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Attention Dynamics in Entrepreneurial and Technology Firms

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by

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FIELD OF STUDY

Attention Dynamics in entrepreneurial ventures and small groups

ABSTRACT OF THE DISSERTATION

Attention Dynamics in Entrepreneurial and Technology Firms

by

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This dissertation applies the behavioral theory of the firm (BTOF) and the attention-based view (ABV) to examine how founder attention influences strategic change and goal setting in entrepreneurial and technology firms. In the first chapter, I explore how performance across competing organizational goals affects founder attention to strategic change. Using detailed data from email correspondence and financial performance of a digital marketing startup from its inception in 2016 through 2022, I address a key gap in the entrepreneurship and ABV literatures, which recognize the importance of founder attention but have lacked the granular data needed to develop and test theories in this area. The second chapter, utilizing a quasi-experimental simulation-based dataset, examines how groups and individuals differ in their attention to factors influencing goal-setting behavior. This paper addresses a significant gap in the organizational goal-setting literature, which acknowledges the importance of varying decision-making structures but lacks empirical evidence on how groups and individuals differ in setting organizational goals.

INTRODUCTION

In the attention-based view (ABV; Ocasio, 1997), the strategic changes that firms implement are less relevant than decision-makers' attention dynamics that direct their attention to specific issues and motivate search for distinct strategic changes that create value for the firm (Ocasio & Joseph, 2018). Thus, to understand the motivations behind managerial pursuit of specific agendas such as business model pivots or investments in new technologies, we need to examine what decision makers attend to. This includes both their strategic agendas and goals or aspirations, which is the subject of this dissertation. Specifically, I study the impact of performance feedback on 1) decision maker (founder) attention to strategic change, and 2) aspiration adaptation.

Research in entrepreneurial strategy has largely concentrated on founders' processes of recognizing and discovering new opportunities, as well as developing initial strategies to capitalize identified opportunities (Nair, Gaim & Dimov, 2022; Ott & Eisenhardt, 2020; Ott, Eisenhardt & Bingham, 2017). Building on the lean startup approach (Ries, 2011), an expanding area of entrepreneurship research now examines how new ventures adapt and undergo strategic change, particularly focusing on what drives pivots, including industry dynamics, founder traits, and the evolution of founders' mental models (Kirtley & O'Mahoney, 2023; Leatherbee & Katila, 2019).

However, there is a noticeable gap in the literature regarding ventures that have already entered the market (e.g., Sanasi & Ghezzi, 2022). Most studies on entrepreneurial strategic change target early-stage ventures before market entry, where resources have not yet been committed to generating revenue and firms lack performance history. As a result, our understanding of when and why young ventures initiate strategic changes, and how startup goals

influence founder attention post market entry remains limited, despite the regularity of startup strategic changes. Chapter 1 expands on existing theories regarding the impact of performance feedback on managerial attention within the frameworks of BTOF and the Attention-Based View (ABV). This chapter examines how feedback across multiple goals influences founder attention to strategic change.

Empirically, I analyze both quantitative data and qualitative insights gathered from a field study of a digital marketing firm in India, spanning from its inception in 2016 through 2022. The firm operates within India's rapidly expanding digital marketing industry, which reached a total market size of $680 billion in 2022, reflecting a compound annual growth rate of 35% since 2016 (Statista, 2022). India, with the world's second-largest internet user base, has also become a major hub for outsourcing digital marketing services from developed countries (Financial Times, 2022). The ongoing advancements in data-driven and performance-oriented digital marketing create a complex, ever-changing decision-making landscape (Kannan, 2017).

My findings reveal that founder attention to strategic change intensifies when revenue falls below aspirations. Interestingly, and in line with theories on established firms, founder attention to strategic change increases when slack performance is above aspirations. Unlike established firms, startup founders are inclined to invest slack resources into exploring new opportunities. Additionally, I find that slack performance is above aspirations moderates the positive effect of poor revenue performance on founder attention to strategic change.

This study offers several key contributions. First, it extends research on antecedents of founder attention to strategic change post market entry, filling a gap left by most previous studies that have focused on change pre market entry (e.g., Kirtley & O'Mahoney, 2023). Further, this study enhances our understanding of multiple goals. Finally, by examining CEO attention, this

study deepens theoretical insights into how performance feedback across multiple goals influences founder attention to strategic change (Ocasio, 1997; 2011; Gaba & Greve, 2019).

As noted earlier, Chapter 2 examines goal setting (aspiration adaptation). This chapter provides a detailed exploration of how aspiration formation and attention rules differ between individuals and organizations. We empirically test this hypothesis by analyzing aspirations and performance data obtained from a simulation involving MBA students and teams. Simulations have been widely used by researchers to explore various aspects of learning and decision-making among decision-makers (Dutton, 1988; Boies et al., 2011; Gary et al., 2017), and have a well-established role in the study of the Behavioral Theory of the Firm (BTOF). For instance, Lant (1992) employed simulation data from MBA students in one of the earliest empirical attempts to estimate aspiration models. In our study, we also compare the original aspiration model proposed by Cyert and March (1963) with three other aspiration models prominent in the literature (Greve 2003, 1998; Bromiley, 1991).

Although previous research has recognized the impact of multiple organizational goals on managerial attention (Ethiraj & Levinthal, 2009; Stevens et al., 2015; Shinkle et al., 2021), most studies have traditionally concentrated on a single goal, analyzing its effect on observable behaviors and resulting performance (Gaba & Greve, 2019). In practice, however, organizations often strive to achieve a range of goals, including profit, sales, and market share (Cyert & March, 1963), as well as more specific metrics like inventory levels and customer satisfaction (Kaplan & Norton, 1996). Further, in many studies, managerial attention is either implied rather than explicitly addressed, or if it is directly theorized, it is often not empirically measured.

The concept of aspiration adaptation across organizational goals is deeply rooted in the Behavioral Theory of the Firm (Cyert & March, 1963). Building on the foundational ideas of

organizational aspirations and adaptation introduced by March and Simon (1958), Cyert and March (1963) developed a widely recognized model of aspirations. According to this model, aspirations are determined by a straightforward linear combination of previous aspirations, past performance, and the performance of comparable organizations. This framework has sparked a significant body of research focused on how organizations compare their performance to their aspirations, effectively turning a continuous performance measure into a binary outcome.

When an organization's performance surpasses its aspiration level, it tends to maintain the current course rather than seeking further improvements. Conversely, if performance falls short of aspirations, organizations actively search for solutions in areas where they have underperformed to boost future outcomes (Cyert & March, 1963). Performance aspirations gaps, or performance feedback, influences a wide range of organizational behaviors, including strategic change (Joseph, Klingebiel & Wilson, 2016), search activities (Posen et al., 2018), innovation (Greve, 2003a; Eggers & Kaul, 2018), research and development spending (Greve, 2003b; Chen, 2008; Chen & Miller, 2007), and new product introduction (Gaba & Joseph, 2013).

However, prior research on organizational goals and resulting effects on managerial attention and organizational changes has two under-addressed areas. First, research largely overlooks a subtle distinction in the literature concerning setting aspirations: differences between individual and organizational attention rules. The early foundational work left some ambiguity on this issue. March and Simon's Organizations (1958, p. 203 in the 1993 second edition) suggested that both individual and organizational aspirations are influenced by similar factors, proposing that "generalizations found for individual aspiration levels will apply to organizational behavior as well".

Cyert and March's Behavioral Theory of the Firm (BTOF, 1963), while focusing exclusively on organizational phenomena (Cyert & March, 1963, p. 123), builds upon the theoretical foundation laid by March and Simon (1958). Though a few studies have since explored how aspirations influence behavior at the individual level (e.g., Boyle & Shapira, 2012; Di Lorenzo & Almeida, 2017; Kostopoulos, Syrigos, & Kuusela, 2023), most research has continued to model aspirations at the organizational level (cf. Shinkle, 2012; Joseph & Gaba, 2020). This indicates need for a more detailed exploration of how aspiration adaptation and attention rules differ between individuals and organizations, which is the focus of Chapter 2.

Results show that individuals use more inputs than groups, suggesting a simplification of the implicit metal model being utilized by individuals in aspiration adaptation, relative to groups. The results hold when adding threat of bankruptcy as a fourth input to the Cyert and March aspirations model.

This chapter contributes to the BTOF literature by addressing how individuals and organizations differ in shaping aspirations, a distinction largely ignored in prior empirical research (Shinkle et al., 2012). This study expands our theoretical understanding of how individuals may uniquely contribute to empirical regularities associated with setting aspirations and offer new insights into the cognitive underpinnings associated with aspiration adaptation, an area for which Carnegie scholars have called for more research (Posen et al., 2018). Moreover, use of a direct aspiration measure enables comparison of different functional models to test which ones offer the best fit indices (Bromiley & Harris, 2014). Prior studies employ alternative assumptions about decision-making structures and the role of information processing in shaping attention to aspiration-levels, because most studies lack direct measures of aspirations and use proxy measures instead.

This study also makes contributions to the literature on information processing and organizational design (cf. Puranam, 2018; Joseph & Gaba, 2020). While earlier studies have studies (1) how organizational structure impacts responses to performance shortfalls (Vissa et al., 2010; Gaba & Joseph, 2013; Joseph et al., 2016; Rhee, Ocasio & Kim, 2019) and conversely, (2) how performance outcomes can influence organizational structure (Sengul & Obloj, 2017), as well as (3) how various decision-making frameworks are modeled to predict performance outcomes (Csaszar & Eggers, 2013. However, there has been little research directly comparing information processing at the individual level with that at the organizational level. By addressing this gap, our study not only explores whether and how organizations and individuals differ in how they adapt aspirations.

Chapter 1

MONEY IN THE BANK: MULTIPLE GOALS, SLACK RESOURCES AND FOUNDER ATTENTION TO STRATEGIC CHANGE

Abstract

Research on entrepreneurial strategic change and pivots examines early-stage ventures pre market commercialization. However, entrepreneurial firms continue to explore strategic changes and potential pivots even post commercialization. With a longitudinal empirical study of a digital marketing and content creation startup, I examine the impact of performance feedback across multiple goals on founder attention to strategic change. Results demonstrate that, in contrast to established firms, entrepreneurial founders increase attention to strategic change when revenue falls below aspirations. Slack performance above aspirations i.e. increasing money in the bank, also increases founder attention to strategic change. I also find that revenue below aspirations coupled with slack above aspirations decreases founder attention to strategic change. Finally, I test and demonstrate that exogenous shocks increase founder attention to strategic change.

Keywords: Entrepreneurship, strategic change, multiple goals, attention, behavioral theory of the firm

INTRODUCTION

Entrepreneurial strategy research has primarily focused on new opportunity recognition, discovery, and the initial strategies formed to exploit such opportunities (Nair, Gaim & Dimov, 2022; Ott & Eisenhardt, 2020; Ott, Eisenhardt & Bingham, 2017). Based on the lean startup approach (Ries, 2011), a growing body of research in entrepreneurship focuses on new venture adaption and strategic change, exploring the antecedents of pivots as explained by industry structures, characteristics of firm founders, and updating of founder mental models (Kirtley & O'Mahoney, 2023; Leatherbee & Katila, 2019). However, few scholars focus on ventures post market entry (e.g. Sanasi & Ghezzi, 2022). Most research on entrepreneurial strategic change focuses on early-stage ventures pre market entry, which do not have resources deployed towards revenue creation when considering strategic change. Therefore, despite its regularity, we know little about when young ventures initiate change post market entry.

At the same time, a large body of research examines how established firms learn and adapt over time (Argote & Levine, 2020). The insights on organizational adaptation from the larger behavioral strategy literature, while not directly applicable to smaller firms, provides a starting point towards building theory on strategic change and pivoting in young ventures (Bromiley & Rau, 2019). Research on established firms suggests that managers identify performance-aspiration gaps (performance feedback), across multiple goals, as an activating mechanism that *directs managerial attention* towards solution search, potentially leading to strategic change and adaptation (Rhee, 2024a; Yang, Goudsmit & Shinkle, 2022; Audia & Greve, 2021; Posen, Keil, Kim & Meissner, 2018).

While research examining the influence of multiple organizational goals on managerial attention has been acknowledged in prior literature (Ethiraj & Levinthal, 2009; Stevens et al.,

2015; Shinkle *et al*, 2021), most existing studies typically focus on just one goal, examining its impact observable behaviors and subsequent performance (Gaba & Greve, 2019). In reality, however, organizations commonly pursue a variety of goals such as profit, sales, and market share goals (Cyert & March, 1963); and even metrics such as inventory units and customer satisfaction (Kaplan & Norton, 1996). Moreover, attention is usually implicit in the models, or if directly theorized, is not measured.

The problem may be especially pronounced when we consider the allocation of managerial attention in entrepreneurial firms (Kirtley & O'Mahoney, 2023). The behavioral theory of the firm (BTOF; Cyert & March, 1963) argues that managers sequentially attend to multiple goals, However, research on performance feedback across multiple goals has yet to address situations where multiple goals hold similar priority, rendering the study of sequential attention unfeasible (Gavetti et al., 2012; Greve & Gaba, 2017). For example, simultaneous performance shortfalls across multiple goals may increase attention to strategic change (Gaba & Greve, 2019), while conflicting feedback across goals may lead to ambiguity and decreased attention to strategic change (Joseph & Gaba, 2015). More empirical evidence is needed to predict managerial attention and organizational responses when performance is measured against two high priority goals: such as revenue and slack resources (Gaba & Greve, 2019).

Thus, our understanding of the implications of managing multiple goals on managerial attention and firm outcomes remains limited, even though managing multiple goals is common in organizations (Obloj & Sengul, 2020; Stevens et al., 2015). Extending research on the influence of multiple goals and managerial attention is not only theoretically and empirically crucial (Hu & Bettis, 2018; Stevens et al., 2015), but can provide relevant insights for managers (Tsui, 2016). Building on established theory on the influence performance feedback across multiple goals on

managerial attention in BTOF and the ABV, this paper advances our understanding of how performance feedback across multiple goals affects founder attention to strategic change. More specifically, I *examine how performance feedback across multiple goals impacts founder attention to strategic change in a startup post market entry*.

Empirically, I use quantitative data and qualitative insights from a field study of a digital marketing firm based in India from its inception in 2016 until 2022. The focal firm in this paper belongs to the evolving and fast-growing digital marketing industry in India, with total industry size of $680 Bn (2022) reflecting a compounded annual growth rate of 35% since 2016 (Statista, 2022). Boosted by the second largest number of internet users, India also serves as a key outsourcing market for digital marketing activities from developed economies (Financial Times, 2022). Continued advancements in data driven-performance oriented digital marketing makes for a complex and dynamic decision-making environment (Kannan, 2017).

Complementing weekly financial data with internal organizational communication, I track how performance across multiple goals directs founder attention towards strategic change. I model attention to strategic exits and additions as the dependent variable, since pivots have been shown to be a result of strategic changes (additions and/or exits) made by an entrepreneurial firm over time (Kirtley & O'Mahoney, 2023). I have detailed first-hand knowledge of the conditions under which the firm was set up, how it developed its initial goals by combining the founder's passion and prior experience, and subsequently how repetitive incremental strategic changes (product, market or technology additions and exits) have enabled the firm to adapt into a multi-divisional organization handling various types of client needs (ranging from video production to digital marketing and brand consulting services). Driven by the senior management team's top order goals and accelerated by the COVID-19 pandemic, the firm has pivoted its activities from a

focus on motion-graphics (a niche service) to focus on more widely demanded digital marketing and brand consulting services, while experimenting with many other ideas along the way.

