al. 2016; Fainshmidt et al. 2019).

6.5.1 Contributions

This study has several implications for both research and practice. First, the approach employed herein offers a methodological contribution that addresses a central aspect of DCs theory and clarifies knowledge in this research stream. Defining DCs based on their functional relationship to OCs directly captures the theoretical mechanisms of change that are fundamental to distinguishing the DCs perspective (Bowman and Ambrosini 2003) but remain underexplored in empirical research (Schilke et al. 2018). In doing so, these analyses provide empirical substantiation of the DCs perspective at scale. This is significant considering that meta-analysis has questioned the relevance of this framework. Assessing 115 studies, Karna et al. (2016) find a lack of support for the OC—DC distinction, showing that both classes of capabilities exhibit similar effects on financial performance, and conclude that this “may well be a theoretical convention” that “lack[s] in discriminant validity” (p.1170). These results contrast this view and suggest that it may arise from methodological issues, whereby operationalisation of capabilities is not aligned with their conceptualisation in the DC perspective. Much prior research is survey-based, measuring capabilities as key decision-makers' appraisals of their firms' success in a given activity. However, defining a capability via assessment of success will invariably lead to positive effects as they cannot, by definition, be ascribed to unsuccessful firms. This may have contributed to the results of Karna et al. (2016), as the inclusion of many such studies potentially overstates positive results. Instead, this study defines capabilities in a way that is conceptually independent of their intended outcome and demonstrate that such non-tautological measures provide more nuanced insights into the role of both DCs and OCs.

Second, these results may serve to clarify the emerging view that DCs are beneficial in both stable and dynamic environments (Fainshmidt et al. 2019) and address the limitation of DCs research that has "emphasised the upsides of dynamic capabilities without accounting for their costs" (Schilke et al. 2018, p. 420). Prior research relies on subjective or industry-level measures of environmental dynamism, whereas both theory (Teece 2014) and empirical evidence (Hoberg and Phillips 2016) suggests that the relevant changes occur at the product-market level. Measuring dynamism in this way, this study offers novel insights into the detrimental or redundant role of DCs in stable conditions and further evidence for their beneficial role in dynamic environments (c.f. Wilhelm et al. 2015; Mikalef et al. 2019). Additional analyses illustrate analogous reversals of effects based on whether internal conditions enable a firm to recoup the costs associated with DC development, evincing the firm- and market-level factors antecedents to the costs and benefits of DCs; a presently understudied phenomenon requiring empirical clarification (Schilke et al. 2018).

Finally, these findings provide actionable insights for managers by corroborating the DCs perspective across a range of industry contexts (c.f. Easterby-Smith et al. 2009). This is notable considering that DCs are seen to require non-routine action and intuitive managerial ‘sensing’ (Teece et al. 1997). This implies that the path to developing DCs exhibits equifinality and thus cannot be generalised across firm and industry contexts (Eisenhardt and Martin 2000); a proposition that is entirely compatible with this study (as it does not examine capability development). However, these findings show that once DCs are developed, their effects may be more predictable than context-specific studies suggest. Specifically, decisions on whether to maintain variety in, or shift between deployment of, OCs may be profitably based on the degree of competitive threat in a firm’s product-market and the strategic positioning of the firm. These results can help to demystify the central role of intuition in the framework (Teece 2014), suggesting that effective utilisation of DCs may be less dependent on individual managers that previously hypothesised (Helfat and Peteraf 2015) and providing practical insights regarding the firm- and market-level antecedents to the costs and benefits of DC deployment (Schilke et al. 2018).

6.5.2 Limitations and Directions for Future Research

This study emphasises the advantages of objective and longitudinal measurement in DCs research (c.f. Schilke et al. 2018). However, whilst it is argued and demonstrated that secondary data provides a sound basis for deriving generalisable conclusions about the deployment of OCs and DCs, this author also recognise the value of qualitative approaches in addressing other important aspects of DCs (c.f. Easterby-Smith et al. 2009). Examining the ‘black box’ of capability development (Sirmon et al. 2007) requires data about conditions internal to the firm. This aspect of DCs cannot be examined using the methods employed in this study; however, providing objective and theoretically consistent measures of the *outcome* of capability development can provide a basis for future research that utilises the advantages of qualitative methods whilst appropriately capturing variables that are outside of the control of the firm. Specifically, recent work has argued for a configurational approach to DCs, examining the antecedents and effects of DCs under multiple interactions between contingencies (Wilden et al. 2016; Fainshmidt et al. 2019). Other external factors, such as market growth or turbulence, can be assessed using secondary data, whilst the internal and unobservable factors hypothesised to be central to DC development, such as managerial cognition (Pandza and Thorpe 2009; Barrales-Molina et al. 2013; Helfat and Peteraf 2015), may require case studies or surveys. These measurement approaches may be combined such that variables under managerial control (e.g., the cognitive processes of capability development) are captured in an appropriately subjective manner whilst remaining detached from assessment of those resulting from and/or outside of this control (e.g., external conditions and the outcomes of capability development) and thus avoiding the issues of tautological capability assessment associated with prior research. This combination of measurement approaches may improve the relevance of future research to practitioners, enabling examination of a broader range of contingencies than addressed here and elucidating firm-specific antecedents to the development of DCs.

7 DISAGGREGATING THE CHARACTERISTICS AND CONTRIBUTION OF MARKETING CAPABILITIES: RARITY, PERSISTENCE, AND DEVELOPMENT IN RESOURCE DEPLOYMENT

7.1 INTRODUCTION

Capabilities are firm-specific configurations of knowledge and skills that enable other resources to be leveraged for value creation (Helfat and Peteraf 2003) and create barriers to competitive imitation (Bharadwaj et al. 1993). Accordingly, resource based theory (RBT) recognises marketing capabilities as central to superior performance (Barney 2014; Kozlenkova et al. 2014), and capability development is reliably reported as the top investment priority for Chief Marketing Officers (CMO Survey 2020). A substantial literature has examined the capability—performance relationship, with meta-analyses reporting consistently positive effects (Krasnikov and Jayachandran 2008; Karna et al. 2016). However, it is arguable whether extant studies have adequately tested the capability—performance relationship as theorised in RBT, as attempts to clarify inconsistencies between theory and empirics in RBT consistently highlight problems in conceptualizing and measuring capabilities and their consequences. Specifically, variation in the operationalisation of both capabilities and performance outcomes (Karna et al. 2016) and the assumption that average effects provide insight into the performance implications of capabilities in individual firms (Hansen et al. 2004; Barney 2014) suggest that many empirical investigations are misaligned with the premises of RBT as a theory of competitive advantage.

This is particularly pertinent to the study of marketing capabilities. Meta-analysis indicates that marketing capabilities exhibit the largest performance benefits among the three key functional areas of marketing, R&D, and operations (Krasnikov and Jayachandran 2008) and studies of environmental contingencies show that these effects are more consistent than those of other functional capabilities (Feng et al. 2017). This suggests that managers should generally seek to increase their firm’s marketing capabilities. However, marketing capabilities are also costly to develop and maintain (Bharadwaj et al. 1993), presenting both tangible and opportunity costs if investments are misaligned with a firm’s competitive environment (Feng et al. 2017). Furthermore, capabilities in different functional areas often have conflicting goals (e.g., short-term cost minimisation in operations versus long-term demand generation in marketing), creating tensions and inefficiencies when attempting to develop multiple capabilities simultaneously (King et al. 2008). Specific knowledge of the value of marketing capabilities is therefore essential for effective resource allocation, as misunderstanding the nature, form, and conditions of the capability—performance relationship may lead managers to pursue costly resource investments with potentially erroneous payoffs.

This study presents a methodology to address the gap between prior empirical studies and RBT and thus clarify the performance effects of capabilities. Established measurement approaches are developed and extended to provide an operationalisation of capabilities that is conceptually aligned with RBT, focusing on the characteristics that are theorised to underlie their contribution to competitive advantage: *rarity* relative to competitors, *persistence* of capability over time, and the ability to continually *develop* capabilities. The validity of these measures is tested using a Bayesian hierarchical model that appropriately accounts for firm- and industry-level heterogeneity in the effect of capabilities. Results indicate that marketing capabilities (in addition to R&D and operations capabilities) are not universally beneficial as previous studies suggest: their role in driving competitive advantage depends to different degrees on these three characteristics. In addition, the performance effects of capabilities differ across industries, demonstrating considerable underexplored heterogeneity in prior research.

This study provides several contributions to the study of marketing capabilities and the RBT literature. In augmenting and extending established methods to improve theoretical consistency and explanatory power, the approach employed here offer a path towards reconciling the persisting gap between conceptualisation and empirics in RBT (c.f. Barney 2014). This has implications for advancing theory regarding the role of capabilities, demonstrating the characteristics of resource deployment that are most consequential for performance across functional areas. Two key insights highlight areas in which explanations of the capability—performance relationship can be improved: these results suggest that previous studies may *underrepresent* the performance effects of marketing and *misrepresent* the role of R&D capabilities. Accordingly, this study also has practical implications for demonstrating the value of marketing. Recent research highlights the problems faced by managers in this regard, with only two percent of CMOs being held accountable for marketing's contribution to firm value (CMO Survey 2020). This creates difficulties in justifying the marketing function at the executive and board level (Edeling et al. 2020), and in the recruitment of marketers in the upper echelons of the firm (Whitler et al. 2020). By highlighting positive effects of marketing on firm performance that have not yet been examined in the study of capabilities, these findings can therefore assist managers in advocating for marketing investment and justifying its value.

7.2 THEORY AND PROPOSITIONS

7.2.1 A Theoretically Consistent Operationalisation of Capabilities

In RBT, resources are tangible or intangible assets that a firm can use to achieve its strategic objectives (Srivastava et al. 2001). Capabilities are a subset of resources that enable firms to acquire, organise, and utilise other resources more effectively (Barney 2014). The RBT concept of capabilities is thus defined by the internal and unobservable *processes* that direct resource deployment (Kozlenkova et al. 2014). Accordingly, capabilities should be measured not by the resources possessed by a firm or the outcome attained, but by the intermediate processes that create value from resources (Dutta et al. 2005).

There are three main approaches to measuring capabilities: perceptual measures, archival data, and stochastic frontier analysis (SFA) (see Table 7.2.1 for representative examples). SFA has emerged in recent years as the preferred method (e.g., Dutta et al. 1999,2005; Narasimhan et al. 2006; Xiong and Bharadwaj 2011,2013; Vandaie and Zaheer 2014; Feng et al. 2017) due to the conceptual limitations of other approaches. Specifically, perceptual measures are tautological (Newbert 2008) as they require assessment of the firm's success by key informants (Sirmon et al. 2010). This cannot ascribe capabilities to poor-performing firms, and has thus been criticised for rendering hypotheses regarding the capability—performance relationship unfalsifiable (Powell 2001; Priem and Butler 2001). Archival data mitigates this issue as it does not require judgements of success. However, many studies utilise measures that more accurately represent the *level* of resources (e.g., marketing or R&D expense) or the *outcome* of their use (e.g., market share or innovation). These variables are misaligned with the concept of capabilities, respectively being upstream and downstream of the capability itself (Dutta et al. 1999).

TABLE 7.2.1 Representative Research on Functional Capabilities.

Study	Capability measures				Dependent variables		Capability effects			Method		
	MK	**RD**	**OP**	**R/A**	**Measure**	**R/A**	**MK**	**RD**	**OP**	**Model**	**Time**	**Context**
Hitt and Ireland (1985)	SR effectiveness in 8 functional activities	SR effectiveness in 5 functional activities	SR effectiveness in 10 functional activities	R	Market returns	A	+/-	NS	NS	OLS	CS	4 sectors, 185 firms
Dutta, Narasimhan, and Rajiv (1999)	SFA: marketing expense, technological know-how, customer base → sales	SFA: R&D expense, marketing capability, tech know-how → patents	SFA: cost of capital and labor, marketing expense, tech know-how → COGS	R	Tobin's Q	R	+	+	+	MSM	1985-1994 (10)	1 industry, 72 firms
Moorman and Slotegraaf (1999)	Market share	Number of patents	None	A	Product quality change	A	NS	NS	NA	Hierarchical regression	1991-1996 (7)	1 industry, 124 brands
Anand and Delios (2002)	Advertising expense/sales	R&D expense	None	A	% entries by acquisition	A	+	+	NA	Fixed effects	1974-1991 (18)	2,175 market entry events
Kotabe, Srinivasan, and Aulakh (2002)	Advertising expense/sales	R&D expense/sales	None	A	ROA	A	+	+	NA	Time series CS analysis	1987-1993 (7)	12 industries, 49 firms
Worren, Moore, and Cardona (2002)	None	None	SR product modularity	A	SR financial	R+A	NA	NA	+	SEM	CS	1 industry, 103 firms
Jayachandran, Hewett, and Kaufman (2004)	SR customer responsiveness	None	None	A	SR financial and market	A	+	NA	NA	SUR	CS	1 industry, 227 firms
Dutta, Narasimhan, and Rajiv (2005)	None	SFA: R&D expense → patents	None	A	Tobin's Q	A	+	NA	NA	Correlations	1980-1998 (19)	2 industries, 64 firms
Song, Droge, Hanvanich, and Calantone (2005)	SR: 3 capabilities	SR: 3 capabilities	None	R	SR financial and market	A	+	+	NA	SEM	1990-1997 (8)	7 industries, 466 firms
Vorhies and Morgan (2005)	SR effectiveness in 8 functional activities	None	None	A	SR customer satisfaction	A	+	NA	NA	SEM	CS	12 industries, 230 firms
Banker, Bardhan, Chang, and Lin (2006)	None	None	SR: 5 capabilities	A	SR change in efficiency and quality	A	NA	NA	+	SEM	CS	20 industries, 1,077 firms
Macher and Boerner (2006)	None	Number of prior projects	None	A	Product development time	A	NA	+	NA	Event history analysis	1993-1999 (7)	1 industry, 26 firms

Krasnikov and Jayachandran (2008)	*Various*						+	+	+	Meta-analysis	NA	114 studies
Ramaswami, Srivastava, and Bhargava (2009)	SR customer responsiveness	SR effectiveness in new product development	SR effectiveness in supply chain management	A	SR financial	A	+	+/-	+	Hierarchical regression	CS	88 firms
Xiong and Bharadwaj (2013)	SFA: marketing expense → sales	None	None	A	Abnormal returns	A	+	NA	NA	Event study	2004-2010 (7)	141 firms
Krush, Sohi, and Saini (2015)	SR effectiveness in 8 functional activities	None	None	A	SR financial	A	+	NA	NA	Latent Variable Scores Approach	CS	4 industries, 152 firms
Wilden and Gudergan (2015)	SR strength or weakness	None	SR strength or weakness	R	SR financial and market	R	+	NA	+	SEM	CS	228 firms
Karna, Richter, and Riesenkampff (2016)	*Various*						+	+	+	Meta-analysis	NA	115 studies
Feng, Morgan, and Rego (2017)	SFA: marketing expense → sales	SFA: R&D expense → patents	SFA: cost of capital and labor → COGS	A	Revenue growth and profit growth	A	+	+	+	First difference regression	1993-2008 (16)	60 industries; 612 firms
Wang, Aggarwal, and Wu (2020)	Number of repeat customers	Patent descriptions	None	A	Small business grants	A	+	+/-	NA	OLS	1996-2006 (10)	1 industry, 533 firms

Capabilities: MK = marketing, RD = R&D, OP = operations.

Measurement approach: SFA = stochastic frontier analysis, SR = self-report.

Level of measurement: R = relative to competitors, A = absolute, i.e. assessed at the firm-level only.

Interactions: C = complementary, S = substitutive.

Time period: Number of years in parentheses. CS = cross-sectional.

Results: NA = not applicable (not studied), NS = not significant; + (-) = positive (negative) overall effect of capabilities on performance

Context: Where number of firms/industries is not stated, this was not reported by the authors.

