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Flipping the Switch – The Role of Activity Load in Temporal Acquisition Patterns of Acquiring Firms

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Abstract

This study presents evidence on the effect of a firm's activity load from acquisitions on its temporal acquisition pattern. Exploiting a panel of the 300 largest Fortune Global 500 firms over the 1990-2010 period, I use a hybrid logit model in which I regress momentum on activity load. I find that increases in the activity load from acquisitions, on average, reduce a firm's likelihood to maintain acquisition momentum. That is, the increase in acquisition activity created by acquisition routines and cognitive maps of managers translates into a higher activity load until firms face a situation of information overload. Rational acquirers neutralize this pressure by reducing their acquisition volume which, in turn, decreases the activity load burden. Moreover, my results reveal that acquirers can switch from targets in a higher-complexity target firm category to targets in a lower-complexity target firm category to reduce their activity load burden while maintaining overall momentum. Yet, I obtain ambiguous results when examining heterogeneity in acquirer responses arising from differences in absorptive capacity. With these findings, my study adds to prior literature on acquisition patterns, strategic momentum, and the interplay between a firm's activity load and absorptive capacity.

Keywords: activity load; M&A; momentum; switching behavior; temporal acquisition patterns

1. Introduction

1.1. Motivational Background

Mergers and acquisitions (M&A) are a phenomenon that has received substantial attention from scholars and practitioners alike. This is in part due to the plethora of reasons why firms engage in M&A, which range from entering new markets and accessing new resources (e.g., Karim & Mitchell, 2000; Lee & Lieberman, 2010) to creating economies of scale/scope (e.g., Biggadike, 1979; Lee & Lieberman, 2010). Also, this is in part due to the sobering performance of M&As, which on average is non-existent or even negative (King et

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al., 2004). Even so, the fascination for and practical importance of M&A remain unbroken as evidenced by a global M&A transaction value of USD 3.9tn in 2019 alone (Roumeliotis & Barbaglia, 2019).

While scholars in the field of M&A have predominantly studied acquisitions as singular events (S. Chatterjee, 2009), they have recently also shown a growing interest in acquisition streams (Shi et al., 2012). Scholars who take this perspective view acquisitions as sequences of interrelated strategic action that can be actively managed by acquirers rather than as isolated, exclusively opportunity-driven events (Schipper & Thompson, 1983; Shi et al., 2012). This interest manifested itself in a growing body of literature that has focused on identifying distinct acquisition patterns (e.g., Shi & Prescott, 2011), their observable properties (e.g., Laamanen & Keil, 2008; Vermeulen & Barkema, 2002), and their firm-level performance implications for acquirers (e.g., Laamanen & Keil, 2008; Shi & Prescott, 2012; Vermeulen & Barkema, 2002).

However, much less attention has been attributed to factors that explain why firms *deviate* from their acquisition patterns. That is, while scholars have examined how such patterns emerge and why acquirers do *follow* their patterns over time (e.g., Amburgey & Miner, 1992), compelling theoretical explanations for and empirical evidence on *how* and *why* firms would *deviate* from their established acquisition patterns has remained surprisingly scarce. This gap is puzzling for two reasons. First, past studies have argued and found that firms show acquisition behavior that is *inconsistent* with their past acquisition pattern (e.g., Vermeulen & Barkema, 2001), indicating that this phenomenon is much more than a merely theoretical question. Second, deviations from previously stable acquisition patterns are detrimental to acquirer performance (e.g., Ellis et al., 2011; Laamanen & Keil, 2008). Considering these implications, managers, M&A advisors, and scholars would benefit from better understanding the factors that cause acquirers to systematically deviate from their established acquisition patterns.

This thesis aims to do exactly that by studying a factor that is novel to acquisition pattern research: Activity load. Specifically, I argue that acquisition streams can create high levels of activity load that overstretch the managerial resources of acquirers and, thus, lead to a situation of 'overload' (Castellaneta & Zollo, 2015; Laamanen & Keil, 2008; Vermeulen & Barkema, 2002). This overload results in 'corporate indigestion' (Kusewitt, 1985), which induces firms to deviate from their stable acquisition patterns to alleviate the strains on their resources. That is, firms can respond in two ways. They can either *switch* to acquisitions that create a lower activity load (e.g., acquire targets that are *relatively* less complex to acquire) or *decelerate* their acquisition pace (i.e., acquire fewer targets without changing the type of target acquired). Both responses allow firms to reduce the activity load from acquisitions, albeit with different implications for their acquisition patterns. Which response prevails is a question that can be empirically answered by studying the effect of activity load on acquisition behavior.

1.2. Focus and Objectives of Thesis

This thesis seeks to bridge the research gap identified in section 1.1 by presenting empirical evidence on *how* and *why* acquiring firms deviate from their established acquisition patterns. Specifically, by investigating the role of activity load in this phenomenon, this thesis aims to answer the following research question:

***Research question**: How does the activity load from acquisitions cause acquiring firms to deviate from their established acquisition patterns?*

To approach this question, I break it down into three subquestions with different objectives as illustrated in Figure 1. Each subquestion and its objectives are briefly outlined in the following.

***Subquestion 1**: How does the volume of acquisitions in an acquisition stream affect a firm's acquisition behavior?*

With subquestion 1, I investigate how the *volume* of acquisitions in an acquisition stream affects the acquisition behavior of firms. I pursue two objectives with this. First, I seek to conceptually understand the core mechanism through which activity load causes firms to deviate from their established acquisition patterns. Since activity load is a complex construct, which consists of a volume *and* a complexity component, this objective is best achieved by isolating the construct's most intuitive-to-understand component: Acquisition *volume*. Thus, the relationship between an acquirer's acquisition *volume* and its acquisition behavior will serve as the baseline effect of activity load in this thesis. Second, building on this theoretical basis, I aim to empirically confirm the baseline relationship between acquisition volume and the acquisition behavior of firms. This would already provide a first answer to my research question and – most importantly – create the basis for subsequent analyses of cross-sectional variation in acquisition behavior.

***Subquestion 2**: How does a firm's change in acquisition behavior vary with the complexity level of acquisitions?*

Subsequently, with subquestion 2, I analyze cross-sectional variation in acquirer responses to activity load with respect to the *complexity* level of acquisitions. With this, I want to reach two objectives. First, from a theoretical standpoint, I seek to identify externally observable structural target firm attributes in literature that drive acquisition complexity and, thus, the activity load of acquirers. With this knowledge, I can go beyond the baseline effect of acquisition volume and theorize more nuanced behavioral responses of acquirers to changes in their activity load. Second, from an empirical standpoint, I aim to corroborate relevant complexity dimensions and the changes in acquisition behavior they induce. This allows me to explore the interaction of both activity load components and provide a more fine-grained answer to my research question.

***Subquestion 3**: Which firm-level factors moderate the relationship between activity load and acquisition behavior?*

Finally, with subquestion 3, I explore a second source of cross-sectional variation in acquisition behavior: Structural characteristics of acquirers. I hope to accomplish two objectives with this. First, as with subquestion 2, I aim to find

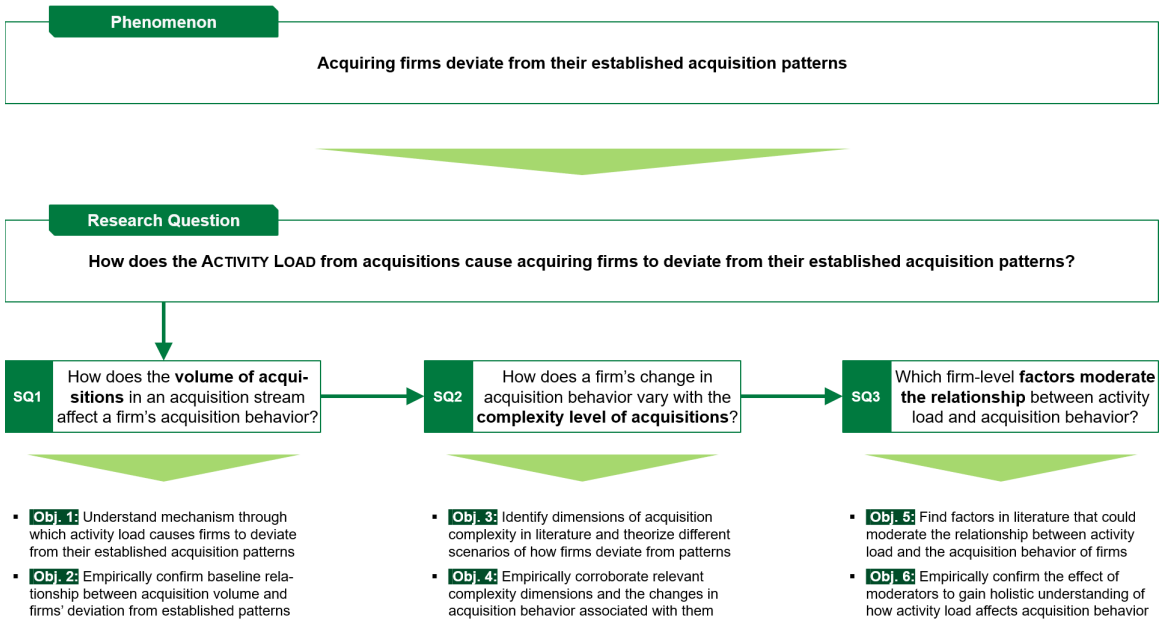


Figure 1: Focus and Objectives of Thesis

firm-level factors in literature that could moderate the relationship between activity load and the acquisition behavior of firms. This allows me to fine-tune my theoretical predictions of changes in acquisition behavior by putting the activity load from acquisitions in relation to a firm's capacity to absorb these acquisitions. Second, I seek to empirically confirm the effect of these moderators. Through this, I can corroborate predictions of earlier studies, which argued that the absorptive capacity of firms can alleviate the effects of activity load (e.g., Penrose, 1959). Most importantly, however, this allows me to gain a holistic understanding of how the activity load from acquisitions affects acquisition behavior of firms.

To derive meaningful insights from my empirical analyses, I made three scoping decisions that allow this thesis to answer the research question while complying with quality criteria used in business research (Bryman & Bell, 2011). First, by investigating a firm-level phenomenon, this thesis focuses on the individual firm as the unit of analysis. Second, my causal inference is based on panel data of acquiring firms and a time-series logit model. This approach accounts for the fact that acquisition patterns evolve over time (Laamanen & Keil, 2008; Shi & Prescott, 2011, 2012). Third, to ensure generalizability of empirical results, this thesis exploits a sample[1] that covers a 21-year acquisition period of acquirers listed in the Fortune Global 500 ranking, resulting in a sample with a long timeframe and broad industry scope. Although not without limitations[2], the chosen scope overall allows me to investigate the phenomenon of interest over a sufficiently long period and exploit a rich sample of firms which are highly acquisitive.

1.3. Definitions of Key Terms

By examining whether activity load stimulates acquiring firms to deviate from their established acquisition patterns, this thesis investigates a research question that builds on four key concepts: Acquisitions, temporal acquisition patterns, strategic momentum, and activity load. These key concepts must be explicitly defined to ensure clarity. Thus, I present their definitions hereafter.

Acquisition. In line with the Refinitiv Eikon M&A database (Refinitiv, n.d.), this thesis defines an acquisition as an economic transaction between an acquirer and the shareholders of a target that involves the transfer of ownership rights at the level of the ultimate parent. This definition allows me to include *all* known deals of an acquiring firm in my analysis, irrespectively of the ownership stake transferred. Through this, I obtain a realistic measure of a firm's activity load from acquisitions, which reflects *all* acquisition-related activities that consume firm resources.

Temporal acquisition patterns. Temporal acquisition patterns are sequences/programs of inter-related acquisitions which are directed at executing a firm's strategy (Laamanen & Keil, 2008; Schipper & Thompson, 1983), capturing the systematic acquisition behavior of firms over time. Literature has defined temporal acquisition patterns in terms of their (i) mathematical properties (i.e., acquisition frequency and variability thereof) (Laamanen & Keil, 2008) and (ii) externally observable structural target firm attributes (e.g., size, industry relatedness, or location) (Ellis et al., 2011; Hayward, 2002). I will use the latter definition (i.e., observable

[1] Please refer to sections 3.1 and 6.1 for an illustration of the rationale behind and limitations of the chosen sample, respectively.
[2] See section 6.1 for details.

target firm attributes) in this thesis to ensure comparability of my results with past studies of strategic momentum.

Strategic momentum. Following Amburgey and Miner (1992), I define strategic momentum as "[a firm's] tendency to maintain or expand the emphasis and direction of prior strategic actions in current strategic behavior" (p. 335). Applied to the acquisition context, momentum can help explain not only why, *in general*, acquirers are more likely to engage in subsequent acquisitions if they acquired firms in the past but also why prior experience in acquisitions *of a specific type* (e.g., cross-border acquisitions or acquisitions in unrelated industries) increases the propensity of acquirers to keep acquiring targets of the same type (Amburgey & Miner, 1992).

Activity load. A firm's activity load corresponds to the level of simultaneous activity in which that firm engages at a given time (Castellaneta & Zollo, 2015). It is driven by the number of parallel activities and their respective complexity (Castellaneta & Zollo, 2015). In the context of acquisitions, high levels of activity load can create an overload situation for acquiring firms (Castellaneta & Zollo, 2015) that could explain deviations from established acquisition patterns.

1.4. Structure of Thesis

This thesis is structured into six sections. Section 1 provides an entry point into the topic by explicating the underlying motivation of this thesis and delineating the research question, which I break down into three subquestions. In section 2, I establish the theoretical foundation of this thesis, based on which I develop my hypotheses. For this, I review literature on (a) temporal acquisition patterns, (b) strategic momentum, and (c) activity load/absorptive capacity to gain a complete understanding of the phenomenon of interest and correctly position this thesis in extant literature. To ensure replicability of my findings, section 3 illustrates the methodological approach used in this thesis, describing all data collection and modification steps, the variables, and the estimation strategy. Subsequently, my descriptive statistics, empirical results of the hybrid logit model, and robustness tests are presented in section 4. Section 5 then reconciles my findings with prior literature, reviewing contributions of this study to academia and practice, discussing limitations of this thesis, and highlighting avenues for future research. Finally, my conclusions are set forth in section 6. Figure 2 summarizes my approach.

2. Theoretical Background

To illustrate my phenomenon of interest and correctly position this thesis in extant research, I begin this section with a brief review of the temporal perspective used in acquisition research, in general, and temporal acquisition patterns, in particular. Subsequently, I introduce the key concepts of (a) strategic momentum, (b) activity load, and (c) absorptive capacity that will form the theoretical basis of this thesis. Finally, I delineate the mechanism through which activity load induces acquiring firms to deviate from their established acquisition patterns and formally develop my hypotheses, which will be tested in section 4.

2.1. Temporal Acquisition Patterns

Over the last three decades, research on acquisitions and related fields, such as alliances, has increasingly adopted a *temporal perspective*, primarily investigating the performance effects of time-related constructs and phenomena (Shi et al., 2012). This rise in popularity has translated into a broad range of research questions and methodological approaches used to study these topics (Shi et al., 2012). For example, extant acquisition research has investigated the timing of acquisitions relative to environmental factors, such as industry M&A waves (e.g., McNamara et al., 2008), acquisition moves of competitors (e.g., Carow et al., 2004), non-M&A corporate development initiatives, such as alliances (e.g., Shi & Prescott, 2011, 2012), and previous acquisitions of acquiring firms (e.g., Haleblian & Finkelstein, 1999; Hayward, 2002), among others. This breadth of research contexts exemplifies the versatility of the temporal perspective and, thus, helps explain its frequent adoption in acquisition research[3].

One growing literature stream which extensively uses this perspective has studied *temporal acquisition patterns* of firms. These patterns are sequences of interrelated acquisitions which are directed at executing a firm's strategy (Laamanen & Keil, 2008; Schipper & Thompson, 1983). Scholars have studied this phenomenon in different ways. For instance, in an exploratory study of acquisition patterns, Shi and Prescott (2011) have developed a pattern taxonomy, deriving seven distinct patterns and grouping those into three clusters (i.e., predictable patterns, unpredictable patterns, no acquisition activity) with different performance implications. Other studies go one step further and either (a) break down these acquisition patterns into numerical subcomponents, such as the *rate* (or *frequency*) of acquisitions within a given period and the *variability* in this acquisition rate over time (or *rhythm*) (e.g., Laamanen & Keil, 2008; Shi & Prescott, 2012; Vermeulen & Barkema, 2002), or (b) identify such patterns based on externally observable target firm attributes, such as target size[4] (e.g., Ellis et al., 2011), industry relatedness (e.g., Hayward, 2002), or geographic location (e.g., Vermeulen & Barkema, 2002). These distinctions allowed scholars to develop a more fine-grained understanding of acquisition patterns and, thus, have frequently been used in recent acquisition pattern research.

Thus far, extant research on these patterns has intensively investigated their performance effects for acquiring firms,

[3] Relevant streams include organizational learning (e.g., Hayward, 2002), internationalization processes (e.g., Vermeulen & Barkema, 2002), and strategic change (e.g., Klarner & Raisch, 2013), to name a few. See Shi et al. (2012) for a comprehensive review.

[4] Although Ellis et al. (2011) did not use the term acquisition pattern, they de facto study acquisition patterns by analyzing how size-specific acquisition experience, which acquirers gain throughout their acquisition history (i.e., acquisition pattern), is related to performance.

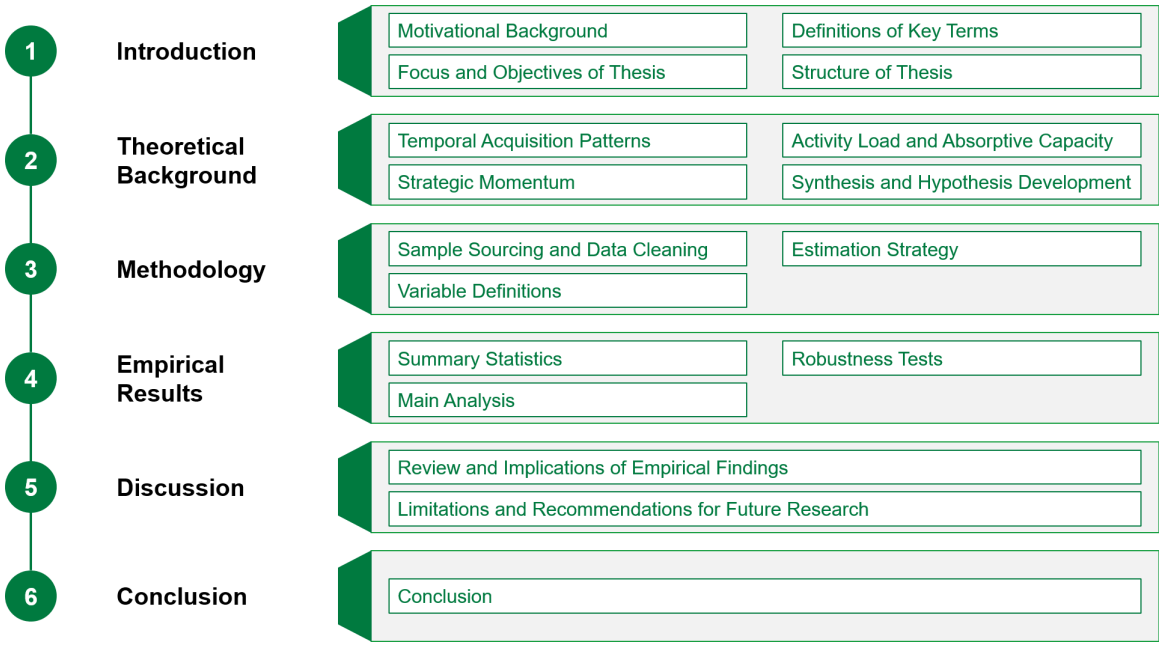


Figure 2: Structure of Thesis

highlighting the practical relevance of this phenomenon. Specifically, most studies[5] find that *stable* acquisition patterns are associated with *positive* performance outcomes for acquiring firms (e.g., Hayward, 2002; Shi & Prescott, 2011), whereas *irregular* patterns or *deviations* from stable patterns *adversely* affect the performance of these firms (e.g., Ellis et al., 2011; Laamanen & Keil, 2008; Vermeulen & Barkema, 2002). To explain these results, studies have primarily drawn on organizational learning theory and Penrosian resource-based logic. That is, acquiring firms perform better (worse) if they acquire targets in predictable (irregular) intervals that (do not) allow firms to infer correct learnings from prior acquisition experience and codify these in routines (Hayward, 2002; Laamanen & Keil, 2008; Shi & Prescott, 2011), refrain from applying (attempt to transfer) the same acquisition routines to dissimilar target firms (Ellis et al., 2011), and more evenly use (abruptly exceed) the limited capacity of their managers (Laamanen & Keil, 2008; Shi & Prescott, 2011). Considering these striking differences in acquirer performance, one would thus expect scholars to have dug deeper into factors that explain the emergence of and deviation from stable acquisition patterns.