I find that founder attention to strategic change increases when revenue performance falls below aspirations. However, consistent with the theory for established firms, founder attention to strategic change also increases when slack resources exceed slack aspirations since unlike established firms, startup founders seek to allocate slack resources to exploring innovation, I also find that performance above slack aspirations moderates the effect of low revenue aspirations on founder attention to strategic change.

This study makes several contributions. First, it advances research on the motivations behind founder attention to entrepreneurial strategic change post commercialization; in contrast to most prior studies that examine entrepreneurial pivoting pre-commercialization (e.g., Kirtley & O'Mahoney, 2023). By providing a deeper understanding of the factors influencing strategic change, this paper contributes to the literature on entrepreneurial behavior and its implications for pivots. By measuring CEO attention, we expand our theoretical understanding of how firm performance and environmental turbulence affect founder attention to exploring new opportunities towards strategic change (Ocasio, 1997; 2011; Gaba & Greve, 2019).

Most prior research on performance feedback models strategic change relative to performance across a single goal or aspiration level (Posen et al, 2018). However, BTOF theorizes that performance across multiple goals affect decision-maker attention to strategic change (Cyert & March, 1963; Audia & Greve, 2021; Yang, Goudsmit & Shinkle, 2022). This study contributes to BTOF by empirically demonstrating the role of performance across multiple goals on founder attention to strategic change. Second, this study extends BTOF to entrepreneurial firms. Similar to decision-makers in established firms, performance below

revenue aspirations result in increases founder attention to strategic change. However, in contrast to established firms, performance above slack aspirations also increase founder attention to strategic change. We also test and demonstrate that exogenous shocks increase founder attention to strategic change.

STRATEGIC CHANGE AND ORGANIZATIONAL GOALS

Strategic change is defined as a reorientation in a startup's strategy through reallocation or restructuring of activities, resources, and attention (Kirtley & O'Mahoney, 2023). Incremental *strategic changes* in a firms' technologies, products, or markets are theorized to lead to pivots (Furr, Cavarretta, & Garg, 2012) and can be key to new venture success; potentially enhancing competitive strategies (Gavetti & Rivkin, 2007), technologies (Furr, Cavarretta & Garg, 2012), and business models (McDonald & Eisenhardt, 2020). Strategic change enhances the probability of new venture success because entrepreneurs rarely get the "architecture of the value creation, delivery, and capture mechanisms" (Teece, 2010: 172) in their firms 'right' the first time and continually reorient these mechanisms to achieve better product-market fits (McDonald & Gao, 2019; Hampel, Tracey & Weber, 2020). Despite its importance for new venture survival, performance, and growth; research on the motivation and factors that lead to strategic change that result in entrepreneurial pivots is still nascent.

Entrepreneurs routinely implement strategic changes and even pivot their businesses in response to environmental turbulence (Folta, 2007; McMullen & Shepherd, 2006), new information (Kirtley & O'Mahoney, 2023) or negative feedback (Leatherbee & Katila, 2018; Grimes, 2018). Strategic change is theorized to be a result of reallocation or restructuring of activities, resources, and attention (Kirtley & O'Mahoney, 2023). Incremental strategic change i.e. *additions or exits to a firm's technologies, products, or markets* over time can lead to pivots,

or radical organizational change (Kirtley & O'Mahoney, 2023; Furr, Cavarretta, & Garg, 2012). Strategic change can be key to new venture success; potentially enhancing a venture's competitive strategies (Gavetti & Rivkin, 2007), technologies (Furr, Cavarretta & Garg, 2012), and business models (McDonald & Eisenhardt, 2020). Using a computational model, Chen, Elfenbein, Posen and Wang (2024) find that while strategic changes and pivots can boost new venture performance, frequent changes may negatively impact performance. In a field study covering five new ventures in the nascent financial-technology market McDonald and Eisenhardt (2020) show that effective business model adaptation helps new ventures achieve competitive distinctiveness. Effective business model design has also been shown to positively influence performance (Zott & Amit, 2007).

Despite the critical role of strategic change and pivots on new venture performance, academic research studying motivations that direct founder attention to strategic change is still nascent (Kirtley & O'Mahoney, 2023). Most entrepreneurship research focuses on new opportunity recognition, discovery, and the initial strategies formed to exploit such opportunities (Ott & Eisenhardt, 2020; Ott, Eisenhardt & Bingham, 2017). Building on the lean startup approach (Ries, 2011), a growing body of entrepreneurship research examines new venture adaptation and strategic change, particularly the factors leading to pivots, such as industry structures, founder characteristics, and the evolution of founder beliefs and mental models (Kirtley & O'Mahoney, 2023; Leatherbee & Katila, 2019). However, much of this research focuses on early-stage ventures pre market entry, where resources aren't yet allocated towards revenue generation. Consequently, despite the frequent occurrence of strategic change, there is limited understanding of the motivations behind young ventures initiating strategic change after

entering the market with a product or service offering (see Sanasi & Ghezzi, 2022 for an exception).

However, insights from behavioral theory of the firm (BTOF; Cyert & March, 1963;) and the attention based view (ABV; Ocasio, 1997) that theorize managerial antecedents of strategic change in established firms provide basis for theory building and empirical testing in the context of entrepreneurial firms and founder attention. BTOF argues that managerial attention to strategic change increases when firm performance falls below organizational goals or aspiration levels (Cyert & March, 1963; Levitt & March, 1988; Ocasio, 1997). Performance below aspirations can result in higher R&D intensity (Chen & Miller, 2007), innovation (Joseph & Gaba, 2015), acquisitions (Iyer & Miller, 2008), and implementation strategic changes (Greve, 1998). This process, where managers respond to poor performance by searching alternative solutions to restore performance, is known as "problemistic search" (e.g., Cyert & March, 1963; Greve, 2003a; Posen et al., 2018).

Cognitively constrained decision makers use scarce and limited cognitive attention to solve problems and pursue new opportunities (ABV; Ocasio, 1997). BTOF and ABV delve into managerial behavior within established firms, and started with a focus on a single goal, usually overall firm profitability (Gavetti et al. 2012, Shinkle 2012). Over time, research has expanded to encompass organizational responses to multiple goals (Baum et al. 2005, Gaba & Joseph 2013; Gaba & Greve, 2019). Since complex organizations pursue multiple goals, researchers need to examine how these goals interact and influence managerial attention (Gaba & Greve, 2019; Greve 2008).

While BTOF predicts managerial attentional switches in response to performance feedback across multiple goals and its influence on strategic change, the theory has been not

applied to examine the dynamics of founder attention and its impact on strategic change in young ventures. Some entrepreneurial studies apply BTOF to entrepreneurship but do not study founder attention to strategic change (e.g., Clough & Vissa, 2022; Angus, 2019; Yavuz, Dutta & Soytas, 2015; Zahra, 2008; see Rhee, 2024b for an exception).

MULTIPLE GOALS AND FOUNDER ATTENTION TO STRATEGIC CHANGE

According to BTOF, organizations pursue goals along several key dimensions; from return on assets, sales, and profitability to corporate social responsibility indexes and consumer safety goals (Audia & Greve, 2021; Gaba & Greve, 2019; Bromiley & Mayer, 2015). Poor performance across one or multiple goals directs managerial attention to problemistic search for solutions that can lead to strategic change (Posen et al, 2018). Goals along specific performance dimensions are usually designed to contribute to overall organizational survival but may, under bounded rationality, be in conflict - where achieving one goal compromises the ability to achieve another (Cohen 1984; Cyert & March, 1963). In such cases, managers are expected to fix performance shortfalls on the goal dimension that has a larger imminent threat on organizational survival (Audia & Greve, 2021; March & Shapira, 1991)

Recent empirical research on performance feedback across multiple goals, despite aligning more closely with original BTOF arguments, has yet to address scenarios where multiple high priority goals compete in directing managerial attention to problemistic search (Gaba & Greve, 2019). The two most high priority goals post market entry for new venture founders are firm revenue and slack resources. Revenue growth indicates increasing business volume and probability of future success while slack resources increase business health and probability of survival (YCombinator, 2023). While revenue and profitability goals, such as the availability of slack resources, can sometimes be compatible with each other, they can also be in

conflict – the same solution may not necessarily improve both revenue and profitability performance (Audia & Greve, 2021).

BTOF argues that high priority organizational goals are often decomposed into specific aspirations levels across multiple goal dimensions. Cyert and March's (1963: 117) examples of "sales, inventory, and production" goals reflect this decomposition toward the overarching aspirations of revenue growth along with availability of slack resources. Surprisingly, research on high priority multiple goals is nascent (see Gaba & Greve, 2019 for an exception), with most studies focusing on hierarchically differentiated goals, where low priority goals interact with higher priority goals (Audia & Greve, 2021). Following Rhee (2024a; 2024b) and, Gaba and Greve (2019), I develop specific hypotheses exploring the influences of founder attention to strategic change as a function of performance feedback across multiple high priority goals, specifically, revenue and slack goals.

Revenue Shortfalls and Founder Attention to Strategic Change

In established firms, performance below financial aspirations, such as revenue goals, results in organizational myopia rather than attention to strategic change (Cyert & March, 1963). Instead of pursuing new product development or exploring untapped markets, underperforming firms tend to enhance existing products and intensify sales (Bromiley & Washburn, 2011; Greve, 2008). Established firms typically engage in problemistic search, looking for solutions within the familiar territory of their current business operations (Joseph & Gaba, 2020), which is unlikely to result in strategic change. Established firms are theorized to search for new opportunities i.e., increase attention strategic change, when faced with a threat of firm survival (March & Shapira, 1991; Posen *et al*, 2018; Ref, Hu, Milyavsky, Feldman & Shapira, 2024).

Cyert and March (1963) and March and Simon (1958) theorize that performance shortfalls trigger solution search in the vicinity of the problem area. When firms face a performance shortfall, they engage in problemistic, local search that does not lead to strategic change. Jung and Lee (2016: 1729) explain this tendency towards local search by noting that firms typically explore knowledge they are already familiar with (Fleming, 2001), or closely related to their existing expertise (Katila & Ahuja, 2002), or capabilities (Rosenkopf & Nerkar, 2001). Reliance on local search has led problemistic search to be theorized as path-dependent (Ahuja & Katila, 2004; Cyert & March, 1963; Rhee & Kim, 2015), often resulting in improvements to existing organizational activities (March, 1991).

However, recent research on search processes even in established firms suggests that search, including problemistic search, might be less local and more oriented towards strategic change than previously theorized (e.g. Baumann & Siggelkow, 2013; Psen & Chen, 2015; Greve, 2015). Billinger, Stieglitz, & Schumacher's (2014) laboratory experiment examining individual search behavior is particularly useful in applying BTOF to founder attention as a response of performance feedback. The authors found that individuals "were prone to over-exploration, since they broke off the search for local improvements too early" (Bellinger *et al*, 2014).

In the context of new ventures, Agarwal et al. (2017) emphasize that experimentation is a "consistent and reoccurring feature" in the process of entrepreneurial response to new information and knowledge. For entrepreneurs, strategic change may not necessarily stem from competitors' innovations but are often driven by insights gained during the commercialization of their initial ideas (e.g., Hargadon & Douglas, 2001; Maggitti, Smith, & Katila, 2013). A notable example is Stewart Butterfield, who, along with his team, developed the online video game "Game Neverending" in 2002. Although the game failed to gain traction, the tools they created

for its design led to the creation of Flickr, the first popular photo-sharing website on the web, which Yahoo purchased in 2005 for a reported $35 million. Butterfield tried his hand at another online game, "Glitch," four years later, but it also flopped. However, the internal messaging system they developed to collaborate on the project became the foundation for Slack (The Economist, 2016; Kirtley & O'Mahoney, 2022).

In sum, the theorized "over-exploration" of individual managers during problemistic search (Billinger *et al*, 2014) combined with high entrepreneurial propensity to search for new opportunities and strategic change in response to negative feedback (Grimes, 2018), leads us to hypothesize that:

> ***Hypothesis 1:*** *Performance below revenue aspirations positively influences founder attention to strategic change*

Slack Resources and Founder Attention to Strategic Change

Organizational slack refers to the buffer of available or potential resources that enables an organization to search for new opportunities and increase attention to strategic change; potentially leading to higher success in executing change (Bourgeois, 1981). Different forms of slack can be differentiated along two dimensions – Fungibility and Availability (Mount, Ertug, Kavusan, George & Zou, 2024).

Availability refers to the ease with which a resource can be accessed and retrieved, depending on whether it is embedded in the firm's operations or exists outside the organization (Bourgeois & Singh, 1983). Fungibility, on the other hand, describes the flexibility with which a resource can be allocated to diverse activities (Mishina et al., 2004: 1183). For example, labor slack has high availability but low fungibility. Similarly, invested capital slack has low

availability but high fungibility. Financial slack in the form of money in the bank falls into the category of highly fungible and available slack – and thus is more likely to increase managerial attention to new opportunities and strategic change as opposed to other forms of slack.

Furthermore, slack search (Chen & Miller, 2007; Cyert & March, 1963)—either begins or persists when performance exceeds aspirations. Problemistic search is specifically triggered by a particular issue and focuses on addressing that problem, often in a somewhat exploitative manner. Slack search occurs independently of immediate problems and is typically more exploratory than problemistic search (Posen *et al.*, 2018). For example, Chen and Miller's (2007) study of US publicly listed companies theorizes and demonstrates that firms' intensity of R&D spending (an indicator of managerial attention to strategic change) increases with firms' slack resources. Thus, examining founder attention with the availability of financial slack, we hypothesize that:

> ***Hypothesis 2:*** *Performance above slack aspirations positively influence founder attention to strategic change*

Multiple goals and Founder Attention to Strategic Change

As noted in the development of hypotheses 1 and 2, both revenue performance below aspirations and slack performance above aspirations individually and positively influence founder attention to strategic change. However, when revenue performance falls below aspirations in the presence of high slack resources (i.e. where slack performance exceeds aspirations), managers may become less responsive to poor revenue performance (Cyert & March, 1963). Financial slack, in particular, can act as a cushion against unexpected challenges (Levinthal & March, 1981;

Milliken & Lant, 1991), potentially delaying the recognition of issues or reducing the urgency with which organizations respond to significant performance shortfalls (Posen *et al.*, 2018).

Further, ambiguity in performance evaluation encourages self-serving responses to feedback that can emerge from factors such as inconsistent aspiration levels (Joseph and Gaba, 2015). A significant source of ambiguity arises from having multiple goals. When performance exceeds aspirations on slack goals and falls below aspirations on revenue goals, the potential for founders to craft defensible, optimistic interpretations increases, often by prioritizing slack goals (where performance exceeds aspirations), while downplaying revenue performance shortfalls (Audia and Brion, 2007). Founders are more likely to prioritize slack goals since slack of money in the bank can more directly be linked to short term venture survival than revenue performance, thus increasing myopia and decreasing founder attention to strategic change. Hene, we hypothesize that:

Hypothesis 3: Slack performance above aspirations moderate the relationship between revenue performance below aspirations and founder attention to strategic change

METHODS

Research Setting

An Indian content creation, digital marketing, and brand consulting startup, '*DaVinci*', served as the site for data collection. The firm was established on 24th May 2016 under the brand name '*DaVinci Studios*' as a content creation agency; primarily creating motion graphics, live action (animated and real-world footage respectively), and creative stills. All creatives were designed for the purpose of advertising on digital media platforms for client brands. In 2016, *DaVinci* was not involved in social media advertising for their clients. Rather, they would send across the

completed creatives to client marketing teams, who would then either execute the advertising campaign internally or utilize a specialist advertising or digital marketing firm for the campaign.