In contrast, SFA captures the notion of capabilities as an intermediate process that creates value from resources (Vandaie and Zaheer 2014).. SFA relates resource inputs to the achievement of specific outcomes, estimating the outcome that can be produced if resources are used most efficiently (Aigner et al. 1977). This 'frontier' is determined by the most efficient firm and "tells us the *best* the firm could have done if it had used the resource level at its disposal efficiently" (Dutta et al. 2005, p. 278). Downward deviations from the frontier among other firms represent "underattainment of the functional objective… attributable to functional inefficiency, or equivalently, to a lower functional capability" (Dutta et al. 1999, p. 547). This overcomes the limitation of measuring an intrinsically internal and unobservable construct via externally available archival data sources(Feng et al. 2017). However, while this *equivalence between capability and efficiency is intuitively appealing, it is arguably inconsistent with RBT*. Superior performance does not require firms to be maximally efficient: the benchmark for performance is not the frontier, but rivals (Vorhies and Morgan 2005).[17] The role of capabilities does not derive from their utilisation in attaining the maximum possible objective, as assumed in SFA, but the differential levels of an objective that can be achieved due to variance in capabilities among competitors (Sirmon et al. 2010). It is therefore debatable whether current best practice accurately measures the

[17] Notably, Dutta et al. (1999) adjust SFA-derived measures of inefficiency to capture capabilities relative to competitors in their first use of this method, but subsequent applications have omitted this step (Dutta et al. 2005; Xiong and Bharadwaj 2013; Feng et al. 2017).

construct of capabilities: SFA assumes *optimisation* behaviour rather than the *competitive* behaviour that motivates the strategic decisions of firms.

The competitive significance of capabilities derives from the limiting conditions that underlie resource-based advantages: imperfect mobility and inimitability (Peteraf 1993). Imperfect mobility refers to the difficulty of buying or selling capabilities: they arise from firm-specific resource interactions and embedded processes, and thus are non-tradeable (Barney 2014). Inimitability refers to the difficulty that competitors face in emulating a firm's capabilities: from an observer's perspective, tacit knowledge and complex resource configurations obscure the source of a capability's beneficial effects (Kozlenkova et al. 2014).

Previous research recognises the importance of imperfect mobility and inimitability in the capability—performance relationship. Regarding the three core functional areas, marketing capabilities are theoretically built via close customer relationships, which are inherently firm-specific and tacit (Day 1994; Vorhies and Morgan 2005). R&D capabilities involve a large 'learning-by-doing' component and so cannot be bought and sold (Irwin and Klenow 1994; Miklós-Thal et al. 2018). Operations capabilities require careful coordination of resources, generating complex interactions that make it difficult for competitors to observe the source of efficiencies (Hayes et al. 1988). However, despite discussion of their theoretical role, previous research has not incorporated these factors into an operational definition (c.f. Dutta et al. 1999; Krasnikov and Jayachandran 2008). This study proposes that three characteristics, obtainable from SFA estimates of efficiency, can improve the operationalisation of capabilities by accounting for imperfect mobility and inimitability. These are herein termed *rarity*, *persistence,* and *development.* By incorporating these measures, efficiency-based measures can be adjusted to appropriately capture the concept of capabilities and thus improve alignment of empirical methods with RBT.

Rarity. In a survey-based study of managerial capabilities, Sirmon et al. (2010, p. 1387) demonstrate that "it is the relative (to competitors) instead of an absolute quantity of capabilities that matters most for competitive advantage". However, with the exception of Dutta et al. (1999), studies of archival data quantify capabilities in absolute terms or relative to the efficient frontier. When all firms possess some level of a capability – as is necessarily the result of SFA – the competitive value of that capability must be a function of variance in levels between competing firms (Sirmon et al. 2010). A high level of capability is not relevant to competition if peer firms possess similarly high levels: in this situation, the capability provides no opportunity to implement a distinct and potentially superior strategy and thus cannot be considered a driver of competitive advantage (Barney 1991; Newbert 2008). This author therefore proposes that rarity is operationalised as the *distance between a focal firm and competitors in levels of efficiency.*

Persistence. As Helfat and Winter (2011, p. 1244) note, "repeated and reliable capacity is a particularly important feature of a capability; otherwise, almost by definition, a firm cannot be said to have a 'capacity' to do something". This 'repeated and reliable' nature of capabilities is largely absent from empirical work, which relies on cross-sectional methods or observation at the firm-year level (see Table 7.2.1). Consequently, whilst SFA enables inference about the unobservable processes that enables resource inputs to be directed towards firm objectives, this can only be seen as representative of a capability if efficiencies persist over time, as transient efficiency does not meet the definition of a capability as embedded (Helfat and Peteraf 2003). This author therefore proposes that persistence is operationalised as *temporal stability in levels of efficiency.*

Development. While persistence, indicative of embeddedness, is critical to the definition of a capability, a theoretically sound measure must also account for the fact that capabilities are internally developed (Helfat 1997; Helfat and Peteraf 2003) and exhibit learning effects (Irwin and Klenow 1994; Miklós-Thal et al. 2018). This implies that capabilities will also be evidenced by an increase in levels of efficiency over time. Without such development, stable levels of efficiency may instead represent ‘core rigidities’ – embedded routines that do not contribute to superior performance and potentially have negative effects (Leonard-Barton 1992; Haas and Hansen 2005). Thus, the ability to sustain efficiency and improve over time can be taken as evidence that efficiency is representative of capability, whereas persistence without development may indicate that a routine is firm-specific (imperfectly mobile) but lacks the processes of internal learning necessary to prevent competitive imitation. This author therefore proposes that development is operationalised as *temporal changes in levels of efficiency.*

In sum, this study is based on the premise that SFA can be augmented with measures of rarity, persistence, and development in order to capture the conditions of imperfect mobility and inimitability that are theorised to underlie the capability—performance relationship. As the above discussion suggests, these characteristics represent the necessary conditions for identifying a capability rather than the sufficient conditions to drive superior performance. Accordingly, the author does not hypothesise directional effects. The aim of these measures is to correct for the assumptions of SFA (i.e., optimisation behaviour in accordance with economic theory) which are erroneous in the context of RBT as a theory of competitive advantage.

> ***Proposition 1:*** *The combination of efficiency and capability characteristics explains more of the variance in the capability—performance relationship than efficiency measures alone.*

7.2.2 Capabilities in a Theory of Competitive Advantage

To incorporate the proposed measures into empirical examination of the capability—performance relationship, operationalisation of performance that appropriately aligns with the theorised role of capabilities is also required. In addition to employing various measures of capabilities, previous studies are divergent in this regard. Dutta et al. (1999) examine the effect of capabilities on Tobin's Q relative to competitors, whilst Dutta et al. (2005) correlate capabilities with absolute levels of Tobin's Q and Feng et al. (2017) use differences regression to examine relationships between the year-to-year change in capabilities and the revenue and profit growth of the firm. Evidently, this obfuscates direct comparison of the effects of capabilities. More importantly, aside from Dutta et al. (1999), these performance outcomes do not correspond to the notion of competitive advantage – the fundamental phenomenon that RBT seeks to explain via capabilities (Peteraf 1993; Barney 2014).

Moreover, many studies examine the effect of capabilities on intermediate outcomes, such as changes in product quality (Moorman and Slotegraaf 1999), customer satisfaction (Vorhies and Morgan 2005), and firm growth (Feng et al. 2017), which may contribute to superior performance but are not indicative of competitive advantage in themselves (Barney 1991; Sirmon et al. 2010). Consequently, prior meta-analyses reporting positive effects of capabilities do not necessarily imply a relationship between capabilities and competitive advantage. For example, Karna et al. (2016) include accounting, capital market, and perceptual measures of financial performance and Krasnikov and Jayachandran (2008) examine efficiency-and market-related outcomes, but do not distinguish between relative and absolute measures.

The most commonly studied functional capabilities – marketing, R&D, and operations – are prevalent as they represent three distinct paths to value creation (Krasnikov and Jayachandran 2008; Feng et al. 2017). Marketing capability refers to the ability to understand and predict customer needs and to align products and services with this knowledge (Day 1994; Morgan 2012). R&D capability refers to proficiency in developing and applying technological innovations to improve both customer offerings and business processes (Dutta et al. 1999). Operations capability concerns the efficiency and flexibility of production processes, enabling a firm to perform at the lowest possible cost whilst maintaining quality (Hayes et al. 1988). Accordingly, dependent variables that capture intermediate, efficiency-, or market-related outcomes rather than overall firm performance may not accurately represent the relative effect of each functional area; for example, the comparatively large effects of marketing capability on revenue growth found in Feng et al. (2017) is understandable given that the marketing function is explicitly focused on demand generation whereas R&D and operations are not.

To avoid misspecification of competitive advantage in capabilities research, performance measures should reflect the superior ability of a firm to derive economic rents relative to competitors (Barney 1991; Sirmon et al. 2010). To ensure that there is a theoretical link between specific functional capabilities and the focal outcome, performance measures should also account for various routes to value creation. This author therefore proposes that capabilities research should employ performance outcomes that are *relative* and capture *overall firm performance*.

> ***Proposition 2:*** *Efficiency and capability characteristics explain more of the variance in overall firm performance when performance is measured relative to competitors rather than in absolute terms.*

7.2.3 Heterogeneity in the Capability—Performance Relationship

Developing measures of the characteristics of capabilities and operationalising performance in relative terms is designed to improve the congruence between theoretical and empirical specification of the capability—performance relationship. Applying these measures requires consideration of a third limitation of extant capabilities research: *the underexplored sources of heterogeneity that may alter the nature and effects of capabilities across firms* (Krasnikov and Jayachandran 2008; Arunachalam et al. 2018).

A key source of heterogeneity that remains underexplored is industry membership, as the relative need for proficiency in marketing, R&D, and operations varies widely by industry (Dutta et al. 1999; Arunachalam et al. 2018). This is important for two reasons. First, the aggregate effect of a capability across all firms in all industries provides little indication of whether a specific functional capability will be beneficial in a given competitive context, and can obscure the true nature of the capability—performance relationship (Krasnikov and Jayachandran 2008). Second, firms benchmark their capabilities against competitors within industries (Vorhies and Morgan 2005), suggesting that substantive findings on the effects of functional capabilities is most relevant to managers when presented at the industry-level. Further empirical examination of the types of functional capability that are most consequential in different industries is therefore required, to improve both the theoretical and managerial relevance of findings (Arunachalam et al. 2018). However, much capabilities research focuses on one or a few industries (Krasnikov and Jayachandran 2008; see Table 7.2.1) or controls for industry differences (e.g., Feng et al. 2017). The former approach limits generalisability and contribution to theory development. The latter, in reporting average effects, obscures industry heterogeneity in the capability—performance relationship, limiting managerial relevance.

Average effects are practically meaningful only when firms are assumed to be homogenous in their resources, capabilities, and environmental conditions—yet this assumption opposes the theoretical premise of firm heterogeneity that is central to the RBT (Powell 2001;

Mackey et al. 2017). Consequently, the frequentist methods that dominate strategic management research are poorly suited to examinations of the capability—performance relationship (Hansen et al. 2004), whereas the marketing discipline is well-positioned to address this limitation due to a greater acceptance of Bayesian and hierarchical models (Barney 2014).

These models offer several advantages for empirical examination of relationships within RBT. First, Bayesian models are not constrained in the managerial relevance of their parameter estimates by average effects but report the *distribution* of firm-specific coefficients. This enables probabilistic inferences about the benefits a specific firm is likely to derive from a specific strategic variable and can reveal relationships that are obscured in averaging across firms (Denrell et al. 2013), consistent with the conceptual foundations of RBT (Hansen et al. 2004). Second, hierarchical models allow the effects of variables at one level (e.g., the firm) to be partially determined by the effects of variables at another level (e.g., the industry) (Kruschke et al. 2012). This aligns with the theoretical role of capabilities, which is embedded in complex, multileveled systems (Dutta et al. 1999; Sirmon et al. 2010). Third, as RBT seeks to explain differences between firms, the generalisability of empirical work requires examination of firms operating in a range of contexts (Greve 2020). Frequentist methods are often impossible to estimate in such circumstances due to convergence issues, whereas Bayesian estimation enables the use of complex models and large samples with many firm-specific effects (Lester et al. 2021). Consequently, Bayesian methods can facilitate theoretical development in the RBT (Hansen et al. 2004).

These methodological considerations therefore provide a practical way to model capabilities in ways that better approximate real-world competitive conditions, facilitating tests of RBT (Powell 2001). This author proposes that the theoretical and practical relevance of capabilities research can be improved by utilising Bayesian and hierarchical methods that account for previously underexplored sources of heterogeneity:

> ***Proposition 3:*** *The effects of efficiency and capability characteristics are contingent on firm- and industry-level heterogeneity.*

7.3 METHOD

7.3.1 Data and Sample

Previous studies vary in terms of the length of panel data and scope of industries included (See Table 7.2.1). In this study, the sample is not restricted to a specific period or industry, such that the findings may inform capability measurement across contexts. To account for variations in levels and effects of capabilities across different competitive environments (c.f. Krasnikov and Jayachandran 2008), estimates of firm capabilities are derived at the industry-level. This is extended to the calculation of capability characteristics. Bayesian methods are used to model firm heterogeneity.

Data was obtained from Compustat, which provides the firm- and industry-level data required for calculating all measures. As most firms in the database do not report R&D expenditures prior to 1988, this determines the census date. The sample was then refined in two steps. First, firms with fewer than 10 consecutive years of data on the *inputs and outputs of* *capabilities* were removed before conducting SFA, as recommended to ensure consistency in the chosen estimation procedure (Belotti and Ilardi 2012). Computing variables at this stage ensures that firm-year measures of efficiency (and therefore characteristics) reflect a firm's position relative to *all* competitors, even if these competitors are excluded from the final sample. Second, after calculating all measures, observations were further restricted to firms with more than 10 consecutive years of data for *all variables.* The final sample consists of 10,867 firm-year observations of 706 firms between 1988 and 2019.

7.3.2 Functional Efficiency

SFA estimates a 'frontier' of efficiency for a specified production process, based on the notion that no producer can exceed the economically optimal utilisation of inputs to create outputs. The model accounts for random statistical noise such that deviations from the frontier represent the individual inefficiencies of decision-making units (Aigner et al. 1977; Meeusen and van Den Broeck 1977). The basic stochastic frontier model, as applied to panel data, can be expressed as:

(7.1) $$y_{it} = a_i + x'_{it}\beta + \varepsilon_{it}$$

Where $\varepsilon_{it} = v_{it} \pm u_{it},\ v_{it} \sim N(0, \sigma_v^2),\ u_{it} \geq 0$ and $u_{it} \sim \mathcal{F}$. y_{it} is the natural log of the productive output of firm *i* in period *t;* x'_{it} is a vector of inputs to the production process and β the vector of parameter estimates. The composite error ε_{it} is the sum of the symmetric, normally distributed stochastic error term v_{it} and the one-sided error u_{it} representing inefficiency, which are assumed to be i.i.d. across observations.[18]

In choosing among the numerous estimation methods for SFA (see Greene 2012; Lampe and Hilgers 2015), three requirements determined the appropriate selection for the objectives of this study. First, a specification was required that accounts for *heterogeneity* between firms. Early models (e.g., Schmidt and Sickles 1984; Battese and Coelli 1988) treat all time-invariant unobserved heterogeneity as inefficiency. In contrast, the True Random Effects (TRE) specification formalised in Greene (2005) removes all time-invariant unobserved heterogeneity from the inefficiency term. This captures inefficiencies (and thus the subsequently derived measures of capability characteristics) independently of firm heterogeneity.