However, as shown in Figure 3 our understanding of the antecedents of temporal acquisition patterns remains rather limited, indicating a substantial gap in acquisition research. This might, at first glance, seem surprising given the myriad of factors that scholars found to influence acquisition behavior of firms. Yet, a closer look at the literature on antecedents of acquisition behavior reveals that this discrepancy likely arises from two different research questions to which scholars have devoted unequal levels of attention: (a) What makes some firms acquire more than others (i.e., differences in acquisitiveness) and (b) what causes the emergence of and deviation from acquisition patterns (i.e., temporal acquisition patterns). Specifically, scholars have extensively focused on the first research question, discussing the role of a vast array of antecedents of acquisition behavior. These antecedents cover factors on the individual/team level, such as CEO characteristics (e.g., A. Chatterjee & Hambrick, 2007; Gamache et al., 2015; Malmendier & Tate, 2008; Seo et al., 2015) and changes within the acquiring firm's top management team (TMT) (e.g., Shi et al., 2017); acquiring firm level, such as a firm's ambition level (e.g., Haleblian et al., 2017; Kim et al., 2015) and past growth history (e.g., Kim et al., 2011); and environmental level, such as imitation of other firms' acquisition behavior (e.g., Baum et al., 2000; Haunschild, 1993; Haunschild & Beckman, 1998) and the culture-/industry-specific context of acquiring firms (e.g., Bertrand et al., 2019), for instance. However, only few studies have attempted to answer the second research question. These studies (e.g., Amburgey & Miner, 1992) have found that past acquisition behavior helps explain how temporal acquisition patterns emerge and why firms systematically adhere to their patterns over time, complementing prior research on acquisitiveness. Yet, it appears that no study that focused on antecedents of acquisition behavior has investigated possible factors that cause acquiring firms to *systematically deviate*[6] from their established acquisition patterns.

[5] Shi and Prescott (2012) argue that firms need to strike a balance between the high internal coordination costs of unpredictable patterns and the flexibility to engage in sudden acquisition opportunities, predicting an inverted u-shape relationship between temporal rhythm and acquirer performance. However, using a single-industry sample, they acknowledge the limited generalizability of their results.

[6] Systematic deviations are permanent shifts in acquisition behavior (e.g.,

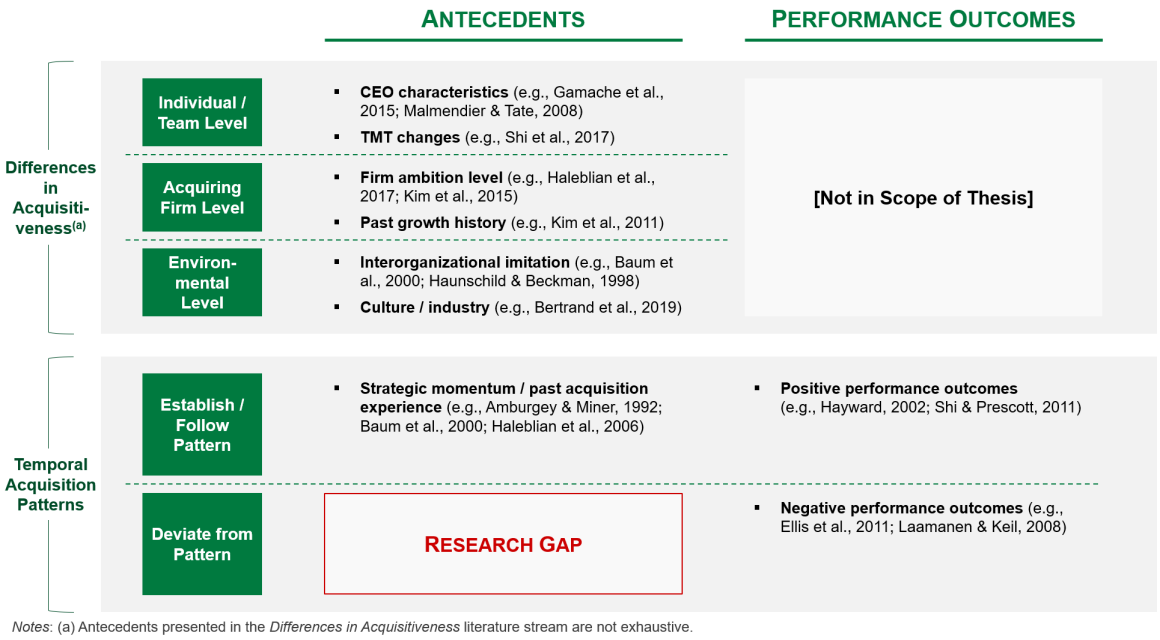


Figure 3: Research Gap in Literature on Antecedents of Temporal Acquisition Patterns

This thesis thus seeks to bridge this gap by introducing activity load as a new concept to acquisition pattern research.

2.2. Strategic Momentum

Scholars in the field of organizational science introduced the concept of *strategic momentum* four decades ago. Defining "momentum as the tendency [of firms] to maintain or expand the . . . direction of prior strategic actions in current strategic behavior" (Amburgey & Miner, 1992, p. 335), early studies of strategic momentum primarily investigated this concept in the context of organizational change (e.g., Kelly & Amburgey, 1991; Miller & Friesen, 1980) and innovation (e.g., Miller & Friesen, 1982), obtaining remarkably consistent results. For instance, scholars of organizational change found not only that firms are more likely to implement changes that are consistent with their adopted strategic and structural orientation (Miller & Friesen, 1980) but also that firms which experience strategic changes of one type (e.g., a change from a generalist strategic orientation to a specialized orientation) keep making strategic changes of the same type (Kelly & Amburgey, 1991). Likewise, studies of innovation patterns of firms showed that past innovation practices evolve in the same direction (Miller & Friesen, 1982), corroborating that actions of one type increase the likelihood of subsequent similar actions (Haleblian et al., 2006) and that the concept of momentum can hold in multiple research settings.

Building on these early studies, Amburgey and Miner (1992) applied the concept of momentum to the context of acquisitions, showing that momentum can help explain acquisition behavior, in general, and the emergence of acquisition patterns, in particular. For this, they distinguished between three different types of momentum: Repetitive momentum (the tendency to repeat past strategic actions), positional momentum (the tendency to maintain or extend current strategic positions), and contextual momentum (the influence of contextual features on strategic actions). Using a multivariate point process model, the authors found empirical support for the existence of repetitive and contextual momentum. Specifically, they observed that past experience in acquisitions of one type, such as horizontal acquisitions, increases the propensity of acquirers to engage in subsequent acquisitions of the same type (repetitive momentum), while acquirers with a decentralized structure are more likely to pursue diversification acquisitions (contextual momentum). Although Amburgey and Miner (1992) could only partially confirm the existence of positional momentum[7], their study was the first to show that firms follow acquisition patterns that are consistent with past experiences, expanding prior research on strategic momentum.

To explain their results, Amburgey and Miner (1992) resorted to organizational learning theory and theories of managerial cognition. Specifically, they argued that, by acquiring

an acquiring firm that previously acquired large targets now switches to small targets). As I will explain in sections 2.3 and 2.4, such a pattern shift involves substantial costs and, thus, can likely not be explained by antecedents of acquisition behavior that primarily explain differences in the number and volume of acquisitions. If firms are influenced by these factors, it thus appears more likely that firms simply adjust the number of deals and deal volume instead of changing their patterns.

[7] Firms with a diversified position in multiple product markets tend to expand their current position through further product market diversification acquisitions. However, conglomerate firms do not seem to engage in further conglomerate acquisitions (Amburgey & Miner, 1992).

targets of a certain type, acquirers accumulate type-specific acquisition experience, which (a) leads to the formation of type-specific acquisition routines and (b) positions these targets more centrally in the cognitive maps of managers. Both concepts explain the creation of acquisition momentum, although for different reasons. *Routines*, on the one hand, "are programs of action that . . . [formalize an organization's] experience . . . with a particular task" (Haleblian et al., 2006, p. 358), constituting a key element of organizations (Cyert & March, 1963; Nelson & Winter, 1982). They are formed through repeated actions, which allow organizations to build up competence and confidence in executing these actions, creating an incentive to repeat learned behaviors (Collins et al., 2009) and, thus, momentum (Amburgey & Miner, 1992). In other words, through routines, "an organization undertakes . . . activities . . . because it knows how to [execute these activities]"[8] (Amburgey & Miner, 1992, p. 336). In the context of acquisitions, routines encompass "templates for selecting . . . [specific] targets or [post-integration] guidelines" (Haleblian et al., 2006, p. 358) and therefore help explain type-specific acquisition momentum (Amburgey & Miner, 1992). *Cognitive maps*, on the other hand, refer to the shared mindsets of managers. They are shaped by experiences in certain strategic actions, such as acquisitions of targets of a specific type, inducing a preference for these actions (Amburgey & Miner, 1992). That is, once managers build up experience with targets of a specific type, these targets "[take] a more central role in [their] . . . cognitive [maps and, thus, are] . . . more likely to be seen as an appropriate [strategic action]" (Amburgey & Miner, 1992, p. 337). Both concepts therefore corroborate that acquisitions are subject to inertial pressures, promoting acquisitions of familiar target types (i.e., more exploitation) while reducing an acquirer's likelihood to buy less-known target types (i.e., less exploration) (Collins et al., 2009).

As presented in Table 1, research on acquisition patterns has frequently adopted the reasoning of Amburgey and Miner (1992) and extensively studied momentum as a firm-level explanation of acquisition behavior, substantiating the repetitive momentum hypothesis. One set of studies, for example, explored *overall* acquisition momentum, finding that prior acquisition experience, *in general*, increases the likelihood of subsequent acquisitions (Haleblian et al., 2006). Other studies chose a more fine-grained perspective by differentiating between externally observable target firm attributes. In a study of local expansion patterns of firms, for example, Baum et al. (2000) showed that firms are more likely to acquire targets that have attributes *similar* to those of previously acquired targets. Likewise, Collins et al. (2009) found that prior experience in cross-border acquisitions increases the likelihood of firms to engage in further acquisitions of that type, corroborating that repetitive momentum holds in a cross-border acquisition context. Both sets of studies therefore found a *positive* relationship between prior acquisition experience and subsequent acquisition activity – a result consistent with predictions of momentum theory.

However, this consensus has been challenged recently. Albeit in the context of organizational change, Beck et al. (2008) found that firms exhibit behavior *opposite* to the repetitive momentum hypothesis, providing both theoretical and methodological explanations for their observation. From a theoretical viewpoint, the authors argued that prior change enables firms "to refine the content of organizational procedures . . . [and] routines that govern change processes" (p. 428) which reduces the need for subsequent change, although they did not directly measure this mechanism. Methodologically (and more dramatically), Beck et al. (2008) showed that accounting for unobserved time-invariant heterogeneity on the firm level *reverses* the direction of the momentum effect (i.e., prior change triggers a *deceleration* in further change of the same type, not an acceleration). They confirmed their observations with three datasets in different research settings, indicating that past studies of momentum, which mostly use random effects models, have likely reported biased results. Moreover, Vermeulen and Barkema (2001) presented findings in a cross-border acquisition context that are similar to those of Beck et al. (2008). That is, after including firm fixed effects in their logit model, Vermeulen and Barkema (2001) showed that prior cross-border acquisitions trigger a *deceleration* in further cross-border acquisition activity[9], demonstrating that the results of Beck et al. (2008) are equally relevant for scholars who study acquisition patterns. Both studies thus challenge the repetitive momentum hypothesis and reveal a major gap in momentum research that, I argue, can (at least partially) be closed by introducing the concept of activity load to momentum research.

2.3. Activity Load and Absorptive Capacity

Like strategic momentum, the concepts of *activity load* and *absorptive capacity* are not new to management research. Specifically, both date back to early studies of organizational behavior (Simon, 1945) and growth (Penrose, 1959), playing a particularly crucial role in Penrose's *The Theory of the Growth of the Firm*. In her study, Penrose (1959) has argued that the capacity of managers to engage in activities of firms (i.e., their absorptive capacity) is limited[10], essentially referring to Simon's (1945) idea of 'bounded rationality' according to which managers have a finite capacity to process information[11]. To grow, however, a firm needs its managers to en-

[8] Seminal studies of routines (e.g., Levitt & March, 1988; Nelson & Winter, 1982) emphasize that this "learning process is largely independent of the performance outcomes of prior experiences" (Haleblian et al., 2006, p. 357) since positive outcomes are interpreted as evidence of successful actions while negative outcomes are attributed to external circumstances or poor execution of routines (Amburgey & Miner, 1992).

[9] The authors report the increase in cross-border greenfield investments as an inverse proxy for the deceleration in cross-border acquisitions.

[10] That is, "there is plainly a physical maximum to the number of things any individual or group of individuals can do" (Penrose, 1959, p. 41).

[11] As Penrose (1959, p. 15) notes, "the general view . . . set forth here does not differ fundamentally from the concepts . . . of Simon [(1945)]".

Table 1: Overview of Studies of Strategic Momentum

Study	Literature Stream	Key Finding	Repetitive Momentum Hypothesis Confirmed
Miller and Friesen (1980)	Organizational Change	Organizations generally implement changes that are *consistent* with their adopted strategy and structure. However, periods of substantial *reversal* can occur if excesses / problems become dominant.	Partially[(a)]
Miller and Friesen (1982)	Innovation	Past innovation practices of proactive innovators (entrepreneurial firms) and reactive innovators (conservative firms) *keep evolving in the same direction*.	Yes
Kelly and Amburgey (1991)	Organizational Change	Firms which experience strategic changes of one type are *more likely* to pursue similar changes in the future.	Yes
Amburgey and Miner (1992)	Acquisition Patterns	Past experience in mergers of one type *increases* the number of subsequent mergers of the same type.	Yes
Baum et al. (2000)	Acquisition Patterns	Building on prior experience, firms are *more likely* to acquire targets which are similar to previously acquired targets than targets which are dissimilar.	Yes
Vermeulen and Barkema (2001)	Acquisition Patterns	Increases in cross-border acquisitions *decrease* the likelihood of engaging in subsequent cross-border acquisitions.	No
Haleblian et al. (2006)	Acquisition Patterns	Prior acquisition experience, positive performance feedback, and their interaction all *increase* the likelihood of engaging in subsequent acquisitions.	Yes
Beck et al. (2008)	Organizational Change	Prior changes trigger a *deceleration* of further changes of the same type.	No
Collins et al. (2009)	Acquisition Patterns	Prior acquisition experience in cross-border acquisitions *increases the likelihood* of engaging in subsequent cross-border acquisitions.	Yes

Notes: (a) This study finds an oscillation pattern. That is, periods of momentum alternate with periods in which a firm's direction of change reverses.

gage in growth-promoting activities[12] that consume their limited capacity (i.e., to shoulder the load imposed by these activities). By synthesizing these two premises, Penrose (1959) concludes that the growth of a firm depends on how much of the managerial capacity *available* to the firm is *consumed* by growth-promoting activities, with the *available* managerial capacity setting the upper growth limit. In fact, the interplay between the *availability* and *consumption* of managerial capacity is so central to her theory that Penrose (1959) even calls it the 'fundamental ratio'[13]. The concepts of activity load and absorptive capacity thus represent two sides of the same coin, adding to our understanding of organizations only in combination with each other.

Later studies have extended the early work of Penrose (1959), defining *activity load* as the level of simultaneous activity in which a firm engages at a given time (Castellaneta & Zollo, 2015) and distinguishing between two different drivers of a firm's activity load. This new distinction led to the emergence of two complementary perspectives in activity load research (Castellaneta & Zollo, 2015). One set of studies (e.g., Barkema & Schijven, 2008; Castellaneta & Zollo, 2015), for instance, has considered the concept of activity load from a purely quantitative view, the *computation* perspective, equating a firm's activity load with the *number* of simultaneous activities in which its managers engage

[12] Growth-promoting activities refer to what Penrose (1959) called "the creation and execution of plans for expansion" (p. 46).

[13] Penrose (1959) defines this ratio as "the ratio between the managerial services available [emphasis added] for expansion and the managerial services required [emphasis added] per dollar of expansion" (p. 175).

(first driver) (Castellaneta & Zollo, 2015). That is, firms bear a higher activity load if they, *ceteris paribus*, engage in a higher number of parallel activities. However, although this purely quantitative perspective offers compelling advantages, such as ease of empirical measurement, to scholars, it abstracts from the fact that activities can vary with respect to the amount of time and effort managers need to invest in them (Castellaneta & Zollo, 2015) and, thus, how much managerial capacity they consume. To bridge this gap, a second set of studies (e.g., Daft & Weick, 1984; Zorn et al., 2019) has adopted a different view of the activity load concept – the *interpretation* perspective. According to this view, the activity load of a firm varies with the level of difficulty its managers face in interpreting the information associated with the activities they pursue, depending on the *level of complexity*[14] of these activities (second driver) (Castellaneta & Zollo, 2015). In other words, firms bear a higher activity load if they, *ceteris paribus*, pursue activities that are more complex. Taken together, both perspectives show that activity load is a multifaceted concept that can only be fully understood once broken down into its components of volume and complexity.

Irrespectively of the activity load perspective adopted by these studies, they have unanimously argued that high levels of activity load can create problems for firms. That is, once the activity load of firms exceeds their *absorptive capacity*, which equals the maximum level of activity that a firm can simultaneously absorb, these firms face a situation of *information overload* (Castellaneta & Zollo, 2015). In such a situation, firms are overwhelmed by the amount and/or complexity of the information they need to digest (Castellaneta & Zollo, 2015). This makes them less able to infer correct learnings from past experience (Haleblian & Finkelstein, 1999; Hayward, 2002) due to 'time compression diseconomies' (Dierickx & Cool, 1989), reduces their capacity to absorb further activities (Vermeulen & Barkema, 2002), and – especially in the acquisition context – causes 'corporate indigestion' (Kusewitt, 1985). Building on this logic, scholars in the field of M&A have argued that an overload situation is particularly likely in the context of acquisitions (Castellaneta & Zollo, 2015), drawing on both activity load perspectives. On the one hand, "[acquiring] firms frequently engage in multiple acquisitions to execute their strategy" (Laamanen & Keil, 2008, p. 663), often managing a high volume of activities in parallel (computation perspective) (Castellaneta & Zollo, 2015). On the other hand, acquisitions themselves are strategic activities and, thus, "particularly complex ..., making information overload more likely" (interpretation perspective) (Castellaneta & Zollo, 2015, p. 142). In sum, research on activity load has agreed on the fact that overload can create considerable problems for firms and highlighted the relevance of information overload in the context of acquisitions.

Scholars generally agree that a firm's absorptive capacity cannot be easily expanded in the short run[15] (Penrose, 1959; Shaver, 2006). Yet, research has shown that some firm-level factors *can* alleviate the strains imposed by high levels of activity load. For this, studies have differentiated between three groups of factors. First, one stream of research (e.g., Kusewitt, 1985; Laamanen & Keil, 2008; Penrose, 1959) has stressed the importance of structural features of acquiring firms, such as size or organizational structure, in alleviating the burden imposed by high levels of activity load. Following Penrosian resource-based logic, these studies have argued that a larger size allows acquirers to not only access a larger pool of managerial resources but also benefit from more "[specialized] structures and processes for managing acquisitions" (Laamanen & Keil, 2008, p. 666) – two ways that cushion the effects of high activity load. Since "decentralization is equivalent to [an increase] . . . in the input of managerial services" (Penrose, 1959, pp. 49-50), scholars have hypothesized a firm's structure to yield effects similar to those of firm size, although empirical evidence on this has remained rather scarce. Second, another research stream (e.g., Castellaneta & Zollo, 2015; Laamanen & Keil, 2008) has emphasized the role of prior acquisition experience. Drawing on organizational learning theory, these studies have stressed that, through repetition of activities, firms build routines that allow them to reduce the attention managers *consciously* need to devote to these activities[16] (Ocasio, 1997) – a process that frees up managerial capacity (Castellaneta & Zollo, 2015; Laamanen & Keil, 2008). Third, a final set of studies (e.g., Zorn et al., 2019) has highlighted that the activity capacity available to acquirers also depends on the managerial capacity of the target firm. Specifically, Zorn et al. (2019) have presented evidence which shows that retaining target firm executives *after* the acquisition can alleviate the strains imposed by a high activity load, arguing that TMT retention increases the managerial capacity available for integration activities. Overall, these firm-level factors have strongly contributed to a more nuanced understanding of the effects of high levels of activity load than the concept of activity load alone.

As presented in Table 2, studies of activity load have extensively investigated the *performance* implications of information overload for acquirers, obtaining mostly consistent results. These studies have frequently stipulated and found a negative linear relationship between the activity load and

[14] I acknowledge that the level of interpretation difficulty can also depend on the "uncertainty, ambiguity, novelty, ... and intensity" of activities (Castellaneta & Zollo, 2015, p. 142). However, given that prior literature on activity load has mostly differentiated activities by their complexity (e.g., Castellaneta & Zollo, 2015; Collins et al., 2009; Ellis et al., 2011; Zorn et al., 2019), I follow this route to ensure comparability of results.

[15] Penrose (1959) argues that firms can only expand their activity capacity over time since "existing managerial personnel provide services that cannot be provided by personnel newly hired from outside the firm . . . because the experience they gain from working within the firm and with each other enables them to provide services that are uniquely valuable for the operations of [that firm]" (pp.41-42). Shaver (2006) agrees, stating that "the capacity effect is not necessarily binding in the long term because of the firm's ability to increase capacity" (p. 966).

[16] That is, managers switch from controlled processing to automatic processing of activities, saving cognitive capacity (Ocasio, 1997).

firm-level performance of acquirers, covering a wide array of research contexts, such as post-merger integration (PMI) (Barkema & Schijven, 2008; Shaver, 2006; Zorn et al., 2019) and acquisition programs (Kusewitt, 1985; Laamanen & Keil, 2008). Yet, a closer look at the literature reveals differences in the extent to which both activity load perspectives have been researched by scholars. For instance, extant literature has predominantly explored the effects of acquisition volume and complexity *in isolation* (e.g., Barkema & Schijven, 2008; Castellaneta & Zollo, 2015; Kusewitt, 1985; Vermeulen & Barkema, 2002; Zorn et al., 2019), mostly finding a negative linear relationship[17] between activity load and firm performance with moderately large effect sizes[18]. By contrast, studies which examine the *joint effect* of acquisition volume and complexity (e.g., Laamanen & Keil, 2008) have been scarce and only partially substantiated the existence of that effect[19]. Overall, despite these differences in perspective, extant research has demonstrated that activity load has important performance implications for acquirers.