To minimize potential disruption from data collection activities and to protect employee privacy and firm and client confidentiality, I agreed to the following: (1) collect email data collection limited to the founder's email communications, (2) convert identifying information such as email addresses into hashed (irreversibly encrypted) identifiers, and (3) clear any firm, client, or employee identifying data from revenue receipts, bank statements, as well as any other documents collected or interviews conducted.

I collected data starting from first establishment (May 216) until January 2022. I worked with HR and IT to gain access to the firm's shared drives which contain: (1) human resource, employment and salary data to identify weekly additions and exits of employee ; (2) client pitch decks, creatives and deliverables as well as notes from client meetings (3) extract of all founder email data since firm establishment, including outgoing and incoming emails, and calendar invites, and (4) monthly bank statements listing each debit and credit transaction. Taken together, these data provided a rare, unobtrusive window into founder communication and financial performance since startup establishment.

During the early days of the startup, *DaVinci's* founder considered motion graphics and 3-D animation as the firm's core expertise and ventured into animated short form content creation for television and internet consumption (YouTube etc). Thus, towards the end of 2016, *DaVinci* envisioned itself as an animation studio in addition to a content creation agency and embarked on two projects: one animated episodic series and one short animated movie. Technological progress and reducing consumer attention spans had decreased startup barriers to entry in the animation studio industry by 2016 (McKinsey, 2016).

DaVinci soon realized that they needed much more than creative content creation expertise to succeed as an animation studio – project managers, studio creative talent such as Director of Photography, talent for background sound effects, music etc. As *Davinci* hire talent, their cost per minute for animation kept increasing. By mid-2017, *DaVinci*'*s* founder found studio operations *"to be expensive and time consuming, [with] low accountability between team members" (founder interview, September 2017)*, and decided to cease the startup's studio related activities, but retained the brand name 'DaVinci Studios'.

During the same time (mid-2017), *DaVinci* was struggling with consistent revenue generation. Their creative projects for clients were one-time engagements with pre-determined end or delivery dates. Re-engaging with the same client often involved pitching for the next project and competing with other firms on a client issued 'request for proposal'.

Looking to enhance long term repetitive engagements, *DaVinci's* founder expanded firm operations to include brand consulting services – which involved activities such as helping clients craft brand identities and create and execute campaigns across digital media platforms. Campaign execution itself includes evaluating the performance of a campaign through metrics such as returns on advertising spending (RoAS). The launch of brand consulting services enabled *DaVinci* to take on longer term retainer projects which were renewable post completion, since clients always need to have marketing campaigns across multiple digital media platforms. By October 2017, DaVinci launched their spin off brand '*DaVinci Digital*', dedicated to brand consulting services while *DaVinci Studios* continued to work on content creation.

Penetration of internet usage grew from ~15% of the Indian population in 2015 to 30% by 2019 (and 46.3% by 2021; Statista, 2023). In the backdrop of growth in internet users, the digital marketing industry in India also experienced exponential growth; from a market size of

INR 62.28 Bn in 2016 to 108.59 bn by 2019 and 213.53 bn by 2021. Capitalizing on this environmental trend, *DaVinci Digital* expanded to offering digital marketing services by March 2018. The addition of digital marketing services led to brand consulting and digital marketing services comprising ~50% of *DaVinci's* revenues by September 2019, with content creation contribution shrinking to ~50% (from 95% in 2017).

Continuing revenue and profitability growth from *DaVinci Digital* prompted the launch of a new performance metric focused, mathematically drive digital marketing services brand, "*Einstein*" in March 2020. By October 2021, the end of the data collection period for this study, operations under the brands *DaVinci Studios* and *DaVinci Digital* had ceased, with *DaVinci* focusing primarily on digital marketing services under the brand *Einstein*.

An overview of DaVinci's key milestones (both failed and successful) are represented in Figure 1.1.

*** Insert figure 1.1 about here***

Data Structure and Variables

Dependent Variable. One of the key empirical challenges of this study is to measure the dependent variable: weekly founder attention to strategic change. Constructing a direct measure of attention is challenging, particularly in studies with longitudinal and cross-sectional data (Rhee, 2024b). Thus, researchers have increasingly relied on textual data analysis as an alternative method. Textual data analysis offers a standardized way to assess attention over time while eliminating retrospective bias.

Furr, Cavarretta and Garg (2012) define entrepreneurial strategic change as additions or exits to the products or service a firm provides, the markets it serves or technologies that it

deploys. Following Furr, Cavarretta and Garg (2012), I measure founder attention to strategic change as additions or exits of *topics* regarding the startup's products, markets and technologies as reflected in the internal organizational email communication of the founder. Email communication serves as important records of exchanges regarding firm strategic changes. While prior research shows that most communication of topics with higher order importance is face-to-face, emails sent to a small number of recipients and face-to-face communication have been demonstrated to be highly correlated (Kleinbaum et al. 2008).

To measure founder attention to additions and exits of topics related to firm products, markets and technologies, I analyze founder emails using topic modeling. Topic modelling a sophisticated text mining technique based on natural language processing and artificial intelligence (Blei, Ng, & Jordan, 2003). This technique identifies latent "topics" within a collection of documents (for us, emails) and capture the distribution of all the topics present in the documents over time (Corritore et al., 2020). The distribution of topics over time allows for examining the weeks when a specific topic first and last appeared in the email communication; thus, tracing the addition and exit of topics over time. Before the topic modelling, I undertook the data cleaning steps outlined below.

First, I analyze only internal emails since discussions of internal strategy typically does not involve inclusion of outside personnel. Thus, analyzing internal email communication only reduces noise. External communication as well, which contain discussions of client and vendor deliverables, payments and invoices, and sales generation related emails, not relevant to firm strategic change.

Second, I excluded repetitive or irrelevant emails. These included calendar invites (unless they were regarding strategy/ brainstorming meetings), out of office emails, and regular internal communication about work policies, holidays, personal days etc.

Third, I pre-processed the data using the following steps: (1) Eliminated the most common stop words in the English language using the standard English language stopword list from Natural Language toolkit (NLTK) python library. I also used the R and Python inbuilt libraries for stop word removal. eliminating high frequency words occurring in the dataset which are specific to email conversations but meaningless for topic modelling; for example, thanks, regards etc.

Topic modelling and natural language processing more generally remove non-English words – however the informal nature of email communication, presence of inter-organizational jargon relevant to firm strategies, and new activities may all be expressed in ways that do not conform to the English language. For example, DaVinci launched a brand monikered *Einstein* as part of an ongoing pivot in 2019 – this would be eliminated if we removed non-English words. This also allowed the analysis to retain proper nouns (names) thus ensuring we capture discussions about key people in the organization being hired, exiting etc. Using this information, I can define timeframes where specific activities were more relevant to the firm than others. For example, the exit of the firm's Creative Head in 2019 cemented their intent to pivot from animation and creative stills development to digital marketing.

Fourth, I stemmed and lemmatized data. Stemming reduces words to their base form (for example, designs, designing, designer will all be reduced to design). Stemming was done with the most commonly used algorithm, the 'Porter Stemmer algorithm' (Porter, 1980). Lemmatization refers to interpreting a words' contextual meaning within its paragraph/

document so that differing words with the same intended meaning are combined into the most commonly used word. I did this using 'spaCy' for Python, and it corrects for errors of omissions from stemming.

Finally, I collated data into 'documents' where each set of emails represents one document for the topic modelling algorithm – which traces the topics across documents. Here, one documents represents one week of data, thus my topic model captures topic distribution over weeks. Once preprocessing was completed, I trained the LDA model on my dataset. This requires hyperparameter (HP) tuning and determining the optimal number of topics in the email dataset, followed by the actual LDA analysis.

To arrive at the total number of unique topics in the dataset, I compute the 'coherence score' and 'Hellinger differences' of the topic modelling results. Coherence score is a measure of the semantic similarity between words within a topic. A higher score implies that topics are individually coherent in terms of the word distribution within them. Hellinger differences measure the similarity of different topics that are generated in a document (as opposed to words within a topic as above). Here, a high score means that topics are unique relative to each other and the aim is to maximize this score as well without introducing too many topics. Optimizing for the Coherence score and Hellinger Differences, I determined the optimal number of topics over 289 weeks to be 225.

Utilizing my own experiences from engaging with the firm since 2018 in a data collection capacity (regular interviews, attending internal meetings etc), I categorized the 225 topics into 4 categories – those related to products, markets, technologies, and neither of the above. The last category contains topics that do not represent founder attention to strategic change, while the first three categories, together, contain topics that represent founder attention to strategic change.

In all, of the 225 topics, 71 were identified to represent founder attention to products, markets and technologies.

I identified the first week (i.e. document) that the topic occurred and marked each week to be the day the topic was 'added' to the pool of information attended to by the founder. Similarly, I identified the last week of a topic's presence in the email corpus as an indication of that topic 'exiting' the pool of information attended to by the founder. Of the 71 topics related to firm products, markets or strategies, the analysis revealed that 37 topics exited founder attention, leading to a total of 108 topics that were added and exited from the founder's attention pool over the course of the study. Topic additions and exits per week, by product, market and technology, are represented in Figure 1.2.

*** Insert figure 1.2 about here***

I cut off data for the first 21 weeks of the organization's establishment and the last 20 weeks of the data collection timeline. All topics in the beginning were new and towards the end, many topics started exiting due to the data terminating. Thus, even though I collected data over 309 weeks from October 2016 to March 2022; I analyze emails from December 2016 until December 2021 for a total of 268 weeks. Figure 1.3 represents word clouds for a sample of 6 topics generated by the topic model.

*** Insert figure 1.3 about here***

Independent Variables. The independent variable for H1 is *revenue performance below aspirations*. Here I calculate the firm's revenue performance aspirations gap as the difference between revenue performance in week t and revenue aspirations in week t. Consistent with prior research (Greve, 2008; Joseph & Gaba, 2015), I calculate revenue aspirations as revenue

performance in week t-1. Some prior research calculates aspirations as a weighed average of 3-4 period of prior performance, but one week lag on performance provided for best model fits (Bromiley, 1991). The variable is splined to measure separate effects of revenue performance above and below aspirations on founder attention to strategic change.

Prior BTOF research also considers peer performance as a separate aspiration level on a specific goal dimension. Cyert and March (1963) note that aspirations are a function of prior aspirations, performance and performance of comparable others. However, in the case of startups in relatively nascent industries, lack of competitor and industry performance histories result an inability to form a base of comparable peers (Cohen, Bingham, & Hallen, 2019).

The independent variable for H2 is slack performance above aspirations. Here I calculate the firm's the slack performance aspirations gap as the difference between slack performance in week t and slack aspirations in week t. Consistent with prior research (Greve, 2008; Joseph & Gaba, 2015), I calculate revenue aspirations as revenue performance in week t-1. Similar to above, the variable is splined to measure separate effects of slack performance above and below aspirations on founder attention to strategic change.

The independent variable for H3 is an interaction term between revenue performance below aspirations (IV for H1) and slack performance above aspirations (IV for H2). This variable is also splined to measure four separate effects: performance above revenue and slack, performance above revenue but below slack, performance below revenue but above slack, and performance below revenue and slack.

Control Variables. First, I include Covid as an indicator of environmental turbulence, which is theorized to increase entrepreneurial search for new opportunities (Berends, Nurg &

Garud, 2021; Kirtley and O'Mahony, 2020). Environmental turbulence is a count variable reflecting 1 when the effects of Covid were strong in India and 0 otherwise. Second, we control for the number of weekly revenue transactions, as a measure of sales frequency. Third, we control for number of employees as a proxy for firm size. Fourth, we control for market size. Finally, we control for the total number of topics and emails in a week proxies for founder attentional load; since high attentional load can reduce attention to new opportunities.

RESULTS

Table 1.1 reports descriptive statistics and correlations for variables in our Poisson regression model.

*** Insert Tables 1.1 and 1.2 about here***

Table 1.2 shows Poisson regression results including control variables. Consistent with H1, I find that performance below revenue aspirations has a positive and significant effect on founder attention to strategic change ($b <= -0.001$, $p<0.001$). Since the independent variable, performance below revenue aspirations, is negative; the negative sign on the co-efficient represents an increase in founder attention to strategic change.

Consistent with H2, performance above slack aspirations has a positive and significant effect on founder attention to strategic change ($b <= 0.001$, $p<0.001$. The actual effect size is less than a 1% increase in expected count of the DV for a 1 unit increase in the IV.

Finaly, and consistent with H3, Slack performance above aspirations moderates the relationship between revenue performance below aspirations and founder attention to strategic change ($b <= -0.001$, $p<0.001$). Since the independent interaction variable is negative; the negative sign on the co-efficient represents an increase in founder attention to strategic change.

The actual effect size is less than a 1% decrease in expected count of the DV for a 1 unit increase in the IV. Such a small effect size is to be expected since the maximum value of the DV in the data set is 10, while the IV ranges into millions (plot represented in figure 1.4)

*** Insert Figure 1.4 about here***

DISCUSSION AND CONCLUSION

This paper builds on a rich body of literature examining the effects of performance across multiple goals on managerial attention and behavior in established firms (Cyert & March, 1963, March & Simon, 1958; Ocasio, 1997), and extends it to the field of entrepreneurship and founder attention (Bromiley & Rau, 2019; Rhee, 2024b). I examine the frequent but understudied phenomena of the antecedents of new venture strategic change post market entry. Within the field of BTO, this paper addresses the growing but understudied question of how multiple goals interact to influence managerial attention to strategic change.

I find that founder attention to strategic change increases when revenue performance falls below aspirations. However, consistent with the theory for established firms, founder attention to strategic change also increases when slack resources exceed slack aspirations since unlike established firms, startup founders seek to allocate slack resources to exploring innovation, I also find that performance above slack aspirations moderates the negative effect of low revenue aspirations on founder attention to strategic change.

The effect sizes are not large. This is to be expected since the IVs are continuous variables ranging in millions while the maximum value of the count DV is 10. Two of the control variables show results meriting discussion. The effect of environmental turbulence is strong, with

a predicted increase of the DV by 7% during the period of high turbulence (measured as the weeks during which the covid pandemic was a significant threat in India).

Further, and as expected, employee count (a proxy for firm growth) shows a significant decrease in founder attention to strategic change. Finally, and most importantly, both proxies for founder attentional load (total number of weekly emails, and total number of topics per week across emails) significantly reduced founder attention to strategic change. This merits further research on the effect of factors such as managerial attentional load and vigilance on founder attention (Rhee, 2024b).

This study offers several key contributions. First, it advances our understanding of what drives founder attention to strategic change in the post-commercialization phase of entrepreneurship, addressing a gap in research that has primarily focused on change decisions before commercialization (e.g., Kirtley & O'Mahoney, 2023). By exploring the factors that influence strategic change after a venture has been commercialized, this paper enriches the literature on entrepreneurial behavior and the dynamics of business strategic change. Specifically, by measuring CEO attention, the study deepens our theoretical understanding of how firm performance and environmental turbulence shape founders' focus on exploring new opportunities for strategic change (Ocasio, 1997; 2011; Gaba & Greve, 2019).