Second, this study requires the estimation of *time-varying inefficiencies* to examine how capabilities change over time. Most SFA models assume inefficiency to be time-invariant, resulting in a two-component error term (Kumbhakar et al. 2015). A three-component model that estimates both persistent and time-varying efficiency is therefore necessary. When the separation of firm heterogeneity from inefficiency is required, TRE is the most appropriate three-component specification (Greene 2012).[19] In this model, time-invariant error is treated as a random

[18] The sign of u_{it} is positive and negative in cost and production functions, respectively, as shown in the models.
[19] In contrast to earlier models which estimate time-variant effects but do not disentangle inefficiency and unobserved firm heterogeneity. See Greene (2012); Belotti et al. (2013) for reviews.

variable representing firm heterogeneity, while time-variant error represents inefficiency for each firm-year.[20]

Third, as the sample spans multiple industries, a model that estimates the efficient frontier *at the industry-level* was required. TRE allows for the inclusion of exogenous determinants of inefficiency:[21] variables that are outside of the control of the firm (i.e., not an input variable) but theoretically capable of influencing the efficiency of input utilisation and therefore the level of output (Wang and Schmidt 2002). This is incorporated by specifying the mean of the distribution of efficiencies as a function of the exogenous covariates (Kumbhakar et al. 1991). The distribution of u_{it} thus becomes:

$$u_{it} \sim N^{+}(\mu_i, \sigma_u^2) \tag{7.2}$$

$$\mu_i = z_i'\psi \tag{7.3}$$

u_{it} is therefore a realisation from a truncated normal distribution, the mean of which is a function of a vector of exogenous variables (z_i'), including a constant, and their associated parameters (ψ). Here, the exogenous covariate is the variable SIC_i, representing a firm's industry identified by 2-digit SIC code. Accordingly, the distribution of firm-year

[20] Recent developments also decompose the time-invariant error term into estimates of unobserved heterogeneity and persistent inefficiency. However, in these models only the time-variant *or* time-invariant efficiency estimates have been found to be accurate (Badunenko and Kumbhakar 2016). The three-component model is therefore used here.

[21] Previous approaches have either omitted such exogenous factors or included them in the production/cost function (Belotti et al. 2013). However, these methods severely bias estimates of inefficiencies (Wang and Schmidt 2002). Wang and Ho (2010) provide an alternative approach to this issue; however, the estimation methods required are unfeasible given the large dimensions of this data. The main advantage of Wang and Ho's model over Greene's is the avoidance of the 'incidental parameters' problem that arises when the number of firms is large relative to the length of the panel. However, for panels of length *T > 10* (as is the case for this dataset), TRE estimates have been shown to be consistent (Belotti and Ilardi 2012).

efficiency estimates is specific to each industry in the sample, capturing the efficiency of firms relative to competitors and accounting for differences in efficiency standards between industries.

Prior research (e.g., Dutta et al. 1999; Xiong and Bharadwaj 2013; Feng et al. 2017) was followed in defining the frontier functions for marketing and operations, and in measuring the inputs for R&D capabilities. However, the measure of R&D output employed in this study differs from previous research due to concerns with the conceptual appropriateness of extant patent-based measures. Patents may not accurately represent the contribution of R&D to value creation (Mann 2018; Cohen et al. 2019) as they demonstrate a firm’s success in producing novel, but not necessarily commercially viable, R&D outputs. Consequently, they represent the achievement of an intermediate objective rather than a contribution of the R&D function toward firm value (Kogan et al. 2017). Firms may also seek to avoid patenting when competition is intense, as this requires public disclosure of proprietary knowledge that could otherwise be protected via confidentiality agreements and noncompete contracts (Saidi and Zaldokas 2020), leading to questionable validity of this measure in empirical examinations of competitive advantage. Patent-based measures may therefore lead to underestimation of the true commercial value of R&D output (Bellstam et al. 2020).

R&D output was instead defined as the value of the firm’s intangible assets minus goodwill and acquired intangible assets. These adjustments to the raw value of intangible assets serve two purposes. First, removing the value of goodwill ensures that this measure does not overlap with outputs of the marketing function, such as brand equity. Second, removing acquired intangible assets ensures that only the portion of value that is generated internally is attributed to a firm's capability. This measure thus includes the value of noncompete covenants, licenses, blueprints, unpatented designs, and the *commercial* value of patents, comprehensively capturing the intended objective of generating technology and technological know-how. In support of this, there is a correlation of .369 between this measure of R&D output and R&D inputs. This is substantially higher than correlations between R&D inputs and patent-based measures (e.g., -.002 in Liu and Wong (2011) and .013 in Giarratana et al. (2018)) and is more comparable to correlations between inputs and outputs for marketing (.774 for SG&A expense and sales; .793 for advertising expense and sales,) and operations (.574 for COGS and labour expense; .384 and .734 for COGS and dividends and interest paid, respectively) in this dataset. This suggests that the relationship between this measure and R&D expense is closer to the input-output relationships in other functional areas than between patent-based outcomes and R&D expense. Furthermore, this is similar to the .400 correlation between text-based measures of innovation and R&D expense found in Bellstam et al. (2020), suggesting that this measure captures a similar input-output relationship with more accessible computation and data sources.

Functional efficiency in marketing, R&D, and operations was estimated using the following models, where SIC_i is an industry dummy representing the firm's 2-digit SIC code, v_{it} is the stochastic error, and u_{it} the firm- and time-specific effects representing relative inefficiency. As the location of the distribution of efficiencies was specified as a function of industry membership, inefficiencies are assumed to follow a truncated normal distribution and stochastic error to follow a normal distribution. For marketing and R&D efficiency, the production function is *output-oriented,* i.e., the objective is assumed to be the maximisation of output for a given level of input. Operations efficiency was estimated with the same model form but *input-oriented,* where the objective is assumed to be the minimisation of inputs at a given level of output (Dutta et al. 1999). Marketing efficiency was estimated as:

$$(7.4) \quad \ln(SALE_{it}) = \alpha_0 + \alpha_1 \ln(XAD_{it}) + \alpha_2 \ln(XAD_{it-1}) + \alpha_3 \ln(XSGA_{it}) + \alpha_4 \ln(XSGA_{it-1}) + \alpha_5 SIC_i + v_{it} - u_{it}$$

Where $SALE_{it}$ is the firm's sales revenue in the current year, XAD_{it} is the current year's and XAD_{it-1} the previous year's advertising expense and $XSGA_{it}$ is the current year's and $XSGA_{it-1}$ the previous year's SG&A expense.[22] R&D efficiency was similarly estimated as:

$$(7.5) \quad \ln(INTAN_{it}) = \alpha_0 + \alpha_1 \ln(XRD_{it}) + \alpha_2 \ln(XRD_{it-1}) + \alpha_3 SIC_i + v_{it} - u_{it}$$

Where $INTAN_{it}$ is the firm's intangible assets minus goodwill and acquired intangible assets in the current year, XRD_{it} the current and

[22] Ptok et al. (2018) argue that SG&A is an inadequate operationalization of marketing capability due to its inability to capture the strategic, intangible and operating (vs. accounting) nature of capabilities and is not, in itself, a suitable measure of efficiency. However, as this study does not rely on SG&A as a variable but derives efficiency estimates from SFA and subsequently develop further measures of capabilities, this approach is aligned with these authors' recommendations regarding the use of SG&A.

XRD_{it-1} the previous years' R&D expense.[23] Operations efficiency was estimated as:

(7.6) $\ln(COGS_{it}) = \alpha_0 + \alpha_1 \ln(XCAP_{it}) + \alpha_2 \ln(XLAB_{it}) + \alpha_3\, SIC_i + v_{it} + u_{it}$

Where $COGS_u$ is the firm's cost of goods sold in the current year, $XCAP_{it}$ is the current year's cost of capital and $XLAB_{it}$ the current year's labour expense.

Assumptions about the distribution of the inefficiency term ($\mathcal{F}$) are required for SFA[24], indicating maximum likelihood (ML) estimation of model parameters. In panel data applications of SFA with unobserved heterogeneity, the likelihood function contains high-dimensional integrals that do not have closed-form solutions (Train 2009). Consequently, all models are estimated with simulated maximum likelihood (SML). Briefly, the simulated log likelihood function (see Greene 2005 for full details) is:

(7.7)

[23] Lag structures of up to three years have been used in previous research on R&D expenditures (e.g. Steenkamp and Fang 2011); however, these lags are highly correlated in this dataset (at least .96) suggesting that a one-year lag is sufficient to capture the effects of prior R&D expenditures.

[24] The nonparametric alternative to SFA, namely data envelopment analysis (DEA), is therefore inappropriate here as the error terms are critical for estimation of capabilities and DEA does not account for statistical noise. While SFA has the disadvantage of requiring assumptions on the functional form and distribution of inefficiencies, the appropriateness of distributional assumptions has been widely examined (see Andor et al. 2019) conferring confidence to the modelling decisions made here.

$$\log L_s$$

$$= \sum_{i=1}^{N} \frac{1}{R} \sum_{r=1}^{R} \left\{ \sum_{t=1}^{T} ln\Phi \left(\frac{[\mu_{ir}/(\sigma_{uir}/\sigma_v)] \pm [(y_{it} - \alpha_{ir} - \beta'_{ir} x_{it})((\sigma_{uir}/\sigma_v)]}{\sqrt{\sigma_{uir}^2 + \sigma_v^2}} \right) \right.$$

$$\left. - \frac{1}{2} \left(\frac{\mu_i \pm \left(y_{it-} \alpha_{ir} - \beta'_{ir} x_{it}\right)}{\sqrt{\sigma_{uir}^2 + \sigma_v^2}} \right)^2 + ln \frac{1}{\sqrt{2\pi}} - ln\Phi \left[\frac{\mu_i}{\sigma_{uir}} \right] - ln\sqrt{\sigma_{uir}^2 + \sigma_v^2} \right\}$$

$$= \sum_{i=1}^{N} \frac{1}{R} \sum_{r=1}^{R} \sum_{t=1}^{T} \log P_{itr}$$

Parameter estimates are of less interest than the firm- (and time-) specific inefficiency estimates derived during estimation (Greene 2005); As SML provides estimates of the composite error $\hat{\varepsilon}_{it}$ only, the conditional distribution of $\hat{u}_{it}$ (the parameter of interest) given $\hat{\varepsilon}_{it}$ is used to separate inefficiency estimates from the stochastic error ($\hat{v}_{it}$). The widely applied JLMS estimator (Jondrow et al. 1982) derives this as follows:

(7.8) $$E[u_{it}|\varepsilon_{it}] = \frac{\sigma\lambda}{1+\lambda^2} \left[\frac{\varphi(a_{it})}{1-\phi(a_{it})} - a_{it} \right]$$

Where $\sigma = [\sigma_v^2 + \sigma_u^2]1/2$, $\lambda = \sigma_u/\sigma_v$, $a_{it} = \pm\varepsilon_{it}\lambda/\sigma$. The standard normal density and cumulative density function evaluated a_{it} are respectively denoted with $\varphi(a_{it})$ and $\phi(a_{it})$. The firm-specific estimates of parameters, used to calculate technical efficiency per the JLMS estimator are computed during simulation of the likelihood function.[25] The resultant parameter $\hat{u}_{it}$ is a score from 0 to 1, where 0 represents the efficient frontier. This estimate of inefficiency does not constitute the measure of capability (as in previous applications of SFA) but serves here as the basis for

[25] Estimation of random parameters is time-consuming but can be expedited with the use of Halton sequences (Train 2009). This study does not use Halton sequences for the estimation but Greene (2005) suggests this can provide a reasonable approximation.

calculating further measurements to refine the operationalisation, as detailed in section 7.3.3.

The suitability of SFA was assessed with two diagnostic tests. The likelihood ratio test (Kumbhakar et al. 2015) assesses the goodness of fit of an unrestricted model (SFA) compared to a restricted model (in this case, OLS based on a single error term). The test statistic is given by:

(7.9) $$-2[L(H_0) - L(H_1)]$$

Where H_0 is the log-likelihood of the restricted model and H_1 is the log-likelihood of the unrestricted SFA model, with 1 degree of freedom representing the imposed constraint. The likelihood is compared with a critical value to determine whether the null hypothesis of no technical inefficiency can be rejected. For marketing ($\chi^2_{(2)} =$ -395317.733, *p* <.001), R&D ($\chi^2_{(2)} =$ -45125.298, *p* <.001), and operations ($\chi^2_{(2)} =$ -226647.345, *p* <.001) the likelihood ratio exceeds the critical value of 9.500, demonstrating significance at the 0.01% level (Kodde and Palm 1986).

As a further test of the suitability of SFA, the proportion of output variation attributable to technical inefficiency was computed as:

(7.10) $$\gamma = \frac{\sigma_\upsilon^2}{\sigma^2}$$

Where $\sigma^2 = \sigma_\upsilon^2 + \sigma_v^2$, i.e., the sum of the variance of the firm- and time-specific error component and the stochastic error component (Kumbhakar et al. 2015). $\gamma = 1$ indicates that 100% of variation in output is attributable to variation in efficiency. For marketing, R&D and operations approximately 99% of variation in output was determined to be due to differences in efficiency rather than unobserved factors or random events (Table 7.3.2), exceeding the 80% threshold advocated by Kumbhakar et al. (2015).

TABLE 7.3.2 Variance Tests for SFA.

	σ^2	σ_v^2	γ
Marketing efficiency	162.231	162.215	99.990
R&D efficiency	1715.130	1714.783	99.979
Operations efficiency	384.792	384.728	99.983

7.3.3 Capability Characteristics

Using the estimates of efficiencies derived from SFA, measures of rarity, persistence, and development were next calculated. These characteristics were measured independently of the focal firm's *level* of efficiency, which is incorporated into the model using the raw estimates derived from SFA. To compute persistence and development required successive years of efficiency estimates. However, there were leading gaps in the panel data for some firms. As most year-to-year changes in efficiency were small, it was reasonable to impute missing values using linear interpolation.[26] Imputation is also theoretically justified as capabilities are characterised by path-dependency and routinization (Helfat and Peteraf 2003). To ensure that imputed values only affect the calculation of variables for the focal firm, only the original efficiency estimates were used for calculating variables that include an industry-level component.

[26] Missing values were imputed after SFA as imputation of production (or cost) function outputs is not advised (Stead and Wheat 2020) and to ensure that imputed values of inputs do not affect the efficiency estimates of other firms.

Rarity (R_{ijt}) was calculated as the distance between a focal firm and competitors in levels of efficiency, measured as the sum of squared differences between a focal firm's level of efficiency ($\mathrm{E}_{\mathrm{ijt}}$) and the efficiency levels of each other firm (E_{jt}) in the focal firm's industry:

(7.11) $$R_{ijt} = \frac{1}{N}\sum_{j=1}^{N}(E_{ijt} - E_{jt})^2$$

This measure is widely accepted as an indicator of the rarity of individuals' characteristics in organisational research (Burt 1982; Tsui et al. 1992), and it is analogously applied here to the characteristics of capabilities. However, in contrast to prior applications, this analysis does not take the square root of the resulting rarity score (R_{it}), such that larger distances between a focal firm and competitors are amplified. This ensures that when efficiency levels in an industry are clustered, firms that fall outside of the cluster are easily identifiable. This measure does not differentiate between positive and negative deviations from the efficiency levels of competitors: as noted above, a distinctively low level of a given capability may also be beneficial if competitors are highly efficient in redundant activities (Porter and Siggelkow 2008).

Persistence (P_{ijt}) is operationalised as the temporal stability in levels of efficiency and was measured using the coefficient of variation: the standard deviation of a firm's efficiency over the prior three years, scaled by firm's mean efficiency over those three years (c.f. Bedeian and Mossholder 2000; Harrison and Klein 2007). This captures the variation in efficiency whilst accounting for its level, thus reflecting the notion that a capability can be persistent whether this is beneficial or detrimental (Leonard-Barton

1992). The inverse of this measure was then used in all models such that higher values represent greater stability in efficiency.

