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Top Management Team Tenure, Competitive Repertoires, and Firm Performance in the 3D Printing Industry (1988 – 2015)

Brian C. Fox, PhD

University of Connecticut, 2017

Prior work suggests that competitive repertoires holistically capture firm-level decision making, and provide insight into how firms create and capture value. However, our understanding of the causes and consequences of competitive repertoires remains limited. While existing evidence suggests environmental forces and managerial backgrounds influence repertoire formation, we do not know how the developmental and competitive state of the industry shapes the salience of prior knowledge. Nor do we understand how the state of the industry influences the relative payoffs of particular repertoire configurations. To further our understanding, I investigate the distribution of industry tenure within executive teams, and examine whether the industry life cycle influences how prior experience translates into complex and / or consistent competitive repertoires. Digging deeper into the implications of the life cycle, I also consider how these different facets of the competitive repertoire influence performance under different levels of competitive pressure. I test the model in a longitudinal sample of 3D printer manufacturers in operation from 1988 – 2015. I use this industry to test these effects because a large proportion of firms can be tracked, firms exhibit a variety of competitive actions, the level of competitor activity varies over time, and firms contain a mix of veteran managers from core industries and new managers from outside the industries that "spawned" 3D printing ventures. I find evidence to suggest that while executive experience distributions are very salient for repertoire formation early in the life cycle, these effects wane as the industry matures. Further, the data suggests that significant relationships exist between repertoire characteristics and performance, but the pattern is nuanced and depends to some degree on the level of competitive pressure.

Top Management Team Tenure, Competitive Repertoires, and Firm Performance in the 3D Printing Industry (1988 – 2015)

Brian C. Fox

B.S., Babson College, 2008

A Dissertation

Submitted in Partial Fulfillment of the

Requirements for the Degree of

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Brian C. Fox

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APPROVAL PAGE

Doctor of Philosophy Dissertation

Top Management Team Tenure, Competitive Repertoires, and Firm Performance in the 3D Printing Industry (1988 – 2015)

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CHAPTER 1 – INTRODUCTION

Motivation

At its core, strategy is the study of a set of organizational choices taken in the pursuit of superior competitive outcomes. Simon (1947: xlvi) stated that, "decision making is the heart of administration [and] must be derived from the logic and psychology of human choice". Essentially, to understand firm decision making patterns, we must understand the decision makers. Relatedly, patterns in firm choices, or competitive action repertoires, shed light on how firms accrue economic rents. As Schoemaker (1990: 1184) notes, "strategy is the means via which economic rent is earned, either by exploiting existing imperfections or by creating suitable levels of uncertainty and complexity", where strategy is an interlocking pattern of decisions.

In line with these sentiments, decision-level theorizing can help to explain how managerial characteristics influence decision processes, resultant firm actions, and firm performance (Gavetti, Levinthal & Ocasio, 2007: 525). By decision-level theory building, I mean that managerial and firm characteristics should be tied to the likelihood of making a particular set of decisions, and that the resultant actions and their aggregations are a meaningful window into firm performance. I claim that the locus of firm behavior and its consequences is situated at the decision level – since decisions and their consequent actions are the most fundamental measure of purposeful activity that entities exhibit (Parsons, 1937; von Mises, 1949). And yet, while a decision-level focus sheds light on how firm behavior is influenced by managerial antecedents, and how firms generate rents through discrete actions, a practical question emerges. How can managerial characteristics be tied to discrete actions? Relatedly, how can a single decision be meaningfully linked to aggregate consequences? It would be difficult, if not impossible, to link single actions taken by a firm to a body of prior activity or managerial traits.

In response to these questions, scholars have invoked the competitive repertoire construct as a conceptual framework to link a group of actions to managerial characteristics and performance (Miller & Chen, 1996). A competitive repertoire is “the set of market actions used by an organization during a given year to attract, serve, and keep customers, [which is] composed of concrete market decisions such as price changes, product line or service alterations, and changes in the scope of operations” (Miller & Chen, 1996: 420). So conceived, a competitive repertoire is an observable artifact that records decisions made by the firm for a certain period of time. Using this and similar concepts such as the competitive attack, prior researchers have demonstrated the repertoire’s predictive validity as it relates to performance (Ferrier, 2001; Andrevski et al., 2014) and that the repertoire’s composition is driven by managerial, firm, and environmental factors (e.g., Chen & Miller, 2012; Ndofor, Sirmon, & He, 2011).

The notion of competitive repertoires also equates decisions made by a firm to observable actions taken in product and factor markets – with all the attendant performance implications. Specifically, competitive actions generate temporary rents by capitalizing on resource or opportunity differentials in economic and social systems (D'Aveni, Dagnino, & Smith, 2010; Winter, 1995). Extant theorizing has largely focused on the argument that firm actions mitigate diverse organizational and environmental forces that are detrimental to performance, such as the competitive reactions of other firms (Chen & Miller, 1994; Derfus, Maggitti, Grimm, & Smith, 2008; Young et al., 1996). Taken together, the competitive repertoire construct provides a means to study aggregate firm behavior patterns, and provides a bridge between firm characteristics, decisions, and performance.