Unlike most prior research that models strategic change based on performance relative to a single goal or aspiration level (Posen et al., 2018), this study draws on the Behavioral Theory of the Firm (BTOF) to examine how performance across multiple goals influences decision-makers' attention to strategic change (Cyert & March, 1963; Audia & Greve, 2021; Yang, Goudsmit & Shinkle, 2022). The study empirically demonstrates the significant role that

performance across multiple objectives plays in directing founder attention to strategic change, thereby contributing to BTOF.

Second, this research extends the application of BTOF to entrepreneurial firms. It shows that, similar to established firms, founders are more likely to focus on strategic change when performance falls below revenue aspirations. However, unlike established firms, higher-than-expected performance relative to slack resources also prompts increased attention to strategic change among founders.

Finally, the study tests and confirms that exogenous shocks increase founder attention to strategic change, while firm size and founder attentional load decrease attention to strategic change – proposing new areas of work into understanding the role of attentional load and vigilance on managerial attention.

Figure 1.1, Timeline of Major Events

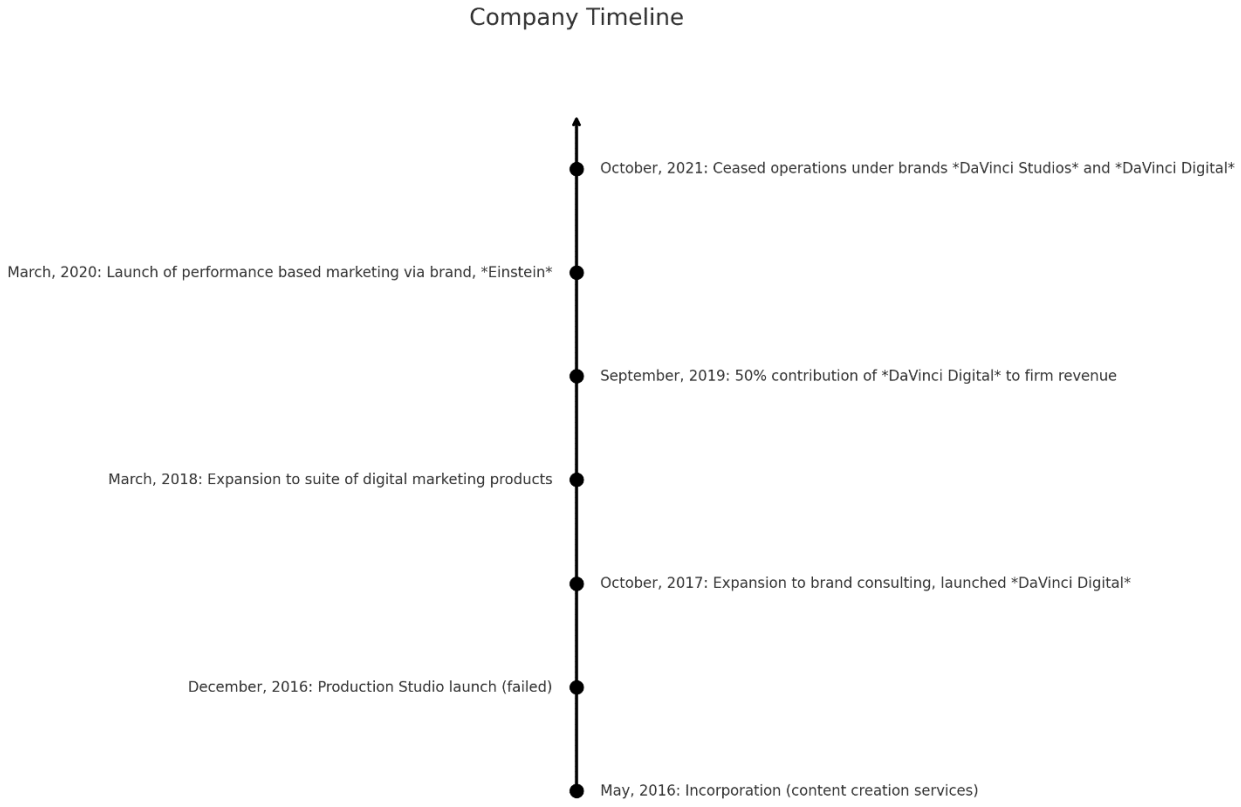


Figure 1.2, Founder attention to strategic change

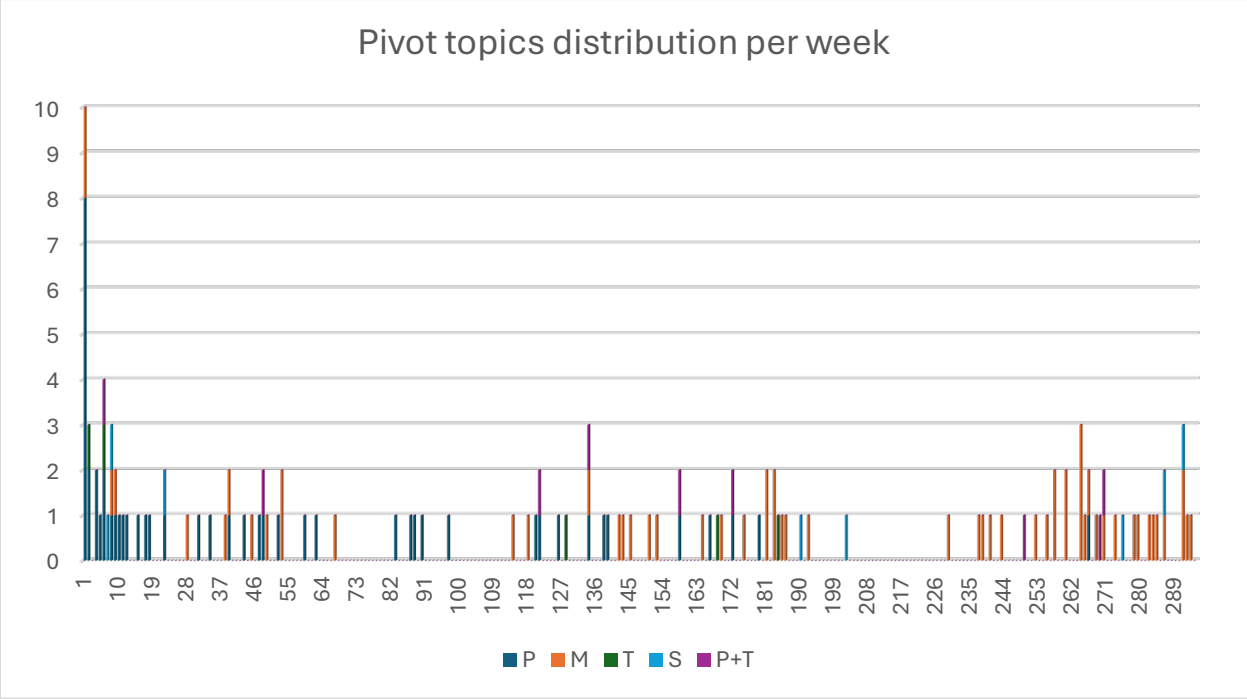


Figure 1.3, Sample topic word clouds

Table 1.1. Descriptive Statistics and correlation table

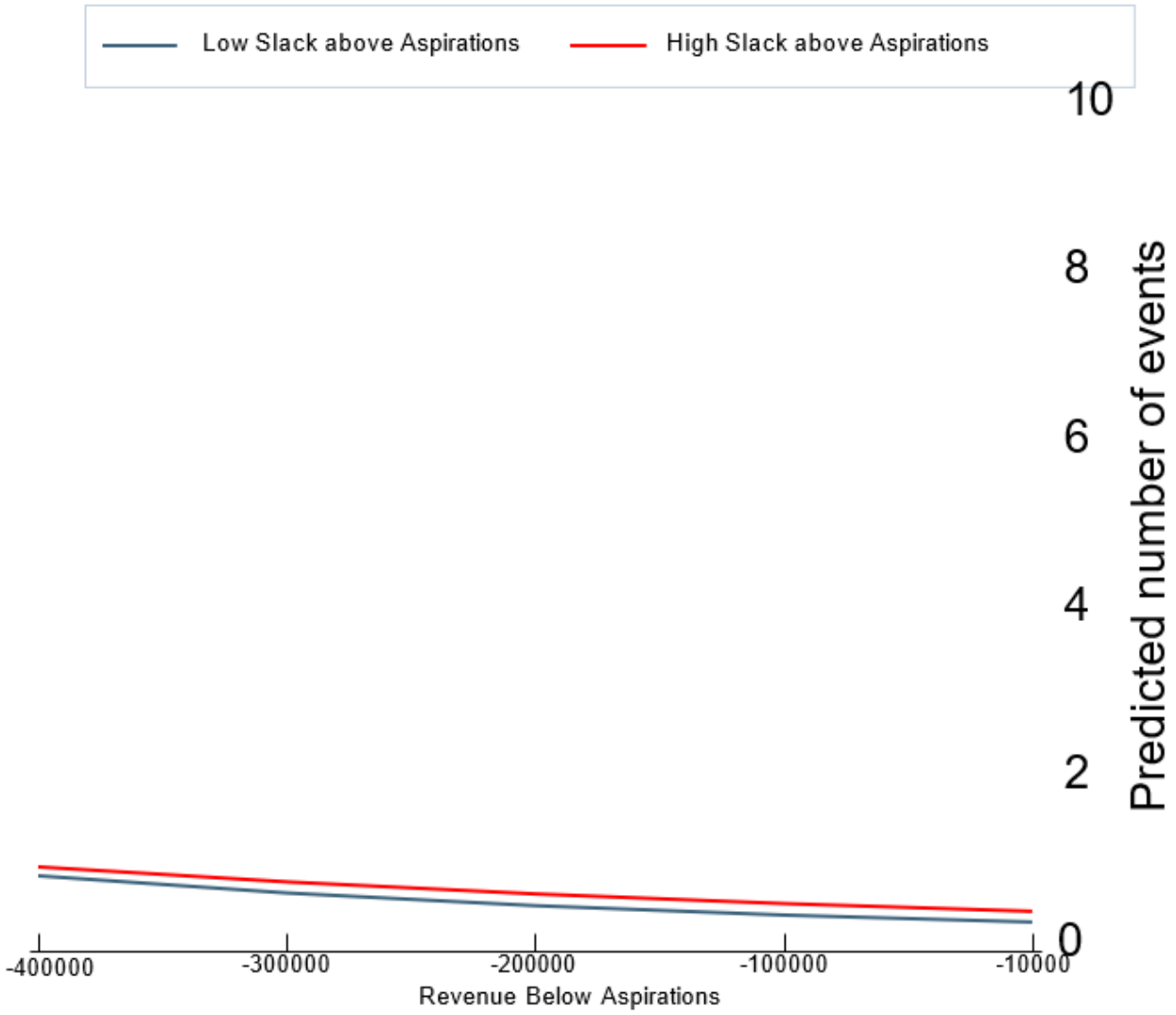
	Variables	N	Mean	Std. Dev	Min	Max	1	2	3	4	5	6	7	8	9	10
1	Attention_To_Pivots	294	0.44	0.87	0	10										
2	Performance Above Revenue Asp	288	88411.73	193102.10	0	1865005	-0.03									
3	Performance Below Revenue Asp	316	-80096.96	187724.20	-1962805	0	-0.07	***0.22								
4	Performance Above Slack Asp	285	80374.24	175001.50	0	1506589	0.16	*-0.13	***-0.63							
5	Performance Below Slack Asp	316	-70303.22	110331.30	-646288	0	0.04	***-0.16	**-0.17	***0.33						
6	Environemntal_Turbulance	316	0.25	0.43	0	1	0.01	0.06	*-0.06	0.00	***-0.11					
7	Weekly_Revenue_Count	289	2.80	2.78	0	18	-0.10	-0.08	***-0.37	0.17	-0.04	***0.40				
8	Emplyoee_Count	314	23.44	13.98	3	52	-0.12	**0.12	-0.11	0.07	-0.12	***0.63	***0.43			
9	Email_Count	294	55.51	45.45	2	307	*-0.12	-0.02	*0.09	***0.10	*0.14	*-0.14	*-0.15	*-0.03		
10	Topic_Count	294	22.94	7.49	0	50	***0.15	0.00	-0.06	0.19	0.00	0.05	0.03	0.04	***-0.21	
11	Market Size	316	254.10	144.65	92	571	-0.10	***0.17	-0.16	0.12	-0.21	***0.58	***0.51	***0.87	-0.17	0.07

Table 1.2. Poisson Regression Results

Variable	Model (1)
Performance Above Revenue Asp	0.001
	(1.032)
Performance Below Revenue Asp	***-0.001
	(9.293)
Performance Above Slack Asp	***0.001
	(2.836)
Performance Below Slack Asp	0.001
	(1.376)
Performance above revenue * Performance above slack	0.001
	(7.662)
Performance above revenue * Performance below slack	0.001
	(5.042)
Performance below revenue * Performance above slack	**0.001
	(1.762)
Performance below revenue * Performance below slack	0.001
	(7.312)
Environemental_Turbulence	***1.070
	(0.318)
Weekly_Revenue_Count	***-0.189
	(0.061)
Employee_Count	-0.280
	(0.020)
Email_Count	-0.006
	(0.003)
Topic_Count	0.021
	(0.013)
Market Size	0.002
	(0.002)
Observations	268
Adjusted R-squared	0.128

***p<0.001, **p<0.01, *p<0.05. Robust standard errors in parentheses.

Figure 1.4, Plot (H3); founder attention to strategic change



Chapter 2

INDIVIDUALS VS ORGANIZATIONS: INFORMATION PROCESSING DIFFERENCES IN SETTING ASPIRATIONS

ABSTRACT

Whether individuals and organizations differ in the attention rules they use to set aspirations is a distinction acknowledged but largely ignored in prior empirical research. To better understand the differences, we examine the models that distinguish individual from organizationally derived aspiration levels and argue that the information aggregation process in organizations results in the use of simpler implicit models than for individuals in determining the inputs to aspirations. We find support for our theory using actual aspirations and performance data gathered from the Harvard Business School Publishing's Back Bay Battery simulation with MBA students and teams. Using AIC and BIC statistics, we estimate and compare, across individuals and organizations, the original aspiration formulation proposed by Cyert and March (1963) with four other models prominent in the literature. We then extend the original aspirations model to examine how a threat of bankruptcy along with the traditionally considered factors influence aspirations levels in both individual and organizational decision-making. We contribute to the Behavioral Theory of the Firm and to theories of organization design by offering new insights into the cognitive underpinning associated with individual vs. organizational attention rules.

Keywords: *aspirations, attention, behavioral theory of the firm, decision-making structures, information processing*

INTRODUCTION

Grounded in the behavioral theory of the firm (BTOF; Cyert & March, 1963), a growing body of research examines the role of aspirations in decision making (Bromiley, 1991; Greve, 2003a; Bromiley, 2009; Shinkle, 2012). Researchers use the concept of aspirations, which Cyert and March (1963) refers to as goals or objectives, to explain how organizations assess performance (March & Simon, 1958; Cyert & March, 1963). Decision makers compare their performance along an important dimension to an aspiration level (attainment discrepancy) and thus simplify performance evaluations by transforming a continuous measure of performance into a discrete measure of success or failure (March & Simon, 1958; Cyert & March, 1963). Cyert & March (1963) propose that aspiration levels depend on prior aspirations, performance, and peer performance and a variety of studies have examined the factors regulating the relative weighting of these inputs—referred to as attention rules—including environmental volatility (Berchicci & Tarakci, 2022), government policy (Shinkle et al., 2021), industry and organizational age (Blettner et al., 2015; Aranda et al., 2017), external and internal social comparison (Hu et al., 2017), and locus of decision making (Berchicci & Tarakci, 2022, Gaba & Joseph, 2023).