However, Table 2 also clearly shows that extant literature has largely abstracted from firm-level consequences other than performance. For instance, only few studies (e.g., Barkema & Schijven, 2008) have examined that overload can also trigger a restructuring response of acquiring firms. Specifically, building on the behavioral theory of the firm (BTF) (Cyert & March, 1963; March & Simon, 1958; Simon, 1945), Barkema and Schijven (2008) have argued that acquirers initially seek solutions to integration problems within target firms (i.e., local search) but eventually need to cut complexity through restructuring (i.e., distant search) since the cumulative inefficiencies from past integrations create an overload situation. Their empirical results, which show that the number of acquisitions since an acquirer's last restructuring is positively related to that firm's likelihood to engage in renewed restructuring, support their logic. Likewise, evidence on the relationship between activity load and acquisition behavior of firms remains surprisingly scarce. That is, although one would intuitively expect high levels of activity load to affect the acquisition behavior of firms (e.g., stop in acquisitions due to indigestion - Kusewitt, 1985), no study has – to the best of my knowledge – hitherto investigated whether activity load influences acquisition behavior. This thesis therefore aims to complement prior activity load research, which is summarized in Figure 4, by studying whether activity load can help explain acquisition behavior of firms, in general, and deviations from temporal acquisition patterns, in particular.

2.4. Synthesis and Hypothesis Development

I derive three essential insights from reviewing the literature. First, acquisition pattern literature exhibits a gap in research on antecedents which explain *systematic deviations* from established acquisition patterns – despite a myriad of factors that are known to influence differences in the acquisitiveness of acquiring firms. Second, research on momentum converged towards a clear consensus on the repetitive momentum hypothesis, which, however, was both theoretically and methodologically challenged by recent studies (e.g., Beck et al., 2008). Third, studies of activity load have extensively investigated performance implications of high levels of activity load for acquirers, largely abstracting from alternative firm-level consequences, such as restructuring (e.g., Barkema & Schijven, 2008) and, in particular, changes in acquisition behavior.

By combining these insights, I argue that high levels of activity load cause acquiring firms to *systematically* deviate from their established acquisition patterns. If true, this relationship could explain acquisition behavior opposite to the repetitive momentum hypothesis. To validate this idea, I follow a three-step approach hereafter, with each step answering one of the subquestions shown earlier in Figure 1. First, I examine how the volume of acquisitions affects acquisition behavior – a relationship that solely draws on the logic of the computation perspective and, thus, serves as a good baseline effect of activity load. Second, I analyze how this baseline effect varies with the complexity of acquisitions, exploring the joint effect of volume (computation perspective) and complexity (interpretation perspective). Third, I investigate whether and how the absorptive capacity of acquirers, which I proxy in two different ways (i.e., acquirer size and organizational structure), alleviates the effect of activity load. By following these three steps, I can disentangle the effects of each activity load driver and develop a nuanced understanding of how activity load affects the acquisition behavior of firms. Figure 5 summarizes my approach.

2.4.1. Baseline Effect: Acquisition Volume

A change in acquisition behavior is the final step in a dynamic process in which firms face an overload situation caused by high levels of activity load. This process starts with the build-up of acquisition experience which acquirers gain from each acquisition they pursue (Haleblian & Finkelstein, 1999; Hayward, 2002), allowing them to successively build up the knowledge of and skills for managing acquisitions[20] (Laamanen & Keil, 2008). Over time, this accumula-

[17] Barkema and Shijven's (2008) study is an exception since it only examines activity load as a moderating variable, corroborating that a higher number of acquisitions strengthens the inverted u-shape relationship between the number of acquisitions since an acquirer's last restructuring and firm-level performance of the acquirer.

[18] For instance, Castellaneta and Zollo (2015) find that an activity load increase (i.e., increase in the number of private equity (PE) investments) by one standard deviation reduces an investment's IRR by ten percent (computation perspective). Likewise, Zorn et al. (2019) observe a USD 217m drop in the market value of acquirers with an asset book value of USD 1bn for each additional nested target within (i.e., higher complexity of) the focal target (interpretation perspective).

[19] Specifically, Laamanen and Keil (2008) find a significant effect for the product term of *acquisition rate* and program scope but not for the product term of *acquisition rate variability* and program scope.

[20] I assume that the time intervals between individual acquisitions are neither too short nor too long because too short (long) intervals make it harder (uneconomical) for firms to infer correct learnings from (codify) past acquisition experience (Hayward, 2002; Laamanen & Keil, 2008).

Table 2: Overview of Studies of Activity Load and Activity Capacity

Study	Literature Stream	Key Finding	Activity Load Perspective	Firm-Level Consequence
Penrose (1959)	Organizational Growth	The growth of a firm is determined by the managerial services available to that firm and those consumed by expansion activities.	-	-
Kusewitt (1985)	Acquisition Programs	A high *number* of acquisitions within a short time can lead to indigestion problems and is negatively associated with acquirer performance. Targets of *large relative size* and from *unrelated industries* are also negatively related to performance. A larger acquirer size and decentralized structure potentially alleviate this burden.	Computation and Interpretation[(a)]	Performance
Vermeulen and Barkema (2002)	International Expansion	A high/temporally concentrated *number* of new subsidiaries and a *broad product/ geographic* expansion scope create an overload that reduces a firm's absorptive capacity, weakening the positive relationship between international expansion and firm performance.	Computation and Interpretation[(a)]	Performance
Shaver (2006)	Post-Merger Integration	The limited cognitive capacity of managers can constrain the realization of synergies in the PMI phase.	-	Performance
Barkema and Schijven (2008)	Post-Merger Integration	The *number* of acquisitions since a firm's last restructuring is positively (negatively) related to further restructuring (performance). A higher acquisition intensity (more acquisition experience) strengthens (weakens) this effect.	Computation	Performance and Restructuring
Laamanen and Keil (2008)	Acquisition Programs	A high *volume*/uneven temporal distribution of acquisitions can overstrain the limited cognitive capacity of managers and inhibit the build-up of additional capacity, both being negatively related to acquirer performance. A *broader, more complex acquisition program scope* strengthens the negative effect of a high acquisition volume. A larger acquirer size and prior acquisition experience can weaken the negative effect of surges in acquisitions.	Computation and Interpretation[(b)]	Performance

(Continued)

Table 2—continued

Castellaneta and Zollo (2015)	Organizational Learning	A higher *number* of parallel PE investments (over-)saturates managers' limited attention capacity and is inversely related to PE investment returns. Prior acquisition experience can weaken this negative effect.	Computation	Performance
Zorn et al. (2019)	Post-Merger Integration	Nested acquisitions are *more complex* and, thus, require more managerial capacity than non-nested ones, reducing post-acquisition performance. Retaining TMT members of the focal target weakens this negative relationship.	Interpretation	Performance

Notes: Study investigates computation and interpretation perspective (a) seperately or (b) jointly and seperately.

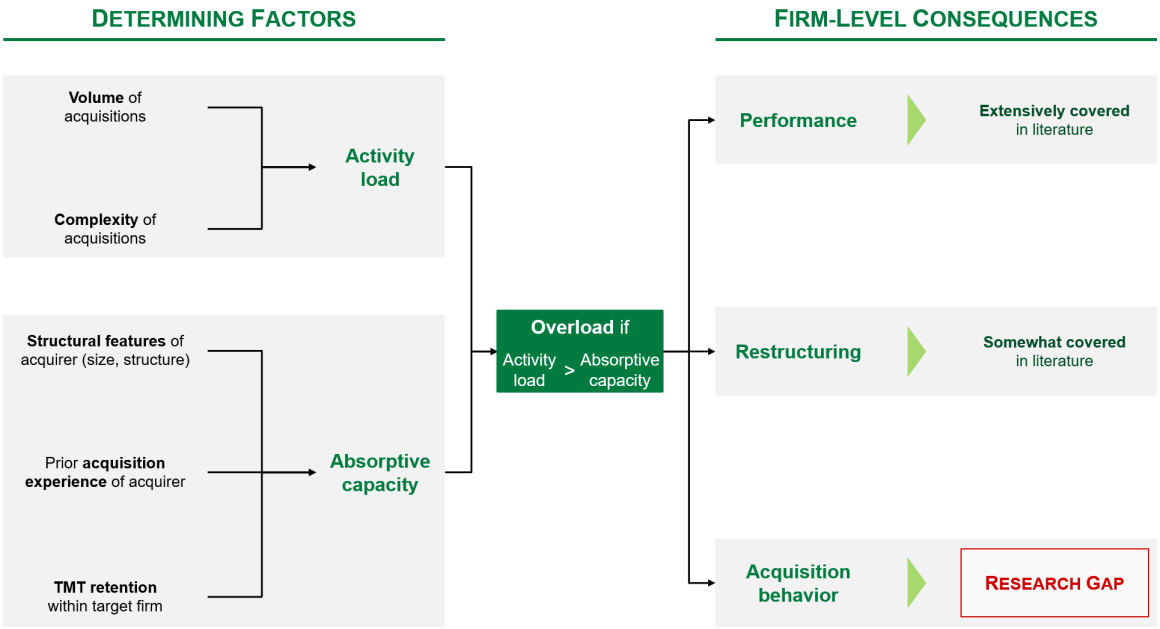


Figure 4: Determining Factors and Firm-Level Consequences of Overload

tion of acquisition experience leads to the formation of acquisition routines and a more central positioning of acquisitions in the cognitive maps of managers, creating repetitive momentum, which incentivizes firms to repeat learned behaviors and, thus, engage in further acquisitions (Amburgey & Miner, 1992). A higher number of subsequent acquisitions, however, directly translates into a higher activity load since acquirers not only need to integrate an ever-growing number of targets from past deals but also – in parallel – refill their deal pipeline by screening for and negotiating with potential targets to maintain acquisition momentum. In fact, the inertial pressures of momentum often are so pervasive (Amburgey & Miner, 1992; Miller & Friesen, 1980, 1982) that the steady increase in acquisition activity driven by momentum likely persists until the activity load from acquisitions exceeds the absorptive capacity of acquirers, creating a situation of information overload (Castellaneta & Zollo, 2015). As the strains of information overload are instantly felt by managers and, thus, must be immediately acted on, I expect the cognitive burden borne by managers in such a situation, *ceteris paribus*, to dominate the inertial pressures of momentum, forcing acquirers to reduce the activity load from acquisitions[21]. The simplest way for them to achieve this is by reducing their acquisition volume in the subsequent period – a change in acquisition behavior that would not only

[21] Expanding a firm's managerial capacity is not an option since it cannot be easily expanded in the short run (Penrose, 1959; Shaver, 2006).

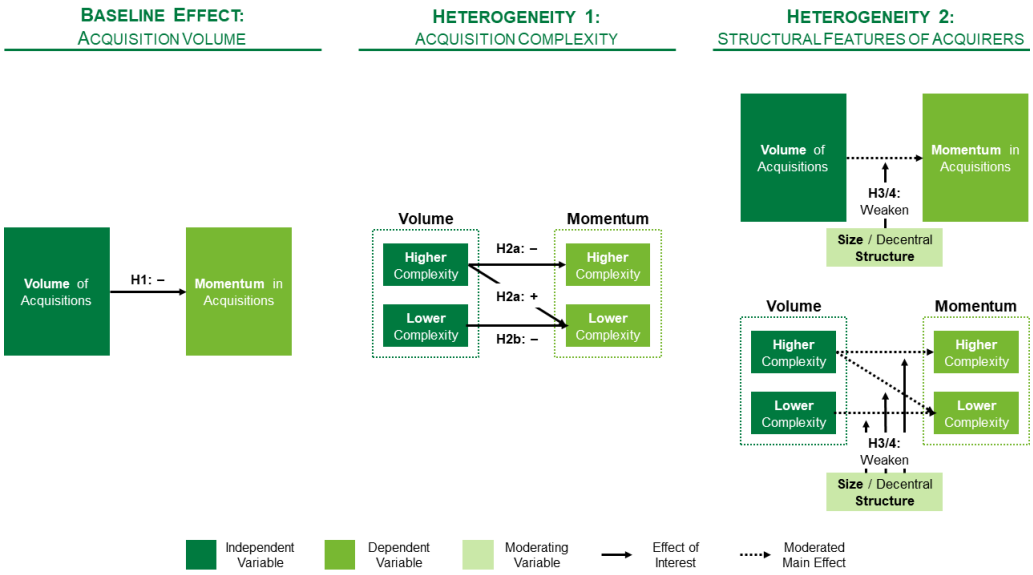


Figure 5: Key Relationships and Tested Hypotheses

allow acquirers to process their backlog of 'undigested' acquisitions (Kusewitt, 1985) but also correspond to a *discontinuation* in acquisition momentum (Beck et al., 2008; Vermeulen & Barkema, 2001). Stated formally:

> ***Hypothesis 1****: Increases in acquisition activity relative to a firm's past acquisition activity level reduce a firm's likelihood to engage in subsequent acquisitions.*

2.4.2. Heterogeneity in Acquirer Responses I: Acquisition Complexity

Because acquisitions are heterogeneous events (Haleblian & Finkelstein, 1999; Hayward, 2002) which differ in their rationale (e.g., Hayward, 2002), process management (e.g., Haspeslagh & Jemison, 1991), and performance (e.g., King et al., 2004), it is not surprising that some scholars (e.g., Zorn et al., 2019) have argued that acquisitions also vary in their degree of complexity and, thus, in their activity load. That is, depending on the characteristics of the target firm vis-à-vis the acquirer, acquisitions can vary in the amount of managerial capacity they consume (Zorn et al., 2019), allowing acquirers to exhibit cross-sectional variation in their behavioral response to an overload situation. Following this reasoning, acquisition research has widely discussed three dimensions of acquisition complexity, which operate on different levels *of aggregation and, thus,* capture different facets of acquisition complexity.

Figure 6 visualizes these dimensions, as well as the externally observable structural target firm attributes associated with them. That is, on the *country* level, acquisition complexity depends on the target's geographic location, which captures differences in cultural and institutional contexts between the home countries of the target and the acquirer (Collins et al., 2009; Ellis et al., 2011; Vermeulen & Barkema, 2002). Such differences add an additional layer of complexity to cross-border acquisitions since they pressure acquirers "to adapt home-grown mental maps, organizational structures, systems, and processes to the international setting" (Vermeulen & Barkema, 2002, p. 638) and absorb new "region-specific practices and business knowledge" (Ellis et al., 2011, p. 1265). Thus, cross-border acquisitions, on average, impose a higher activity load on acquirers than domestic ones. Likewise, on the *industry* level, acquisition complexity depends on the industry relatedness of the target and the acquirer. Since every industry operates on a different business logic (Prahalad & Bettis, 1986; Vermeulen & Barkema, 2002), which is reflected in different product offerings (Ellis et al., 2011) and internal structures (Finkelstein & Haleblian, 2002; Haleblian & Finkelstein, 1999), firms that acquire targets which operate in unrelated industries must manage "more complex . . . interdependencies across a wider variety of functions and products [during and after the acquisition]" (Ellis et al., 2011, p. 1264). Thus, unrelated acquisitions, on average, consume more managerial capacity than acquisitions of targets in related industries, imposing a higher activity load on acquiring firms (Zorn et al., 2019). Finally, on the *firm* level, acquisition complexity depends on the size of the target relative to the acquirer. That is, since the scale of operations of large targets requires large-scale integration activities, large acquisitions increase coordination costs for acquirers due to a higher number of "interrelated decisions . . . [and the] involvement of more . . . members across business[es]. . . and functional areas" (Ellis et al., 2011, p. 1263) and create a stronger disruptive effect within the acquirer's organization due to large-scale internal reorganization (Barkema & Schijven, 2008). Thus, large targets, on average, are more resource-consuming and complex to inte-

grate than smaller ones[22], imposing a higher activity load on firms (Zorn et al., 2019). Overall, the literary discourse on the dimensions of acquisition complexity highlights that the relationship between activity load and the acquisition behavior of acquirers can only be fully understood by examining the *joint* effect of acquisition volume and complexity (i.e., by combining both activity load perspectives).

Drawing on both activity load perspectives, I therefore argue that a firm's acquisition behavior response to information overload varies with the complexity level of acquisitions. Specifically, I expect firms to reduce the activity load from acquisitions in two ways. On the one hand, they can, *ceteris paribus*, cut the complexity of newly made acquisitions by switching from targets in a higher-complexity category (e.g., overseas targets) to ones in a lower-complexity category (e.g., domestic targets). By definition, such a response would represent a *deviation* from a firm's established acquisition pattern (e.g., shift from a pattern of overseas targets to one of domestic targets), allowing firms to maintain their overall acquisition momentum[23] while alleviating the strains of information overload. On the other hand, if acquirers have established an acquisition pattern of targets in a lower-complexity category, they have no choice to reduce their activity load other than by, *ceteris paribus*, decreasing the volume of newly made acquisitions. In doing so, firms can alleviate the strains of information overload only by discontinuing their acquisition momentum as there is no other target firm category to which they can switch. Thus, it follows:

> ***Hypothesis 2a**: Increases in acquisition activity within a higher-complexity target firm category relative to a firm's past acquisition activity level within that category reduce (increase) that firm's likelihood to engage in subsequent acquisitions within that higher-complexity (lower-complexity) category.*

> ***Hypothesis 2b**: Increases in acquisition activity within a lower-complexity target firm category relative to a firm's past acquisition activity level within that category reduce a firm's likelihood to engage in subsequent acquisitions within that category.*

2.4.3. Heterogeneity in Acquirer Responses II: Structural Features of Acquirers

Cross-sectional variation in the behavioral response of acquirers, however, could result not only from differences in acquisition complexity but also from differences in acquirer characteristics. Building on this idea, I argue that differences in acquirer size can explain why some acquirers can bear a higher activity load burden and, thus, are less likely to deviate from their stable acquisition pattern than others. That is, according to Penrosian resource-based logic, a larger firm size allows acquirers to access a larger pool of managerial resources and more specialized internal acquisition processes (Laamanen & Keil, 2008). Through this, acquirers *de facto* extend their absorptive capacity, which alleviates the strains imposed by high levels of activity load. This, in turn, reduces their likelihood of reaching a situation of information overload and, thus, helps them maintain their acquisition momentum. Following this rationale, I hypothesize:

> ***Hypothesis 3**: Increases in acquisition activity relative to a firm's past acquisition activity level less strongly affect that firm's likelihood to engage in subsequent acquisitions if that firm is larger.*

Using the same logic, I expect a more decentralized organizational structure to yield the same effect for acquirers as an increase in firm size or managerial capacity. That is, a higher degree of decentralization allows acquirers to distribute the activity load from acquisitions more evenly across organizational members, avoiding a too strong concentration of activity load within one single part of the organization. Like an increase in firm size, a more decentralized organizational structure expands the absorptive capacity of acquirers, alleviating the strains imposed by high levels of activity load. Consequently, I expect firms with a more decentralized structure, *ceteris paribus*, to be less likely to deviate from their established acquisition pattern. Thus, it follows:

> ***Hypothesis 4**: Increases in acquisition activity relative to a firm's past acquisition activity level less strongly affect that firm's likelihood to engage in subsequent acquisitions if that firm has a more decentralized organizational structure.*

3. Methodology

In the following, I outline the methodological approach taken to answer my research question. This outline consists of three parts. First, I delineate the data sources of my sample and the steps taken to modify the raw data. Second, definitions of all variables and the rationale for including them in

[22] I acknowledge that organizational learning literature (e.g., Castellaneta & Zollo, 2015; Ellis et al., 2011) has argued and found that repeated acquisitions of large targets (targets within the same geography/industry) reduce the *perceived* complexity of acquisitions of the same type due to routinization effects. However, I argue that routinization cannot eliminate the differences in complexity between larger (overseas/unrelated) and smaller (domestic/related) acquisitions for two reasons. First, routines are formed through repeated actions and, thus, need time to evolve (Collins et al., 2009). Second, if routines are not regularly used, past learnings which are not properly codified become irrelevant or are forgotten since employees, in which these learnings reside (Levitt & March, 1988), may move to different units or leave the company (Hayward, 2002).

[23] More specifically, by switching from targets in a higher-complexity category to targets in a lower one, firms shift their acquisition momentum from one target firm type to the other, discontinuing momentum for targets in the higher-complexity category while building up type-specific acquisition experience – and momentum – for targets in the lower-complexity category (Amburgey & Miner, 1992; Haleblian et al., 2006).