Development (D_{ijt}) was measured as the temporal change in efficiency for the focal firm relative to competitors. Based on analogous measures of shifts in resource deployment (Fombrun and Ginsberg 1990; Nadkarni and Narayanan 2007) this was calculated as the year-to-year increase or decrease in efficiency. This measure was scaled by the mean year-to-year change in a firm's industry to account for differences in learning effects (Nenonen et al. 2019).

7.3.4 Dependent Variables and Controls

In line with the notion that performance measures in RBT should capture overall firm performance, *Tobin's Q* was selected as the dependent variable. Tobin's Q is an appropriate outcome in the study of capabilities as it represents the abnormal returns that can be expected from a firm's collection of resources, i.e., the premium that capital markets attribute to the firm's assets beyond the replacement cost of those assets (Amit and Wernerfelt 1990; Chung and Pruitt 1994). As Tobin's Q is a forward-looking metric that adjusts for market risk, this ensures that the measure of performance used in this analysis reflects the effects of both demand-generating (i.e., marketing and R&D) and cost-minimising (i.e., operations) capabilities, whereas accounting measures may be biased towards the latter (c.f. Germann et al. 2015). To ensure conceptual alignment with the RBT notion of capabilities as drivers of competitive advantage, models were estimated with the dependent variable operationalised *relative to* *competitors* (i.e., divided by the median across firms in the focal firm's industry). To enable the comparison required for Proposition 2 all models were also estimated with the dependent variable measured in absolute terms.

All models include firm-level dummies and industry-level covariates rather than controlling for unobserved heterogeneity. Nevertheless, common control variables were also used to allow comparison with extant studies. At the firm level these include *past performance*, the dependent variable lagged by one period, *firm age*, and *firm size.* At the industry level, *industry turbulence* and *industry concentration* were included as these factors been shown to influence the magnitude, direction, and interaction of effects of functional efficiency (Feng et al. 2017). Table 7.3.4.1 provides a summary of all variables and details the operationalisation of these controls. Table 7.3.4.2 presents descriptive statistics and correlations.

TABLE 7.3.4.1 Variable Descriptions.

Variable	Description
Tobin's Q	Tobin's Q of the focal firm, calculated as the market value of the firm divided by the replacement value of assets.
Relative Tobin's Q	Tobin's Q of the focal firm scaled by the median Tobin's Q in the firm's 2-digit SIC code.
Efficiency	Efficiency score obtained from SFA using Greene's TRE specification, estimated with JLMS. 0 to 1 scale where 1 represents the efficient frontier. Calculated for marketing, R&D, and operations.
Rarity	Sum of the squared distances in efficiency estimates between a focal firm and each other firm in the same 2-digit SIC code. Calculated for marketing, R&D, and operations.
Persistence	Coefficient of variation in a firm's efficiency estimate over prior three years. Calculated for marketing, R&D, and operations.
Development	Year-to-year change in a firm's efficiency estimate scaled by the average year-to-year change among other firms in the same 2-digit SIC code. Calculated for marketing, R&D, and operations.
Firm age	Number of years elapsed since firm first appears in Compustat database.
Firm size	Natural log of total assets.
Industry turbulence	Variability in revenues in a focal firm's 2-digit SIC, scaled by industry size. Calculated as the standard deviation of total industry revenues over the preceding three years, divided by mean industry revenues over those four years.
Industry concentration	Hirschmann-Herfindahl Index (HHI): Sum of market shares of firms in the focal firm's 2-digit SIC code.

TABLE 7.3.4.2 Descriptive Statistics and Correlations.

		Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	Tobin's Q	1.600	1.496	1.000																
2	Relative Tobin's Q	1.226	1.035	.917*	1.000															
3	Marketing efficiency	.772	.146	-.036*	-.049*	1.000														
4	R&D efficiency	.458	.213	-.074*	-.084*	.089*	1.000													
5	Operations efficiency	.313	.175	.145*	.140*	-.469*	-.119*	1.000												
6	Marketing rarity	.066	.048	.141*	.135*	-.494*	.001	.203*	1.000											
7	R&D rarity	.086	.050	.045*	.044*	-.042*	-.276*	.121*	.625*	1.000										
8	Operations rarity	.066	.050	.194*	.168*	-.310*	-.074*	.576*	.406*	.113*	1.000									
9	Marketing persistence	-.056	.159	.062*	.021*	.265*	.024*	-.183*	-.229*	-.044*	-.190*	1.000								
10	R&D persistence	-.329	1.361	-.013*	-.011	.021*	.150*	-.034*	-.016	-.104*	-.031*	.021*	1.000							
11	Operations persistence	-.160	.178	.003	-.006	.052*	.014	.016	-.050*	-.027*	-.075*	.116*	.003	1.000						
12	Marketing development	.001	.078	.065*	.073*	.225*	-.006	-.052*	-.061*	.033*	-.004	-.057*	-.005	.039*	1.000					
13	R&D development	.008	.144	.024*	.017*	.033*	.256*	-.003	.001	.041*	-.006	.024*	-.101*	-.003	.044*	1.000				
14	Operations development	.003	.106	-.058*	-.067*	-.118*	-.020	.255*	.038*	-.004	.144*	.002	.002	-.118*	-.367*	-.047*	1.000			
15	Firm age	27.534	17.902	-.069*	-.067*	.108*	.096*	-.246*	.008	-.052*	-.169*	.109*	.024*	.147*	-.025*	.002	.048*	1.000		
16	Firm size	7.044	2.179	-.064*	-.080*	.199*	.155*	-.297*	-.080*	-.106*	-.235*	.133*	.040*	.149*	-.023*	.020*	.023*	.434*	1.000	
17	Industry turbulence	.061	.071	.033*	.030*	-.036*	-.023*	.100*	.017	.053*	.077*	-.006	-.050*	-.109*	.017*	.030*	.015*	-.097*	-.038*	1.000
18	Industry concentration	.052	.043	-.061*	-.052*	.009	-.002	-.070*	-.122*	-.043*	-.170*	.023*	-.004	.046*	.006	-.016	.001	.032*	.049*	.125*

Significance: * = 5% level

7.3.5 Model Specification and Estimation

The relationship between capabilities and performance is specified as:

$$Y_{it} = \beta_{0_i} + \sum_{k=1}^{3} \beta_{k_i} E_{k_{it}} + \sum_{k=1}^{9} \beta_{k_i} C_{k_{it}} + \gamma_i X_{it} + \varepsilon_{it} \quad (7.12)$$

Where Y_{it} is the dependent variable of firm performance, E_{it} represents the three firm-year efficiency estimates derived from SFA, C_{it} represents the characteristics (i.e., rarity, persistence and development) for each of the three functional areas, and X_{it} is a vector of control variables.

As this study aims to address the underexamined sources of heterogeneity in prior capabilities research but also compare the results with these previous studies, Equation 7.12 was estimated in two ways. First, a model was estimated that pools the estimates of all parameters, as is common practice in capabilities research, enabling comparison of the addition of characteristics with prior studies utilising only the estimates from SFA. Second, a hierarchical model was estimated, in which a second level is introduced to explain differences in the effects of capabilities across industries. Each estimation procedure included three models: (1) only the efficiency variables E_{it}, (2) only the capability characteristics C_{it}, and (3) including both C_{it} and $E_{it.}$ All models included the controls $X_{it.}$ Each model was also estimated with both relative and absolute performance outcomes.

For the hierarchical model, Equation 7.13 specifies performance as a function of the effects of capabilities (characteristics and/or efficiencies) and control variables:

$$\Theta_i = f(\beta_i, \gamma_i) \quad (7.13)$$

A second level equation for each β and γ models each firm-year-specific parameter as a function of the time-invariant firm-specific variation (Θ) around the hypermean $\overline{\Theta}$, such that prior beliefs on the firm-specific parameters in Equation 7.13 come from the average and firm-specific parameters estimated in Equation 7.14:

$$\Theta_i = \overline{\Theta} + \Theta + \eta_i \tag{7.14}$$

Where $\varepsilon_{it} \sim N(0, \sigma_i^2)$ and $\eta_i \sim N(0, \sigma^2)$. Industry groups were used as second level covariates, as differences between industries are a key source of unexplored heterogeneity (see above and Krasnikov and Jayachandran 2008; Arunachalam et al. 2018). As the sample covers 40 industries by 2-digit SIC code, firms were classified into eight industry groups to ensure that each group contained enough observations for the hypermean to be estimated with sufficient confidence while also enabling meaningful differentiation between industry contexts. Large industries (>100 firms) were first identified and separated, and the remaining firms were then categorised according to the 11 major groups used in the SIC system. Combining groups with fewer than ten firms produced the categories shown in Table 7.3.5.

TABLE 7.3.5 Industry Groups Used as Second-Level Covariates.

2-digit SIC code	Category	Number of firms
00 to 19	Primary Industries: Agriculture, Forestry, Fishing, Mining, and Construction	15
28	Manufacturing: Chemical and Allied Products	106
35	Manufacturing: Industrial Machinery and Equipment	96
36	Manufacturing: Electronic and Other Electrical Equipment	108
38	Manufacturing: Instruments and Related Products	104
20 to 39	Manufacturing: Other	169
40 to 59	Transportation and Retail Trade	20
60 to 89	Services	88

Estimation for all models was performed with MCMC, with 10,000 draws for burn-in and an additional 10,000 draws for inference, as detailed in Appendix B.

7.4 RESULTS

Table 7.4.1 presents the results of pooled models, representing the average effects of capabilities. The pooled models are used examine Propositions 1 and 2, assessing the inclusion of measures of capability characteristics (versus established measures of functional efficiency), and the operationalisation of performance in competitive (versus absolute) terms. While no directional hypotheses for the relationship between each capability variable and performance were presented, the following sections explore how the average effects of capabilities conform or diverge from prior research that utilises only efficiency estimates. Based on these comparisons, the examination of Proposition 3 (industry heterogeneity) is focused on the most suitable model specification, presented in Table 7.4.2. Alternative model specification pertaining to industry heterogeneity are included in Appendix C.

TABLE 7.4.1 Average Effects of Efficiency and Capability Characteristics on Competitive Advantage and Firm Value.

Dependent variable	Relative Tobin's Q			Tobin's Q		
	(1)	(2)	(3)	(4)	(5)	(6)
Capabilities						
Marketing efficiency	0.824***		0.857***	0.921***		1.026***
R&D efficiency	-0.063		-0.233***	-0.080		-0.235***
Operations efficiency	0.221***		0.280***	0.395***		0.467***
Marketing rarity		2.054***	2.663***		1.424***	2.065***
R&D rarity		0.301	0.347		0.410*	0.428*
Operations rarity		0.467	0.421		0.977***	0.799**
Marketing persistence		0.051	-0.100		0.064	-0.079
R&D persistence		0.042	0.204***		0.035	0.195***
Operations persistence		-0.059	-0.057		0.029	0.010
Marketing development		0.769***	0.327**		0.710***	0.239
R&D development		-0.015	0.127		-0.037	0.100
Operations development		-0.217**	-0.336***		-0.194*	-0.374***
Controls						
Industry turbulence	1.225***	1.355***	1.325***	0.885***	1.001***	0.984***
Industry concentration	-1.208**	-1.230**	-1.123**	-0.568	-0.675	-0.461
Firm size	0.027***	0.026***	0.027***	0.035***	0.034***	0.035***
Firm age	-0.415***	-0.389***	-0.404***	-0.395***	-0.377***	-0.381***
Past performance	0.466***	0.463***	0.456***	0.351***	0.449***	0.344***
DIC	29525.779	29501.649	29425.956	29763.979	29774.240	29690.244
ρ	.665	.664	.661	.648	.648	.645

Significance: * = 10% level, ** = 5% level, *** = 1% level, based on the highest posterior density interval.

TABLE 7.4.2 Industry Group Effects of Efficiency and Capability Characteristics on Competitive Advantage.

Dependent variable	Relative Tobin's Q (7)							
Industry	Primary	Chemical	Machinery	Electronics	Instruments	Other Manufacturing	Transport & Retail	Services
Capabilities								
Marketing efficiency	0.464	-0.063	0.797***	0.835***	0.645**	0.494***	0.850*	1.042***
R&D efficiency	-0.349	0.214	0.040	0.247**	-0.025	0.030	-0.030	0.390***
Operations efficiency	0.540	0.095	0.052	0.353**	-0.339*	-0.159	0.594	-0.233
Marketing rarity	0.843	3.863***	2.483**	1.086	4.560***	0.143	0.178	-1.402
R&D rarity	-0.566	0.339	-0.282	-0.125	0.753*	0.344*	0.113	0.234
Operations rarity	-0.818	-0.378	-1.277*	0.047	-1.104	-0.303	0.182	0.944
Marketing persistence	0.342	0.009	0.117	0.192	0.620	0.008	-0.153	0.069
R&D persistence	-0.005	-0.073	-0.035	-0.110	0.176	-0.138**	-0.038	-0.305**
Operations persistence	0.407	-0.195	-0.022	-0.327***	0.019	-0.220***	-0.115	-0.189
Marketing development	0.587	-0.125	0.437**	0.288*	0.791***	0.243**	0.319	0.561**
R&D development	0.291	-0.070	-0.037	-0.033	0.088	-0.029	-0.192	-0.226**
Operations development	0.137	-0.020	-0.199	-0.372***	-0.033	-0.035	0.121	-0.262*
Controls								
Industry turbulence	-0.273	1.956***	0.812**	-0.255	2.788***	-0.187	1.093*	0.837*
Industry concentration	-0.468	-4.384	-0.303	1.344	-2.154	-0.732	-1.185	2.732
Firm size	0.009	0.039***	0.017***	-0.003	0.017**	0.016***	0.016	-0.001
Firm age	-0.157	-0.533***	-0.354***	-0.197***	-0.422***	-0.354***	-0.181	-0.416***
Past performance	-0.065	0.660***	0.269***	0.133***	0.414***	0.225***	0.219**	0.464***
N	15	106	96	108	104	169	20	88
DIC	9679.526							
ρ	.835							

Significance: * = 10% level, ** = 5% level, *** = 1% level, based on the highest posterior density interval.

7.4.1 Effects of Functional Capabilities

The effects of capabilities vary across the six pooled models presented in Table 7.4.1. Support for Proposition 1 can be found in (a) changes in the effects of efficiencies when characteristics are added to the model and/or (b) increases in the explanatory power of models when characteristics are included, evident in improvements in correspondence between observed effects and the predictions of RBT.

Models 1 and 4 represent the extant approach to measuring capabilities, utilising only the efficiency estimates derived from SFA. Comparing each functional area with Models 3 and 6, which also include capability characteristics, the effect sizes of marketing, R&D, and operations efficiency increase when the new measures are included. Furthermore, characteristics in each functional area have significant effects on both firm value and competitive advantage in models that estimate performance as a function of characteristics only (2 and 5) and as a function of both efficiency and characteristics (3 and 6). These results indicate that *both* efficiencies and characteristics are important to explain variance in the capability—performance relationship and that operationalising capabilities in terms of efficiencies *only* may underestimate or misrepresent effects in each functional area, supporting Proposition 1. Models 3 and 6 are therefore most important in examining the substantive implications of these results and comparing effects on competitive advantage and firm value. Each functional area is discussed in turn below.

Marketing. Consistent with prior studies using SFA, marketing efficiency has a positive effect on performance, greater in magnitude than both R&D and operations efficiency (c.f. Feng et al. 2017). This effect is larger when Tobin's Q is measured in absolute (1.026) rather than relative terms (0.857), indicating a greater contribution of marketing efficiency to firm value than to competitive advantage. Furthermore, marketing rarity exhibits the largest effects among functional areas on both absolute (2.065) and relative (2.663) performance. This indicates that marketing rarity contributes more to competitive advantage than firm value—the inverse of differences in the effects of efficiency. Similarly, marketing development has consistently positive effects, but these only reach statistical significance for relative performance (0.327). Together, these results suggest that marketing capability characteristics are more consequential for competitive advantage while efficiency contributes more to absolute levels of performance, in line with the RBT notion of capabilities and Proposition 2 regarding the measurement of performance in relative terms. However, capability characteristics are not uniformly beneficial: persistence has a negative but nonsignificant effect in both models, indicating that the relevant areas of capability for marketing success are rarity and development, i.e., improving, rather than maintaining, marketing capabilities is most advantageous.