Despite this body of work, research largely overlooks a subtle distinction in the literature concerning setting aspirations: differences between individual and organizational attention rules. Research guided by the Carnegie perspective has long recognized the role of the organization in problem solving and decision making and how an organizational context shapes individual behavior (Levinthal & Newark, 2023). Although most theorizing in the Carnegie perspective tends to be organizationally oriented, individual-level analysis is playing a greater role. An emphasis on individual accounts is helping researchers expand BTOF and increase the explanatory power of their models (e.g., Boyle & Shapira, 2012; Gaba, Lee, Meyer-Doyle, &

Zhao-Ding, 2023; Audia & Brion, 2023). However, these streams are pursued independently, without sufficient recognition that the way in which aspirations are influenced by individuals may differ from those generated by individuals in an organizational context.

Foundational work was unclear on this point. March and Simon's *Organizations* (1958, p. 203 in second edition, 1993) assumes individual and organizational aspirations reflect attention to similar inputs: "generalizations that have been found to hold for individual aspiration levels will continue to hold in the area of organizational behavior". Cyert and March's BTOF (1963) addresses strictly organizational level phenomena (Cyert & March, 1963, p. 123) but rests on March and Simon's (1958) theorizing. Although a few studies since have modelled aspirations and their effect on behavior at the individual level (e.g., Boyle & Shapira, 2012; Di Lorenzo & Almeida, 2017; Kostopoulos, Syrigos, & Kuusela, 2023), most studies model aspirations at the organizational level (cf. Shinkle, 2012; Joseph & Gaba, 2020). This points to the need for a more nuanced understanding of the difference between individual and organizational attention rules and aspiration formation, the subject of our study. An organization in this study is represented by a group of individuals aggregating information and integrating effort toward a common goal, consistent with a variety of definitions of organizations (e.g., Puranam, 2018).

Our primary thesis is that the aggregation of information in organizations results in the use of simpler implicit models than those of individuals and a focus on fewer inputs when determining aspirations. Empirically, we test this proposition using actual aspirations and performance data gathered from a simulation using MBA students and teams. Researchers have used simulations involving decision makers to study a range of learning and decision-making outcomes (Dutton, 1988; Boies et al., 2011; Gary et al., 2017), and simulations have a long

history in BTOF. For example, Lant (1992) used data from a simulation with MBA students in one of the first empirical efforts to estimate aspiration models. In addition, we use AIC and BIC statistics to compare, across individuals and organizations, the original aspiration formulation proposed by Cyert and March (1963) with the Weighted average model (Greve, 2003a), Switching model (Bromiley, 1991), and the Separate model (Greve, 1998, 2003b; Harris & Bromiley, 2007), all prominent in the literature.

Our results show that individuals use more inputs than groups, suggesting a simplification of the implicit model being used in determining aspirations. The results hold when adding threat of bankruptcy as a fourth input. Further, the Cyert and March model shows the best model fits for individuals. For groups, however, both the Cyert and March, Weighted average, and Separate models have roughly equivalent fits while the switching model has poorest fit. Thus, when groups set aspirations, lack of actual aspiration data can be compensated for by using the Weighted average or Separate models.

Our study contributes to the BTOF literature by addressing how individuals and organizations differ in shaping aspirations, a distinction largely ignored in prior empirical research (Shinkle et al., 2012). By unpacking the models that distinguish individual from organizationally derived attention rules, we expand our theoretical understanding of how individuals may uniquely contribute to empirical regularities associated with setting aspirations and offer new insights into the cognitive underpinnings associated with aspiration adaptation, an area for which Carnegie scholars have called for more research (Posen et al., 2018). Moreover, our use of a direct aspiration measure enables comparison of different functional models to test which ones offer the best fit indices (Bromiley & Harris, 2014). Prior studies employ alternative assumptions about decision-making structures and the role of information processing in shaping

attention to aspiration-levels, because, with a few exceptions (e.g., Bromiley, 1986a; 1986b; Lant, 1992; Mezias et al., 2002; Washburn & Bromiley, 2012; Blettner, Hu & Bettis, 2015; Aranda et al., 2017; Berchicci & Tarakci, 2022), almost all lack direct measures of aspirations and use proxy measures instead. Moreover, only a few prior studies using actual aspirations data compare the different aspiration models used in the literature (e.g., Bromiley & Harris, 2014). For example, Blettner et al. (2015), Aranda et al. (2017), and Berchicci and Tarakci (2022) use actual aspirations data to model aspirations, but, with the exception of Washburn and Bromiley (2012), none compare the different models, and none estimate differences in aspiration adaptation between individuals and organizations.

We also contribute to the literature on information processing and organization design (cf. Puranam, 2018; Joseph & Gaba, 2020). While prior empirical work studies how organizational structure influences responses to attainment discrepancy (Vissa et al., 2010; Gaba & Joseph, 2013, Joseph et al., 2016; Rhee, Ocasio & Kim, 2019) and vice versa (Sengul & Obloj, 2017), and modelers now examine various decision-making structures in estimating performance outcomes (Csaszar & Eggers, 2013),
few studies compare individual information processing with organizational information processing. In doing so we provide further insights into not only *whether* organizations and individuals differ concerning aspiration formation, but also *how* they differ.

INFORMATION AGGREGATION AND ASPIRATION ADAPTATION

The literature on aspiration adaptation derives primarily from the *Behavioral Theory of the Firm* (Cyert & March, 1963). Drawing on the concepts of organizational aspirations and adaptation initially advanced by March and Simon (1958), Cyert and March (1963) provides the most frequently cited aspirations model: aspirations are a simple linear function of prior

aspirations, prior performance and the performance of comparable organizations. These works inspired a research tradition based on organizations comparing performance to aspirations, which transforms a continuous performance measure into dichotomous outcomes. When performance exceeds the aspiration level, organizations favor the status quo over searching for ways to improve performance. But when performance falls below the aspiration level, organizations search in the area of the failure for ways to raise expected performance (Cyert & March, 1963). The comparison of performance to aspirations has been shown to affect a variety of firm behaviors including risk taking (Bromiley, 1991; Bromiley, Wiseman & Bromiley, 1996), organizational change (Joseph, Klingebiel & Wilson, 2016), search (Posen *et al.*, 2018), innovation (Greve, 2003a; Eggers & Kaul, 2018), research and development expending (R&D; Greve, 2003b; Chen, 2008; Chen & Miller, 2007), and new product introduction (Gaba & Joseph, 2013).

March and Simon's (1958) discussion of aspiration formation rests on prior insights from psychology on individual behavior (Hoppe, 1930; Frank, 1935; Lewin et al., 1944), and applies such aspiration levels to both individual and organizational-level decision making. Correspondingly much of this empirical research on aspirations assumes –implicitly – that attention rules in setting aspirations are the same across individuals and organizations (Shinkle, 2012). In making this assumption, these efforts largely ignore the latter's information aggregation process required for coordinating individuals to integrate their efforts to reach a collective decision (despite BTOF's emphasis on internal conflict). Our argument, which addresses this assumption, is that the aggregation process affects the underlying models setting

aspirations: individuals, may implicitly utilize more complex aspiration models than organizations.

To better understand what underlies such differences, we consider the aspiration model to be reflective of what Simon referred to as "simplified models": internal symbolic representations of the problem space or a particular aspect of the problem space (Simon, 1995) which direct attention to a few stimuli (i.e., inputs that influence aspirations). These simplified models reflect features of *individuals'* limited attention and simplified cognitive representations (see e.g. Gavetti & Levinthal, 2000; Csaszar, 2018) or heuristics (Gavetti et al., 2005). Decision makers bring these simplified models to the problems they identify, the feedback they receive, and the solutions they find (Gavetti & Levinthal, 2000; Gavetti, Levinthal & Rivkin, 2005; Simon, 1991). Hence, simplified models influence information processing (Carley, 1997; Gary & Wood, 2010) and have been shown to assist individuals in categorizing environmental signals, managing uncertainties, and focusing attention (Levinthal, 2011; Csaszar & Eggers, 2013; Eggers & Suh, 2019; Gaba, Meyer-Doyle, Lee & Zhao, 2019).

However, whereas individual decision making reflects an individual's simplified model, organizational decision making reflects shared models, which are the outcome of an aggregation process (Puranam, 2018). Information aggregation emerges from the interactions among individuals, and this social process reflects an effort to construct a shared model of the problem. Prior research has shown that different managers often perceive the same objective business environment differently (Barr et al., 1992; Bourgeois, 1985; Tripsas & Gavetti, 2000), requiring some effort to reach a consensus even when sharing the same goal. Social interactions activate certain pieces of information among organizational members and transform individual acts of

meaning construction into collective ones reflecting the cognitive process behind complex problem representation (Cszasar & Ostler, 2020).

Recent studies posit that individuals embedded in organizational decision-making structures aggregate information, leading to an implicit, common model of real-life situations which are more simplified than individuals' models (see, for instance, Maciejovsky et al., 2013; Csaszar & Eggers, 2013; Greve & Gaba, 2017; Gladstein & Reilly, 1985). That is, shared models in organizational decision making may result in considering fewer factors than an individual might. For example, Maciejovsky et al. (2013) demonstrate that teams achieve consensual decision making with "weaker, less specific performance feedback than individuals" (i.e., attending to fewer inputs than individuals.)

Two aspects to the aggregation process contribute to such an effect. First, simplified models are difficult to observe, existing in the mind of the individual and sometimes employing unarticulated features. Implicit decision-making models are a kind of tacit knowledge (Nonaka & Takeuchi, 1995; Polanyi, 1966; Szulanski, 1994); individuals using such models may be unaware of the model's details (Knight et al., 1999) making such details impossible to share. Tacit knowledge is often characterized by complexity and causal ambiguity, and as a result, the sender's ability to explain an intuitive understanding of a problem or situation is often incomplete (e.g., Attewell, 1992; Kogut & Zander, 1992). Put differently, being implicit makes simplified models hard to communicate with others; individuals can only share the parts of their implicit model that they are aware of and can clearly articulate within the available time for others to understand.

Second, groups tend to emphasize a subset of the information cues presented (Steiner, 1972; Wallace & Hinsz, 2019). Communication in groups tends to restrict rather than amplify the

range of data actively considered in decision making. As a result, information aggregation encourages shared attention on a few salient dimensions (Walsh, Henderson, & Deighton, 1988). Echoing these claims, Doise (1978) argues that the implicit model a group holds in common will emphasize those features on which the group members can agree. This narrows their attention to fewer dimensions relevant to the stimuli, which then dominate the group's perceptions. Employing a shared model can result in groups attending to different inputs or even ignoring inputs individuals attend to. Our argument is consistent with the groups literature which describes the general tendency that group behavior is often overly influenced by information the group members share (Kameda, Tindale, & Davis, 2003; Tindale & Kameda, 2000). This literature notes that when making decisions, groups tend to focus on information that all or most of the group members share at the expense of information held uniquely by few or only one member (Wittenbaum, Hubbell, & Zuckerman, 1999; cf. Lu, Yuan, & McLeod, 2012).

In sum, individuals may rely on more complex models while groups rely on simpler shared understandings and suggests the following proposition: *Individuals implicitly rely on aspiration models that consider performance, prior aspirations, and social comparison but groups rely on simpler models that consider a subset of these inputs*. To address this proposition, we look at statistical models that relate data available to individual and organizational decision-makers to the aspirations they set. However, the literature includes a variety of models of what determines aspirations. Consequently, we estimate the four different aspiration models commonly used in the literature. In what follows, we outline the alternate models prevalent in the aspiration adaptation literature, then we examine how variations in decision-making contexts influence aspirations. We also compare alternate models on fit indices

across individual and organizations decision making, to address which model best explains aspirations.

MODELS OF ASPIRATION ADAPTATION

According to Cyert and March (1963, p. 123), three variables influence the model of aspirations: firm prior values for aspirations, performance, and the performance of comparable organizations (social comparison). Formally, as written in Cyert and March (1963):

$$A_{i,t} = a_1 A_{i,t-1} + a_2 P_{i,t-1} + a_3 C_{i,t-1}. \quad (1)$$

Here $A_{i,t}$ denotes the aspirations of firm i, for time t. $A_{i,t-1}$, $P_{i,t-1}$, and $C_{i,t-1}$ denote (respectively) aspirations, performance, and social comparison in time period $t-1$. Cyert and March (1963) proposes that $a_1 + a_2 + a_3 = 1$. Cyert and March (1963) refers to organizational goals although subsequent researchers refer to these as aspiration levels. Behavior is then influenced by the difference between aspirations and performance.

Most aspiration models reference the formulation in equation 1 above. However, lacking direct measures, researchers typically use proxies for $A_{i,t}$, and they tend to test models that combine aspirations and performance into attainment discrepancy (see Bromiley, 1991; Wiseman & Bromiley, 1996; Blettner *et al*., 2015; Hu *et al*., 2017; Aranda *et al.,* 2017 for exceptions). These proxies for aspirations reflect different behavioral assumptions about managerial decision making (Bromiley & Harris, 2014). Some models combine prior aspirations and social comparison into one aspiration level and create one attainment discrepancy value (e.g., Greve, 2003a; 2008; 2019) while others treat prior aspirations and social comparison as separate aspiration levels creating two attainment discrepancy values (e.g., Greve, 2003b; Harris and Bromiley, 2007).

The few studies that estimate models using actual aspirations disagree on the inputs that most strongly influence aspirations. Using planning and outcome data from a bank's branches, Mezias *et al*. (2002) finds prior aspirations have the greatest influence. Using planning and outcome data from an automaker, Washburn and Bromiley (2012) finds attainment discrepancy has the greatest influence. Using aspirations data from a travel company, Aranda *et al*. (2017) finds performance influences aspirations.

Blettner *et al*. (2015) and Hu *et al*. (2017) use data from the German magazine industry and measure business unit aspirations as the number of magazines printed. Follow-up interviews with executives in several companies confirmed that, in this context, this was a reasonable proxy for aspirations. By directly estimating and extending the Cyert and March model, these studies enhance our understanding of aspiration adaptation but, with the exception of Washburn and Bromiley (2012), none of these studies directly compare different aspiration models using actual aspirations data.

We compare the Cyert and March model with the three most prominent alternate aspiration models cited in the literature (Bromiley & Harris, 2014; see Figure 2.1). First, Greve's (2003a) *weighted average model* that uses a weighted average of social comparison and prior aspirations (proxied by performance) to determine overall *weighted aspirations*. Second, the *separate* model – a variant of the weighted-average model – employs separate measures of social comparison and a proxy for prior aspirations (Greve, 1998, 2003b; Harris & Bromiley, 2007). Third, Bromiley's (1991) *switching* model sets aspirations equal to the social comparison aspiration level for firms with performance below social comparison, and slightly higher than own performance for those above average peer performance.