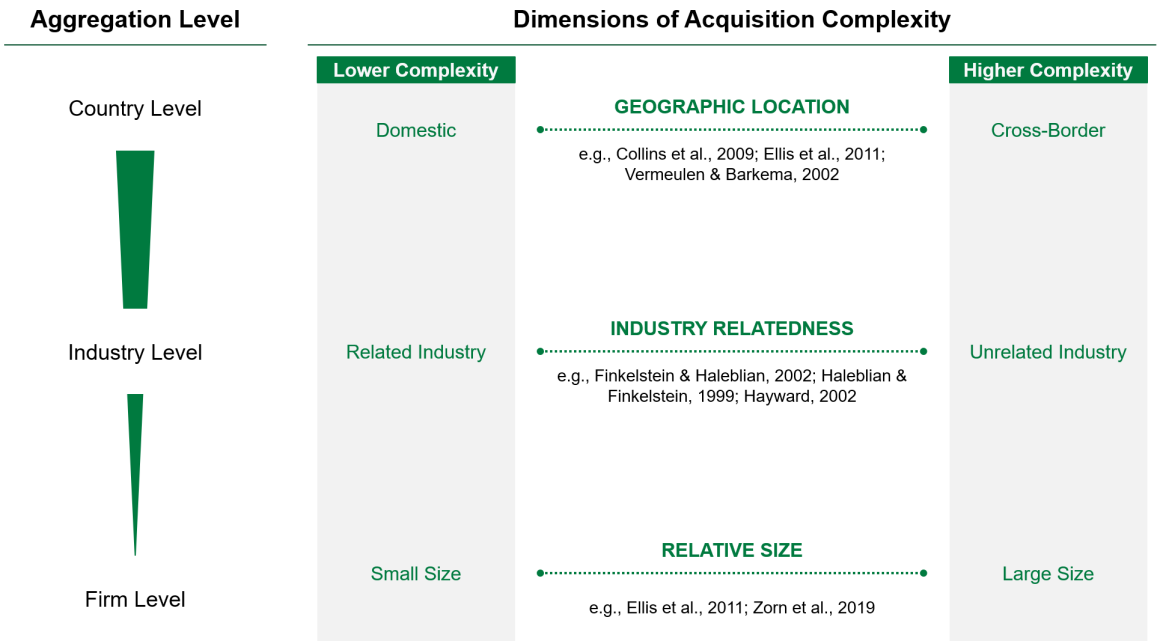


Figure 6: Dimensions of Acquisition Complexity by Aggregation Level

my analysis are presented.[24] Third, I elaborate on the empirical model used in this study.

3.1. Sample Sourcing and Data Cleaning

To corroborate my hypotheses, I compiled a panel dataset of publicly disclosed acquisitions of the 300 largest Fortune Global 500 firms over the 1990-2010 period. My rationale for choosing this particular sample is threefold. First, to ensure that all acquirers in the sample are sufficiently acquisitive, I only included acquirers that are large in size (Audia & Greve, 2006; Baysinger & Hoskisson, 1989). Firms listed in the Fortune Global 500 ranking meet this criterion particularly well since they are the largest ones by revenue and, thus, have sizable operations and acquisition activities. Second, I limited my sample to acquirers that were listed in the 1990 Fortune Global 500 ranking to avoid any survivorship bias. Third, to ensure that firms have acquisition streams that are sufficiently long for temporal dynamics to be visible, I selected a 21-year time horizon with high levels of historical acquisition activity (Cools et al., 2007; Kengelbach & Roos, 2011). Meeting all these criteria, my selected sample seems to be well suited to test my hypotheses.

This sample combines data from multiple data sources. For instance, in line with prior studies (e.g., Laamanen & Keil, 2008), all acquisition data stem from Refinitiv's Eikon M&A database (formerly Thomson One and Datastream), ensuring a comprehensive coverage of acquisitions over the sample period. In addition, to create the two controls *CEO overconfidence* and *CEO succession*, I extracted data from Compustat Execucomp. This dataset was complemented by human-coded data on TMT member titles as originally found on Execucomp, through which I proxied a firm's *degree of decentralization*. Finally, Standard & Poor's (S&P) Compustat North America database served as the source of company-level financials and business-segment data, which I used to create firm-level controls and cluster acquisitions by their observable attributes. All data on acquisitions, human-coded TMT member titles, and business-segment fundamentals were generously provided by Prof. Johannes Luger, who used them in prior research projects.

After merging these raw data into one comprehensive dataset, I executed several data cleans and transformations to avoid implausible data values and ensure consistency in my data. First, I eliminated duplicate M&A transactions in my acquisition raw data to ensure that deals in my final sample are unique, excluding 59 duplicate transactions. Second, I mapped acquisitions in a given calendar year (CY) to an acquirer's fiscal year (FY) with the same year identifier. That is, an acquisition occurring in August 2000, for instance, is counted towards an acquirer's FY 2000 even though the acquirer's fiscal year end (FYE) is in June, technically making that deal part of an acquirer's FY 2001. My rationale behind using this simplified mapping approach was twofold. On the one hand, only 45 (24 percent of) firms in my sample have a FYE that deviates from the calendar year end (CYE). On the other hand, since my research question investigates a phenomenon that evolves over multiple years, different FYEs likely do not distort my results. Third, I assumed that acquisitions with unreported deal values or target total assets were small and, thus, assigned them a value of zero for missing values of these variables. This simplifying assumption allowed me to include acquisitions with originally missing

[24] Please refer to Table A.1 in the appendix for detailed definitions and data sources of all variables used in this study.

data values that would have been dropped from my dataset otherwise, increasing my coverage. Fourth, I converted all firm-level financials reported in CAD to USD using the daily CAD/USD exchange rate at the respective reporting date provided by Compustat North America. This was necessary to ensure that all financials were denoted in the same currency and, thus, comparable.[25] Finally, I did not define control variables for firm-year observations with negative revenue or total asset values. This approach allowed me to only include observations with plausible values in my analyses while preserving the multi-year acquisition sequence of acquirers. In sum, these transformations and cleans resulted in a final baseline sample comprising 2,267 firm-year observations of 187 firms (i.e., an average of 12.1 years per firm), creating an unbalanced panel that is cross-section dominated (i.e., $N>T$), where N and T represent the number of firms and years, respectively.

3.2. Variable Definitions

3.2.1. Dependent Variables

To examine how the activity load from acquisitions affects the acquisition behavior of firms, I construct a binary measure of momentum which equals one if the sum of known deal values in period *t* is greater than or equal to the sum of known deal values in period *t-1* and zero otherwise. With this approach, I deviate from the methodology used in prior studies of momentum (e.g., Amburgey & Miner, 1992), which have used acquisition volume as a proxy for momentum. My rationale for this deviation is twofold. First, deal values likely are a more responsive indicator of (highly) short-term changes in acquisition behavior. To understand this, we need to consider a firm's option space during the negotiation phase of a deal. That is, if a firm intends to reduce its commitment to acquisitions (i.e., cut acquisition expenses), it can (i) adopt a more aggressive negotiation tactic to reduce the target's price or (ii) walk away from a deal. However, while the first option would still allow acquiring firms to close the deal[26], the second option would make it impossible for them to reach the strategic goal for which they initially pursued the deal. This suggests that firms are likely more flexible in adjusting the value of ongoing transactions than in changing their acquisition volume if they want to reach their *ex-ante* strategic goal with the currently negotiated deal. Second, historical patterns of acquisition volumes and deal values are fairly congruent[27] (Cools et al., 2007; Kengelbach & Roos, 2011), showing that increases (decreases) in acquisition volumes are often associated with increases (decreases) in deal values. In sum, both arguments indicate that deal values are a reasonable proxy for momentum.

Accounting for the three-level structure of my hypotheses[28], I use different operationalizations of momentum, depending on the tested hypothesis. Specifically, I distinguish between two sets of definitions. First, to test the baseline effect of acquisition volume (i.e., hypothesis 1), I use a firm's *total* known deal values as a measure of momentum, creating the binary variable *total acquisition momentum* which equals one if the sum of total known deal values in period *t* is greater than or equal to the sum of total known deal values in period *t-1* and zero otherwise. Second, to test how the baseline effect of acquisition volume varies with acquisition complexity (i.e., hypotheses 2a and 2b), I split a firm's *total acquisition momentum* by deal type (e.g., cross-border versus domestic), creating two mutually exclusive and collectively exhaustive (MECE)[29] subgroups of momentum – one subgroup of higher-complexity deals (i.e., *cross-border / cross-industry / large acquisition momentum*[30]) and another subgroup of lower-complexity deals (i.e., *domestic / within-own-industry / small acquisition momentum*). These deal-specific momentum measures are defined analogously to *total acquisition momentum* except that I use deal values of acquisitions of the respective deal type in the construction of these measures (e.g., deal values of cross-border deals for *cross-border acquisition momentum*). Finally, to test how the prior two effects vary with structural features of acquirers (i.e., hypotheses 3 and 4), I run models with both sets of momentum definitions (i.e., *total acquisition momentum* and deal-specific measures).

3.2.2. Independent Variables

Building on prior research (e.g., Castellaneta & Zollo, 2015; Laamanen & Keil, 2008; Zorn et al., 2019), I proxy the concept of activity load with a firm's number of completed acquisitions in the period *t-2* to *t*, choosing a three-year time window to account for a time lag between a deal's closing date and the completion of integration activities. As I did with my dependent variables, I distinguish between two sets of definitions. That is, on the one hand, I measure the activity load of a firm as that firm's *total acquisition activity* (i.e., its *total* number of completed acquisitions in years *t-2* to *t*), allowing me to test hypothesis 1, which examines the baseline effect of acquisition volume on acquisition behavior. On the other hand, to test hypotheses 2a and 2b, I split a firm's *total acquisition activity* by deal type, creating two MECE subgroups of acquisitions which differ by their relative complex-

[25] Specifically, Compustat displays financial data in the company's reported currency, whereas Refinitiv Eikon reports acquisition data only in USD. This is a problem when calculating the target-asset-to-acquirer-asset ratio as some acquirers only report their financials in CAD.

[26] Provided the target does not walk away from the deal.

[27] See Figure A.1 and Figure A.2 in the appendix.

[28] That is, the baseline effect of acquisition volume (first level), heterogeneity in that baseline effect due to differences in acquisition complexity (second level), and heterogeneity in the prior two effects due to differences in structural features of acquiring firms (third level).

[29] Please note that momentum measures *within* a subgroup are *not* MECE. For instance, a deal can be a cross-border deal and a large deal at the same time. This overlap is unproblematic because I only regress deal-specific momentum measures on acquisition activity measures of the same complexity dimension (e.g., *cross-border acquisition momentum* on *cross-border acquisition activity*).

[30] Please refer to Table A.1 in the appendix for precise definitions of the terms 'cross-border', 'cross-industry', and 'large'.

ity level (i.e., higher-complexity deals, which include *cross-border (cross-industry; large) acquisition activity*, and lower-complexity deals, which cover *domestic (within-own-industry; small) acquisition activity*) and allow me to assess the *joint* effect of acquisition volume and complexity. Finally, to ensure consistency with my dependent variable definitions, I run models with both sets of activity load definitions (i.e., *total acquisition activity* and deal-specific acquisition activity measures) to test hypotheses 3 and 4.

3.2.3. Control Variables

To account for alternative explanations of acquisition behavior, I include an extensive set of control variables which captures the effect of specific acquisition characteristics, acquiring firm characteristics, and industry-level acquisition activity on the acquisition behavior of acquiring firms. For this, I followed a two-step selection procedure to ensure only relevant variables are incorporated in the model. First, I screened extant literature for factors that are known to affect a firm's acquisition behavior and selected those for which past studies provided solid theoretical arguments and, ideally, robust empirical evidence.[31] With this, I directly responded to King et al. (2004) who called for greater consistency of empirical measurement in acquisition research, ensuring comparability of results across studies. Second, in case prior acquisition literature did not cover factors which are core to my hypothesis development, such as *proportion of large acquisitions* and *acquirer degree of decentralization*, I included such factors as novel variables. The following control variables are the result of this two-step selection procedure:

Acquisition complexity. Scholars who adopt the interpretation perspective of activity load (e.g., Zorn et al., 2019) have found that the acquisition behavior of firms can vary with the complexity level of acquisitions. To account for this effect, I include three distinct proxies of acquisition complexity.[32] First, in line with prior literature (e.g., Laamanen & Keil, 2008), I control for the *proportion of cross-border acquisitions* made by firm *i* in years *t-2* to *t*, where the term 'cross-border' refers to acquisitions of targets *not* based in the US. This variable captures differences in cultural and institutional contexts of targets and acquirers that drive acquisition complexity and, thus, a firm's activity load from acquisitions. Second, I include the *proportion of cross-industry acquisitions* over the same period and expect cross-industry acquisitions to be more complex than acquisitions within the acquirer's own industry due to differences in business logic and organizational setups across industries (e.g., Prahalad & Bettis, 1986; Vermeulen & Barkema, 2002). Following prior studies (e.g., Ellis et al., 2011; Laamanen & Keil, 2008; Zorn et al., 2019), I classify acquisitions as 'cross-industry acquisitions' if the first two digits of the target's and acquirer's primary SIC codes are not identical. Third, I control for the *proportion of large acquisitions* from *t-2* to *t* since the integration of larger targets imposes a higher strain on the acquirer's organization than the integration of smaller ones (Barkema & Schijven, 2008; Ellis et al., 2011) and, thus, limits the availability of organizational resources for subsequent acquisitions. Targets are considered 'large' if their relative size (measured relative to acquirer total assets) is greater than or equal to the sample mean of 8.9 percent.

CEO overconfidence. Scholars have found that overconfident CEOs overestimate their abilities and, thus, are more likely to engage in acquisitions than non-overconfident CEOs (Malmendier & Tate, 2005, 2008). I account for this finding by adding *CEO overconfidence* to the model, using the stock-option-based measure developed by Malmendier and Tate (2005, 2008), which assumes that late exercise of stock options signals higher confidence. Specifically, I define *CEO overconfidence* as a dummy variable which is equal to one if a CEO has not exercised at least 67 percent of his/her exercisable in-the-money stock options in a given year and zero otherwise.

CEO succession. A phenomenon extensively discussed by management scholars (e.g., Karaevli, 2007; Zajac, 1990), *CEO succession* not only affects the performance of firms but also likely influences their acquisition behavior. This is because CEOs, as individuals, differ in their level of risk appetite and, thus, likely show variation in the strategic decisions they make, including acquisitions. To account for this effect, I include a dummy variable for *CEO succession* which is equal to one if a firm experienced a CEO change in a given year and zero otherwise.

Degree of decentralization. I control for a firm's *degree of decentralization* to account for the Penrosian argument that a more decentralized organizational structure allows firms to distribute the workload from acquisitions across a larger pool of managerial resources and, thus, absorb the activity load from acquisitions more effectively. For this, I use the percentage of executives with divisional or geographic titles (as opposed to functional, matrix, or general manager titles) in period *t*, where a value of one (zero) represents a fully decentralized (centralized) structure.

Performance relative to aspirations. Prior acquisition research has shown that the performance of firms relative to their own prior performance (i.e., historical aspiration level) affects their acquisition activity such that acquisition activity increases (falls) if firms are performing below (above) their historical aspiration level (Iyer & Miller, 2008). In line with past studies, I measure a firm's performance relative to its historical aspiration level via the recursive formula $P_t - A_t$, where P_t is a firm's ROA in period t and A_t is a firm's aspiration level in period t that is given by $0.3\ P_{t-1} + 0.7\ A_{t-1}$ (Greve, 2002), and model it as a spline function (i.e., two distinct variables (i) *Performance above aspirations* and (ii)

[31] See section 2.1 for a review. Please note that I only included variables for which I had database access.

[32] I only include measures of acquisition complexity that are *not* captured by the acquisition activity measure in the given model. For instance, I include *proportion of cross-industry acquisitions* and *proportion of large acquisitions* in models in which I regress *cross-border acquisition momentum* on *cross-border acquisition activity*, omitting *proportion of cross-border acquisitions*, which is already captured by *cross-border acquisition activity*.

Performance below aspirations) (Shinkle, 2012).[33]

Growth desperation. Kim et al. (2011) have presented evidence that firms face higher pressure to engage in acquisitions (and overpay) if their organic growth rate is below that of prior years and if they have historically grown stronger through acquisitions than their industry peers. To account for the effect of *growth desperation* on a firm's acquisition behavior, I incorporate the growth of firms relative to their own prior growth as a control, measuring it as a spline function analogously to *performance above/below aspirations* (i.e., (i) *growth above aspirations* and (ii) *growth below aspirations*) but using a firm's year-on-year sales growth instead of its ROA.

Slack resources. According to the BTF (e.g., Cyert & March, 1963; Levinthal & March, 1981), excess resources give firms more room to experiment and pursue new strategic opportunities, such as acquisitions. Recent empirical work has confirmed this by showing that resource slack is positively related to a firm's acquisition propensity (Iyer & Miller, 2008). Yet, contrary to prior studies, I refrain from using a firm's debt-to-equity (D/E) ratio and instead take a firm's debt-to-total-assets ratio as an inverse proxy for *slack resources* since the total equity of a substantial proportion (∼7 percent) of firm-years in my sample is negative. This allows me to keep firm-years with negative equity in my sample and avoid implausible, negative D/E values. Correspondingly, a higher debt-to-total-assets ratio signals a lower level of slack resources.

Acquirer size. Since size is related to the number of resources available to firms (e.g., Laamanen & Keil, 2008; Penrose, 1959) and their risk appetite (e.g., Audia & Greve, 2006; Baysinger & Hoskisson, 1989), I control for firm size by including a proxy which is often used in literature: The natural logarithm of total assets (e.g., Iyer & Miller, 2008; Laamanen & Keil, 2008).

Diversification. Diversified firms may be exposed to more acquisition opportunities than their undiversified peers (Sanders, 2001). I account for this by including the control *diversification*, which I operationalize with the Jacquemin-Berry entropy index (Palepu, 1985; Sanders, 2001).

Industry acquisition activity. The acquisition activity within an industry can strongly affect an individual firm's acquisition behavior (e.g., Baum et al., 2000; McNamara et al., 2008) due to imitation/bandwagon effects and exhaustion of potential targets. To ensure these factors do not drive my results, I control for *industry acquisition activity* by including the average number of acquisitions per industry (based on first two digits of primary SIC code) in the period *t-2* to *t*.

Year dummies. To account for potential contemporaneous correlation (i.e., residuals of firms *i* and *j* are correlated in period *t*), I include a full set of year dummies in all model specifications (excluding one year for identification purposes) (Certo & Semadeni, 2006). Contemporaneous correlation can severely bias estimates in panel regression and is of particular concern in cross-section-dominated panel data like mine (Certo & Semadeni, 2006; Wooldridge, 2010).

3.3. Estimation Strategy

To estimate the effect of activity load from acquisitions on acquisition behavior, I constructed the following non-linear regression model which uses the logistic distribution as a link function and the maximum likelihood (ML) method for parameter estimation (Wooldridge, 2010):

$$P(Momentum_{i,t} = 1 \,|\, A_{i,t-1}, \Gamma_{i,t-1}, T_t) = \Lambda(\beta_0 + \beta_1 A_{i,t-1} + \delta_1 \Gamma_{i,t-1} + \delta_2 T_t + \varepsilon_{i,t}),$$

where $\Lambda(x) = e^x/(1+e^x)$ is the logistic function, A is a vector of acquisition variables, Γ is a vector of time-varying controls, and T is a full set of year dummies (excluding the base year). Subscripts t and i denote the fiscal year in which the acquisition was completed and the acquirer, respectively. In addition, all independent variables (except year dummies) are lagged by one period to eliminate concerns about endogeneity[34] (Dobbins & Jacob, 2016; Iyer & Miller, 2008).

Albeit the use of a binary dependent variable does not immediately call for a non-linear model specification (Wooldridge, 2010), I preferred a non-linear model over a linear one, such as a linear probability model (LPM). My rationale for this was twofold. First, given the nature of my data, a non-linear model produces better estimates of the marginal effects of my covariates than an LPM. That is, an LPM is suitable "if most . . . [covariates] are discrete and take on only a few values" (Wooldridge, 2010, p. 564). Yet, many of my covariates (e.g., activity load) have continuous – and sometimes even extreme – values that violate this assumption.[35] This conclusion is supported by the fact that roughly a third of my baseline sample observations have predicted probabilities that lie outside the unit interval if an LPM is used (Wooldridge, 2010). Second, consistent with prior studies of momentum (e.g., Beck et al., 2008), I used a logit model to ensure comparability of results across studies. Thus, a non-linear model seems warranted.

Building on this specification, I selected a hybrid logit model[36] – an estimation strategy that has received increased attention by management scholars (e.g., Allison, 2005, 2009;

[33] Parameter a=0.3 used to ensure consistency with prior literature (e.g., Iyer & Miller, 2008). Iyer and Miller (2008) chose a=0.3 because this provided the best model fit. Also, like Kim et al. (2015), I set a firm's historical aspirations to zero the first time a firm entered the sample.

[34] This approach follows the one of Iyer and Miller (2008), who model the effect of performance feedback on the likelihood of an acquisition. This is necessary to satisfy a key condition for causality. That is, if a relationship XY is to be causal, a change in X must precede a change in Y (Wolfolds & Siegel, 2019). Given that I define momentum (Y) as a dummy which indicates the change in deal values from *t-1* to the focal year *t*, I can only include acquisitions (X) that occur *before* the focal year *t* (i.e., *t-3* to *t-1*). Likewise, controls based on *end-of-year* balance sheet data, such as ln(total assets), cannot explain a change in momentum occurring *during* period *t*. Consequently, I lag these variables, too.

[35] Please refer to Table A.2 in the appendix for a detailed set of descriptive statistics for all variables used in the baseline model.

[36] Please note that I performed all my analyses with a manually constructed

Certo et al., 2017; Schunck, 2013; Schunck & Perales, 2017). A hybrid model allows for the simultaneous estimation of within-unit effects (i.e., changes that occur *within* units over time) and between-unit effects (i.e., changes that occur *between* units) within the same model by decomposing each independent variable into two distinct variables: (i) a group-centered variable (i.e., within-unit effect) and (ii) a group mean variable (i.e., between-unit effect) (Certo et al., 2017; Schunck, 2013; Schunck & Perales, 2017). A random effects model is then used to estimate the within- and between-unit effects for each independent variable (Certo et al., 2017). Correspondingly, to disentangle these two effects, vectors A and Γ include both a firm-centered variable and a variable for the time-invariant firm mean for each independent variable as distinct regressors.