Operations. Operations efficiency has positive effects that are smaller than marketing (see also Krasnikov and Jayachandran 2008). As for marketing, this is lesser in magnitude for relative (0.280) than absolute (0.467) performance, indicating that operational efficiency is more consequential for firm value than competitive advantage. However, the effect of capability characteristics in operations contrast the above observations for marketing. Rarity is consistently positive but only reaches statistical significance when the dependent variable is measured in absolute terms (0.799). Persistence, while nonsignificant across models, also has a negative effect on competitive advantage and a positive effect on firm value. The effects of efficiency, rarity, and persistence thus reflect conceptualisations of functional capabilities which suggest that operations is important for ensuring competitive parity rather than driving superior performance and may therefore be conceptually distinct from other capabilities as theorised in the RBT (Varadarajan 1985; Winter 2003; Krasnikov and Jayachandran 2008). Operations development has a negative effect on both absolute (-0.374) and relative (-0.336) performance. In contrast to the effects of capability characteristics in marketing, this suggests that maintaining, rather than changing, levels of operational efficiency is most beneficial.

R&D. For marketing and operations, the above analyses show positive effects of efficiency that are augmented by positive effects of selected characteristics. Results for R&D contrast this, implying that the beneficial effects of R&D capability are *not* derived from efficiency but from characteristics alone. Without correcting for capability characteristics (Models 1 and 4), R&D efficiency has nonsignificant effects. This becomes negative and significant when characteristics are added for both relative (-0.233) and absolute (-0.235) performance, while the effects of rarity, persistence, and development are all consistently positive across the full models. While only some of these effects reach statistical significance, this suggests that the cumulative effect of R&D characteristics accounts for the negative coefficients observed for efficiency.

Persistence exhibits the most consistent positive effect, being similar in magnitude across relative (0.204) and absolute (0.195) performance outcomes. This aligns with the notion that R&D capabilities are the most costly to develop (Dutta et al. 1999,2005) and involve the largest learning effects among functional capabilities (Irwin and Klenow 1994; Miklós-Thal et al. 2018). Accordingly, the ability to achieve and sustain efficiency in R&D is particularly consequential for firm performance. R&D rarity also exerts a large, positive effect on firm value (0.428), though effects on competitive advantage are nonsignificant. Section 7.4.2, regarding industry heterogeneity, provides further insight into the mixed effects of R&D variables.

The deviance information criterion (DIC) across the pooled models provides further evidence for the value of including capability characteristics. The DIC approximates the amount of information lost in each model, such that lower values indicate a better model fit (Spiegelhalter et al. 2002). This measure was chosen as unlike other fit statistics, the DIC penalises complexity – a pertinent concern given the addition of a large number of variables to these models. Thus, an improvement in the DIC when both efficiencies and characteristics are included would indicate that the information provided by the latter measures outweighs the additional complexity of these models. Furthermore, the DIC allows comparison across dependent variables in these analyses. The operationalisation of competitive advantage in the above model specificcations utilises the same performance metric as the measure of firm value but adds an industry average component. Each model of competitive advantage is therefore effectively nested in the corresponding model of firm value (i.e., Models 1 and 4, 2 and 5, 3 and 6).

Across the pooled models, the DIC is lower in those that estimate performance as a function of capability characteristics rather than efficiencies, suggesting that the rarity, persistence, and development of efficiency in marketing, R&D and operations capture more information about the causes of firm performance than the level of efficiency per se. Furthermore, the lowest DIC is observed for models that include both efficiencies and characteristics. This suggests that utilising only the measures of efficiency derived from SFA does not fully account for the characteristics of capabilities that influence firm performance, and thus that inclusion of these measures can improve model fit in estimations of the capability—performance relationship, lending further support to Proposition 1.[27]

The DIC is lower in models where the dependent variable is operationalised relative to competitors, indicating that capabilities explain more of the variance in competitive advantage than firm value and supporting Proposition 2. While the above discussion highlights differences across functional areas in terms of the contribution of capabilities to firm value versus competitive advantage, examination of model fit therefore

[27] The same pattern of improvement in the DIC is evident across models with efficiencies, characteristics, and all variables in the hierarchical models and alternative specifications (see Table 7.4.1 and Appendix C).

supports the RBT notion that the effects of capabilities should be examined in relative rather than absolute terms.

7.4.2 Industry Heterogeneity

In the pooled models in Table 4, the effects of capabilities are more consistent with the predictions of RBT and observe improvements in model fit when (1) capability characteristics are included and (2) performance is measured relative to competitors, supporting this author's Propositions. Examination of Proposition 3, pertaining to heterogeneity in the capability—performance relationship, is therefore conducted with a focus on the effects of efficiencies and characteristics on competitive advantage (Table 7.4.2). Alternative model specifications corresponding to each pooled model in Table 4 in terms of independent and dependent variables are presented in Appendix C.

As the results of the pooled models suggest that marketing and R&D capabilities are most consequential for relative performance, the following discussion is also limited to these two functional areas. Only theoretically meaningful differences between industries are examined, as the large number of individual coefficients precludes full examination of each effect. Additionally, while this discussion focuses on statistically significant effects, the small number of firms in some industry groups limits the ability to detect significant differences. Differences in the magnitude and direction of nonsignificant effects may therefore also be of managerial relevance. Beyond the overview provided here, the author therefore encourages further exploration of heterogeneity in the effects of operations capabilities; effects on absolute firm value; theoretically minor but potentially managerially pertinent effects; and nonsignificant effects in small industry groups.

Marketing. Marketing efficiency, rarity, and development exhibit the most consistently positive and significant effects across industries. In line with the pooled results, the magnitude of these effects is also generally larger than other capability variables. Notably, marketing efficiency has the largest effect in services (1.042) and transport and retail (0.850). The small number of firms in the latter group, and consequent lack of other significant effects, further supports the centrality of marketing efficiency in these contexts. In contrast, marketing rarity exhibits large effects across manufacturing industries (e.g., chemicals: 3.863; machinery: 2.483; instruments: 4.560) and nonsignificant, negative effects in services. These differences suggest that the importance of different aspects of marketing capability varies across industry contexts, while marketing remains the most significant functional capability for competitive advantage.

R&D. Industry differences clarify some of the counterintuitive effects of R&D efficiency and characteristics in the pooled models. In services, for example, there is a large, positive effect of R&D efficiency (0.390). This is in line with the notion that such firms are likely to focus to a greater extent on intangible assets developed through human capital and customer relationships rather than product development; thus, efficiency in R&D may signal that service firms are not overinvesting in product-centric asset development (Castaldi and Giarratana 2018). This model also shows positive effects of R&D efficiency in electronics manufacturing (0.247). Notably, prior research examining the effect of SFA-derived R&D

capabilities on competitive advantage focuses on the semiconductor industry, a subclassification of electronics manufacturing (Dutta et al. 1999,2005), suggesting that the positive results found in these studies may arise from focusing on a specific industry in which R&D efficiency is most likely to be beneficial. It is also notable that there are two industries in which R&D rarity appears to be a key driver of relative performance: instruments (0.753) and other manufacturing (0.344). As the pooled models indicate that R&D rarity is important for firm value but not for competitive advantage, these effects are pertinent in highlighting industry contexts in which R&D rarity is a significant basis of competition.

7.5 DISCUSSION

This study presents the case that prior research may not adequately capture the concept of capabilities as theorised in RBT due to three main issues: (1) operationalising capabilities as functional efficiency without accounting for the characteristics that underpin their importance in driving firm performance; (2) examining the effects of capabilities in ways that do not capture their effects on competitive advantage; and, (3) estimating average effects that overlook differences in the implications of capabilities across firms. To address these issues, the author proposed and implemented a methodology for examining the capability—performance relationship that: (1) develops existing measures of functional efficiency to capture the key characteristics of capabilities; (2) measures performance outcomes in relative, rather than absolute, terms; and, (3) accounts for heterogeneity in the role of capabilities across firms. These modifications to extant approaches yield results that are more consistent with RBT and improvement in model fit in an empirical examination of the capability—performance relationship. Applying this methodology to the examination of marketing, R&D, and operations capabilities in a sample of 706 firms spanning 40 industries and 31 years uncovers new substantive insights into the effects of capabilities and highlight where previous research may erroneously estimate these.

Specifically, these findings indicate that the nature of a capability—the characteristics that are important to performance—differs across functional areas. The effects of these characteristics and of functional efficiency also depend on whether performance is operationalised in absolute or relative terms, indicating that the characteristics of capabilities that contribute to competitive advantage differ from those that enhance firm value. Furthermore, these analyses explicate differences between industries and find heterogeneity in the importance of rarity, persistence, development, and efficiency in each functional area. These results thus provide a more nuanced perspective on the forms of capability investment that are most beneficial across functional areas, industries, and performance objectives, demonstrating that extant approaches to examining the capability—performance relationship are limited in terms of both operationalisation and model specification. These findings have several implications for both theory and practice.

7.5.1 Limitations and Directions for Future Research

A key objective of this study was to compare the results of this methodology with those of prior research on firm capabilities. To achieve this, the analysis was limited to the theoretically most salient aspects of the capability—performance relationship. The findings indicate several opportunities for future research that may address some of these limitations.

First, this study focused on three key capabilities at the functional level – marketing, R&D, and operations – due to their prevalence in the literature and the distinct contributions of these areas to value creation (Krasnikov and Jayachandran 2008; Feng et al. 2017). However, the marketing literature has explored a range of capabilities *within* the marketing function (Song et al. 2005; Krush et al. 2015). Accordingly, the author acknowledges that these findings provide a high-level overview of the effect of marketing capabilities. Further research could adapt the methodology presented here to examine how efficiency, rarity, persistence, and development in discrete marketing activities, such as customer service or market intelligence, contributes to both proximal marketing objectives and firm-level outcomes. Beyond the marketing literature, this method can be applied to other firm capabilities. Future research to apply these developments to the study of dynamic capabilities; for example, by examining the characteristics of managerial attributes and decision-making processes that contribute to firms' ability to adapt and reconfigure functional capabilities (Di Stefano et al. 2014; Helfat and Peteraf 2015).

Examining additional covariates could also expand upon the insights provided here. This empirical investigation was limited to industry-level differences to address the key source of heterogeneity suggested but unexplored in the capabilities literature. However, there are numerous levels of analysis that could further explicate the role of marketing and other functional capabilities. Given the growing interest in top management- and board-level influences on the marketing function (Whitler et al. 2020; You et al. 2020), this may be a pertinent area for further investigation. The hierarchical approach demonstrated here offers a method of examining multilevel effects that have not previously been incorporated into the capabilities literature (Hahn and Doh 2006; Mackey et al. 2017).

7.5.2 Contributions

This study offers several contributions to research on marketing capabilities and the broader RBT literature. First, bringing the measurement of firm capabilities in line with their conceptualisation provides a contribution to theory regarding the role of capabilities, adding nuance to the prevailing positive view (Krasnikov and Jayachandran 2008; Karna et al. 2016). In disaggregating the RBT ‘characteristics’ of capabilities, this study demonstrates which aspects of resource deployment affect its contribution to firm performance. Results demonstrate that rarity, persistence, development, and efficiency differentially affect performance across functional areas. Two substantive insights that challenge current knowledge about the role of firm capabilities are particularly noteworthy. First, the large effects of characteristics – namely, rarity and development – in addition to efficiency for the marketing function suggest that previous research, relying only on efficiency estimates, may *underrepresent* the contribution of marketing capabilities towards firm performance. This is pertinent in the case of marketing rarity, which exhibits the most consistently positive effects of any capability variable and thus indicates a key area of capability that has been overlooked. Furthermore, the positive effects of marketing are most stable across characteristics, performance outcomes, and industries. This is line with prior evidence that marketing exhibits the largest effects across functional capabilities (Krasnikov and Jayachandran 2008; Feng et al. 2017), but adds important distinctions regarding the areas of marketing investment that are most consequential. Second, the negative or nonsignificant effects of R&D efficiency once characteristics are accounted for suggests that previous research may *misrepresent* the nature and effects of R&D capabilities. These results have implications for the conceptualisation of firm capabilities in future research and the interpretation of extant evidence for the capability—performance relationship.

Second, these findings have practical relevance for managers, particularly in demonstrating the value of the marketing function. Developing firm capabilities is costly and often requires prioritisation of certain functional areas at the expense of others. While previous research has elucidated the potential for substitutive effects when the development of capabilities is misaligned with the environment (Feng et al. 2017), this study provides further insight into the aspects of functional capabilities in which improvements may be beneficial, allowing inference about more targeted investments in capabilities that are most likely to contribute to firm performance across different industry contexts. Furthermore, the most consistent positive effects are observed for the marketing function, particularly in terms of rarity, suggesting that improvements in marketing capabilities are more likely to be beneficial than improvements in R&D and operations. Given recent concern about the contribution of marketing to firm performance, with only 2 percent of CMOs being held accountable for marketing's contribution to firm value (CMO Survey 2020) and difficulties justifying the marketing function at the executive and board level (Edeling et al. 2020) and in recruitment (Whitler et al. 2020), these findings can assist managers in advocating for marketing investment.

Third, this study develops a methodology for assessing the performance effects of firm capabilities that is aligned with their conceptualisation within RBT and appropriately accounts for firm-level heterogeneity. This approach augments and extends current practice, substantially increasing the explanatory power of empirical models and their congruence with theoretical arguments advanced in the study of firm capabilities. This can be applied to the study of capabilities in other functional areas, with alternative performance outcomes, and/or including additional contingencies, offering a path towards reconciling the persisting gap between theory and measurement in the literature. This answers recent calls for demonstrating the value of Bayesian approaches in validating and extending RBT (Hansen et al. 2004; Hahn and Doh 2006).

8 CONCLUSIONS & IMPLICATIONS

This thesis seeks to develop a framework for understanding strategic decisions under uncertainty, focusing on board cognition and firm capabilities as central aspects of strategic direction and execution, respectively, and examining the role of these factors under multiple environmental contingencies that are of primary importance in the contemporary business environment. A conceptual exploration of this broad issue leads to three core research questions (Chapter 1), which are addressed via six empirical studies (Chapters 2 to 7). Taken together, the substantive contributions of these studies offer implications for theoretical and methodological development in both upper echelons theory (UET) and resource-based theory (RBT). Furthermore, by focusing on firm heterogeneity and the alignment between theory and practice in UET and RBT, these studies provide novel insights that can inform practice among managers, directors, and other firm stakeholders. The substantive findings from which these implications are derived are summarised in Table 8.1 and discussed in the following two sections. Table 8.2 provides an overview of these implications, their relationships to the specific contributions to each empirical study, and the avenues for future research and managerial practice that they indicate.

TABLE 8.1 Summary of Substantive Findings.

RQ1	**RQ2**	**RQ3**
How are boards with the ability to deal with uncertainty formed?	*How does heterogeneity in the characteristics of the board affect strategic direction under uncertainty?*	*How does heterogeneity in the execution of strategy affect firm performance under uncertainty?*
A. The ideology of incumbent directors affects the composition of boards (Ch. 2) B. The ideology of incumbent directors affects the connectedness of boards (Ch. 2)	C. Board composition affects the likelihood of strategic deviation during recessions (Ch. 3) D. Board connectedness affects the likelihood of strategic deviation during recessions (Ch. 3) E. Board composition affects the firm's strategic emphasis (Ch. 4) F. Board connectedness affects the firm's strategic emphasis (Ch. 4)	G. Functional capabilities affect performance contingent upon the regulatory environment (Ch. 5) H. Functional capabilities affect performance contingent upon the product-market environment (Ch. 6) I. Functional capabilities affect performance contingent upon the nature of capabilities within the firm (Ch. 7) J. Functional capabilities affect performance contingent upon the industry environment (Ch. 7) K. Dynamic capabilities affect performance contingent upon the product-market environment (Ch. 6)

TABLE 8.2 Summary of Implications.