*** Insert Figure 2.1 about here ***

1. Weighted average model (e.g., Greve, 2003a) The weighted average model calculates a single measure of aspirations: a weighted average of social comparison and prior aspirations as proxied by prior performance. Social comparison is calculated as the average performance of all firms in the industry (excluding the focal firm), lagged by one year, which for firm i we denote by $(Social\_comparison)_{i,t-1}$. The measure of historical aspirations (HA; as prior aspirations are termed in this model) is calculated as an additive function of own prior aspirations and performance:

$$\mathrm{HA}_{i,t} = a_2 \mathrm{HA}_{i,t-1} + (1 - a_2) P_{i,t-1}. \quad (2)$$

In this equation, $\mathrm{HA}_{i,t}$ denotes firm i's aspirations in year t, $P_{i,t-1}$ is the firm's performance in year $t-1$, and a_2 is an empirically estimated parameter. Repeatedly substituting for past values of historical aspirations gives us HA as a function of prior year performance levels:

$$\mathrm{HA}_{i,t} = (1 - a_2) \sum_{s=0}^{\infty} a_2^s P_{i,t-1-s}. \quad (3)$$

Overall aspirations equal a weighted average of $(Social\_comparison)_{i,t-1}$ and $\mathrm{HA}_{i,t-1}$. Thus:

$$A_{i,t} = a_1 (Social\_comparison)_{i,t-1} + (1 - a_1)(1 - a_2) \sum_{s=0}^{\infty} a_2^s P_{i,t-1-s}. \quad (4)$$

Here $A_{i,t}$ represents overall aspirations, $(Social\_comparison)_{i,t-1}$ denotes social comparison in year $t-1$, and a_1 and a_2 are empirically estimated parameters. The values of a_1 and a_2 are nonnegative and sum to 1. Greve (2003a) estimates them via a grid search and uses the combination (viz., $a_1 = 0.8$ and $a_2 = 0.2$) that results in the highest maximum likelihood in the final modeling. A high value of a_1 means that average peer performance affects aspirations

much more than the firm's performance. A higher value of a_2 means that performance in $t-1$ has a substantially greater effect than performance in previous years. That is, ignoring $(1-a_1)+(1-a_2)$ which does not vary, the weight for $t-1$ (s=0) is $a_2^0=1$, the effect for $t-2$ (s=1) is $a_2^1=0.2$, but the effect for $t-3$ is $a_2^2=0.04$.

Finally, the model is splined to allow for performance above and below aspirations. This results in the model having four estimated parameters, not only a_1 and a_2 but also the parameters on attainment discrepancy above and below aspirations.

2. Separate model (e.g., Greve, 1998, 2003b; Harris & Bromiley, 2007). This model allows for social comparison and prior performance to have independent effects in influencing aspirations. With independent measures, researchers can observe separate influences of social comparison and prior aspirations in aspiration adaptation. This model, likewise, features four parameters: a_1 and a_2 (as in the weighted-average model) plus two additional parameters that reflect positive and negative effects of performance versus aspirations (Bromiley & Harris, 2014).

Greve (1998, 2003b) calculates prior performance as an exponentially weighted moving average of cumulative prior performance, while Harris and Bromiley (2007) create a proxy equaling prior year performance. Both calculate social comparison as average peer performance.

3. Switching model (e.g., Bromiley, 1991). In laying out a theory of aspiration adaptation, Cyert and March (1963, p. 123) argues that the attention a firm gives to its own performance versus social comparison depends on whether it has met prior aspirations (i.e., on the extent of attainment discrepancy). However, equation (1) does not accurately reflect this theoretical argument. The switching model captures this change in aspirations as a function of attainment discrepancy, arguing that "firms with performance above the industry would not be

satisfied with lower performance even if they performed above the industry average (i.e., average peer performance)" (Bromiley & Harris, 2014). In this view, aspirations are influenced by social comparison for firms performing below the average peer performance and by the firm's own performance when it surpasses social comparison (average peer performance):

$$\begin{aligned} A_{i,t} &= (Social\_comparison)_{i,t-1} && \text{if } P_{i,t-1} < (Social\_comparison)_{i,t-1} \\ &= a_1 P_{i,t-1} && \text{if } P_{i,t-1} \geq ((Social\_comparison)_{i,t-1} \end{aligned} \quad (5)$$

here $a_1 > 1$. Bromiley (1991) fixes this parameter at 1.05, noting that minor changes in a_1 do not affect empirical results.

All three models share several properties with the Cyert and March model. They all emphasize the importance of prior performance in influencing aspirations. In addition, they all incorporate social comparisons such as average peer performance (see e.g., Fiegenbaum & Thomas, 1988; Bromiley, 1991) assuming that comparison with relevant peers influences aspirations (Lewin et al., 1944).

However, the four models offer different functional expressions of the possible ways their assumptions about how firms update aspirations based on experience. The Cyert and March (1963) model is unique in explicitly incorporating both a prior aspiration level and a separate prior year performance variable. Only the switching model allows for different inputs to influence aspirations as a function of attainment discrepancy. These models also differ in their assumptions concerning managerial attention. Only the separate model assumes that managers have two distinct aspiration levels, which renders performance evaluation potentially inconsistent (Baum et al., 2005) or ambiguous (Joseph and Gaba, 2015). Signals of performance from multiple indicators may vary, and when they do, further confound the performance evaluation process. Consistent with Cyert and March (1963), the weighted-average model and

switching models assume boundedly rational decision makers "economize" their attention by creating a single value of a given performance dimension, reflecting an individual's capacity for establishing such a model. The switching model, unlike the other three models, suggests that attention switches from past comparisons with own performance to social comparisons. Less frequently cited passages in Cyert and March (1963, p. 123) also mention this possibility.

In what follows, we examine each of these models and the attention they give to their respective inputs, across both individual and organizational decision-making structures. This analysis enhances our understanding of how attention to reference points varies by decision-making structure (individual versus organizational). Additionally, comparing models across fit indices clearly articulates the best correspondence between the assumptions of aspiration adaptation theory and actual behavior.

METHODS

Research Setting

To examine differences between individual and organizational attention rules, we studied data from MBA students engaged in Harvard Business School Publishing's strategic innovation simulation titled *Back Bay Battery* (Shih & Christenson, 2008), hereafter simply "the simulation". The simulation has two advantages over using archival data on managers (cf., Fréchette, 2015; 2016). First, the simulation offers an efficient way to collect – across many simulated organizations as well as individual decision makers – cleaner, less noisy data than field data. Everyone starts from the same competitive position and faces the same decision-making environment with access to identical information. This methodology allows for modeling observable aspirations data with less ambiguity regarding managerial construction of reference points, a common issue with data from actual organizations (Katila et al, 2012), with the added

benefit of ease of replicability (Newbery et al., 2018). Business simulations can be a rich source for aspiration data especially since such data are difficult for researchers to obtain from real firms because organizations rarely open their budgets to researchers (Washburn & Bromiley, 2012). Lant (1992) set the precedent for using data derived from business simulation for aspiration models, and others have used simulation data to address a variety of research questions in strategy and management research (Katila et al., 2012; Lucas et al., 2016; Jung et al., 2017; Reypens & Levine, 2018). Since *Back Bay Battery* is used in MBA classrooms worldwide, this approach offers future researchers the opportunity to replicate and augment our study.

Second, simulations provide decision makers with complex situations and evolving decisions, providing an environment that better replicates practitioners' decision-making situations than true experiments might (Zantow et al., 2005; Haro & Turgut, 2012). And because simulations relate to a common strategic problem faced by real-life organizations, they have "ecological validity" meaning they closely mimic real-world scenarios (Lant & Montgomery, 1992). In particular, the Back Bay Battery simulation requires setting aspiration levels across multiple decisions rounds or trials (i.e. simulated years) and gives participants information, for each simulated year, on which they can base decisions for the next year. Furthermore, each set of decisions involves complications which are similar to real life. The simulation's algorithm establishes budget limits and penalties for poor performance outcomes. This structure ensures that, when setting aspirations over time, groups or individuals consider constraints on resource allocation and the implications of performance – just as any real-world manager does (Keum & Eggers, 2018). Also, given the assumption that higher-level aggregations reflect lower-level

elements and interactions 14-*(Simon, 1996; Puranam, 2018), our approach provides a reasonable approximation to organizational level aspiration setting.

Sample

We use data collected at a major research university where the core strategy class mandates the simulation for all first-year MBA students. Students were informed that the winning groups (individuals) at the end of three attempts would receive an "Innovator of the Year" award. Hence participants had a motivation to make credible choices for both class participation points and peer recognition, similar to other studies (Audia & Brion, 2007; Hewlin, Dumas & Burnett, 2017). One set of students competed in randomly assigned groups of three to five members (groups were assigned at the start of the term). The second set of students competed in the simulation as individual decision-makers. Groups and individuals undertook the simulation up to three times. To examine learning effects across attempts, we analyzed models independently by attempt (one to three) and then for all three combined. We found no difference across the models with different attempts, so we report results using the full sample.

Our total data set contains 318 "firms" (122 groups and 196 individuals) – each a unique attempt (or iteration) by a group (individual) interacting with the simulation. The simulation spans up to eight periods, or "years". We lose observations because many firms go bankrupt before the final period and because aspiration models have lagged variables. To incorporate lags in our models, we use data only for those firms that survive at least two years in the simulation (excluding the three-year historical data the simulation provides users at the start). This gave a sample of 1,457 unique firm-year observations (122 firms with 571 observations led by groups, and 196 firms with 886 observations for individuals). Adjusting for observations dropped due to lags on our independent variables, our mean firm-year observations are 3.9.

Procedure and materials

Participants received verbal and extensive written (seven pages) instructions one week before the in-class simulation. These instructions were provided by Harvard Business School Press as part of the simulation. Participants were informed that Back Bay Battery, a division of a large consumer electronics manufacturer, sells batteries to three different markets (power packs, two-way radios, and power tools).

Groups and individual participants need to set unit-sales goals (number of batteries sold) and prices for the products for the next year. We will refer to the unit sales goal as the aspiration level. This is consistent with Cyert & March (1963) that primarily discusses goals and targets which later research refer to as aspirations. Students also allocate R&D funds to five battery features across two battery technologies: nickel-metal hydride (NiMH) and ultracapacitor (UC), aiming to maximize cumulative profits earned in the simulation. Many permutations and combinations of investment patterns exist; there is no "one way" to win the simulation (i.e., to survive for eight periods while meeting aspirations and generating positive operating profit). For a detailed view of the firm's annual decisions involving these technologies. Achieving high cumulative profits requires balancing sales aspirations with R&D spending to maintain positive annual profitability and increase the chances of future profitability.

Participants were told the aspirations they set have consequences and limitations. First, students can allocate no more than 3% of the dollar value of the sales goal to R&D. This limitation encourages students to set aspiration levels high to let the firm make R&D investments needed to boost future sales. However, higher aspirations produce problems if sales turn out to be lower than expected. Firms with either a sequence of three small or one large negative variance(s) between sales and the dollar value of the sales goal or three successive operating

profit losses go bankrupt. Bankruptcy results in the firm exiting the simulation. Together, these restrictions on the relations among aspirations, R&D investment levels, and survival ensure that each firm has a strong incentive to set achievable aspirations; they also aid in simulating the decisions made in real-world organizations where managers typically face a variety of similar constraints (Arrfelt & Hult, 2013; Lin & McCann, 2013; Keum & Eggers, 2018).

Simulated firms begin with identical performance histories which eliminates many forms of heterogeneity that complicate cross-unit comparisons based on actual firm data. Outcomes for each firm are independent of those for other simulated firms. This set-up controls for exogenous influences on strategy and firm evolution that hamper meaningful comparisons (Noda & Collis, 2001), providing us with a controlled environment as well as the ability to observe information flow to firms. This environment helps rule out competing explanations of constructs, such as firms using different performance dimensions or social comparison reference points (Kacperczyk, et.al., 2015).

Firms start with three years of past performance history that updates annually (after each decision-round) in the simulation. Subsequent years' data includes aspirations/sales targets, performance, and R&D investments. The data also include market size and penetration along with information on numerous factors such as changes in customer preferences and demand. In the simulation, the only industry data firms receive is the industry's total unit sales in each year. We further instruct participants that their firm is one of three firms in the industry that offer the specific products outlined in the simulation (batteries for power packs, two-way radios, and power tools), which provides the only means of social comparison. Thus, we measure, in line with foundational theory, the only observable social comparison aspiration dimension – average peer performance. Participants could play the simulation up to 3 times (each up to 8 simulated

years but often less due to bankruptcy) and were informed that their best score (cumulative profits) would be used for evaluation. All participants engaged in the exercise remotely.

Measures and Model Estimation

Given our direct data from the simulation, our measures are straightforward. We calculate aspirations (DV) for all models as total unit sales goals across each firm-year (Cyert & March, 1963). We outline the explanatory variable calculations for each model below.

Cyert & March model (Cyert & March, 1963; 1992). We estimated the Cyert and March (1963) model directly (see Equation 1 above). We measure aspirations as a sum of the unit sales goals across the two battery technologies for each firm in each period. We measure performance as total units sold across the two technologies. The simulation does not break down industry sales by technologies. Given the industry measure is a sum of technologies, we cannot specify theoretically robust aspiration models differentiated between the two technologies. Hence, we sum up the aspirations and performance measures to estimate firm-level rather than technology-level aspiration models.

In line with prior research (e.g., Bromiley & Harris, 2014; Greve 2003a;b), we measure social comparison as average peer performance (total industry sales minus the focal firm's sales divided by the number of other firms in the industry). Further, we test the hypothesis that the model's coefficients ($a_1, a_2,$ and a_3) sum to 1, a key assumption in the original Cyert and March model. Although the assumption underlies much of the quantitative research in this field, only Washburn and Bromiley (2012) attempts to test that assumption, with inconclusive results.

Weighted-average model (Greve, 2003a) (see equation 4 above). Consistent with past research, we measured prior performance as one period lagged firm performance (Greve, 2003a). Averaging past performance over additional years did not improve model fit. Next, social

comparison equals average peer performance (total industry sales minus focal firm sales divided by the remaining number of firms in the industry) in $t-1$. The model's independent variable, labelled *Weighted aspirations*, is a weighted average of prior performance and social comparison.

Following Greve (2003a) and Bromiley and Harris (2014), we calculate the aspirations variable (labelled *Lagged Weighted aspirations*) by assigning values for a_1 and a_2 from 0 to 1 in increments of 0.1; we select the values for which the log-likelihood is highest: $a_1 = 0.9$ and $a_2 = 0.1$ (for both teams and individuals separately). We interacted the aspirations variable with a dummy variable indicating whether performance is above or below calculated aspirations to estimate separate parameters for aspirations above and below performance.

Separate model (Greve, 2003b; Harris and Bromiley, 2007). This model has independent measures of prior performance (as a proxy for prior aspirations) and social comparison. We calculate social comparison (labelled *Lagged social comparison*) as average peer performance, as in the two models above. Prior performance, labeled *Lagged performance is* calculated as firms' prior year performance since fit indices favored a one-period lag on performance (Harris and Bromiley, 2007), rather than a weighted average of two or more years' performance. We spline the model to estimate separate parameters for performance above and below these two aspiration dimensions.

Switching model with one year of industry and firm data (Bromiley, 1991). For firms performing below average peer performance, average peer performance serves as social comparison, in line with previous models. For firms performing above average peer performance, the aspiration level is instead 1.05 times the firm's performance i.e., an aspirations proxy. In line with Bromiley (1991), modest changes in the $a = 1.05$ value did not substantially

affect the results The switching aspirations variable is labeled as *Lagged Attainment Discrepancy* in the model.