At first glance, a hybrid logit model seems unusual since my research question solely explores a within-firm relationship. Such a relationship can be easily analyzed with a fixed effects model, which would eliminate unobserved time-invariant heterogeneity at the firm level (Dobbins & Jacob, 2016; Herold, 2019; Wooldridge, 2010). Also, a fixed effects logit model would ensure methodological consistency with prior acquisition literature, following the call of Beck et al. (2008), who have shown that prior literature on momentum has likely produced biased results due to overreliance on random effects models. A fixed effects model therefore seems appealing.

Yet, two reasons support the hybrid model specification. First, from a theoretical standpoint, the parameter estimates of a hybrid logit model are approximately identical to those of a fixed effects logit model (Allison, 2009; Schunck & Perales, 2017).[37] The difference is the estimation technique. That is, whereas the hybrid logit model uses a parametric approach to estimate the fixed effects (i.e., includes them as separate regressors in the model), the fixed effects logit model uses a more restrictive, non-parametric approach (i.e., a conditional ML estimator) to eliminate unobserved time-invariant heterogeneity at the firm level (Allison, 2009; Schunck & Perales, 2017; Wooldridge, 2010). Second, from a practical standpoint, a hybrid logit model allows for the estimation of partial effects on response probabilities (Wooldridge, 2010). These cannot be readily estimated in a fixed effects logit model since doing so would require either a precise value or a distribution for the fixed effect to be specified (Wooldridge, 2010). However, since momentum theory does not justify any exact value or distribution for the fixed effect, neither of these options are plausible if I aim to quantify the partial effects on my response probabilities. Due to these points, I favored a hybrid logit model over a fixed effects alternative.

hybrid logit model, which I preferred over STATA's *-xthybrid-* command for two reasons: (i) *-xthybrid-* allows for neither the *-margins-* command nor any factor notation of variables (Schunck, 2013), which are both critical for estimating interactions, and (ii) the results of the manually constructed model are identical to those of the *-xthybrid-* model.

[37] For comparison, results of a fixed effects logit model are shown in Table A.4 in the appendix.

4. Empirical Results

In this section, I present the results of my empirical analysis in three steps. First, I explore the summary statistics and correlations of my raw data to find first indications for the existence of my postulated relationships. Second, I dive into my main regression analysis. Finally, in my robustness tests, I test for the robustness of the relationships discovered in my main analysis.

4.1. Summary Statistics

Table 3 presents descriptive statistics and pairwise correlations of all variables used in my main analysis. All statistics are based on variables in their raw form (i.e., not split into their within- and between-firm components) and, thus, reflect both within- and between-firm variance.

The pairwise correlations in Table 3 only offer ambiguous initial support for the existence of my hypothesized relationships. Two observations lead to this conclusion. First, while bivariate correlations between momentum and acquisition activity variables within the same target firm category are significant ($p<.01$), these variables are *positively* correlated (colored in light green in Table 3). These relationships thus have a sign opposite to the one predicted in hypotheses 1 and 2, tentatively indicating the existence of repetitive momentum (Amburgey & Miner, 1992). However, since the correlation coefficients in Table 3 include both within- and between-firm variance, the overall positive correlations could stem from a positive between-firm effect (i.e., repetitive momentum) offsetting a negative within-firm effect (i.e., momentum discontinuation due to high levels of activity load).[38] Thus, the correlation matrix shown in Table 3 does not provide sufficiently fine-grained information to indicate the existence of my postulated within-firm relationships. Second, the correlations between momentum in a lower-complexity target firm category (e.g., *domestic acquisition momentum*) and acquisitions in a higher-complexity target firm category (e.g., *cross-border acquisition activity*) are positive and mostly significant ($p<.01$) (colored in dark green in Table 3). Although this can indicate the existence of a firm's 'switching response' as predicted in hypothesis 2a, these correlations include both within- and between-firm variance, making their interpretation ambiguous in my research setting. In sum, the correlations in Table 3 do not clearly indicate the existence of my postulated relationships.

Table 3 further reveals that multicollinearity issues are unlikely to arise in my analysis as most correlations are either rather weak (i.e., below $|.30|$) or moderate (i.e., around $|.50|$) (Judge et al., 1982). This holds true even though strong pairwise correlations between momentum (acquisition activity) variables, with values of 0.83 (1.00), would initially suggest the opposite. In fact, these high values are not

[38] In fact, the correlations between momentum and acquisition activity in Table 3 should be positive. This is because prior momentum studies have found a positive relationship between acquisition activity and momentum when using random effects models (Amburgey & Miner, 1992).

Table 3: Descriptive Statistics and Correlation Matrix

Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
1. Total Acquisition Momentum	0.38	0.48																											
2. Cross-Border Acquisition Momentum	0.25	0.43	0.43***																										
3. Domestic Acquisition Momentum	0.32	0.47	0.77***	0.11***																									
4. Cross-Industry Acquisition Momentum	030	0.46	0.60***	0.35***	0.54***																								
S. Within-Own-Industry Acquisition Momentum	0.26	0.44	0.61***	0.36***	0.50***	0.09***																							
6. Large Acquisition Momentum	0.11	0.31	0.38***	0.08***	0.41***	0.20***	0.33***																						
7. Small Acquisition Momentum	0.35	0.48	0.83***	0.46***	0.61***	0.62***	0.49***	0.06***																					
8. Total Acquisition Activity	14.15	23.35	0.06***	0.20***	0.11***	0.13***	0.05**	0.06***	0.09***																				
9. Cross-Border Acquisition Activity	6.29	12.26	0.05**	0.18***	0.09***	0.11***	0.04*	0.05**	0.08***	0.95***																			
10. Domestic Acquisition Activity	7.86	12.37	0.06***	0.19***	0.12***	0.14***	0.05**	0.07***	0.09***	0.95***	0.80***																		
11. Cross-Industry Acquisition Activity	9.53	21.25	0.05**	0.16***	0.09***	0.11***	0.00	0.04*	0.07***	0.95***	0.89***	0.90***																	
12. Within-Own-Industry Acquisition Activity	4.62	7.59	0.04**	0.15***	0.10***	0.09***	0.15***	0.09***	0.06***	0.43***	0.42***	0.39***	0.11***																
13. Large Acquisition Activity	0.53	0.92	-0.01	0.04**	0.02	0.07***	0.03	0.14***	0.07***	0.18***	0.13***	0.22***	0.11***	0.25***															
14. small Acquisition Activity.	13.63	23.20	0.06***	0.20***	0.11***	0.13***	0.05**	0.06***	0.09***	1.00***	0.95***	0.95***	0.95***	0.42***	0.14***														
15. Proportion of Cross-Border Acquisitions	0.42	0.30	-0.01	0.03	-0.05**	-0.02	-0.02	00	-0.02	0.04**	0.21***	-0.13***	02	0.08***	-0.11***	0.05**													
16. Proportion of Cross-Mum Acquisitions	0.60	0.32	0.04**	0.06***	0.06***	0.12***	-0.06***	-0.01	0.04**	0.14***	0.10***	0.17***	0.27***	-0.31***	-0.06***	0.15***	-0.05***												
17 Proportion of Large Acquisitions	0.08	0.18	-0.08***	-0.09***	-0.08***	-0.08***	-0.05**	02	-04**	-0.14***	-0.13***	-0.12***	-0.12***	-0.09***	0.47***	-0.15***	-0.20***	-0.20***											
18 CEO Overconfidence	0.68	0.47	0.04**	0.06***	0.04**	0.05**	0.04*	00	0.05**	0.06***	0.07***	0.04*	0.05**	0.05**	01	0.06***	0.03	-0.01	-0.02										
19. CEO Succession	0.13	0.34	0.00	0.03	0.00	0.00	0.02	0.00	0.01	0.00	0.01	-0.01	0.00	0.01	-0.02	0.00	0.03	0.01	-0.04*	-0.04*									
20. Degree of Decentralization	0.19	0.18	0.00	-0.02	-0.01	-0.01	01	02	-0.01	-0.04**	-0.06***	-0.03	-0.04*	-0.04*	0.00	-0.04**	-0.03	-0.03	-0.01	-0.01	0.00								
21 Performance Above Aspirations	0.02	0.03	0.08***	0.01	0.09***	0.09***	0.05**	0.06***	0.07***	-0.10***	-0.09***	-0.10***	-0.10***	-0.04**	0.04**	-0.10***	-0.05***	-0.08***	0.13***	0.05**	-0.03	-0.05**							
22. Performance Below Aspirations	-0.01	0.03	0.11***	0.08***	0.10***	0.08***	0.06***	0.06***	0.09***	02	03	02	03	-01	-0.03	02	02	03	-0.02	0.10***	-02	-0.09***	0.33***						
23. Growth Above Aspirations	0.06	0.11	-0.06***	-0.04**	-0.03	-0.01	-0.03	-0.03	-0.03	-0.02	-0.04**	-0.01	-0.02	-0.02	0.13***	-0.03	-0.07***	-0.01	0.12***	0.04**	0.00	0.02	0.14***	0.00					
24. Growth Below Aspirations	-0.06	0.13	0.05**	0.07***	0.04*	03	0.06***	-0.01	0.06***	01	02	00	00	03	01	01	01	-0.04*	00	0.04**	-03	-0.03*	0.17***	0.35***	0.25***				
25. Slack Resources	0.64	0.17	-0.09***	-0.05**	-0.12***	-0.11***	-0.07***	-0.07***	-0.08***	01	0.05**	-0.02	0.04*	-0.06***	-0.06***	02	0.06***	-0.03	0.04**	-0.02	0.04*	0.00	-0.14***	-0.04**	-0.05**	0.03			
26. Acquirer Size	9.00	1.28	0.08***	0.22***	0.09***	0.13***	0.10***	0.04*	0.12***	0.55***	0.53***	0.51***	0.48***	0.35***	0.13***	0.55***	0.11***	0.15***	-0.18***	0.07***	00	-0.01	-0.13***	-0.01	-0.04*	-0.05**	0.02		
27. Diversification	0.90	0.48	0.00	0.05**	0.01	0.05***	-0.03	-0.02	02	0.27***	0.22***	0.29***	0.27***	0.06***	01	0.27***	-0.04*	0.22***	-0.13***	01	00	01	-0.17***	0.03*	-0.05**	01	0.04*	0.25***	
28. industry Acquisition Activity	44.97	35.71	0.05**	0.13***	0.08***	0.06***	0.13***	0.07***	0.08***	0.30***	0.28***	0.30***	0.24***	0.26***	0.18***	0.30***	0.03*	-0.03	-0.08***	0.08***	0.05'	0.05***	-0.09***	-0.01	-0.01	0.00	0.00	0.24***	0.13***

Notes: N=2,267. All statistics are based on raw variables (i.e., before decomposing independent variables into their within- and between-firm components). Light green cells indicate correlations between momentum and acquisition activity variables within the same target firm category (i.e, hypotheses 1 and 2). Conversely, dark green cells indicate correlations between momentum in a lower-complexity target firm category and acquisition activity in a higher-complexity target firm category (i.e., second part of hypothesis 2a).
$^{***}p < 0.01$, $^{**}p < 0.05$; $^{*}p < 0.1$.

surprising as all momentum (acquisition activity) variables which proxy different acquisition complexity dimensions are subcomponents of *total acquisition momentum* (*total acquisition activity*). As such, these variables are strongly correlated with each other by definition. In addition, 91.1 percent of acquisitions in my baseline sample are small, thus explaining the particularly strong correlations between *small acquisition momentum* (*small acquisition activity*) and all other momentum (acquisition activity) variables. Furthermore, I only include one (two MECE) momentum (acquisition activity) variable(s) in the same model, creating a setup in which multicollinearity issues are unlikely to arise.

To corroborate the absence of multicollinearity, I ran variance inflation factor (VIF) tests of all variables which are split into their within- and between-firm components and used in my main model (see section 4.2). Table A.3 in the appendix shows that (almost) all variables have a VIF statistic that is below the advocated threshold value of (five) ten (Neter et al., 1989). The only two variables with VIF coefficients of approximately five are the between-firm components of *cross-border acquisition activity* and *domestic acquisition activity*. However, I decided to retain these in the model for consistency with all other model specifications. From these results, I thus conclude that multicollinearity issues are unlikely to arise in my analysis.

4.2. Main Analysis

Table 4 presents the empirical results of my main analysis. For simplicity, only the coefficients for the group-centered variables (i.e., within-firm effects) are reported as my theoretical interest solely lies in those. Models 1 and 2 in Table 4 use an acquirer's *total acquisition momentum* as the dependent variable to investigate the baseline effect of activity load. Models 3 to 14 go one step further and address six different momentum definitions, which are based on observable target firm attributes, to measure heterogeneity in acquirer responses due to differences in acquisition complexity. Furthermore, all odd-numbered (even-numbered) model specifications include controls only (all independent variables), enabling sanity checks of the effect directions and effect sizes of controls across models with the same dependent variable (e.g., to detect common-factor multicollinearity (Kalnins, 2018)). Finally, in line with reporting standards for logit models, all coefficients represent odds ratios – exponentiated coefficients that express the e^{β}-times change in the odds of an event due to a one-unit change in a variable (Hoetker, 2007).[39]

Recalling hypothesis 1, I expect an increase in an acquirer's acquisition activity relative to that firm's past acquisition activity level to lead to a discontinuation in acquisition momentum. That is, the greater the increase in the number of acquisitions in a given acquisition stream, the higher the activity load borne by the acquiring firm's managers. This increase in activity load, in turn, increases the likelihood of an information overload, which eventually forces acquirers to reduce the number of acquisitions to alleviate the strains associated with this overload. The significant ($p<.05$) and smaller-than-one odds ratio in Model 2 (highlighted in light green in Table 4) shows a decrease in the odds of *total acquisition momentum*, thereby confirming hypothesis 1.

Odds ratios, however, are not very informative if I seek to estimate the effect of a variable on the *predicted probability* of a given event (Hoetker, 2007) – "the natural metric of the dependent variable [in a logit model]" (Mize, 2019, p. 84). To do this, I estimate the marginal effects of my variables of interest, using two best practice approaches advocated in recent methodological studies (e.g., Hoetker, 2007; Mize, 2019; Mize et al., 2019). First, following Hoetker (2007) and Train (1986, 2009), I calculate the average marginal effects (AME) of my variables of interest in Table 5 to estimate the average response across my sample. That is, I compute the marginal effects for every firm-year and average these across my sample (Mize, 2019), finding that a one-unit increase in the number of acquisitions relative to a firm's past acquisition level, on average, is associated with a 0.3 percentage-point (pp) decrease in the predicted probability of that firm's *total acquisition momentum*. Second, to account for the fact that the effect of a change in any variable varies with the values of all covariates (i.e., with the initial likelihood of an event) (Hoetker, 2007), I plot the relationship between a change in a firm's *total acquisition activity*[40] (i.e., within-firm effect) and that firm's probability of *total acquisition momentum* in Figure 7 (e.g., Mize, 2019). The downward-sloping area in Figure 7 corroborates that larger increases in acquisition activity are associated with lower likelihoods of acquisition momentum. In sum, these two best practices allow me to properly estimate and interpret the effect of activity load on the probability of acquisition momentum, ensuring a solid understanding of my results.

In hypothesis 2a, I predict a negative (positive) relationship between an acquirer's activity load in a higher-complexity target firm category and that firm's acquisition momentum within that category (in a lower-complexity category). Specifically, since acquisitions vary in their relative complexity level, acquirers can, *ceteris paribus*, cut the activity load of newly made acquisitions by switching from targets in a higher-complexity category (e.g., overseas targets) to those in a lower-complexity category (e.g., domestic targets). This would equal a deviation from a firm's established acquisition pattern (e.g., shift from a pattern of overseas targets to one of domestic targets) that allows acquirers to maintain their overall acquisition momentum while alleviating the strains of information overload. However, my results in Table 4 only provide mixed support for this prediction. That is, while I find significant ($p<.01$) and smaller-than-one odds ratios in Model 4 and Model 12, the smaller-than-one

[39] In line with the recommendations presented by Hoetker (2007), I omitted measures of model fit from Table 4 since all available pseudo-R^2 measures for logistic regressions do not equal the R^2 used in ordinary least squares (OLS) regression, thus avoiding potential sources of confusion.

[40] To eliminate the effect of extreme outliers, I limit the plot to values between the 1st percentile and 99th percentile of my independent variable.

Table 4: Hybrid Panel Logit Regression Analysis with Different Acquisition Momentum Definitions as the Dependent Variable

	Total Acquisition Momentum		Cross-Border Acquisition Momentum		Domestic Acquisition Momentum		Cross-Industry Acquisition Momentum		Within-Own--Industry Acquisition		Large Acquisition Momentum		Small Acquisition Momentum	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
Hypotheses														
Total Acquisition Activity		0.987**												
		(0.005)												
Cross-Border Acquisition Activity				0.962***		1.017								
				(0.011)		(0.011)								
Domestic Acquisition Activity				1.023**		0.979**								
				(0.010)		(0.009)								
Cross-Industry Acquisition Activity								0.994		1.007				
								(0.006)		(0.009)				
Within-Own-Industry Acquisition Activity								1.013		0.931**				
								(0.017)		(0.017)				
Large Acquisition Activity												0.747***		1.062
												(0.066)		(0.070)
Small Acquisition Activity												0.999		0.987**
												(0.008)		(0.005)
Controls														
Proportion of Cross-Border Acquisition.		1.165						1.371		0.859		2.074*		1.018
		(0.266)						(0.347)		(0.227)		(0.775)		(0.232)
Proportion of Cross-Industry Acquisition.		1.724**		1.900**		1.552*						1.181		1.689**
		(0.422)		(0.563)		(0.400)						(0.463)		(0.408)
Proportion of Large Acquisitions		0.432**		0.961		0.406**		0.665		0.515				
		(0.161)		(0.435)		(0.159)		(0.273)		(0.216)				
CEO Overconfidence	1.042	1.051	1.160	1.193	1.137	1.131	1.165	1.171	0.950	0.941	0.899	0.893	1.077	1.082
	(0.119)	(0.121)	(0.152)	(0.158)	(0.136)	(0.137)	(0.144)	(0.145)	(0.123)	(0.122)	(0.163)	(0.167)	(0.125)	(0.126)
CEO Succession	1.092	1.082	1.293*	1.332*	1.082	1.065	1.113	1.109	1.115	1.102	0.944	0.932	1.125	1.137
	(0.152)	(0.152)	(0.199)	(0.206)	(0.157)	(0.155)	(0.166)	(0.166)	(0.172)	(0.171)	(0.209)	(0.209)	(0.158)	(0.160)
Degree of Decentralization	0.717	0.780	0.769	0.767	0.627	0.687	0.694	0.705	1.063	1.126	1.736	1.678	0.688	0.708
	(0.275)	(303)	(0.338)	(0.337)	(0.252)	(0.280)	(0.288)	(0.292)	(0.459)	(0.491)	(1.043)	(1.061)	(0.267)	(0.277)
Performance Above Aspirations	15.186	21.776	0.542	0.508	47.251*	77.910**	205.963**	242.875***	73.127*	47.506*	94.949	274.854*	18.094	19.237
	(30.730)	(44.525)	(1.305)	(1.237)	(98.737)	(164.228)	(437.159)	(517.693)	(169.045)	(111.153)	(299.211)	(888.588)	(36.755)	(39.404)
Performance Below Aspirations	450.238**	323.504**	81.899	52.238	142.939*	97.699*	11.529	12.199	0.251	0.135	130.485	34.713	21.415	16.089
	(1,151.197)	(832.282)	(246.806)	(156.569)	(381.292)	(261.396)	(30.014)	(31.824)	(0.684)	(0.369)	(548.508)	(145.470)	(52.861)	(39.877)
Growth Above Aspirations	0.041***	0.048***	0.116***	0.123***	0.078***	0.090***	0.211***	0.221***	0.107***	0.130***	0.072***	0.098**	0.147***	0.147***
	(0.025)	(0.030)	(0.077)	(0.083)	(0.047)	(0.055)	(0.121)	(0.128)	(0.069)	(0.084)	(0.068)	(0.093)	(0.084)	(0.084)
Growth Below Aspirations	2.366*	2.322*	6.464***	6.873***	1.935	1.873	1.351	1.347	4.537***	4.650***	0.724	0.799	2.922**	3.028**
	(1.147)	(1.145)	(4.048)	(4.368)	(0.966)	(0.959)	(0.675)	(0.684)	(2.637)	(2.715)	(0.492)	(0.550)	(1.467)	(1.528)
Slack Resources	0.206***	0.213***	0.413	0.382	0.154***	0.172***	0.370*	0.394	0.182***	0.162***	0.045***	0.037***	0.401*	0.419
	(0.110)	(0.114)	(0.265)	(0.244)	(0.088)	(0.099)	(0.219)	(0.233)	(0.113)	(0.102)	(0.040)	(0.034)	(0.215)	(0.226)
Acquirer Size	0.646***	0.649***	1.018	1.019	0.679***	0.668***	0.847	0.852	0.674***	0.687***	0.670**	0.593***	0348**	0.771**
	(0.082)	(0.084)	(0.147)	(0.147)	(0.089)	(0.089)	(0.111)	(0.112)	(0.095)	(0.097)	(0.125)	(0.113)	(0.095)	(0.099)
Diversification	1.012	1.050	0.727*	0.683**	0.928	0.975	0.960	0.976	1.111	1.146	1.272	1.486	0.947	0.954
	(0.163)	(0.172)	(0.134)	(0.128)	(0.156)	(0.167)	(0.166)	(0.171)	(0.202)	(0.212)	(0.322)	(0.379)	(0.154)	(0.157)
Industry Acquisition Activity	0.998	1.000	1.003	1.003	0.998	0.999	0.998	0.998	1.004	1.006*	0.998	1.001	1.000	1.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)
Constant	0.087***	0.140***	0.006***	0.018***	0.059***	0.106***	0.031***	0.073***	0.032***	0.029***	0.015***	0.043***	0.055***	0.067***
	(0.046)	(0.082)	(0.004)	(0.013)	(0.032)	(0.065)	(0.019)	(0.045)	(0.023)	(0.021)	(0.014)	(0.042)	(0.030)	(0.039)
Observations	2,267	2,267	2,267	2,267	2,267	2,267	2,267	2,267	2,267	2,267	2,267	2,267	2,267	2,267
Number of Firms	187	187	187	187	187	187	187	187	187	187	187	187	187	187
Mundlak Instruments	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Regression coefficients represent odds ratios. Standard errors in their exponentiated form are presented in parentheses. Odd-numbered (even-numbered) model specifications include control variables only (all variables of interest). Only within-firm effects are reported. Between-firm effects (i.e., Mundlak instruments) and year dummies are included in all models but not reported. Light green cells indicate relationships between momentum and acquisition activity variables within the same target firm category (i.e., hypotheses 1 and 2). Conversely, dark green cells indicate relationships between momentum in a lower-complexity target firm category and acquisition activity in a higher-complexity target firm category (i.e., second part of hypothesis 2a).
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

odds ratio in Model 8 is statistically insignificant (p>.10) (coefficients highlighted in light green in Table 4). In other words, whereas increases in cross-border (large) acquisitions seem to reduce cross-border (large) momentum[41], increases in cross-industry acquisitions appear to not affect their corresponding momentum. Moreover, I cannot corroborate my predicted switching behavior. That is, albeit the odds ratios for higher-complexity acquisitions in Models 6, 10, and 14 exceed a value of one, they remain insignificant (p>.10), indicating the absence of my predicted relationship (coefficients colored in dark green in Table 4). The respective AMEs in Table 5 and graphs in Figure 8 support these findings.