Key Conclusions	Implications for Research	Future Directions	Implications for Practice	Managerial Actions
Dispositional and social factors affect the formation of boards and board interlock networks (RQ1).	• Director ideology provides a rich and valid operationalisation of board cognition to supplement commonly employed demographic and/or professional proxies (Ch. 2-4). • Effects of individuals' ideological biases may be context-specific and temporally situated, requiring further examination in the organisational setting (Ch. 2).	• How can data on directors' ideology further inform the study of board cognition? For example, can this be obtained outside of the US context to improve the generalisability of these findings? • How does director ideology compare to traditional measures of board diversity in its effects? For example, are aspects of board composition unaffected by ideology but determined by demographic and other psycho-social considerations?	• Considerations of diversity in director appointments should incorporate cognitive/ideological aspects (Ch. 2 & 4). • Awareness of personal ideological biases among directors can help form more effective boards and network connections (Ch. 2 & 4).	• HR can explicitly acknowledge viewpoint diversity as a key factor in both formal and informal diversity, equity and inclusion policies and initiatives. • Diversity training that extends beyond consideration of demographic biases may help to raise awareness of the prevalence of bias and homophily along ideological lines.
The effect of dispositional and social factors on board decision-making differ according to the level and form of environmental uncertainty (RQ2).	• Board decision-making must be considered within the social context of the interlock network (Ch. 3-4). • Environmental contingencies should be accounted for in examining the relationship between board- and network-level variables and their effects (Ch. 3-4).	• What other firm-level outcomes are influenced by board ideology? • How can Bayesian methods be applied in other contexts to improve understanding of the contingencies involved in board decision-making? • In which other contexts is overembeddedness an	• Managers should consider the cognitive biases and network connectedness of boards when advocating for strategic decisions, functional discretion, and board-level representation (Ch. 2-5) • Greater attention to the potential negative effects of connectedness can improve	• Mapping the firm's board network could help to identify (a) which connections, under what conditions, can best inform decision-making, and (b) where the firm can benefit from building (or severing) network ties that could open access to new information. • When implementing recommendations from

	• Probabilistic approaches to studying the effects of board-level variables can provide greater nuance and clarity regarding contingent effects (Ch. 3)	addressable problem in research on board networks? For example, can established research on interlocks and acquisition behaviour be improved by the incorporation of dispositional antecedents?	board decision-making under uncertainty (Ch. 3 & 4) • Interpretation of research on the effects of board-level variables must account for the potential for average effects to obscure inter-firm heterogeneity (Ch. 3)	research on boards, consider whether firm-specific factors are addressed, how these apply to the firm, and how they may affect expected outcomes.
The nature and effects of firm capabilities differ according to the level and form of environmental uncertainty (RQ3).	• Valid and reliable operationalisation of firm capabilities is necessary to clarify conflicts and/or ambiguity in previous research (Ch. 6 & 7). • Environmental uncertainty needs to be conceptualised and measured at the level that is appropriate to the capabilities under investigation (e.g., industry, product-market) (Ch. 5-7). • Probabilistic approaches to studying the effects of firm capabilities can provide greater nuance and clarity regarding contingent effects (Ch. 7).	• How can the operationalisation of firm capabilities be improved in other areas? For example, can similar measures be applied to the particularised study of marketing capabilities (i.e., creative strategy, digital, branding, etc.) to provide similar clarifications of their practical effects? • How can Bayesian methods be applied in other contexts to improve understanding of the contingent effects of capability development and deployment?	• Capabilities should not be considered as universally beneficial – their development and/or deployment may have negative effects on firm performance in certain contexts (Ch. 5-7). • Dynamic capabilities are not necessarily superior to strong functional capabilities, dependent on the level of environmental uncertainty (Ch. 6). • Interpretation of research on the effects of capabilities must account for the potential for average effects to obscure inter-firm heterogeneity (Ch. 7).	• A capabilities audit which identifies current and desired capabilities should be used as a foundation for more contextual analysis. Recognise strengths, but ensure that the conditions under which they will add value are clearly articulated and prioritised. • When implementing recommendations from research on capabilities, consider whether function-, firm-, and industry-specific factors are addressed, how these apply to the firm, and how they may affect expected outcomes.

8.1 IMPLICATIONS FOR RESEARCH

The phenomena under investigation in this thesis fall under the scope of two of the most influential theories in management research: UET and RBT. Theoretical contributions to these frameworks are difficult due to their maturity and widespread application (see, for example, Hambrick 2007; Barney et al. 2011; Whitler et al. 2020; McGahan 2021). However, environmental uncertainty and firm heterogeneity represent two nascent themes within these literature streams (e.g., Hahn and Doh 2006; Barney 2014; Boivie et al. 2016; Boivie et al. 2021). By focusing RQ1 to 3 on these themes, this thesis contributes to the future development of UET and RBT, particularly as growing levels of uncertainty raises questions regarding the future applicability of established conclusions in these areas (e.g., George et al. 2016b; Hitt et al. 2020).

Regarding UET, these contributions are mainly derived from examination of RQ1 and RQ2: *how are boards with the ability to deal with uncertainty formed*, and *how does heterogeneity in the characteristics of the board affect strategic direction under uncertainty?* A point of departure from prior research in addressing these questions in Chapters 2 to 4 is the focus on the ideology of directors and the network of connections between boards of differing cognitive frameworks. A core premise of UET is the recognition that board decision-making is a socially embedded process, influenced by individual and interpersonal factors beyond the economic considerations of the firm (Westphal and Zajac 1995; Van Ees et al. 2009; Westphal and Zajac 2013). However, these factors are underexplored in empirical board research, which has focused on situational antecedents to the composition of boards (Withers et al. 2012) and their influence on strategy (Shropshire 2010; Gupta and Wowak 2017),

A major contribution of this research is to empirically demonstrate the relevance of these dispositional and social factors in the formation and effects of boards and interlock networks (see Table 8, A-F). Beyond substantiating a hitherto underexamined central tenet of UET, these findings explicate a fruitful avenue and methodology for future research in this theoretical tradition. A key issue in board research is the difficulty in operationalising the “values and cognitive bases of powerful actors in the organisation” that UET posits as the driver of firm outcomes (Hambrick and Mason 1984, p. 193). This is a likely reason for the overemphasis of situational factors, which are more easily observed and measured (c.f. Bromiley and Rau 2016; Gupta and Wowak 2017). Drawing upon evidence from psychology and political science, the studies in this thesis present the justification and methodology for utilising director ideology as a measure of values and cognitive biases, providing a more accurate representation of board cognition than can supplement the demographic and/or professional characteristics commonly employed as proxies (Gerber et al. 2012; Duarte et al. 2015; Triana et al. 2021)

Implications for RBT arise primarily from addressing RQ3: *how does heterogeneity in the execution of strategy affect firm performance under uncertainty?* Much prior research has examined firm capabilities as a central aspect of strategic execution across a range of environmental contingencies (see Krasnikov and Jayachandran 2008; Karna et al. 2016). The substantive contributions of this thesis (Table 8, G-K) thus reflect a long empirical tradition within RBT. However, the unique methodologies employed in Chapters 5 to 7 offer valuable implications for extending and improving research in this stream, in two ways.

First, a key focus in examining RQ3 is the proper measurement of environmental uncertainty. In particular, Chapters 5 and 6 present novel methods for capturing uncertainty at the country- and product-market level. These chapters present implications for the appropriate measurement and interpretation of environmental contingencies within the RBV, explicating how this may underly the similarities and divergences in results between these studies and prior research on strategic execution. This is particularly pertinent to future research on dynamic capabilities, in which there is ongoing debate over this issue (e.g., Schilke et al. 2018; Fainshmidt et al. 2019; Suddaby et al. 2019).

Second, these studies are concerned with appropriate operationalisation of firm capabilities. The methodologies presented in these chapters, while firmly grounded in accepted precedent, include novel measures intended to better capture the concepts of dynamic (Chapter 6) and functional (Chapter 7) capabilities as theorised in RBT and implemented in practice. Discrepancies between theory, measurement, and practice are a common source of criticism in the capabilities literature (c.f. Barney 2014). These chapters explicate how data availability and study design is a key source of these discrepancies and offer paths towards development of more theoretically consistent and managerially actionable capabilities research. Central to this contribution is the focus on appropriate levels of analysis and relationships between them; for example, how functional capabilities relate to dynamic capabilities (Chapter 6) and whether the nature and effects of functional capabilities can be discerned at the level of the industry, firm, or function (Chapter 7). These considerations are important to the future study of capabilities as a means of strategic execution under uncertainty, as the predictability, manipulability, and ramifications of uncertainty vary dependent upon the level at which it occurs and the degree of interrelatedness with other aspects of the internal and external environment (Dequech 2011; Packard et al. 2017).

In sum, the principal contribution of this thesis lies in its implications for aligning theory and empirics in both UET and RBT research. The studies herein present conceptual developments and methodologies that offer novel ways to access and operationalise phenomena that are central to these frameworks but inherently difficult to observe (see Chin et al. 2013; Kozlenkova et al. 2014). Consequently, a key contribution of this work is to inform future research that can address further questions arising from the substantive findings presented here..In developing these new approaches, the empirical analyses presented in this thesis provide substantive contributions to both theories that further present understanding of how UET and RBT apply in real firms, particularly under conditions of uncertainty. Accordingly, this work also offers numerous practical implications for managers, directors, and other stakeholders.

8.2 IMPLICATIONS FOR PRACTICE

Reflecting the dual focus on strategic direction and execution and corresponding contributions to UET and RBT, this thesis offers implications for practice in two key areas: the formation and operation of boards, and the allocation of resources.

First, this research explicates the role of dispositional and social factors in the composition of boards and board networks. Chapter 2 provides the first known empirical evidence for an ideological component in director selection and interlock network formation, while Chapters 3 and 4 demonstrate the role of these factors in determining firms' strategic direction. As explicated in the development of RQ1 (section 1.2 above), knowledge of dispositional and social antecedents is particularly important in a contemporary environment of heightened uncertainty. Under these conditions, the situational influences that have been more widely studied (Shropshire 2010; Gupta and Wowak 2017) are more difficult to understand and manipulate (Townsend et al. 2018), whereas personal and interpersonal factors remain relatively stable over time and under greater control of actors within the firm (c.f. McPherson et al. 2001; Tasselli and Kilduff 2021).The substantive contributions of this research therefore offer implications for various stages of board operations.

At the stage of director nomination and selection, these findings highlight the role of incumbent directors' biases in determining the future cognitive framework of the board. Chapter 2 is a cautionary demonstration of the increasing prevalence of ideological homophily, particularly among politically liberal directors. These findings mirror investigations into the ideological composition of various academic fields, in which diversity of political thought is shown to be similarly narrowing (Inbar and Lammers 2012; Duarte et al. 2015; Haidt and Lukianoff 2018). The benefits of such diversity for decision-making have been thoroughly expounded (e.g., Post et al. 2021) and may be particularly consequential for boards, given substantial evidence that the political orientations of decision-makers affects multiple firm-level outcomes (e.g., Hutton et al. 2014; Park et al. 2020; Chin et al. 2021, and Chapter 4 of this thesis). While individuals – including directors – are unlikely to overcome preferences to associate with ideologically similar others (McPherson et al. 2001), these findings are important for raising personal awareness of, and thus the opportunity to mitigate, this tendency (see Baumeister 2015). Furthermore, this implies that greater involvement of managers and shareholders in the director selection process may be an effective method of reducing the influence of directors' biases (c.f. Mizruchi 2013; Withers et al. 2020).

This research has similar implications for the actions of directors once appointed, with Chapters 3 and 4 providing novel insights into the role of board characteristics in determining the strategic direction of the firm. The key practical implication of these studies derives from the exposition of synergistic and contingent effects of board composition and connectedness: a lack of integration of these aspects in prior research has provided limited guidance on how the agency of directors can affect firm outcomes (Srinivasan et al. 2018; Tasselli and Kilduff 2021). In demonstrating how board cognition interacts with information exposure to affect strategic direction under multiple forms internal and external uncertainty, these studies strengthen the imperative for directors to exercise awareness of the effects of their biases and connections in decision-making.

Additionally, the findings of Chapters 3 and 4 are relevant for managers advocating for resource allocation decisions, showing how the characteristics of the board influence the *likelihood* of such decisions under differing conditions of uncertainty. For example, while these analyses demonstrate multiple benefits of ideological diversity on the board, marketing executives may face greater resistance to advertising investment decisions in this situation (Chapter 4). These findings are important considerations when examining the practical implications of Chapters 5 to 7. In these studies, numerous contributions are presented regarding the *effectiveness* of resource allocation in different environments.

This constitutes the second major area of practical application of this research, concerning strategic execution. Similar to the contributions explicated in regard to board operations, this area of practice is particularly important under uncertainty as it pertains to internal variables that are within the purview of managerial agency, even if the ultimate effects are moderated by environmental forces (Feng et al. 2017; Arunachalam et al. 2018). The studies in this thesis examine multiple resource allocation strategies, empirically demonstrating their effectiveness under relevant environmental contingencies and therefore providing guidance for managers; for example, in explicating the potential negative effects of marketing and R&D capabilities under differing conditions of regulatory risk (Chapter 5) and appropriate conditions of product-market volatility in which to deploy dynamic capabilities (Chapter 6).

Furthermore, by adopting a conceptual and methodological focus on firm heterogeneity, these studies highlight the importance of variability in the effectiveness of these decisions across firms. This is an aspect of strategic execution that has been overlooked in prior RBT research, contributing to the discrepancy between theoretical rigor and practical relevance that is discussed above (see also Powell 2001; Barney 2014; Mackey et al. 2017). Chapter 7 provides the most comprehensive discussion of this issue, addressing it by examining the specific attributes of functional capabilities that managers can expect to be most beneficial across functions, firms, and industries. Accordingly, these findings have implications for both top management, in determining which functional capabilities require strategic focus in a specific environment, and functional specialists, in terms of which aspects of their specific function should be developed and maintained to optimise this configuration of capabilities. At both the strategic and operational level, these studies provide novel and actionable insights into resource allocation decisions by focusing on underexamined forms of uncertainty.

In sum, the unique practical implications of this thesis derive from the consideration of multiple levels of analysis, examining strategic direction and execution at the level of the corporate network, firm, and function, and contingencies in the macroeconomic, institutional, industry, and product-market environment. Explicating the role of uncertainty and firm heterogeneity regarding each of these issues provides new evidence of the role of market conditions, network position, and managerial agency in shaping firms' success in the contemporary business environment. Each chapter provides concrete and actionable implications for board composition and resource allocation decisions, with a focus on the likely benefits firms can realise from factors that remain within organisational control under differing and shifting conditions of immitigable uncertainty.

8.3 CONCLUSION

Increasing levels of immitigable uncertainty in the contemporary business environment complicate the strategy process at every stage, from direction to execution (Ahlstrom et al. 2020; Rouleau et al. 2020; Ehrig and Schmidt 2022). These changes in the extent and nature of institutional uncertainty raise fundamental questions about the continuation of established theory and practice in strategic management (Howard-Grenville 2020). Foundational frameworks for understanding the business environment, such as upper echelons theory (UET) and resource-based theory (RBT), must adapt to account for heightened variation in both external conditions and firms' responses (Hitt et al. 2020).