We estimate models using fixed firm and year effects because theories of aspiration adaptation address within-firm changes in aspirations over time. The models for both individuals and groups were identically specified. Following Bromiley and Harris (2014), we compare the models using the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). Lower values of both indicate a better model fit (Long & Freese, 2000); the most robust indication is when the two criteria agree (Kuha, 2004). So-called penalized model selection criteria, such as the AIC and BIC, are suitable for comparing non-nested models and provide guidance for choosing among unrejected models (Kuha, 2004).

RESULTS

Tables 2.1a and 2.1b report descriptive statistics and correlations for selected variables in the models we estimate for groups and individuals, respectively. A t-test reveals that means of aspirations for groups are significantly higher than for individuals; (Groups' Mean = 24.77, SD = 6.81 versus Individuals' Mean = 22.29, SD = 9.89), $t(1455) = 5.249$, $p < 0.001$) . Similarly, the means for performance are significantly higher for groups than for individuals; (Groups' Mean = 22.09, SD = 6.17 versus Individuals' Mean = 20.40, SD = 7.43), $t(1379) = 4.452$, $p < 0.001$).

Because it is unclear how rapidly the respective factors influence aspirations, we estimated models with multiple lags for the independent variables and chose the one with maximum log-likelihood. In each of the estimates and for each of the variables, a one period lag gave the best log-likelihood.

*** Insert Tables 2.1a and 2.1b about here ***

Table 2.2 presents regression estimates with firm and year fixed effects for the Cyert and March (1963) and Weighted Average (Greve, 2003) models for groups (Models 1 & 3) and individuals (Models 2 & 4). Table 2.3 similarly presents estimates for the Separate (Greve, 2003b; Harris and Bromiley, 2007) and Switching (Bromiley, 1991) aspiration models for groups (Models 5 & 7) and individuals (Models 6 & 8). To check for possible bias in our results from lagging our dependent variable as an independent variable (Achen, 2000), we re-run the C&M model using four instruments - prior prices and performance of each battery technology (cf. Correia, 2019). The resulting two-staged least-squares regression analysis reveals no meaningful differences in effect sizes or fit indices as compared with the OLS estimation, hence, we retain the OLS estimation as our main model.

Next, we discuss the differences in parameters among the four alternate aspiration models across group and individual decision makers, as estimated in Tables 2.2 and 2.3.

*** Insert Tables 2.2 and 2.3 about here ***

Interpreting and comparing the Cyert & March model for groups (Table 2.2, Model 1) and individuals (Table 2.2, Model 2): Beginning with Model 1 (Table 2.2), we find that groups' aspirations depend on lagged aspirations, but the parameter is negative instead of the positive parameter proposed in the theory ($b = -0.075$, $p = 0.084$). Consistent with the theory, we find a positive influence of lagged performance ($b = 0.797$, $p < 0.001$). The parameter on lagged social comparison has a large standard error making it consistent with a true parameter of zero ($b = -0.352$, $p = 0.347$). For groups, a one standard deviation increase in lagged aspirations decreases predicted aspirations by 0.5, a one standard deviation increase in lagged performance increases predicted aspirations by 5.4, and a one standard deviation increase in social comparison decreases predicted sales by 3.1. Given the standard deviation of aspirations is 6.8, the effect of

prior aspirations is small, and the effect of prior performance is moderate. Despite the moderate effect size on social comparison, the parameter size relative to the standard error does not give us confidence it has a non-zero influence. These results on social comparison align with our theoretical logic and some prior empirical research that did not find social comparison to be important in explaining behaviors such as firm growth and risk-taking (Audia & Greve, 2006; Lim & McCann, 2013).

The negative effect of prior aspirations, contrary to the theory, merits comment. Holding the lagged performance constant changes the understanding of lagged aspirations. That is, higher aspirations holding lagged performance constant will increase the likelihood of negative performance relative to aspirations, repeated instance of which causes bankruptcy in the simulation. Whether such effects would appear in conditions with less severe penalties for performance below aspirations or in more rapidly growing industries is unclear (see, for instance, Keum & Eggers, 2018).

In contrast to groups, all three variables appear to influence individuals' aspirations (Model 2, Table 2.2). Lagged (prior) aspirations has a negative parameter instead of the positive parameter assumed in the theory ($b = -0.364$, $p < 0.001$). Lagged performance ($b < 1.591$, $p < 0.001$) and lagged (social) comparison ($b = 1.364$, $p = 0.001$) both increase aspirations. For individuals, a one standard deviation increase in lagged performance increases predicted aspirations by 15.7, a one standard deviation increase in social comparison increases predicted sales by 13.5, and a one standard deviation increase in lagged aspirations decreases predicted aspirations by 3.6. That is, lagged performance and social comparison have much larger influences on predicted aspirations than lagged aspirations. Given the standard deviation of

aspirations is 9.8, the effects of lagged performance and comparison have substantial effect sizes and lagged aspirations has a moderate effect size.

Consistent with our theoretical analysis, all three variables in the Cyert and March model influence individual aspirations but only one or potentially two influence group aspirations suggesting that individuals use more complex mental models in setting aspiration levels than groups. We also tested the equality of the parameters between the group and individual analyses (Chow, 1960). The Chow test shows that the relation between the independent variables and the dependent variable differs significantly between groups and individuals ($F(2, 1127) = 17.44$, $p < 0.001$). The parameters for individuals are larger in magnitude than those for groups, suggesting groups react less strongly than individuals to all three factors.

We also find that the Cyert and March model's parameters sum to less than 1 for groups although the difference is not statistically significant (sum of *b's* = 0.369, test versus sum of *b's* = 1, $p = 0.441$), but to substantially more than one for individuals (sum of *b's* = 2.590, test versus sum of *b's* = 1, $p < 0.001$); hence rejecting the "sum to 1" assumption in Cyert and March (1963) for individuals but not groups.

Finally, the model's assumption of all positive parameters also does not hold: prior aspirations has negative coefficients for both individuals and groups. Thus, our results cast new light on qualitative discussions of aspirations – arguing theory should consider the possibility of a negative effect of prior aspirations, accounting for penalties associated with future performance below predicted aspirations.

Interpreting and comparing the Weighted Average model for groups (Table 2.2, Model 3) and individuals (Table 2.2, Model 4): Both positive ($b = 1.002$, $p < 0.001$) and negative ($b = 0.959$, $p < 0.001$) lagged weighted aspirations relative to performance positively

influence group aspirations (Model 3). For groups, a one standard deviation increase in lagged weighted aspirations increases predicted aspirations by 6.8 when performance is below aspirations and 6.5 when above. The parameters are extremely close indicating that the switch from performance below aspirations to performance above aspirations did not change the relation between lagged weighted aspirations and aspirations.

Similarly, individuals (Model 4) appear to attend to lagged weighted aspirations when performance is both below aspirations (the positive influence assumed in the theory (b = 1.335, p <0.001)), and above aspirations (b = 1.325, p <0.001). The magnitude of the parameters demonstrates that lagged weighted aspirations have a large influence when performance is both below and above aspirations. For individuals, one standard deviation increase in lagged weighted aspirations increases predicted aspirations by 13.21 when performance is below aspirations and 13.11 when above. Again, the parameters are extremely close indicating that the switch from performance below aspirations to performance above aspirations did not change the relation between lagged weighted aspirations and aspirations.

Using the weighted average model, we do not find evidence that individuals attend to more inputs than groups. Such a result is expected since the model already reduces the different variables down to one variable splined for when performance is above aspirations and one when it is below. A Chow test suggests that the parameters for individuals differ from those on groups (F (2, 1129) = 30.29, p <0.001).

Interpreting and comparing the Separate model for groups (Table 2.3, Model 5) and individuals (Table 2.3, Model 6): In the separate model, prior performance (labelled as *lagged performance*) influences group aspirations both when performance is below (b = 0.749, p <0.001), and above prior performance (b = 0.777, p <0.001). Lagged social comparison

appears to not influence group aspirations when performance is either below social comparison ($b = -0.358$, $p = 0.339$), or above social comparison ($b = -0.374$, $p = 0.320$). For groups, one standard deviation increase in prior performance increases predicted aspirations by 5.1 when performance is below aspirations and 5.29 when above, and one standard deviation increase in lagged social comparison decreases predicted aspirations by 2.4 when performance is below aspirations and 2.5 when above. The parameters for above and below are extremely close indicating that the switch from performance below aspirations to performance above aspirations did not change the relation between either prior performance or lagged social comparison and aspirations.

Similar to that of groups, performance both above ($b = 1.258$, $p < 0.001$) and below prior performance ($b = 1.297$, $p < 0.001$), positively influences individual aspirations (Model 6). Both influences are positive (as assumed in theory), with similar magnitude and significance of effect. Social comparison does not appear to influence aspirations set by individuals in both situations (performance below social comparison ($b = 0.326$, $p = 0.420$), and above social comparison ($b = 0.029$, $p = 0.595$)). For individuals, one standard deviation increase in performance increases predicted aspirations by 12.45 when performance is below prior performance and 12.8 when above. A one standard deviation increase in social comparison increases predicted aspirations by 3.2 when performance is below prior performance and 0.28 when above. The parameters for prior performance are extremely close indicating that the switch from performance below aspirations to performance above aspirations did not change the relationship between lagged aspirations and predicted aspirations. A Chow test suggests that the parameters differ significantly between groups and individuals as in the previous models ($F(4, 681) = 10.74$, $p < 0.001$).

Interpreting and comparing the Switching model for groups (Table 2.3, Model 7) and individuals (Table 2.3, Model 8): Both Groups (Model 7; $b = 0.803$, $p < 0.001$) and individuals (Model 8; $b = 0.907$, $p < 0.001$) appear to attend to lagged attainment discrepancy. For groups, a one standard deviation increase in lagged attainment discrepancy increases predicted aspirations by 5.47. While for individuals, a one standard deviation increase in lagged attainment discrepancy increases predicted aspirations by 6.45.

The switching model shows no significant difference in the number of inputs considered by individuals compared to groups but that is to be expected since the model only includes one variable. A Chow test ($F(1, 1131) = 42.15$, $p < 0.001$) suggests the parameter on groups differs from the parameter on individuals.

In almost all of the models, the parameters for individuals are larger in magnitude than those for groups suggesting groups serve to moderate reactions to feedback. However, the mean for group aspirations (24.77 million units) is higher than for individual aspirations (22.9 million units) indicating that groups set higher aspirations.

Next, we compare the four alternate models on organizational (group) decision-making structures Models (1, 3, 5, and 7) using fit indices, followed by comparison of fit indices from models on individual decision-making structures (Models 2, 4, 6, and 8).

Organizational (Group) Decision-Making model fit comparison (Tables 2.2 and 2.3): Comparing fit indices of models across the four organizational (group) decision-making structures, reveals that the Cyert and March (Table 2.2, Model 1, AIC = 2,666, BIC = 2,709) and weighted average models (Table 2.2, Model 3, AIC = 2,666, BIC = 2,709) exhibit the exact same fit values. These are also the best fit values of the four group model estimates with the separate model third best (Table 2.3, Model 5, AIC = 2,668, BIC = 2,716) and the switching model

performing worst (Table 2.3, Model 7, AIC = 2,692, BIC = 2,727). BIC puts a higher penalty on models with more parameters than AIC (Raftery (1995). The BIC values for the Cyert and March model, weighted average model and separate model are not significantly different, with very strong evidence that the switching model provides significantly poorer fit (differences in BIC of over 10 points from the other models, since differences over 5 are considered significant (Raftery, 1995)). Following Burnham, Anderson, and Huyvaert (2011), an analysis of the ratios of AIC values yields the same conclusions. A comparison of adjusted R^2 values across models aligns well with the AIC and BIC.

Individual Decision-Making model fit comparison (Tables 2.2 and 2.3): Comparing fit indices for individual decision makers reveals that the Cyert and March model (Table 2.2, Model 2, AIC = 4,821, BIC = 4,869) provides significantly better fit statistics than the separate model (Table 2.3, Model 6, AIC = 4,853, BIC = 4,905), weighted average model (Table 2.2, Model 4, AIC = 4,855, BIC = 4,903), and the switching model (Table 2.3, Model 8, AIC = 4,895, BIC = 4,934). R^2 values across models align well with the AIC and BIC.

Robustness test: Survival level

While our results clearly confirm the narrow attention argument for the Cyert and March model, we further strengthen our findings with the addition of a fourth aspiration input. Research has offered a variety of additional reference points including historical social comparison (Moliterno et al., 2014), historical performance below or above aspirations (Ref & Shapira, 2017), internal social comparison (Hu et al., 2017; Kacperczyk, Beckman, & Moliterno, 2015), and survival (March & Shapira, 1992; Miller & Chen, 2004; Gaba & Greve, 2019). We chose the latter because the Back Bay simulation allows for such a calculation. Specifically, we measure *threat of bankruptcy* as a categorical variable indicating a threat of bankruptcy when

firms have two consecutive shortfalls between performance and aspirations, since three continuous years of performance below aspirations lead to bankruptcy as per the rules of the simulation. We enter *threat of bankruptcy* as an additional variable to the Cyert and March aspiration model (Model 9 and 10 for groups and individuals respectively).

When threat of bankruptcy is high, decision makers use survival as a reference point (March & Shapira, 1991). Attention to a new reference point (survival), results in even higher information processing demands for groups, in particular, as they need to update not only their own cognitive models but also the groups' shared understanding. In contrast, individual decision makers do not need to share, with other organizational members, an unobservable and difficult to articulate update in their mental model.

Table 2.4, models 9 and 10, add threat of bankruptcy to the Cyert and March model. For groups (Model 9), the threat of bankruptcy significantly influences aspirations (b = -1.230, p =0.001) and reduces the influence of prior aspirations (b = -0.049, p =0.261), relative to Model 1 (without the bankruptcy variable). The effect of lagged performance (b = 0.770, p <0.001) remains significant while the effect of social comparison (b = -0.315, p =0.395) remains not significant, similar to Model 1.

*** Insert **Table 2.4** about here ***

The Cyert and March model for individual decision makers (Model 10) shows that the threat of bankruptcy has a significant influence in reducing aspirations (b = -2.215, p <0.001) but does not change the significance of prior aspirations (b = -0.344, p <0.001), performance (b = 1.523, p <0.001), or social comparison (b = 1.327, p <0.001). Overall, the robustness test supports our main findings that information processing within groups results in attention to fewer information parameters relative to individuals. Individuals, in contrast to organizational decision-

making structures, more closely align with the original Cyert and March (1963) aspiration conceptualization.

DISCUSSION AND CONCLUSION

Building on a rich body of work, we examine and compare individual and organizational attention rules. We examine one of the central assumptions of aspiration adaptation theory – that behavior of individuals, as derived from literature on psychology, regarding aspiration levels generalizes to the organizational (group) level (March & Simon, 1958, Cyert & March, 1963, Shinkle et al, 2012). Contrary to this assumption, our results show individuals use more variables than groups in determining aspirations. Individuals attend to all the three variables in the Cyert and March model while groups do not. Thus, it appears that the need to reach consensus results in simplification of the implicit model being used; groups use fewer inputs than individuals when setting aspirations. In supplementary analysis, we find this also holds true when including bankruptcy risk in the Cyert and March model, suggesting that overall, the original Cyert and March (1963) aspiration adaptation function aligns more closely with individual information processing behavior than group information processing behavior in aspiration adaptation, which reflects the results of information aggregation.