Next, I test hypothesis 2b, which predicts that an increase in a firm's acquisition activity in a lower-complexity target firm category vis-à-vis that firm's past acquisition activity level in that category leads to a discontinuation in acquisition momentum in that category. That is, if firms have established an acquisition stream in a lower-complexity category (e.g., small acquisitions), they have no choice to reduce their activity load other than by, *ceteris paribus*, decreasing the volume of acquisitions in that category as there is no other target firm category to which they can switch to reduce their activity load. In other words, acquirers with such acquisition patterns can only alleviate the strains of information overload by discontinuing their momentum. This prediction is supported by statistically significant and smaller-than-one odds ratios in Model 6 (p<.05), Model 10 (p<.01), and Model 14 (p<.05) (coefficients colored in light green in Table 4). Based on these results, a one-unit increase in the number of

[41] The substantially smaller odds ratio for *large acquisition activity* in Model 12 (odds ratio = 0.747) in Table 4 and the 2.2 pp decrease in the predicted probability of *large acquisition momentum* for every additional large acquisition indicate the relative rarity of this type of acquisition.

Table 5: Tests of AMEs for a One-Unit Increase in Acquisition Activity - Baseline Sample

	Total Acquisition Momentum	Higher-Complexity Acquisition Momentum	Lower-Complexity Acquisition Momentum
Total Acquisition Activity	-0.003**		
	(0.001)		
Cross-Border Acquisition Activity		-0.006***	0.003
		(0.002)	(0.002)
Domestic Acquisition Activity		0.004**	-0.004**
		(0.002)	(0.002)
Cross-Industry Acquisition Activity		-0.001	0.001
		(0.001)	(0.001)
Within-Own-Industry Acquisition Activity		0.003	-0.012***
		(0.003)	(0.003)
Large Acquisition Activity		-0.022***	0.013
		(0.006)	(0.014)
Small Acquisition Activity		-0.000	-0.003**
		(0.001)	(0.001)

Notes: The baseline sample comprises N=2,267 firm years, covering 187 unique firms. Standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, two-tailed tests.

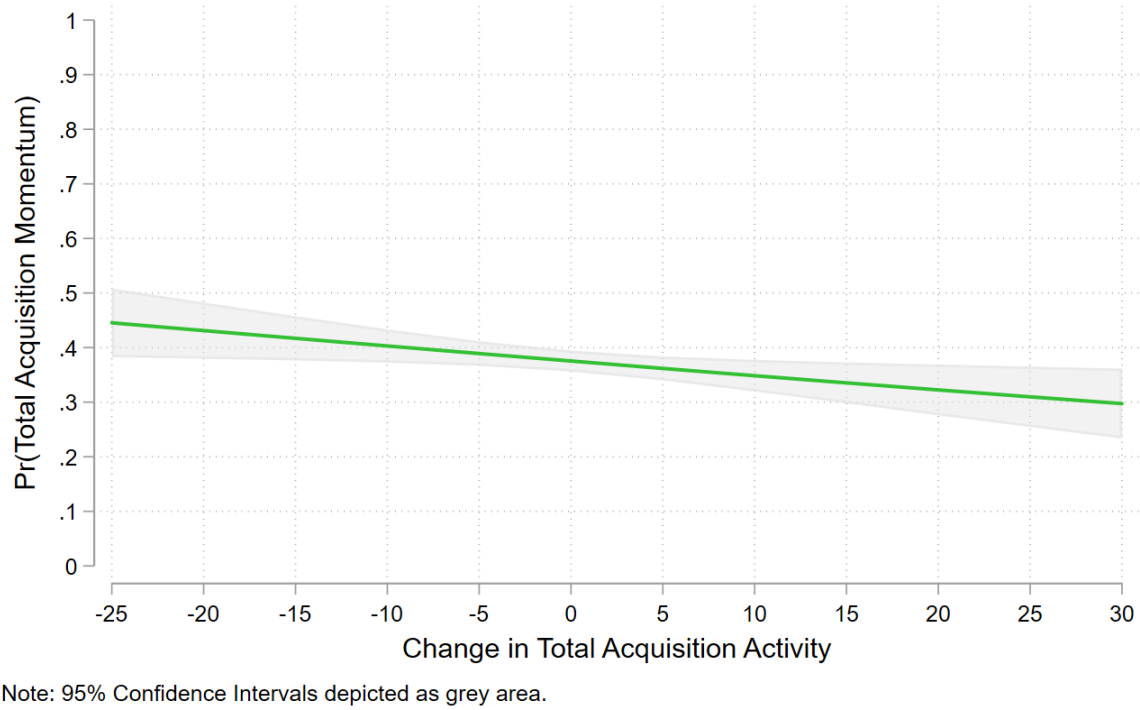


Figure 7: Predicted Probability of Total Acquisition Momentum by Change in Total Acquisition Activity: Main Effect of Total Acquisition Activity

domestic (within-own-industry; small) acquisitions relative to a firm's past acquisition level, on average, corresponds to a 0.4 (1.2; 0.3) pp decrease in the predicted probability of a firm's *domestic (within-own-industry; small) acquisition momentum*. This can also be seen graphically in Figure 8, *which* supports the conclusion that increases in activity load reduce a firm's ability to maintain its momentum.

Furthermore, Table 4 reveals a seemingly surprising relationship between *domestic acquisition activity* and *cross-border acquisition momentum*. More specifically, Model 4

in Table 4 shows that the odds ratio of *domestic acquisition activity* is significant ($p<.05$) and *larger* than one, indicating a 'reverse switch' (i.e., a switch from a lower-complexity category to a higher-complexity category). While this result seems unintuitive from an activity load viewpoint (e.g., Castellaneta & Zollo, 2015), a plausible explanation for it can be found in the international management literature (e.g., Lasserre, 2003; Vermeulen & Barkema, 2001, 2002). That is, as a firm matures, it seeks to expand internationally to benefit from demand in new markets and supply-side cost advantages, among other reasons (e.g., Lasserre, 2003; Vermeulen & Barkema, 2002). One way to achieve this is by acquiring foreign targets, especially if no suitable target can be found in a firm's domestic market (Lasserre, 2003; Vermeulen & Barkema, 2002). Therefore, the positive relationship between *domestic acquisition momentum* and *cross-border acquisition momentum* likely represents the internationalization behavior of the firms in my sample – a behavior which should not surprise as my sample consists of Fortune Global 500 firms, which operate globally.

To explore heterogeneity in acquirer responses due to differences in the absorptive capacity of firms (i.e., hypotheses 3 and 4), I modify my estimation procedure in two ways. First, to assess hypothesis 3 (4), I split my baseline sample into the MECE subgroups *Large Firms* (*Decentralized Firms*) and *Small Firms* (*Centralized Firms*). Doing so, I follow a call of Hoetker (2007), who has argued that fitting separate models for each group should be preferred over interacting my variable of interest with an indicator variable for a firm's group membership when examining cross-group differences in non-linear models. Two facts support his claim: (a) The odds ratio coefficients and significance levels of interaction terms in binary choice models are *observation specific*, rendering them uninformative in their raw form[42] (Ai & Norton, 2003; Hoetker, 2007); (b) using an interaction term and estimating the subsequent binary choice model for *all observations* assumes the unobserved variation for all subgroups to be identical – a strong assumption that produces incorrect estimates if violated (Hoetker, 2007). I thus construct two subsamples using the median of the *Acquirer Size* (*Degree of Decentralization*) distribution in a given year as the cut-off value, creating subgroups that are of roughly equal size. Second, using Mize et al.'s (2019) general framework for comparing effects across non-linear models, I estimate a Generalized Structural Equation Model (GSEM) with the logistic distribution as the link function.[43] Unlike a standard logit model, the GSEM allows me to correctly estimate cross-group differences across separately fitted models, whose calculation requires an estimate of the covariance between the activity load estimates of both subsamples (Mize et al., 2019). In fact, estimating this covariance through a GSEM is crucial as observations from non-overlapping samples do *not* always have a cross-model covariance of zero (Mize et al., 2019). Together, these modifications allow me to test my hypothesized cross-group differences and express these as predicted probabilities (Mize, 2019; Mize et al., 2019).

Recalling hypothesis 3, I expect larger acquirers to respond less strongly to changes in activity load than smaller acquirers. This is because larger acquirers can access a larger pool of managerial resources and more specialized internal acquisition processes (Laamanen & Keil, 2008) that expand their absorptive capacity. A higher absorptive capacity, in turn, alleviates the strains imposed by activity load and, thus, helps larger acquirers maintain their momentum for longer. To corroborate my prediction, I estimate the AMEs of each subsample (i.e., test of first differences) and test for their equality across both groups (i.e., test of second differences). Table 6 reports the results of these tests for a one-unit increase in acquisition activity. Unfortunately, albeit most cross-group differences show the signs predicted by hypothesis 3[44], almost all are not significant ($p>.10$). For instance, the tests in the left column of Table 6 show that a one-unit increase in *total acquisition activity*, on average, is associated with a 0.3 pp and 0.9 pp decrease in the predicted probability of an acquirer's *total acquisition momentum* for large firms and small firms, respectively ($p<.05$ for both AME first differences). However, the insignificant second difference (-0.003 – -0.009 = 0.006; $p>.10$) reveals that the effect of a one-unit increase in activity load, on average, does not differ across groups. That is, larger acquirers, on average, do *not* respond differently to increases in activity load than smaller ones, providing no support for my predictions. The same holds for all other acquisition activity and momentum definitions shown in Table 6, with the significant cross-group effect of *domestic acquisition activity* in the *domestic acquisition momentum* model (-0.003 – -0.017 = 0.013; $p<.05$) presenting an anomaly.

However, although no acquirer size differences in responses to activity load, *on average*, exist across the sample, the non-linear nature of my logit model implies that acquirer size differences can exist *at specific values* (or across a range of values) of activity load (Mize, 2019). A plot of the marginal effects of both subgroups is therefore warranted to identify if and where significant firm size differences exist

[42] I do not report odds ratios for these tests in this section as they provide little meaningful information about interaction effects (Ai & Norton, 2003; Mize, 2019; Mize et al., 2019). In fact, comparing odds ratio coefficients between samples with non-overlapping observations – as one would do in OLS regression – is inappropriate for logit models "because a change in the size of the coefficient across models can reflect both confounding and rescaling of the model [(Karlson et al., 2012)]" (Mize et al., 2019, p. 162). I thus compare my subsamples in the natural metric of my dependent variable: Predicted probabilities, which can be compared across subsamples (Breen et al., 2018; Mize, 2019; Mize et al., 2019). However, for completeness, odds ratio results are presented in Table A.5 and Table A.6 in the appendix.

[43] Note that my overall model specification remains unchanged. That is, I still use a hybrid logit model, and my theoretical interest lies in the within-firm effect of activity load. The only difference is the simultaneous estimation of models that are separately fitted to each subsample.

[44] That is, I expect a positive (negative) cross-group difference in models that regress acquisition momentum on acquisition activity of the same (of a different) complexity level. *Cross-industry acquisition activity* is the only activity load definition which does not show this behavior.

Table 6: Tests of AMEs and Second Differences for a One-Unit Increase in Acquisition Activity - Small Firm and Large Firm Subsamples

	Total Acquisition Momentum			**Higher-Complexity Acquisition Momentum**			**Lower-Complexity Acquisition Momentum**		
	AME_{Small}	AME_{Large}	Second Difference	AME_{Small}	AME_{Large}	Second Difference	AME_{Small}	AME_{Large}	Second Difference
Total Acquisition Activity	-0.009**	-0.003**	0.006						
	(0.004)	(0.001)	(0.004)						
Cross-Border Acquisition Activity				-0.009	-0.006***	0.003	0.003	0.002	-0.001
				(0.006)	(0.002)	(0.006)	(0.007)	(0.002)	(0.008)
Domestic Acquisition Activity				0.008	0.004*	-0.004	-0.017***	-0.003*	0.013**
				(0.006)	(0.002)	(0.006)	(0.005)	(0.002)	(0.006)
Cross-Industry, Acquisition Activity				0.000	-0.001	-0.002	-0.002	0.001	0.003
				(0.005)	(0.001)	(0.005)	(0.005)	(0.002)	(0.005)
Within-Own-Industry Acquisition Activity				0.006	0.001	-0.005	-0.021***	-0.011***	0.009
				(0.008)	(0.003)	(0.009)	(0.006)	(0.003)	(0.007)
Large Acquisition Activity				-0.037***	-0.016*	0.020	0.032	-0.000	-0.032
				(0.011)	(0.008)	(0.014)	(0.025)	(0.016)	(0.030)
Small Acquisition Activity				*0.001*	*-0.000*	*-0.001*	-0.004	-0.003**	0.001
				(0.003)	(0.001)	(0.003)	(0.004)	(0.001)	(0.004)

Notes: The small firm (large firm) subsample comprises N=1,138 (N=1,129) firm years, covering 112 (131) unique firms. Standard errors are in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, two-tailed tests.

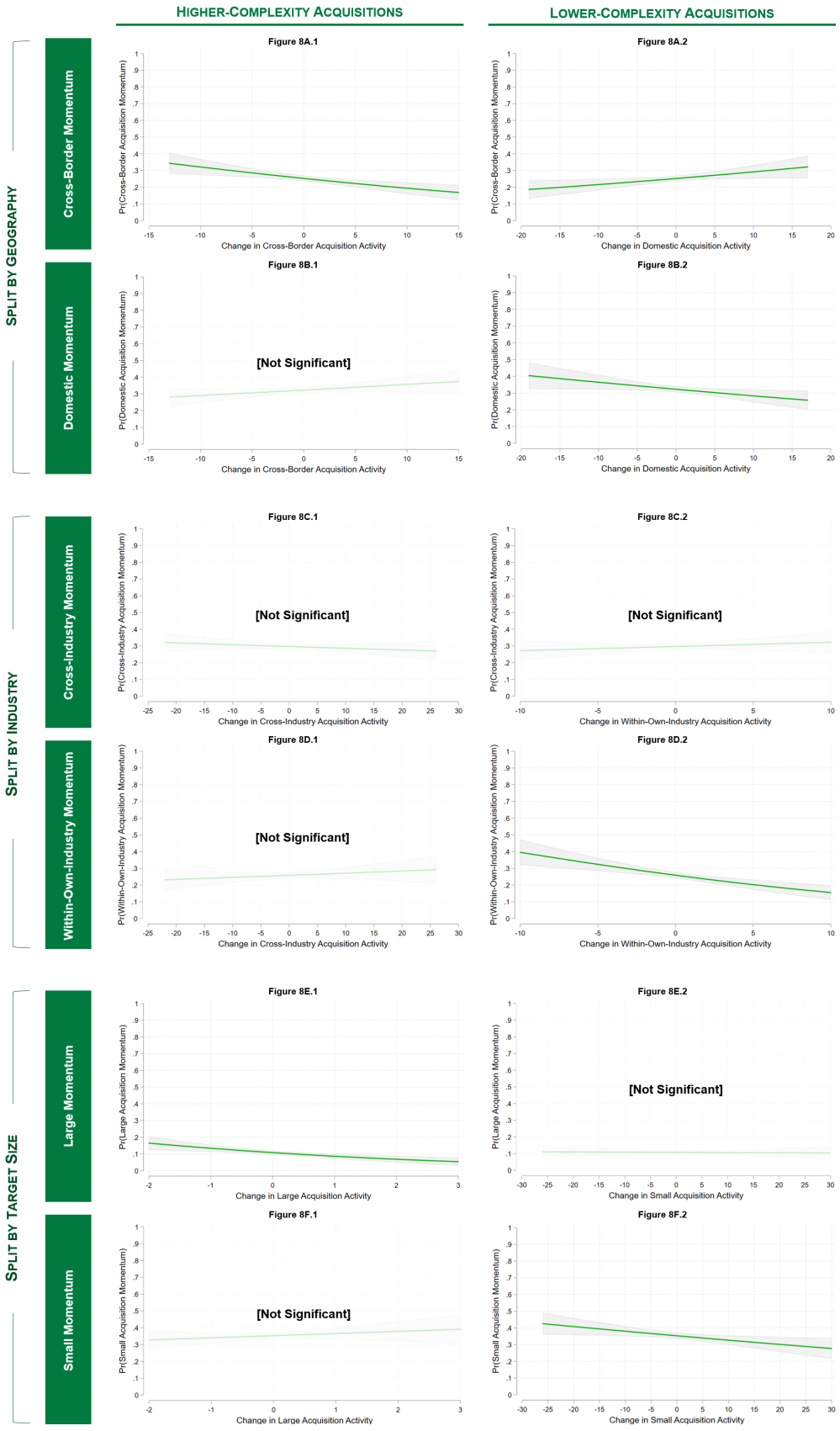


Figure 8: Predicted Probability of Dimension-Specific Acquisition Momentum by Change in Dimension-Specific Acquisition Activity: Heterogeneity in Acquirer Responses due to Differences in Acquisition Complexity

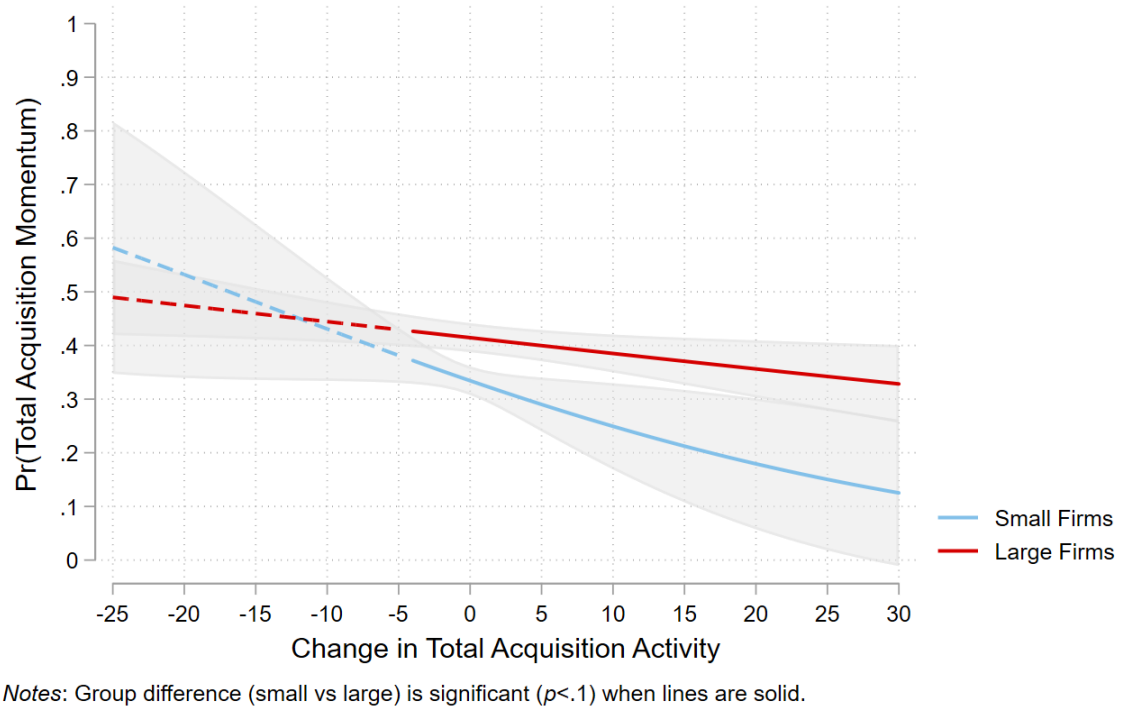


Figure 9: Predicted Probability of Total Acquisition Momentum by Acquirer Size and Change in Total Acquisition Activity: Interaction Effect Between Acquirer Size and Total Acquisition Activity

across the range of acquisition activity values in my sample (Hoetker, 2007; Mize, 2019). Figure 9 presents the predicted probability of large and small acquirers to maintain their *total acquisition momentum* across the range of *total acquisition activity*. A solid line indicates intervals with significant ($p<.10$) acquirer size differences. Specifically, Figure 9 shows that acquirer size differences are significant — with large acquirers having a higher likelihood of maintaining their momentum — when comparing firms that reduce the number of acquisitions by less than five acquisitions or even increase it relative to their past acquisition activity level (all contrasts $p<.10$). In other words, larger acquirers are more likely to maintain their acquisition momentum in the face of increases in activity load due to their relative resource abundance. Intuitively, this *level difference* in the probability of maintaining momentum seems to grow between both subgroups as the activity load from acquisitions increases.[45] Conversely, no cross-group differences in the probability of maintaining momentum exist when acquirers reduce the number of acquisitions by five or more relative to their past acquisition activity level (all contrasts $p>.10$). A detailed visual inspection of the *slopes* of both groups further indicates that cross-group differences in responses to a one-unit increase in *total acquisition activity* may exist *at specific values* of my independent variable.[46] This pattern is mostly robust to changes in acquisition activity and momentum definitions as shown in Figure 10. Overall, these results reveal that larger acquirers can bear a higher activity load burden – and possibly respond less strongly to changes in activity load – for certain levels of acquisition activity due to their relative resource abundance, partially confirming hypothesis 3 and its underlying Penrosian logic.