This thesis aimed to contend with this problem, presenting six empirical studies conducted within the frameworks of RBT and UET with a focus on developing new insights into the role of environmental uncertainty and firm heterogeneity. These studies address three core research questions that encompass the strategy process from direction to execution: (1) *how are boards with the ability to deal with uncertainty formed?*, (2) *how does heterogeneity in the characteristics of the board affect strategic direction under uncertainty?*, and (3) *how does heterogeneity in the execution of strategy affect firm performance under uncertainty?*

The implications of these six studies, presented in the preceding chapters and synthesised above, demonstrate the centrality of uncertainty and heterogeneity in understanding and influencing firm-level outcomes. Some aspects of extant theory are corroborated and strengthened by these findings, such as the importance of dispositional factors in the formation and operation of boards, illustrating how established frameworks can serve to guide firms despite increasing uncertainty. Other evidence presented here, such as the nature and effects of firm capabilities in varying environments, challenges the conclusions of prior research and highlight new contingencies that must be considered in the strategy process. In both cases, novel data sources and methodological developments are used to elucidate understudied phenomena in both UET and RBT to further present knowledge and open avenues for future research. Taken together, these studies evince key aspects of the external environment, corporate ecosystem, and agency of decision-makers that may serve to inform and guide the decisions of directors and managers in navigating new and enduring forms of uncertainty.

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10 APPENDIX A: CLASSIFICATION OF JOB DESCRIPTIONS

This Appendix describes the guided Latent Dirichlet Allocation (LDA) model used to classify directors' previous employment into functional areas. Whilst prior research has not used LDA for this purpose, it is increasingly used in corporate disclosure research and shows strong correspondence to human coding and robustness to computerized validation (Dyer et al. 2017). The below sections first briefly describe the basic (unsupervised) LDA model and preprocessing steps, followed by details of the guided LDA implementation.

Preprocessing

Directors' job descriptions are obtained from the BoardEx Employment History database. Each job description constitutes a 'document' in the 'corpus' (i.e. collection of all documents). Prior to topic modeling, this corpus is created by converting all documents to lower case, removing stop words (e.g. 'and', 'the', 'of') and removing punctuation and numbers. The next step in preprocessing is to count overall word frequencies and, where appropriate, remove commonly occurring words (e.g. 'non' and 'NED', indicating a non-executive position). Examining overall word frequencies also assists in identifying seed words, which are specified manually based on prior knowledge of core functional areas then refined in accordance with the prevalence of these words within the sample.

Unsupervised LDA

LDA (Blei et al. 2003) begins with the assumption that each document within a corpus is characterised by a distribution over latent topics and each topic characterised by a distribution over words. Each document is created via a generative probabilistic process where, for every *n*th word in document *d*;

1. Choose a topic z_{dn} from a multinomial distribution θ_d
2. Choose a word w_{dn} from a multinomial distribution conditioned on the topic z_{dn}: $p(w_{dn}|z_{dn}, \phi_{z_{dn}})$

LDA estimates the probability distribution over topics (θ_d) and the probability distribution over words for a given topic (ϕ_t) such that the probability of the actual content of the corpus being observed is maximised. Topics (z) and words (w) are discrete random variables following multinomial distributions with Dirichlet priors $p(\theta_d) \sim Dirichlet(\alpha)$ and $p(\theta_t) \sim Dirichlet(\beta)$, where α and β are known parameters (see Blei et al., 2003, p. 996 for further details).

Applying this process iteratively generates a probabilistic estimate of the prevalence of topics within each document and the prevalence of words within each topic. The former can be used to derive measures of the thematic content of a document (here, the functional areas represented in a job title) and the latter to manually check the validity of the generated topics (see Huang et al. 2018).

Figure A1 illustrates the levels of the LDA process, with repeated sampling steps represented by boxes around the variables. D signifies a corpus comprising d documents. α and β are corpus-level parameters that are assumed to be known and fixed once the generative process has begun. The distribution over topics θ_d is a document-level variable which is sampled for each document. The distribution over words for each topic ϕ_t is sampled for each topic z to generate the word probabilities for T latent topics. The words in any specific document, represented by N_d, are generated by repeated sampling of topics and words. Words (w_{dn}) are observed; other parameters are estimated during the sampling process, including the assignment of words to topics based on their probabilities (z_{dn}).

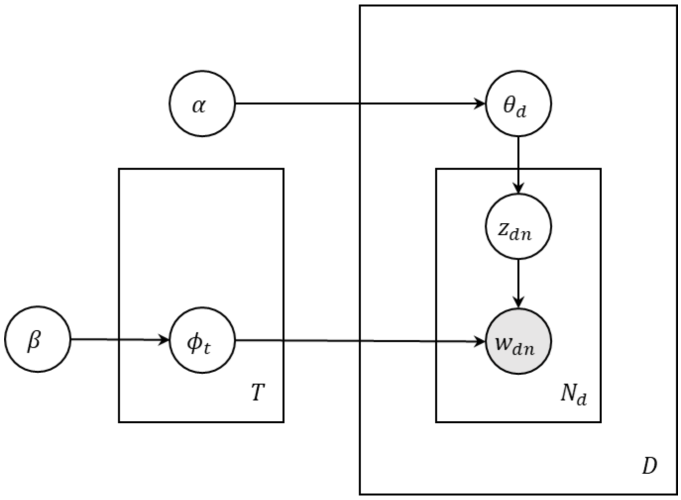

FIGURE A1 Graphical Representation of LDA.
Adapted from Blei et al. (2003, p. 997).

The probability of word being assigned to a topic (z_{dn}) conditional on all other topic assignments (z_{-dn}) and model parameters (notation above) is given by:

$$p(z_{dn} = t \mid w_{dn} = m, z_{-dn}, \alpha, \beta)$$

$$\propto \frac{C^{WT}_{mt,-dn} + \beta}{\Sigma_{m'} C^{WT}_{m't,-dn} + W\beta} \times \frac{C^{T}_{t,-dn} + \alpha}{\Sigma_{t'} C^{T}_{t',-dn} + T\alpha}$$

The posterior conditional probability of a word is thus the probability of that word m, given topic t, multiplied by the probability of topic t, i.e. the distribution over topics and words are given by:

$$\phi_t = \frac{C^{WT}_{mt,-dn} + \beta}{\Sigma_{m'} C^{WT}_{m't,-dn} + W\beta}$$

$$\theta_d = \frac{C^{T}_{t,-dn} + \alpha}{\Sigma_{t'} C^{T}_{t',-dn} + T\alpha}$$

$C^{WT}_{mt,-dn}$ and $C^{T}_{t,-dn}$ are the count matrices containing the topic assignment of all words in all documents other than the current word where each element p_{mt} is the probability of word m in topic t. The topic vector of a given document (T_d), i.e. the thematic composition of a document, can thus be constructed by summing the probabilities of each word for each topic to estimate the probability of a given sentence being generated from each topic, then assigning each sentence to the topic for which the sum of per-topic word probabilities is highest. For documents composed of multiple sentences, topic vectors can then be constructed by calculating the proportion of sentences assigned to each topic (Huang et al., 2018); however, as the documents in this corpus comprise only a single sentence, the topic vectors are simply the highest-probability topic for each job description.

Guided LDA

In many practical applications of LDA, a high frequency of certain themes or words may obscure the detection of semantically meaningful latent topics (Griffiths et al. 2007; Blei and McAuliffe 2008) occurs because LDA seeks to maximise the probability of observing the actual content of the corpus and will therefore, with diffuse priors, focus on themes that are prevalent across all documents. In this context, words such as ‘director’ and ‘manager’ – which are common across most job descriptions – thus pose issues of interpretability and relevance when using unsupervised LDA.

Guided LDA (Jagarlamudi et al. 2012) extends the unsupervised model to incorporate lexical priors in two ways: (1) specifying topics that preferentially generate words from a set of seed words and words related to these words (to improve the topic-word distribution ϕ_t) and (2) biasing the model towards selecting document-level topics based on observation of the seed words (to improve the document-topic distribution θ_d). Importantly, this retains the probabilistic generative process, allowing distributions to emerge from the observed data and thus ensuring that relevant words that are omitted from the seed word list are included in the final model.

In the first step, the distribution of topic *t* over words (ϕ_t) is instead defined as a mixture of two multinomial distributions; the regular distribution and the seed distribution, which is constrained to only generate words from the specified list of seed words.[28] Each document is thus a distribution over T topics where each t is a mixture of the regular topic distribution (ϕ_t^R) and the seed distribution (ϕ_t^S), with the parameter π_t specifying the probability of drawing a word from ϕ_t^S instead of ϕ_t^R for each topic and the binary variables x_{dn} specifying whether each word is drawn from the seed or regular topic distribution in a given document. Thus, the generative process becomes:

[28] As with the regular distribution the probability distribution of words is inferred by the model; the user only provides the words.

1. For each topic *t* = 1, … , *T*,
    a. Choose regular topic $\phi_t^R \sim Dirichlet(\beta_R)$
    b. Choose seed topic $\phi_t^S \sim Dirichlet(\beta_S)$
    c. Choose $\pi_t \sim Beta(1,1)$
2. For each document *d* = 1, … , *D*, choose $\theta_d \sim Dirichlet(\alpha)$
3. In in document *d*, for each word *n* = 1, … , N_d
    a. Choose a topic $z_{dn} \sim Mult(\theta_d)$
    b. Choose an indicator $x_{dn} \sim Bern(\pi_{z_{dn}})$
    c. If $x_{dn} = 0$, choose a word from the regular topic $w_{dn} \sim Mult(\phi_{z_{dn}}^R)$
    d. If $x_{dn} = 1$, choose a word from the seed topic $w_{dn} \sim Mult(\phi_{z_{dn}}^S)$

In the second step, seed words are used to improve the distribution of document *d* over topics. Each g group of seed words representing a topic is associated with a multinomial distribution over the regular topic distribution θ_d, denoted as the group-topic distribution ψ_g. The generative process samples a group of seed words and uses ψ_g to draw θ_d, as follows:

1. For each topic *t* = 1, … , *T*, choose regular topic distribution $\phi_t^R \sim Dirichlet(\beta_R)$
2. For each group of seed words *s* = 1, … , *S*, choose group-topic distribution $\varphi_s \sim Dirichlet(\alpha)$
3. For each document *d* = 1, … , *D*,
    a. Choose a binary vector $\vec{b}$ of length *S*

b. Choose a document-group distribution

$\zeta^d \sim Dirichlet(\tau\vec{b}\,)$

c. Choose a group variable $g \sim Mult(\zeta^d)$

d. Choose a document-topic distribution

$\theta_d \sim Dirichlet(\psi_g)$

4. For each word n = 1, … , N_d

   a. Choose a topic $z_{dn} \sim Mult(\theta_d)$

   b. Choose a word $w_{dn} \sim Mult(\phi^R_{z_{dn}})$

The binary vector $\vec{b}$ is an observed variable representing which seed words exist in a document, which defines the mean of the distribution from which the document-group distribution ζ^d is sampled (the hyperparameter τ is specified manually). The group variable g drawn from the resulting distribution enables grouping of documents with high probabilities for the same seed sets. Thus, drawing the document-topic distribution θ_d with the group's topic distribution as the prior means that the topic distributions of documents within each group are related, before proceeding to the standard LDA sampling of words and topics.

Combining the above generative processes in the guided LDA procedure gives the following process:

1. For each topic t = 1, … , T,

   a. Choose regular topic $\phi^R_t \sim Dirichlet(\beta_R)$

   b. Choose seed topic $\phi^S_t \sim Dirichlet(\beta_S)$

   c. Choose $\pi_t \sim Beta(1,1)$

2. For each group of seed words *s* = 1, … , *S*, choose group-topic distribution $\varphi_s \sim Dirichlet(\alpha)$
3. For each document *d* = 1, … , *D,*
    a. Choose a binary vector $\vec{b}$ of length *S*
    b. Choose a document-group distribution $\zeta^d \sim Dirichlet(\tau\vec{b})$
    c. Choose a group variable $g \sim Mult(\zeta^d)$
    d. Choose a document-topic distribution $\theta_d \sim Dirichlet(\psi_g)$
4. For each word *n* = 1, … , N_d
    a. Choose a topic $z_{dn} \sim Mult(\theta_d)$
    b. Choose an indicator $x_{dn} \sim Bern(\pi_{z_{dn}})$
    c. If $x_{dn} = 0$, choose a word from the regular topic $w_{dn} \sim Mult(\phi^R_{z_{dn}})$
    d. If $x_{dn} = 1$, choose a word from the seed topic $w_{dn} \sim Mult(\phi^S_{z_{dn}})$

Figure A2 illustrates the differences from the standard LDA sampling process using the same plate notation as Figure A1.

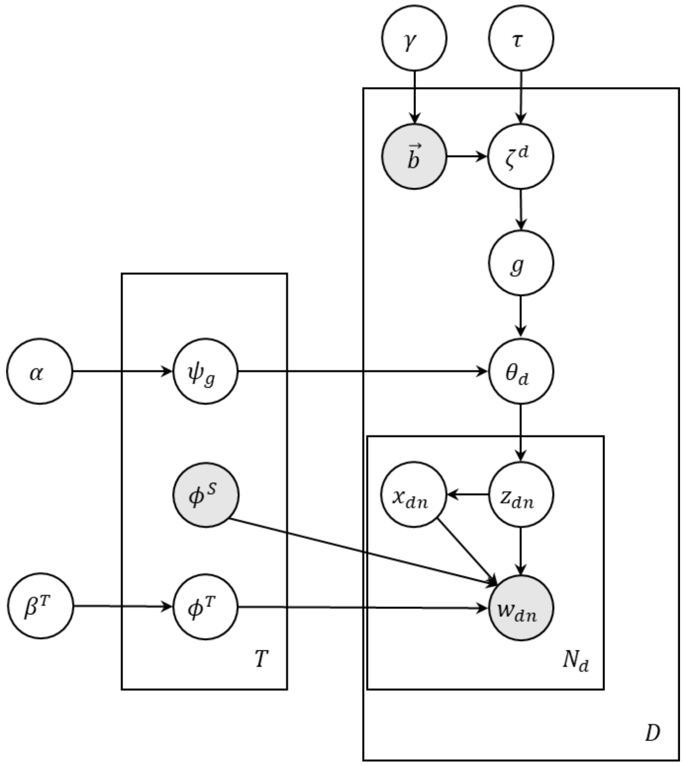

FIGURE A2 Graphical Representation of Guided LDA.

Adapted from Jagarlamudi et al. (2012, p. 207)

Implementation

As the distributions of latent variables are inestimable with closed-form solutions, the guided LDA model is estimated with collapsed Gibbs sampling (see Steyvers and Griffiths 2007) with standard hyperparameters $\alpha = 1.0, \beta = 0.01, \tau = 1.0$ (Jagarlamudi et al., 2012). Six seed topics are specified, representing functional areas, each initialised with two seed words.

Table A1 shows the two seed words and five representative words[29] characterizing each topic following guided LDA. As illustrated, five of the six functional areas show strong correspondence between seed words and

[29] i.e. five of the ten words with the highest per-topic probabilities for each topic, removing those that are variations such as 'marketing' and 'mktg'.

the output of LDA. However, despite a strong prevalence of 'operations'-related words in the corpus as a whole (as identified via word frequencies), these seed words appear to have been overridden by the LDA algorithm to produce an additional finance-oriented topic, demonstrating the probabilistic nature of the analysis.

TABLE A1 Seeded and Final Terms Characterising Functional Area Topics.

Functional area	Seed words	Representative words in LDA topic
Marketing	Marketing Sales	Sales Marketing Global Representative Communications
Technology	Technology Digital	Development Business Technology Strategy Information
Engineering	Engineering Engineer	Engineer Founder Engineering Committee Project
Finance (Legal)	Attorney Finance	Counsel Attorney Investment Management Compliance
HR	Human Relations	Analyst Professor Services HR Editor
Finance (Operational)	Operations Planning	Treasurer Finance COO Investor Accounting

Manual validation against a sample of job descriptions suggests that the LDA output more accurately characterizes the dominant functional areas in directors' employment histories. This is also supported by the dominance of finance backgrounds among board members (Whitler et al. 2018), which suggests that the distinction between legal and operational aspects of the finance function is a valid categorisation at board-level.