Comparing the coefficients across Models 1-8 helps interpret the differences in aspiration adaptation between groups and individuals, as well as differences between the models and their explanatory power regarding aspirations. First, comparing the differences between individual and organizational decision-making behavior using the Cyert and March model (Models 1 and 2), individual decision-makers (Model 2) attend to all three variables (prior aspirations, performance, and social comparison) in setting aspiration levels. However, organizations (Model 1) only attend to firm performance and (marginally) to prior aspirations. These results

demonstrate that information aggregation in organizational decision-making structures increases the likelihood that boundedly rational decision-makers will narrow their attention across decisions in complex environments. Organizations may economize on joint information processing by adopting a shared (and more simplified) model which considers fewer inputs compared to individual decision-makers when setting aspirations.

Second, our results show that – even though models that incorporate prior aspirations, performance, and social comparison independently do not show all variables significantly influencing aspirations (Model 1, 2, and to an extent 5 and 6) – models which contain single measure proxies of prior aspirations and social comparison, such as attainment discrepancy or weighted aspirations show high significance for these variables (Models 3, 4, 7 and 8). This suggests that the effects of attainment discrepancy and weighted aspirations, on both aspiration adaptation and subsequent firm behavior, should be studied independently from the effects of actual aspirations and performance on similar outcomes.

Moreover, the comparison of model fit indices shows that, for individuals, the Cyert and March (1963) model shows the best fit statistics relative to the other models, followed by the separate and weighted average models. For groups, fit statistics do not significantly differ across three of the models. The switching model has substantially worse fit across both decision-making contexts. This suggests that in the absence of actual aspirations (which is needed for the Cyert and March model), researchers should estimate the weighted average model or the separate model.

Third, we challenge Cyert and March model's assumption that the weights of the model's individual components sum to one, which has only been addressed in Washburn and Bromiley (2012) using data from one firm. Our analysis does not support this assumption for individuals

and is suggestive the assumption does not work for groups (where the sum of parameters is far from one, but the difference has a high standard error). This raises questions about the common practice of a grid search to set relative weights on performance and social comparison that sum to one, as in the weighted average model. Further, the assumption of all non-negative parameters is contradicted by the negative parameter estimates for prior aspiration and social comparison variables. Our findings, therefore, introduce a new perspective on the qualitative debates around aspirations, suggesting that theories should account for the potential negative impact of prior aspirations in punitive decision scenarios (Keum & Eggers, 2018).

Also, with differing signs on the factors influencing aspirations, the possibility of odd response patterns over time exists. This might result in unnecessary problemistic search and/or a host of other and quite possibly unwarranted behaviors associated with performance falling below aspirations (Dahlin et al., 2018). This aligns with research that finds, for example, that "stretch" goals can impair organizational performance and learning because of the difficulty in interpreting performance evaluations when pursuing excessively high goals (Sitkin et al., 2011).

Further, we extend the original Cyert and March (1963) aspirations model, demonstrating that a threat of bankruptcy influences aspiration levels in both individual and organizational decision-making. However, only past performance and the threat of bankruptcy influence group aspirations but all four inputs influence individual aspirations. Prior work suggests that threat of bankruptcy (survival level) changes the effective reference point (March & Shapira, 1992; Boyle & Shapira, 2012) and that decision makers set more conservative targets when faced with higher costs of missing targets (Keum & Eggers, 2018). The survival focus intensifies for firms with repeated negative deviations from aspirations since the simulation penalizes three small consecutive performance shortfalls with bankruptcy. In a world that severely punishes negative

deviations from aspirations, it makes sense for decision makers, whether individually or in groups, to react negatively to high aspirations that are poorly aligned with actual outcomes. Decision-makers, aspiring for business continuity, and to avoid bankruptcy (March & Shapira, 1987; Miller & Chen, 2004; Keum & Eggers, 2018), reduce aspiration levels, thereby decreasing the chances of performance shortfalls and increasing chances of survival.

Our lack of findings for social comparison is consistent with prior work. Greve (2003a) noted that the peer performance that forms the basis for social comparison is more problematic than the organization's own prior performance. Often, the available peers differ in many ways, making comparison difficult. For example, a great many firms have diversified product portfolios – comparing firms that produce and sell different things is questionable. Furthermore, timely data on peers often does not exist. For example, in industries dominated by privately held companies, data on peers may simply not be available. Even if data are eventually available, they may not be available in a timely manner. For example, while the law requires much of the information non-profits file with the government to be, in theory, publicly available, the organizations providing such data do so with substantial, multi-year lags. Even firms selling similar products may sell in different regions and so face different competitive environments (Bromiley, Papenhausen & Borchert, 2002). For these reasons, social comparison is likely to be less available and more ambiguous than the firm's own prior performance – evidenced by studies which show that organizations may not initiate change or corrective action after failing to meet a social comparison-based aspiration level (Audia & Greve, 2006; Desai, 2008; Lim & McCann, 2013). If the group simplifies from the individual's model, social comparison is an obvious factor to ignore.

We offer two main contributions to literature. First, to the BTOF, we highlight that individuals and organizations determine aspirations in different ways. Organizational decision-making results in fewer factors influencing aspirations than for individuals. This reduction in factors is significant in that it challenges a long-held implicit assumption in the literature – that the same aspiration model ($A_{i,t} = a_1 A_{i,t-1} + a_2 P_{i,t-1} + a_3 C_{i,t-1}$) extends to both individuals and organizations. Moreover, our empirical approach and use of the Back Bay simulation allows us to make direct comparisons across four different models as well as compare aspiration adaptation behavior across decision-making contexts. Most research in this area rests on Cyert and March's (1963) formulation, which we extend to show the impact of threat of bankruptcy on aspirations. We find that, under a threat of bankruptcy, the shared models in organizational decision-making are further simplified as information processing demands increase due to the addition of risk of survival as an input in aspiration setting, a trend not observed for individuals. Future research should explore other external threats and their influence on aspiration levels.

Most studies lack data on actual aspirations, and as a result use proxies like attainment discrepancy or weighted average aspirations as explanatory variables. Although some studies estimate models using actual aspirations data (e.g., Washburn & Bromiley, 2012; Blettner, Hu & Bettis, 2015; Aranda et al., 2017; Hu, et al., 2017, 2017), they do not – as we do in this paper – compare different models. Our findings highlight the need for more studies that use actual aspirations data from real-world settings to enable further testing. The results derived here show that, as one might expect, the Cyert and March model shows the best model fit for individuals, since the model is derived from theories on individual behavior in setting aspirations. For groups however, both the Cyert and March and Weighted average models show better model fits than the other models. Thus, in scenarios where groups set aspirations, lack of actual aspiration data

can be compensated for by using the Weighted average model but that is not true, as others (e.g., Shinkle, 2012) have argued, when individuals set aspirations.

Our second contribution is to extend the organization design research. Prior work has either theorized or empirically demonstrated a relation between decision making context and attention (e.g., Ocasio, 1997; Dutt & Joseph, 2018). Related work on information aggregation focuses on voting rules present in various information aggregation structures (e.g., Christen, Dahl & Knudsen, 2010; Csaszar &Eggers, 2013; Piezunka & Shilke, 2023) and their impact on performance and behavior. We extend theory by highlighting that decision-making contexts, with different degrees of complexity, influence how individuals construct representations of the same information and the implications for attention. That is, the aggregation process in organizations (but not in individuals) may reshape the common models of their members by narrowing their perspectives to a more restrictive view of the information. By examining the implicit weights put on the various inputs to their aspiration models, we not only reinforce theory which supports a relationship between organization and attention (Ocasio, 1997; Koçak, Levinthal, & Puranam, 2023), but we also build theory on how individuals – through their use of simple models – shape the formation of aspirations. More broadly, we link information processing to the degree of complexity in representations held by decision makers and the implications for attention.

Conclusion

This paper explores how differences in individual and organizational information processing affects setting of aspirations. We theorize and show that individuals use more complex models in setting aspirations relative to organizations because of the information aggregation process required for group decision-making. Further, we empirically demonstrate

that threat of bankruptcy is a critical input to aspirations (for individuals and organizations), extending the original Cyert and March model of aspiration adaptations. Our study contributes to a better understanding of the differences between individual and organizational accounts of attention rules and setting aspirations and organization design studies of information aggregation.

Figure 2.1: Prominent Aspirations models (Bromiley & Harris, 2014)

Model	Number of Parameters	Aspirations	Notes
Cyert and March Model	3	$A_{i,t} = a_1\ A_{i,t-1} + a_2\ P_{t-1} + a_3\ C_{i,t-1}$	• *a_1, a_2, and a_3 are non-negative and sum to one.*
Switching Model	1	$A_{i,t} = Social\_comparison_{i,t-1}$ if $P_{i,t-1} < Social\_comparison_{i,t-1}$ $A_{i,t} = 1.05 * P_{i,t-1}$ if $P_{i,t-1} \geq Social\_comparison_{i,t-1}$	• *aspirations adapt as a function of social comparison if the firm is below average peer performance, but as a function of prior year performance if the firm is above average peer performance.*
Weighted-Average Model	4	$A_{i,t} = a_1 Social\_comparison_{i,t-1}$ $+ (1 - a_1)\ (-a_2)\ \sum_{j=0}^{\infty} a_2^j\ P_{i,t-1-s}$	• *a_1, and a_2 are non-negative and sum to one.* • *Model is splined for differing influences of attainment discrepancy above and below aspirations.*
Separate Model	4	$Prior\ A_{i,t} = P_{t-1}$ $Social\ A_{i,t} = Social\_comparison_{i,t-1}$	• *Social- and prior aspirations have individual effects on aspiration adaptation.*

Table 2.1a. Descriptive statistics and correlation table (Groups, Sample size: 122)

	Variables	Mean	S.D.	Min	Max	2	3	4	5	6
1	Time-periods (years completed)	4.04	1.65	2.00	8.00					
2	Aspirations (Units, Millions)	24.77	5.96	11.52	39.04					
3	Lagged Aspirations (Units, Millions)	26.50	5.15	12.92	40.18	0.58				
4	Lagged Performance (Units, Millions)	24.99	5.58	13.21	35.77	0.86	0.64			
5	Industry Sales (Units, Millions)	125.72	14.22	92.41	149.42	-0.71	-0.51	-0.75		
6	Lagged Comparison (Units, Millions)	50.36	9.43	30.33	63.17	-0.79	-0.58	-0.86	0.98	
7	Lagged Threat of Bankruptcy (Dummy)	0.21	0.36	0.00	1.00	-0.36	-0.34	-0.46	0.43	0.46

All correlations are significant at $p<0.001$

Table 2.1b. Descriptive statistics and correlation table (Individuals, Sample size: 196)

	Variables	Mean	S.D.	Min	Max	2	3	4	5	6
1	Time-periods (years completed)	3.90	1.52	2.00	8.00					
2	Aspirations (Units, Millions)	22.29	9.89	0.00	68.10					
3	Lagged Aspirations (Units, Millions)	25.60	5.51	8.70	42.50	0.61				
4	Lagged Performance (Units, Millions)	23.56	6.93	0.18	32.70	0.86	0.60			
5	Industry Sales (Units, Millions)	123.84	14.02	89.52	149.20	-0.69	-0.40	-0.74		
6	Lagged Comparison (Units, Millions)	50.13	10.09	29.81	65.22	-0.80	-0.50	-0.88	0.97	
7	Lagged Threat of Bankruptcy (Dummy)	0.18	0.34	0.00	1.00	-0.53	-0.46	-0.52	0.44	0.50

All correlations are significant at $p<0.001$

Table 2.2: Explaining Aspiration Levels – OLS Regression, Fixed Effects Estimates

VARIABLES	Model (1) Cyert-March (Group)	Model (2) Cyert-March (Individual)	Model (3) Weighted Avg. (Group)	Model (4) Weighted Avg. (Individual)
Lagged aspirations	-0.075 (p =0.084) (0.043)	-0.364 (p <0.001) (0.068)		
Lagged performance	0.797 (p <0.001) (0.125)	1.591 (p <0.001) (0.131)		
Lagged social comparison	-0.352 (p =0.347) (0.374)	1.364 (p < 0.001) (0.395)		
Lagged Weighted aspirations (p<a)			1.002 (p <0.001) (0.066)	1.335 (p <0.001) (0.077)
Lagged Weighted aspirations (p>a)			0.959 (p <0.001) (0.719)	1.325 (p <0.001) (0.166)
Lagged performance ($p_{t-1}<p_{t-2}$)				
Lagged performance ($p_{t-1}>p_{t-2}$)				
Lagged social comparison (p<a)				
Lagged social comparison (p>a)				
Lagged Attainment discrepancy				
Observations	571	886	571	886
Adjusted R-squared	0.781	0.791	0.781	0.783
Number of groups/ individuals	122	196	122	196
AIC	2,666	4,821	2.666	4,855
BIC	2,709	4,869	2,709	4,903

Robust standard errors in parentheses. Year and firm fixed effects not reported.
AIC and BIC not comparable across models with different samples.

Table 2.3: Explaining Aspiration Levels – OLS Regression Fixed Effects Estimates (cont.)

VARIABLES	Model (5) Separate (Group)	Model (6) Separate (Individual)	Model (7) Switching (Group)	Model (8) Switching (Individual)
Lagged aspirations				
Lagged performance				
Lagged social comparison				
Lagged Weighted aspirations (p<a)				
Lagged Weighted aspirations (p>a)				
Lagged performance ($p_{t-1}<p_{t-2}$)	0.749 (p <0.001) (0.123)	1.258 (p <0.001) (0.120)		
Lagged performance ($p_{t-1}>p_{t-2}$)	0.777 (p <0.001) (0.124)	1.297 (p <0.001) (0.121)		
Lagged social comparison (p<a)	-0.358 (p =0.339) (0.373)	0.326 (p =0.420) (0.404)		
Lagged social comparison (p>a)	-0.374 (p =0.320) (0.376)	0.029 (p =0.595) (0.429)		
Lagged Attainment discrepancy			0.803 (p <0.001) (0.054)	0.947 (p <0.001) (0.060)
Observations	571	886	571	886
Adjusted R-squared	0.780	0.784	0.770	0.773
Number of groups/ individuals	122	196	122	196
AIC	2,668	4,853	2,692	4,895
BIC	2,716	4,905	2,727	4,934

Robust standard errors in parentheses. Year and firm fixed effects not reported
AIC and BIC not comparable across models with different samples.

Table 2.4: Explaining Aspiration Levels Under Threat of Bankruptcy – OLS Regression Fixed Effects Estimates

VARIABLES	Model (9) Cyert-March (Group)	Model (10) Cyert-March (Individual)
Lagged aspirations	-0.049 (p =0.261)	-0.344 (p <0.001)
	(0.044)	(0.067)
Lagged performance	0.770 (p <0.001)	1.523 (p <0.001)
	(0.124)	(0.130)
Lagged social comparison	-0.315 (p =0.395)	1.327 (p <0.001)
	(0.369)	(0.391)
Lagged Threat of bankruptcy	-1.230 (p <0.001)	-2.215 (p <0.001)
	(0.377)	(0.523)
Observations	571	886
Adjusted R-squared	0.785	0.796
Number of groups/ individuals	122	196
AIC	2,654	4,800
BIC	2,702	4,853

Robust standard errors in parentheses. Year and firm fixed effects not reported.
AIC and BIC not comparable across models with different samples.

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