Finally, in hypothesis 4, I expect acquirers with a more decentralized organizational structure to respond less strongly to changes in activity load relative to acquirers with a more centralized organizational structure. That is, a higher degree of decentralization allows firms to distribute the activity load from acquisitions more evenly across their resources, avoiding a too strong concentration of activity load within one single part of the organization. Like an increase in firm size, a more decentralized organizational structure thus expands the absorptive capacity of acquirers, making acquirers with such a structure more likely to maintain their momentum. Table 7 presents tests of subsample AMEs and second differences for a one-unit increase in acquisition activity, revealing that almost all cross-group differences are insignificant ($p>.10$) and rarely show the effect directions predicted by hypothesis 4.[47] For instance, the tests in the left column of Table 7 indicate that the AME of a one-unit increase in *total acquisition activity*, on average, corresponds to a 0.3 pp decrease in the probability of an acquirer's *total acqui-*

[45] That is, small acquirers are disproportionately strongly affected by large increases in acquisition activity due to their relative resource scarcity.

[46] I refrained from testing second differences at specific values of acquisition activity for their significance due to time and space constraints.

[47] That is, as I did for acquirer size differences, I expect a positive (negative) acquirer structure difference in models that regress acquisition momentum on acquisition activity of the same (of a different) complexity level.

Table 7: Tests of AMEs and Second Differences for a One-Unit Increase in Acquisition Activity - Centralized Firm and Decentralized Firm Subsamples

	Total Acquisition Momentum			**Higher-Complexity Acquisition Momentum**			**Lower-Complexity Acquisition Momentum**		
	$\text{AME}_{Central}$	$AME_{Decentral}$	Second Difference	$\text{AME}_{Central}$	$AME_{Decentral}$	Second Difference	$\text{AME}_{Central}$	$AME_{Decentral}$	Second Difference
Total Acquisition Activity	-0.003*	-0.003	0.000						
	(0.002)	(0.002)	(0.002)						
Cross-Border Acquisition Activity				-0.005**	-0.008***	-0.003	0.005	0.000	-0.004
				(0.002)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)
Domestic Acquisition Activity				0.001	0.006**	0.005	-0.005*	-0.003	0.002
				(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
Cross-Industry Acquisition Activity				-0.002	-0.001	0.001	0.001	0.002	0.001
				(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Within-Own-Industry Acquisition Activity				0.000	0.004	0.004	-0.011***	-0.012***	-0.001
				(0.004)	(0.005)	(0.006)	(0.004)	(0.004)	(0.006)
Large Acquisition Activity				-0.025**	-0.026***	-0.001	0.027	-0.002	-0.029
				(0.012)	(0.009)	(0.015)	(0.021)	(0.018)	(0.028)
Small Acquisition Activity				-0.003*	0.003***	0.006***	-0.003	-0.004*	-0.001
				(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)

Notes : The centralized firm (decentralized firm) subsample comprises N=991 (N=1,276) firm years, covering 144 (168) unique funs. Standard errors are in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, two-tailed tests.

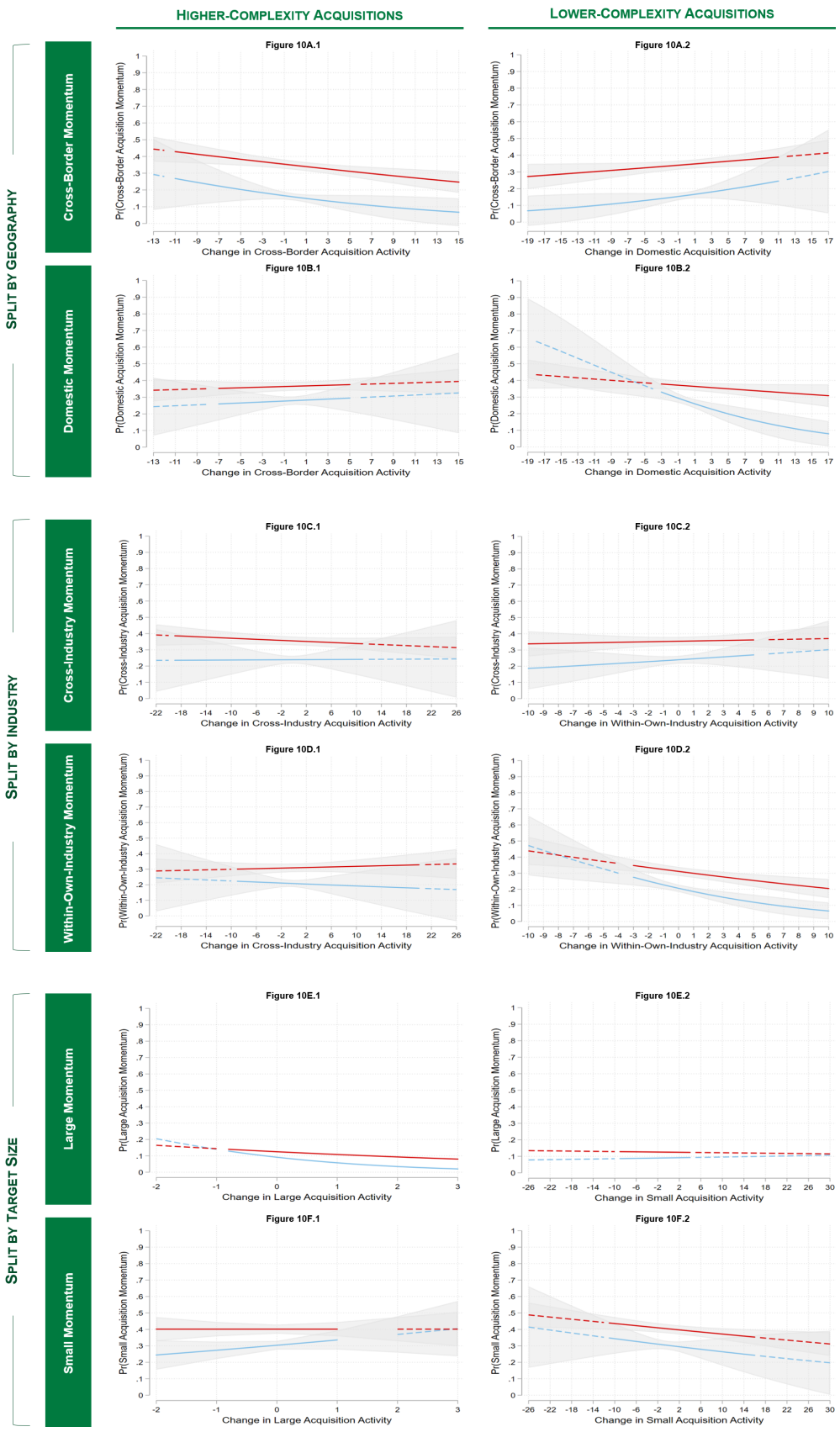
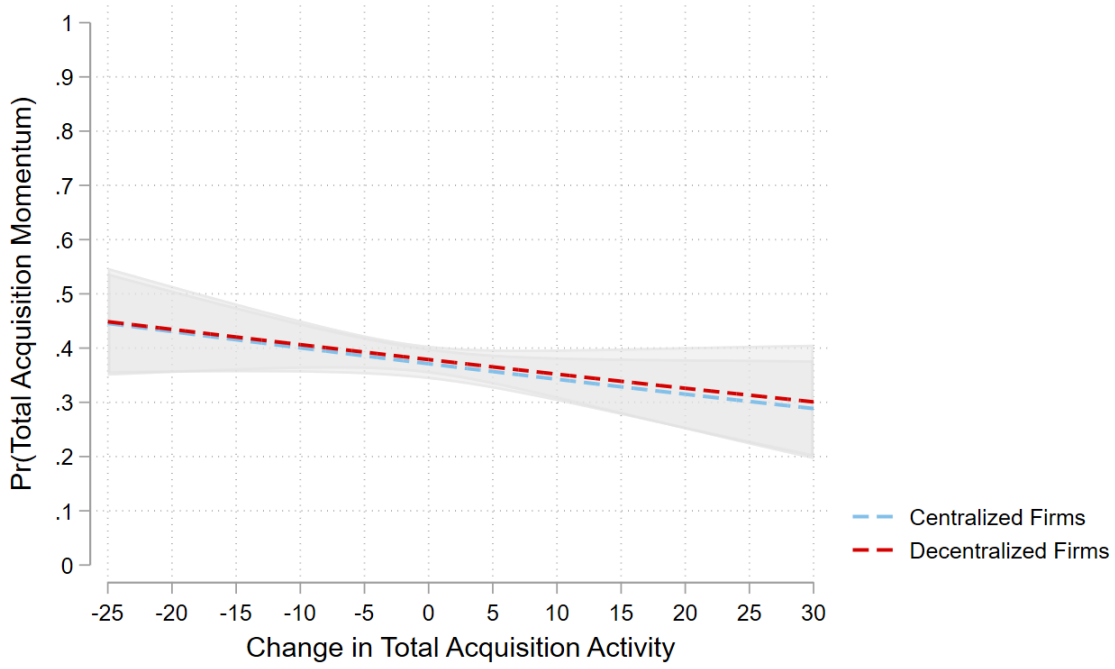


Figure 10: Predicted Probability of Dimension-Specific Acquisition Momentum by Acquirer Size and Change in Dimension-Specific Acquisition Activity: Heterogeneity in Acquirer Responses due to Differences in Acquirer Size and Acquisition Complexity



Notes: Group difference (central vs decentral) is significant (p<.1) when lines are solid.

Figure 11: Predicted Probability of Total Acquisition Momentum by Acquirer Structure and Change in Total Acquisition Activity: Interaction Effect Between Acquirer Structure and Total Acquisition Activity

sition momentum for centralized firms (p<.10), whereas the AME for decentralized firms is insignificant (p>.10). Similarly, the insignificant second difference (-0.003 – -0.003 = 0.000; p>.10) shows that the effect of a one-unit increase in activity load, on average, does not differ across groups. In other words, firms with a decentralized structure, on average, do *not* respond differently to increases in activity load than their centralized counterparts, providing no support for my predictions. This result holds consistently across the acquisition activity and momentum definitions shown in Table 7, with the significant cross-group effect of *small acquisition activity* in the *large acquisition momentum* model (0.003 – -0.003 = 0.006; p<.01) being an outlier.

As I did before, I plot the marginal effects of both groups to test whether cross-group differences exist at specific values of my independent variable (Mize, 2019). Figure 11 shows the predicted probability of decentralized and centralized firms to maintain their *total acquisition momentum* across the range of *total acquisition activity*. Interestingly, Figure 11 reveals that no significant *level differences* in the probability of maintaining momentum exist between decentralized and centralized acquirers (all contrasts p>.10). That is, decentralized acquirers are *not* more likely to maintain their acquisition momentum than centralized acquirers. Furthermore, given that both curves look almost identical *slope-wise*, cross-group differences in responses to a one-unit increase in *total acquisition activity* appear to not exist across all values of my independent variable. Substantively, this indicates that decentralized acquirers do not respond less strongly to changes in acquisition activity, rejecting hypothesis 4. This pattern is mostly robust to changes in acquisition activity and momentum definitions as shown in Figure 12. In sum, these findings indicate that an acquirer's degree of decentralization barely affects that firm's absorptive capacity and, thus, does not explain heterogeneity in firm responses to activity load.

4.3. Robustness Tests

There are four major concerns about the results from my main analysis. First, one could doubt whether the selected acquisitions in my baseline sample accurately reflect the intuition behind my stipulated activity load mechanism. That is, while all acquisitions are resource-consuming endeavors, minority-stake acquisitions appear to be less likely to cause an information overload due to the absence of post-merger integration activities. In fact, such acquisitions are frequently treated as financial investments and, thus, likely consume less resources than acquisitions that require the integration of the target organization. Second, it could be argued that my baseline operationalization of momentum does not account for the extended multi-year time horizon that is normally associated with acquisition streams (e.g., Laamanen & Keil, 2008). In other words, my current operationalization, which defines momentum as the change in known deal values from period *t-1* to *t*, appears to examine a time horizon that is too short to make inferences about the long-term acquisition behavior of firms. Third, one could question whether suitable proxies are used for the acquisition complexity dimensions in my main analysis – a concern that applies to all

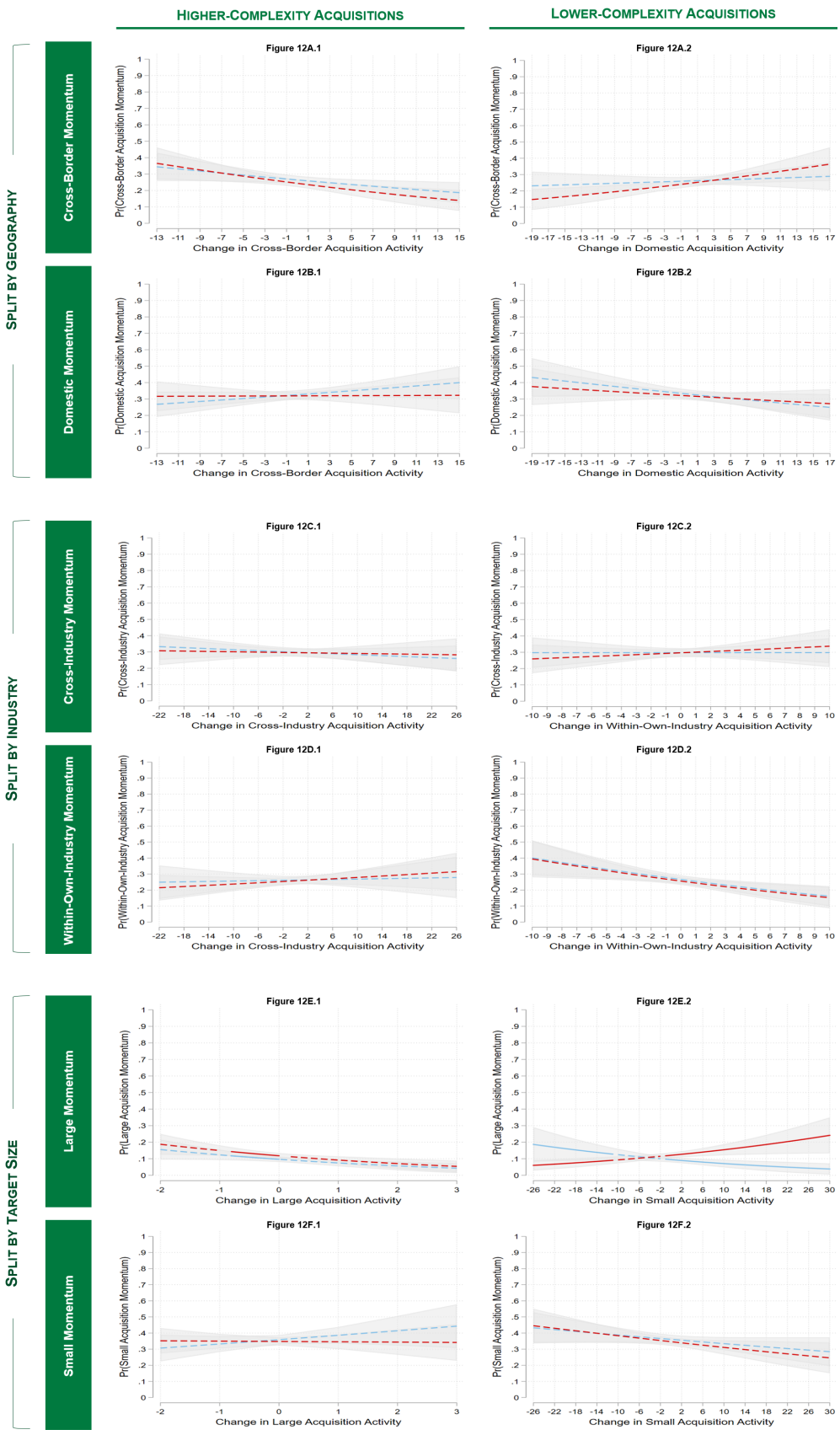


Figure 12: Predicted Probability of Dimension-Specific Acquisition Momentum by Acquirer Structure and Change in Dimension-Specific Acquisition Activity: Heterogeneity in Acquirer Responses due to Differences in Acquirer Structure and Acquisition Complexity

aggregation levels shown in Figure 6.[48] Fourth, one could have reservations about the construct validity of my variable *degree of decentralization*. Specifically, it could be criticized that executive titles may not accurately proxy structural features of acquirers and, thus, produce incorrect results in my analysis of heterogeneity in acquirer responses.

To eliminate these concerns, I adapt the models in my main analysis in four ways. First, I re-run my main analysis with two modified samples, of which the first only covers majority-stake acquisitions and the second comprises majority-stake acquisitions and acquisitions for which no acquired stake was reported in the Refinitiv database. Second, to address concerns about my baseline operationalization of momentum, I adapt the definition of momentum in two ways. On the one hand, I broaden the time window of my variable from two consecutive one-year periods (i.e., *t-1* to *t*) to two consecutive two-year and three-year periods. That is, I define momentum as the change in known deal values from periods *t-2* and *t-1* (*t-3*, *t-2*, and *t-1*) to *t* and *t+1* (*t*, *t+1*, and *t+2*). On the other hand, I change the operationalization of momentum by replacing monetary deal values with an acquirer's number of acquisitions, using the three different time windows from before to discern effects of alternative time structures. Third, I operationalize my acquisition complexity dimensions differently. For instance, I account for the particularly strong homogeneity between firms from Anglo-Saxon countries (Ronen & Shenkar, 2013) by distinguishing between cross-region and intra-region acquisitions, with 'intra-region' denoting acquisitions of targets which are headquartered in Australia, Canada, Ireland, New Zealand, the United Kingdom, or the United States. Similarly, I define a firm's industry based on the first three digits of that firm's SIC code and distinguish between large and small acquisitions through an acquirer-specific mean of the target-to-acquirer-total-assets ratio, which I compute based on my baseline sample. Fourth, to ensure the validity of my variable *Degree of Decentralization*, I re-run my analysis of heterogeneity in acquirer responses with an operationalization that uses an acquirer's number of business units as a proxy for that firm's organizational structure.[49]

Table A.7 in the appendix presents results of my first set of robustness tests, which use samples that exclude minority-stake acquisitions from the analysis.[50] Overall, it seems that my results are very robust to the exclusion of minority-stake acquisitions – both in terms of significance levels and effect sizes. Yet, two findings should be noted. First, in Model 5 and Model 6, the effect of *domestic acquisition activity* on *domestic acquisition momentum* in my main analysis appears to be driven by minority-stake acquisitions. This is indicated by odds ratio coefficients of *domestic acquisition activity* that are less significant ($p<.10$) or insignificant ($p>.10$) and have values closer to one relative to those in my main analysis. Second, in Models 11 and 12, it seems that acquisitions for which no stake was disclosed drive the effect of *large acquisition activity* on *large acquisition momentum* in my main analysis. Like before, this is shown by odds ratio coefficients of *large acquisition activity* that have values closer to zero (one) and are more significant ($p<.01$) (insignificant ($p>.10$)) in Model 11 (12) than those in my main analysis.

The results of my second set of robustness tests, which assess different operationalizations of momentum, are shown in Table A.8 and Table A.9 in the appendix. In sum, it appears that my results are very robust to changes in the time structure of momentum as shown in Table A.8. A closer inspection of Table A.8, however, reveals two interesting findings. First, almost all model specifications have odds ratio coefficients that are more extreme in magnitude[51] compared to those in my main analysis, and the extremity of this magnitude increases with the length of the time window used. In other words, the longer the time window that is used to define momentum, the more pronounced the effect of activity load. Second, unlike in my main analysis, increases in *cross-industry acquisition activity* reduce an acquirer's likelihood of pursuing further cross-industry acquisitions, providing further support for hypothesis 2a. This is indicated in Model 8 by a significant ($p<.05$) and lower-than-one odds ratio coefficient of *cross-industry acquisition activity*. The results presented in Table A.9, in which monetary deal values are replaced by an acquirer's number of acquisitions, further solidify these conclusions. That is, my hypothesized effects are stronger and often more significant in Table A.9 than in my main analysis, and these effect sizes increase with the length of the time window used for defining momentum. In addition, almost all relationships predicted in hypotheses 1, 2a, and 2b are highly significant ($p<.01$) in model specifications that use a three-year-on-three-year time structure in their definition of momentum.[52] The consistency of this finding across different proxy variables in Table A.8 and Table A.9

[48] For instance, my distinction between cross-border and domestic acquisitions abstracts from structural similarities between countries in the same regional cluster (e.g., Ronen & Shenkar, 2013) and, thus, might measure complexity differences between acquisitions in different geographies in an overly simplistic way. Likewise, the first two digits of a target's SIC code might not sufficiently reflect homogeneity of acquisitions on the industry level as targets in the same major group (i.e., with identical first two digits in their SIC code) exhibit lower levels of similarity than targets in the same industry group (i.e., with identical first three digits in their SIC code), potentially pooling non-homogenous acquisitions within the same complexity cluster. Also, my distinction between large and small acquisitions, which is based on the sample mean of the target-to-acquirer-total-assets ratio, may be too one dimensional as the relative size of an acquisition likely is acquirer specific.