11 APPENDIX B: BAYESIAN ESTIMATION

This Appendix details the sampling procedure used in estimating the Bayesian models in Chapters 4 and 7. These models use a hybrid sampler that utilises both Metropolis Hastings and Gibbs sampling steps (i.e. sampling from the full conditional distribution when possible and using Metropolis steps otherwise). However, as the models specify conjugate priors, this sampling procedure utilises only Gibbs sampling in practice. As each iteration samples all parameters the order of the steps is not consequential for model estimation.

As specified in the Chapters, the system of questions includes two levels. In the first level, performance is modeled as a function of the focal independent variables and controls. A second-level equation for each β and γ sets the priors for firm-specific parameter estimates based on a hypermean:

$$\Theta_i = f(\beta_i, \gamma_i)$$

$$\Theta_i = \overline{\Theta} + \eta_i$$

Errors in both levels are heteroskedastic with different variance terms for each parameter (denoted by subscript k). The first stage equation contains X variables and a second stage equation is estimated for each parameter; thus k_1 and k_2 = 1 , … , X.

$$\varepsilon_{it,k_1} \sim N(0, \sigma^2_{i,k_1})$$

$$\eta_{i,k_2} \sim N(0, \sigma^2_{k_2})$$

As both analyses have a large and unbalanced panel, no covariance between errors is assumed. However, as detailed in step 4, parameters are sampled in a way that enables extension to a full covariance matrix if required.

Initialisation

Before sampling, starting values for all parameters are specified, denoted by the superscript *0*. For $\left(\Theta_{ij}\right)^0$, this is a vector of zeros and for $(\overline{\Theta})^0$ a matrix of zeros of dimensions k_1 variables in the first level equation by k_2 second-stage covariates. For $\left(\sigma_j^2\right)^0$ and $\left(\sigma_{ij}^2\right)^0$ this is an identity matrix. Diffuse normal priors for the mean and variance of $\bar{\Theta}$, with $\mu_{\bar{\Theta}}^{prior} = 0$ and $\sigma_{\bar{\Theta}}^{2,prior} = 10{,}000$ are specified. The shape and scale parameters of the inverse gamma distributions used to sample σ_j^2 and σ_{ij}^2 are given diffuse priors of $v_{\eta}^{prior} = 1$, $S_{\eta}^{prior} = 0.01$ and $v_{\varepsilon}^{prior} = 1$, $S_{\varepsilon}^{prior} = 0.01$ respectively. The priors for Θ_{ij} come from the common distribution from the second level; for the *s*-th iteration, $N\left(\overline{\Theta}_{k_2}^{S-1}, \left(\sigma_{\eta,k_2}^2\right)^{S-1}\right)$.

Sampling $\boldsymbol{\Theta}$

This process first samples the second level hyperparameter $\overline{\Theta}$ conditional on the variance σ^2. The *s*-th iteration is:

$$\overline{\Theta}^S |\, \Theta^S, \left(\sigma_{\eta,k_2}^2\right)^{S-1}$$

The hypermean for each of the k_2 variables is sampled from the posterior $N\left(\left(\iota_n'\iota_n + \left(\sigma_{\bar{\Theta}}^{2,prior}\right)^{-1}\right)^{-1} \left(\iota_n' vec\left(\Theta_{k_2}^S\right) +\right.\right.$

$\left(\sigma_{\bar{\Theta}}^{2,prior}\right)^{-1}\mu_{\bar{\Theta}}^{prior}\right), \left(\sigma_{\eta,k_2}^{2}\right)^{S-1} * \left(\iota_n'\iota_n + \left(\sigma_{\bar{\Theta}}^{2,prior}\right)^{-1}\right)\right)$, where ι_n is a unit vector of size *n*.

Sampling $\boldsymbol{\sigma^2}$

Next, the process samples each element of σ^2 separately for each of the k_2 parameters of the second level equation conditional on the hypermean $\bar{\Theta}$. The *s*-th iteration is:

$$\left(\sigma_{\eta,k_2}^{2}\right)^{S} | \bar{\Theta}^{S}, \Theta^{S}$$

This is sampled from an inverse gamma distribution with prior $IG\left(\frac{v_{\eta}^{prior}}{2}, \frac{S_{\eta}^{prior^{-1}}}{2}\right)$. The conditional posterior distribution is $IG\left(\frac{v_{\eta}^{prior} + n}{2}, \frac{\left(S_{\eta}^{prior^{-1}} + \Sigma_i\left(\Theta^{S,k_2} - \bar{\Theta}^{S,k_2}\right)^2\right)^{-1}}{2}\right)$.

Sampling $\boldsymbol{\Theta ij}$

Although the model has a diagonal covariance matrix (i.e. dependent variables are uncorrelated), this process uses a seemingly unrelated regression (SUR) specification to sample the firm- specific parameters (denoted here as $\tilde{\Theta}$) such that estimation can be extended to a full covariance matrix if modelling with a balanced panel). Using the block structure of SUR, these parameters are sampled together, with different priors as specified above. The *s*-th iteration is:

$$\tilde{\Theta}^{S} | \, Y_{it}, \, X_{it}, \bar{\Theta}^{S-1}, \left(\sigma_{\varepsilon,k_1}^{2}\right)^{S}, \left(\sigma_{\eta,k_2}^{2}\right)^{S-1}$$

Dependent variables are stacked in a T by Y vector (where T is the total number of firm-year observations). Independent variables including firm dummies are stored in a block structure of dimensions Y by $\tilde{\Theta}$. The vector Y and matrix X are transformed using the root of the covariance matrix η in $\left(\sigma_\eta^2\right)^S = cov(\eta) = \eta'\eta$, to correct for correlations between the equations. The process then samples $\tilde{\Theta}$ using $\tilde{Y}$ and $\tilde{X}$ of an uncorrelated system of equations, with $\tilde{Y} = (\eta^{-1} \otimes I_T)Y$ and $\tilde{X} = (\eta^{-1} \otimes I_T)X$, from the multivariate normal distribution $N\left(\left(\tilde{X}'\tilde{X} + A^{-1}\right)^{-1}\left(\tilde{X}'^{\tilde{Y}} + V^{-1} * M\right), \left(\tilde{X}'^{\tilde{X}} + V^{-1}\right)^{-1}\right)$ where V is a diagonal matrix with the variance and M a vector of the mean of the prior distributions from the second level for the first level parameters, and from the diffuse priors for the second level parameters.

Sampling σ_i^2

The process samples each element of σ_i^2 separately for each of the k_1 parameters of the first level equation conditional on the parameters. The *s*-th iteration is:

$$\left(\sigma_{\varepsilon,k_1}^2\right)^S |\, \Theta_i^S$$

This is sampled iteratively for each of *n* observations from an inverse gamma distribution with prior $IG\left(\frac{v_\varepsilon^{prior}}{2}, \frac{S_\varepsilon^{prior^{-1}}}{2}\right)$. The conditional posterior distribution is $IG\left(\frac{v_\varepsilon^{prior} + n}{2}, \frac{\left(S_\varepsilon^{prior^{-1}} + \Sigma_i\left(\Theta_i^{S,k_1}\right)^2\right)^{-1}}{2}\right)$.

12 APPENDIX C: SUPPLEMENTAL ANALYSES FOR CHAPTER 7

This Appendix presents analyses that supplement the main results included in Chapter 7.

TABLE C1 Industry Group Effects of Efficiency and Capability Characteristics on Competitive Advantage.

Dependent variable	Relative Tobin's Q															
Industry	Primary		Chemical		Machinery		Electronics		Instruments		Other Manufacturing		Transport & Retail		Services	
Capabilities																
MK E	1.023*		0.452*		0.838***		0.891***		1.417***		0.609***		0.799*		1.227***	
RD E	-0.490**		0.088		0.035		0.160**		0.109		-0.008		-0.124		0.109	
OP E	0.116		0.172		-0.136		0.148		-0.275*		-0.121		0.547*		-0.355**	
MK R		0.802		3.458***		2.254**		1.529**		4.579***		0.472		-0.568		-1.129
RD R		-0.589		0.450		-0.285		-0.084		0.689*		0.386**		0.234		0.161
OP R		-0.767		-0.357		-1.224**		0.363		-0.710		-0.401		0.944		0.547
MK P		0.140		-0.054		0.363		0.153		1.021***		0.304		0.010		0.469
RD P		-0.169		0.078		-0.002		0.028		0.137		-0.110*		0.050		-0.094
OP P		0.449		-0.221		-0.035		-0.267***		-0.065		-0.254***		-0.148		-0.267**
MK D		0.604		-0.164		0.701***		0.491***		0.950***		0.316***		0.729**		0.797***
RD D		0.150		0.056		-0.003		0.132*		0.047		-0.013		-0.175		-0.014
OP D		0.220		-0.033		-0.151		-0.284***		-0.167		-0.121		0.352*		-0.429***
Controls																
Turb.	0.345	-0.258	1.587***	1.767***	0.646**	0.925***	-0.047	0.135	2.503***	2.629***	-0.132	-0.170	0.978*	1.024*	1.144**	0.735
Conc.	-0.221	-0.434	0.244	2.003	0.135	-0.382	-0.464	0.606	-7.845**	-1.071	-0.518	-1.026	-1.637	-2.378	4.190*	3.752*
Size	0.003	0.010	0.037***	0.037***	0.016***	0.016***	-0.001	-0.004	0.012*	0.019***	0.014***	0.015***	0.011	0.018	-0.007	-0.008
Age	-0.173	-0.212	-0.482***	-0.493***	-0.380***	-0.286***	-0.213***	0.146***	-0.410***	-0.358***	-0.341***	-0.296***	-0.223*	-0.263**	-0.401***	-0.259***
Past DV	0.185	-0.003	0.692***	0.677***	0.328	0.323***	0.196***	0.192***	0.470***	0.468***	0.280***	0.278***	0.252**	0.251**	0.511***	0.517***
N	15		106		96		108		104		169		20		88	
DIC	15694.159	11992.936														
ρ	.816	.828														

Significance: * = 10% level, ** = 5% level, *** = 1% level, based on the highest posterior density interval.

Abbreviations: MK = marketing, RD = R&D, OP = operations, E = efficiency, R = rarity, P = persistence, D = development. Turb. = industry turbulence. Conc. = industry concentration, Size = firm size, Age = firm age, Past DV = past performance, N = number of firms in each industry group.

TABLE C2 Industry Group Effects of Efficiency and Capability Characteristics on Firm Value.

Dependent variable	Tobin's Q															
Industry	Primary		Chemical		Machinery		Electronics		Instruments		Other Manufacturing		Transport & Retail		Services	
Capabilities																
MK E	0.243		0.410**		0.914***		0.812***		1.394***		0.457***		0.405		1.084***	
RD E	-0.005		0.044		-0.016		0.039		0.037		-0.014		-0.169		-0.069	
OP E	0.220		0.288**		0.183		0.271**		0.391***		0.223**		0.369		0.043	
MK R		-0.721		0.661		-1.035		1.496**		1.059		0.316		-0.007		-0.153
RD R		-0.282		-0.128		-0.381*		-0.243		1.345***		0.143		0.275		-0.295
OP R		2.508**		-1.573***		1.266**		1.034**		0.276		0.385		1.099		0.950*
MK P		-0.331		0.094		0.152		0.329		0.519*		0.333**		-0.207		0.236
RD P		0.007		-0.023		-0.048		-0.069		-0.037		-0.089*		-0.080		-0.277***
OP P		0.328		-0.121		0.010		-0.059		0.078		-0.047		0.246		-0.156
MK D		0.170		0.408**		0.525***		0.418***		0.340**		0.200*		0.431		0.759***
RD D		-0.067		0.081		-0.083		0.080		-0.051		0.035		-0.088		-0.004
OP D		-0.615*		0.259**		-0.339***		-0.245**		-0.234**		0.007		0.077		-0.224*
Controls																
Turb.	-0.095	0.311	-1.336***	-1.647***	-0.172	0.029	-0.925***	-0.602***	2.648***	2.429***	-0.090	-0.082	-0.351	0.179	0.842*	0.655*
Conc.	0.292	-0.211	10.687***	21.273***	-3.833***	-2.200***	6.052***	4.909***	6.545***	8.187***	0.264	0.237	-2.455***	0.111	0.033	-2.428***
Size	-0.007	-0.001	0.030***	0.030***	0.018***	0.017***	-0.006	-0.005	0.054***	0.053***	0.022***	0.023***	0.006	0.007	0.032***	0.034***
Age	-0.103	-0.158	-0.303***	-0.274***	-0.298***	-0.214***	-0.109**	-0.090**	-0.430***	-0.374***	-0.271***	-0.254***	-0.096	-0.169*	-0.257***	-0.179***
Past DV	0.291***	0.304***	0.475***	0.484***	0.321***	0.346***	0.260***	0.292***	0.382***	0.415***	0.400***	0.420***	0.348***	0.343***	0.381***	0.403***
N	15		106		96		108		104		169		20		88	
DIC	16452.458	15566.505														
ρ	.819	.821														

Significance: * = 10% level, ** = 5% level, *** = 1% level, based on the highest posterior density interval.

Abbreviations: MK = marketing, RD = R&D, OP = operations, E = efficiency, R = rarity, P = persistence, D = development. Turb. = industry turbulence. Conc. = industry concentration, Size = firm size, Age = firm age, Past DV = past performance, N = number of firms in each industry group.

TABLE C3 Industry Group Effects of Efficiency and Capability Characteristics on Firm Value.

Dependent variable	Tobin's Q							
Industry	Primary	Chemical	Machinery	Electronics	Instruments	Other Manufacturing	Transport & Retail	Services
Capabilities								
Marketing efficiency	0.358	0.366	0.935***	0.777***	1.356***	0.488***	0.492	1.042***
R&D efficiency	-0.120	0.088	0.044	0.071	0.292***	0.008	-0.173	0.145
Operations efficiency	0.512	0.000	0.360**	0.549***	0.575***	0.340***	0.635*	0.121
Marketing rarity	-0.702	-0.527	-1.195	1.424**	-0.296	0.329	0.807	-0.324
R&D rarity	-0.098	-0.280	-0.461*	-0.271	1.162***	0.037	0.604	-0.377
Operations rarity	2.497**	-1.257**	1.279**	0.842	0.293	0.092	0.512	1.009***
Marketing persistence	-0.412	0.113	-0.191	0.159	0.365	0.306	-0.423	-0.037
R&D persistence	0.096	-0.093	-0.088	-0.121	-0.268**	-0.127**	0.002	-0.404***
Operations persistence	0.247	-0.091	0.001	-0.049	0.078	-0.055	0.092	-0.088
Marketing development	0.032	0.390**	0.183	0.096	0.045	0.055	-0.020	0.361*
R&D development	-0.059	0.050	-0.128*	0.035	-0.222**	0.034	0.086	-0.095
Operations development	-0.582***	0.325**	-0.527***	-0.471***	-0.376***	-0.150*	-0.155	-0.199
Controls								
Industry turbulence	-0.040	-1.510***	0.110	-0.238	2.594***	-0.068	0.008	0.619*
Industry concentration	-0.389	2.289***	-5.947***	5.151***	-1.356*	0.323	-2.440	-1.781
Firm size	-0.000	0.030***	0.019***	-0.003	0.051***	0.024***	0.012	0.036***
Firm age	-0.152	-0.313***	-0.252***	-0.075	-0.429***	-0.269***	-0.049	-0.255***
Past performance	0.276***	0.444***	0.286***	0.210***	0.349***	0.354***	0.261***	0.361***
N	15	106	96	108	104	169	20	88
DIC	13476.620							
ρ	.828							

Significance: * = 10% level, ** = 5% level, *** = 1% level, based on the highest posterior density interval.