[49] Based on Compustat business segment data.

[50] Due to space constraints, the results of my robustness tests are presented in multiple tables in the appendix.

[51] That is, odds ratio coefficients have values that are closer to zero or infinity, depending on the hypothesized effect direction.

[52] More specifically, all predicted relationships that were supported in my main analysis also hold in Models 3, 6, 9, 15, 18 and 21 in Table A.9. However, unlike in my main analysis, the effect of *cross-industry acquisition activity* is significant ($p<.01$) in Model 12. Combining this observation with the positive and significant ($p<.01$) odds ratio coefficient of *cross-border acquisition activity* (*cross-industry acquisition activity*) in Model 9 (15), I find support for the 'switching' behavior from higher-complexity targets to lower-complexity targets as predicted in hypothesis 2a. In fact, only the odds ratio coefficient of *large acquisition activity* in Model 21 remains insignificant ($p>.10$), implying that no switch from

implies that momentum definitions that use longer time windows likely are superior operationalizations in the context of research questions that explore phenomena which unfold over extended periods, such as acquisition patterns.

Table A.10 in the appendix illustrates results of my third set of robustness tests, which explore alternative operationalizations of my acquisition complexity dimensions. Overall, it seems that my results are mostly robust to definitory changes in my complexity dimensions – both in terms of effect sizes and significance levels. Two exceptions should be noted, however. First, the effect of *intra-region acquisition activity* in Model 3 is insignificant ($p>.10$). This indicates that my results are not robust to changes in the definition of country-level complexity, possibly because the Anglo-Saxon region is a region with high acquisition activity[53] that allows firms to maintain their momentum by acquiring targets in other countries within that region if targets in one specific country become exhausted. Second, unlike in my main analysis, the effect of *small acquisition activity* is significant ($p<.10$) in Model 6. Although this finding is counterintuitive, a closer look at the regression output reveals that the odds ratio coefficient of *small acquisition momentum* is marginally significant[54], indicating that the substantive importance of this finding is limited. Thus, my results are rather robust to definitory changes in all complexity dimensions.

Finally, Table A.11 in the appendix presents results of my last set of robustness tests, which use an acquirer's number of business units as a proxy for that firm's *Degree of Decentralization*. In sum, it seems that my results are *not* robust to alternative operationalizations of a firm's *Degree of Decentralization*. Specifically, I make two observations in Table A.11. First, the robustness of my results varies with the dependent variable. For instance, in most model specifications, the main effects in my subsample of centralized (decentralized) firms are slightly stronger (weaker) than those in main analysis, which are illustrated in Table A.6 in the appendix. This is indicated by slightly more (less) extreme odds ratio coefficients for centralized (decentralized) firms in Models 1 to 4 and Models 9 to 12 in Table A.11. Conversely, the odds ratio coefficients in Models 5, 6, 13, and 14 show the opposite behavior with varying magnitudes and unsystematic changes in their significance levels. This implies that model specifications in which *domestic acquisition momentum* or *small acquisition momentum* are the dependent variable show lower levels of robustness than models with other dependent variables. Second, across almost all model specifications, it seems that decentralized firms, on average, *might* respond less strongly than centralized ones. This is indicated by odds ratio coefficients that have values closer to one for decentralized firms in Models 2, 4, 10, 12, and 14. This pattern, if corroborated by tests of second differences, would support my predictions in hypothesis 4 and, thus, indicate that a firm's number of business units likely proxies structural features of firms more accurately.

large to small acquisitions occurs – a finding that could indicate that target size may not be a relevant complexity dimension.

[53] Almost 70 percent (= 8,311 / 11,951) of acquisitions in my baseline sample occur in the Anglo-Saxon regional cluster as defined by Ronen and Shenkar (2013). Please see Figure A.3 in the appendix for a visual breakdown of all acquisitions by their country of origin.

[54] More specifically, this odds ratio coefficient has a p-value of $p=.087$.

5. Discussion

In this section, I put my empirical findings into perspective by benchmarking them against evidence in extant literature. For this, I resort to the literature streams introduced in section 2, highlighting the implications of my results for the literature on temporal acquisition patterns, strategic momentum, and activity load. Moreover, acknowledging the high practical relevance of acquisitions, I discuss the practical implications of my findings for managers. Finally, this section presents the limitations of my study as well as potential alleys for future research.

5.1. Review and Implications of Empirical Findings

In this thesis, I aim to contribute to our understanding of the factors that cause acquiring firms to systematically deviate from their established, externally observable acquisition patterns. For this, I explore the role of a factor that has not yet been studied in acquisition pattern research: Activity load. Building on this construct, I find empirical support for my baseline hypothesis, which predicts that increases in a firm's activity load from acquisitions are negatively related to that firm's likelihood of pursuing future acquisitions. In other words, increases in the volume of acquisitions induce acquirers to decelerate their acquisition pace to alleviate the strains on their resources imposed by high levels of activity load. However, I cannot find robust support for my second predicted acquirer response: A switch from acquisitions in a higher-complexity target firm category to acquisitions in a lower-complexity target firm category. That is, firms may or may not switch to target firms that are less complex to acquire – and, thus, change the observable structural properties of their acquisition pattern – to reduce their activity load from acquisitions, depending on the operationalization of momentum. Likewise, I can only partially corroborate that structural features of acquirers, such as their size or organizational structure, explain differences in the acquisition behavior of these firms. Specifically, while an acquirer's size seems to be related to that firm's capacity to absorb acquisitions, I find no robust support for the moderating effect of a firm's organizational structure. Thus, it seems that the availability of resources influences a firm's absorptive capacity and, through this, its acquisition behavior, but the precise nature of this moderating relationship has yet to be fully understood.

These findings have important implications for scholars and practitioners alike:

5.1.1. Contributions to Research on Temporal Acquisition Patterns

This thesis contributes to extant research on temporal acquisition patterns in two ways. First, by exploring whether

a firm's activity load from acquisitions can explain deviations from stable acquisition patterns, this thesis adds to our understanding of the antecedents of these patterns. More specifically, it complements prior studies that have largely focused on the performance implications of acquisition patterns (e.g., Ellis et al., 2011; Hayward, 2002; Laamanen & Keil, 2008; Schipper & Thompson, 1983; Shi & Prescott, 2011; Vermeulen & Barkema, 2002) or explored factors that solely explain differences in acquisitiveness between firms (e.g., Baum et al., 2000; Bertrand et al., 2019; Haleblian et al., 2017; Kim et al., 2011; Malmendier & Tate, 2008; Shi et al., 2017). Closing this research gap was essential given the detrimental firm-level performance effects associated with systematic deviations from previously stable acquisition patterns (Ellis et al., 2011; Laamanen & Keil, 2008; Vermeulen & Barkema, 2002). Second, this thesis offers new insights to scholars who identify acquisition patterns based on externally observable target firm attributes (e.g., Ellis et al., 2011; Hayward, 2002). That is, while prior studies have explored the timing of acquisitions in acquisition patterns (e.g., Hayward, 2002) and the transferability of learnings across targets with different observable attributes (e.g., Ellis et al., 2011), this thesis assesses structural changes within acquisition patterns that unfold over time. Specifically, my robustness tests reveal that such structural changes *potentially* exist and manifest themselves in a switching response – from targets in a higher-complexity category to targets in a lower-complexity category – that allows acquirers to reduce their activity load while maintaining their overall momentum. In fact, it almost seems as if high levels of activity load flip a switch within the organization of acquirers that induces these firms to deviate from their established acquisition patterns. This novel insight, combined with a mechanism that draws on Penrosian resource-based logic and the BTF (e.g., Cyert & March, 1963; March & Simon, 1958; Simon, 1945), adds to prior research, which has largely investigated this phenomenon from an organizational learning perspective, and thus furthers our understanding of acquisition patterns.

5.1.2. Contributions to Research on Strategic Momentum

Besides adding to our understanding of temporal acquisition patterns, my findings make two contributions of theoretical nature to the debate on strategic momentum. On the one hand, my results warrant the separation of within- and between-firm effects in momentum research – both in theory development and empirical measurement. This need arises as my results confirm prior empirical findings of Beck et al. (2008), who have discovered that firms show behavior *opposite* to the repetitive momentum hypothesis once unobserved time-invariant heterogeneity on the firm level is accounted for (i.e., once the within-firm effect is fully isolated). Substantively, this indicates not only that the repetitive momentum hypothesis in its original formulation does not hold but also that past studies of strategic momentum that used random effects models, which do not separate within- and between-firm effects, have likely reported biased results. Separating within- and between-firm effects thus seems warranted to mitigate any biases and allow for a more fine-grained theory development in momentum research. On the other hand, my stipulated causal mechanism expands the theoretical underpinnings of prior momentum research. That is, whereas past studies have drawn on organizational learning theory and theories of managerial cognition to explain their findings, this thesis uses Penrosian resource-based logic as a novel theoretical lens. Doing so, I corroborate that the finite cognitive capacity of managers limits a firm's ability to maintain momentum, going beyond the mechanisms of routine formation and cognitive maps that were heavily emphasized in prior research (e.g., Amburgey & Miner, 1992).

Additionally, this thesis contributes one methodological insight to extant research on strategic momentum. That is, my robustness tests indicate that the length of the time window used in the operationalization of momentum strongly affects the effect size and significance level of the effect of activity load. Although this finding may surprise at first glance, it can be explained by a key characteristic of my phenomenon of interest: Temporal acquisition patterns evolve over time. Thus, meaningful structural changes in these patterns only become visible after a certain period of time has elapsed. Empirically, this implies that longer time intervals of acquisitions need to be contrasted with each other to discern true structural changes. By deriving this insight, this thesis makes an important methodological contribution to extant momentum research, which has predominantly relied on event history analysis (e.g., Amburgey & Miner, 1992).

5.1.3. Contributions to Research on Activity Load and Absorptive Capacity

This thesis also contributes to research on activity load and absorptive capacity in three ways. First, my findings complement prior research on activity load by studying whether activity load can explain the acquisition behavior of firms. That is, while prior research has largely explored the performance implications of (e.g., Kusewitt, 1985; Laamanen & Keil, 2008; Shaver, 2006; Zorn et al., 2019) and structural responses to activity load (e.g., Barkema & Schijven, 2008), this thesis presents evidence on activity load being an antecedent of acquisition behavior, closing a major gap in extant research. Second, this thesis adds to past studies by assessing the joint effect of acquisition volume and complexity. Specifically, my robustness tests reveal that acquirers *potentially* switch from targets in a higher-complexity target firm category to targets in a lower-complexity target firm category to reduce their activity load burden while maintaining their overall momentum. With this insight, my thesis contributes to prior research, which has mostly investigated the effects of acquisition volume and complexity in isolation (e.g., Barkema & Schijven, 2008; Castellaneta & Zollo, 2015; Kusewitt, 1985; Vermeulen & Barkema, 2002; Zorn et al., 2019) or only partially substantiated the existence of a joint effect of acquisition volume and complexity (e.g., Laamanen & Keil, 2008). Third, this study adds to our understanding of the interplay of activity load and absorptive

capacity in two ways. That is, my results confirm results of past studies which have shown that the size of acquirers weakens the negative effect of activity load (Laamanen & Keil, 2008). Thus, it appears that a larger firm size, *ceteris paribus*, helps firms manage the strains of activity load more effectively. In addition, my results provide no robust support for the moderating effect of a firm's organizational structure as predicted by Penrose (1959). This insight is crucial because this thesis is – to the best of my knowledge – the first to empirically test this moderating effect in the context of acquisitions. Yet, this result does not necessarily preclude the existence of the moderating effect of a firm's organizational structure, mainly due to methodological reasons.[55] Taken together, my findings largely corroborate that the concepts of activity load and absorptive capacity represent two sides of the same coin, supporting the rationale behind Penrose's (1959) 'fundamental ratio'.

5.1.4. Managerial Implications

Beyond these contributions to academia, this thesis sensitizes managers to the consequences of high levels of activity load. That is, when making decisions about acquisitions, managers need to be cognizant of the level of activity load already borne by members within the organization. This is because the finite cognitive capacity of these members limits the number of acquisitions a firm can do in a given period (Penrose, 1959). Otherwise, the activity load from acquisitions can lead to information overload on the individual level (Castellaneta & Zollo, 2015) and corporate indigestion on the organizational level (Kusewitt, 1985) – two consequences that are associated with negative performance implications for acquirers (Laamanen & Keil, 2008).

Finally, this thesis provides managers with a set of practical actions. That is, my results suggest that managers *can* actively manage the activity load from acquisitions. Specifically, managers can choose between three options that vary in their ease of implementation. First, managers can consciously regulate the volume of acquisitions to benefit from inorganic growth while avoiding a situation of information overload. While easy to implement, this option may not always be aligned with the strategic goals of the acquirer. Second, if this option is not desired, managers can decide to acquire targets that are less complex to acquire or integrate. However, the feasibility of this option depends on a firm's ability to switch to a lower-complexity target firm category and, thus, may not be available to all acquirers. Third, instead of regulating the activity load of acquisitions, managers can increase the absorptive capacity of their firm. While this can be achieved, for instance, by hiring and training additional people, this option is hard to implement in the short run because the accumulation of knowledge in new hires with respect to M&A processes and specificities of the acquirer organization requires time (Penrose, 1959). Managers therefore need to carefully evaluate these trade-offs in accordance with the strategic goals of and resource base available to their organization before choosing a specific option.

5.2. Limitations and Recommendations for Future Research

My study has two main limitations that may affect the validity of my findings. First, my analysis fully abstracts from a key driver of acquisition behavior: Strategic intent (e.g., Biggadike, 1979; Karim & Mitchell, 2000; Lasserre, 2003; Lee & Lieberman, 2010). In fact, given the multitude of rationales behind acquisitions, the acquisition behavior of firms likely is more opportunistic than assumed in this study. This could raise concerns about unaddressed confounding factors in my analysis and, thus, limit the explanatory power of my results. Second, albeit I extensively draw on prior theory to explain the underlying mechanics of my predicted activity load effect, I did not directly measure my proposed causal mechanism. This implies that my results could reflect a spurious correlation instead of a causal effect. Thus, to prove the validity of my causal mechanism, future research needs to explicitly rule out competing mechanisms, such as changes in a firm's strategic intent (e.g., Biggadike, 1979; Karim & Mitchell, 2000; Lasserre, 2003; Lee & Lieberman, 2010) and a firm's past acquisition performance (e.g., Kusewitt, 1985; Laamanen & Keil, 2008; Zorn et al., 2019). This can, for instance, be achieved through qualitative research designs, which are particularly well suited to examine process-based mechanisms like mine due to "their capacity to capture temporally evolving phenomena in rich detail, something that is hard to do with methodologies . . . [that use archival data]" (Langley & Abdallah, 2011, p. 202).

Furthermore, two methodological choices in my study could limit the explanatory power of my results. First, my chosen sample of acquirers may compromise the generalizability of my results to the full population of acquirers. This is because my sample only includes firms that are large in size and mainly located in the United States. However, while this choice could induce a firm-size and/or geographic bias, it ensures that my study only analyzes acquirers that are sufficiently acquisitive – a pre-condition for examining acquisition patterns that evolve over time. Second, some operationalizations of variables in this study might raise concerns about construct validity. For example, the results of my robustness tests indicate that my baseline operationalization of structural features of firms, which is based on executive titles, could suffer from this problem, potentially causing inconclusive results. Similar concerns could apply to my operationalization of activity load. That is, although my study followed prior research (e.g., Castellaneta & Zollo, 2015) by using externally observable target firm features as proxies for a firm's activity load, my proxies fully abstract from internally observable or unobservable acquisition characteristics that could influence the activity load from acquisitions, such as differences in organizational cultures and the degree of structural integration in the PMI stage (Haspeslagh & Jemison, 1991). Moreover, even if externally observable target

[55] That is, my baseline operationalization of *Degree of Decentralization* might not accurately proxy structural features of acquiring firms.

firm attributes were valid proxies for activity load, the construct validity of my measures can still be questioned. This is because, unlike prior studies that use *relative* proxies, such as target-to-target similarity, to measure heterogeneity in acquisitions (e.g., Hayward, 2002; Laamanen & Keil, 2008), I use *absolute* proxies, such as the number of domestic acquisitions, to account for differences in acquisition complexity. These proxies, however, are rather static and, thus, abstract from the dynamic properties of activity load (Castellaneta & Zollo, 2015), possibly limiting the explanatory power of my findings.

Considering these limitations, future research could add to our understanding of the effect of activity load by exploring four topic areas. First, given the complex nature of the construct of activity load, scholars could examine alternative, more advanced operationalizations of activity load. Future studies could, for instance, re-run my analyses with an acquirer's target-to-target similarity as a measure for heterogeneity in acquisitions. Alternatively, scholars could construct a multi-dimensional index as shown in Figure A.4 in the appendix instead of analyzing possible dimensions of activity load separately, thereby complementing the approach used in this thesis. Second, future research could further explore factors that moderate the effect of activity load. This would be critical since our understanding of variables that moderate the effect of activity load remains limited, both with respect to variables that were explored and not explored in this study. Third, scholars could investigate the relationships between different types of firm-level responses to activity load, including reductions in the performance of acquirers (e.g., Kusewitt, 1985; Laamanen & Keil, 2008; Zorn et al., 2019), changes in their organizational structure (e.g., Barkema & Schijven, 2008), and – as shown in this study – changes in their acquisition behavior. Following this rationale, researchers could, for instance, examine the boundary conditions of these individual responses or even assess whether a hierarchy of firm-level responses to activity load exists. Fourth, scholars could investigate the effect of activity load in non-M&A research contexts, such as strategic alliances (e.g., Shi & Prescott, 2011, 2012), international expansion (e.g., Vermeulen & Barkema, 2002), and organizational change (e.g., Kelly & Amburgey, 1991; Miller & Friesen, 1980). Doing so, future studies would not only explain firm behavior that is relevant to their respective fields but also add to our understanding of the effect of activity load.

6. Conclusion

In this study, I present first empirical evidence on the effect of an acquirer's activity load from acquisitions on that firm's acquisition behavior, with a particular emphasis on how the activity load from acquisitions causes acquirers to deviate from their established acquisition patterns. For this, I exploit changes in the acquisition activity of acquirers in my panel of the 300 largest Fortune Global 500 firms over the 1990-2010 period. My results are based on a hybrid logit model, in which I regress seven operationalizations of an acquirer's acquisition momentum on different definitions of activity load. As predicted, increases in an acquirer's activity load from acquisitions, on average, reduce that firm's ability to maintain its acquisition momentum. Also, my results reveal that acquirers potentially switch from targets in a higher-complexity target firm category to targets in a lower-complexity target firm category to reduce their activity load burden while maintaining their overall momentum. Albeit this finding cautiously indicates that the activity load from acquisitions can explain deviations from established acquisition patterns, the observed effect strongly varies with the operationalization of momentum and, thus, warrants further investigation of this phenomenon. Similarly, I obtain ambiguous results in my analysis of heterogeneity in firm responses arising from differences in the absorptive capacity of firms.

The negative average acquisition response of firms can be explained by an overload situation that is caused by high levels of activity load. That is, as the inertial pressures of momentum induce acquirers to engage in further acquisitions (Amburgey & Miner, 1992; Miller & Friesen, 1980, 1982), the steady increase in acquisition activity directly translates into a higher activity load until the cognitive burden borne by managers exceeds their ability to process this activity load, creating a situation of information overload (Castellaneta & Zollo, 2015). As the strains of information overload are instantly felt by managers and, thus, must be immediately acted on, acquirers are forced to decrease their activity load by reducing their acquisition volume. Yet, while this mechanism is supported by multiple theories, such as Penrosian resource-based logic and the BTF (e.g., Cyert & March, 1963; March & Simon, 1958; Simon, 1945), it is not directly measured in this study and, thus, needs to be further examined to verify its causal interpretation.

Finally, my findings have important implications for scholars and practitioners. That is, on the one hand, this thesis helps scholars better understand a phenomenon of high practical relevance: Deviations from temporal acquisition patterns. Beyond this contribution, scholars benefit from new empirical insights that add to the debate on strategic momentum and past studies of activity load and absorptive capacity. On the other hand, this study makes managers more cognizant of the implications of activity load and provides them with a set of practical actions. Specifically, my findings suggest that managers can actively manage the activity load from acquisitions by (i) regulating the volume of acquisitions, (ii) acquiring targets that are less complex to acquire or integrate, and (iii) increasing the absorptive capacity of their organization. This option space thus suggests that managers are in the driver's seat and ideally should flip the switch before the strains imposed by a firm's activity load do. Therefore, the concept of activity load offers plenty of relevant insights and, thus, should be high up on the research agendas of strategy scholars.

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