Unanswered questions

While prior work in the upper echelons literature (e.g., Wowak, Mannor, Arrfelt, & McNamara, 2016), and studies specific to competitive actions have begun to shed light on the influence of managers on the overall pattern of firm behavior (e.g., Ferrier, 2001; Hambrick, Cho, & Chen, 1996), existing studies have yet to articulate the constraints and tradeoffs associated with the pattern of managerial experience across different industries. A detailed investigation of these tradeoffs is important to undertake because there are conflicting views regarding the value of industry experience on firm behavior and performance when viewed both as a stock (Finkelstein, Hambrick, & Cannella, 2009) as well as a type of diversity (Harrison & Klein, 2007). Moreover, prior work has not fully considered how salient and pervasive contextual factors such as the industry life cycle determines what experiences managers accrue or the payoffs to the actions that managers select (Chen & Miller, 2012).

Moreover, while existing competitive dynamics research provides a link between firm actions and performance, it has yet to conceptually separate or empirically test the extent to which observed performance effects are due to firm-centric value creation, or from mitigating environmental conditions that hamper value capture. This distinction is relevant because it is currently unclear whether repertoires result in superior performance due to synergies between different actions undertaken by firms, whether repertoire configurations stymie competitor imitation, or a combination of the two. In both cases, by not incorporating the influence of the industrial and competitive context when theorizing about repertoires, the construct's potential to explain how managerial experience translates to performance remains untapped.

Conceptual and tested model

To address these unresolved questions, I investigate the critical role of managerial experience on the composition and consequences of competitive repertoires (see Figure 1). Specifically, I consider the distribution of within and outside industry tenure inside the management team, and how this reservoir of experience shapes the firm's repertoire of actions. Tenure within and outside the industry are key upper-echelons characteristics to consider because the prior experiences conferred by tenure shape the beliefs, social context, and knowledge structures that affect individual and group decision making (Finkelstein, Hambrick, & Cannella, 2009). Beyond examining the direct effect of tenure distributions, I also consider how these effects are conditioned by the industry life cycle. Understanding the influence of the industry life cycle on these tenure to repertoire relationships is essential for two reasons: the life cycle shapes the experiences that managers accrue during their tenure, and molds the competitive context in which they must apply their knowledge and judgment.

When examining how repertoires are shaped by managerial tenure, I conceptualize the competitive repertoire as a vector that captures all observable actions taken over the course of a year which is situated within a space of possible actions (Lamberg, Tikkanen, Nokelainen, & Suur-Inkeroinen, 2009). This form provides a compact representation of the firm's realized strategy (Mintzberg, 1978). While this form is not readily amenable to empirical analysis, I consider two key summary statistics, or facets, of this vector: its complexity (Connelly et al., 2016) and consistency over time (Lamberg et al., 2009). The facets are considered in concert because the first captures the firm's flexibility to adapt to changed circumstances and generate uncertainty to keep competitors off balance (Ferrier, 2001), while the second illuminates the stability of the repertoire trajectory over time. Together, they provide a holistic summary of the firm's pattern of action and partially capture the tradeoff between specialization and flexibility.

I then examine how these two facets of the competitive repertoire influence firm performance, and explicitly test how these effects are modulated by the intensity of competitor activity (Derfus et al., 2008) – a key distinguishing characteristic of different life cycle stages. In so doing, I attempt to separate the arguments regarding value creation and capture in the conceptual development, and empirically test to what extent these effects depend on allaying the effects of competitive pressure. Taken together, the model seeks to better understand the causes and consequences of the repertoire in an evolving industry.

I test this model and its associated hypotheses using a data set from a longitudinal sample of 3D printer manufacturers in operation from 1988 - 2015. This sample is appropriate for analyzing these research questions for several reasons. First, I can observe a wide variety of managerial backgrounds since new firms are started through spin-outs, firm dissolutions, and as new managers and owners enter the industry because the underlying technological bases of the industry continue to shift (Wohler's Report, 2013). I am also able to track a near census of firms within the industry from the beginning of the sample frame to the present, enabling me to capture changes in life cycle stage and partially account for selection effects.

Moreover, the size and complexity of the market as well as the number of competitors vary over time. This allows me to capture a variety of competitive actions and differing levels of competitive pressure over time. In comparison to very new and very established industries, the potential range of competitive repertoires is such that established recipes for acting have not yet fully disseminated, while the industry is also not so new where firms are still struggling to establish access to basic resources. Firms continue to assess their place within the industry vis-à-vis other players, and determine what competitive moves are best suited to capture customers (D'Aveni, 1994). Finally, given the disruptive nature of this industry, a more in-depth understanding of its competitive dynamics is warranted.

Summary of findings

I find broad support for the assertion that TMT prior industry experience is related to increased levels of repertoire consistency. Contrary to my predictions, outside experiences are associated with more complex repertoires in early life cycle stages, but this relationship weakens over time instead of becoming stronger. Digging deeper into this effect, I examined the relative balance between inside and outside industry experience and uncovered that firms in the sample seem to be converging towards a common level of complexity and consistency, regardless of their particular distribution of experience in the management team. This seems to suggest that firms have access to alternative means of achieving similar repertoire profiles, in spite of different management team compositions.

As it relates to my hypotheses regarding the effect of competitive repertoires on firm performance, several specifications indicate that there is a positive main effect between repertoire complexity, consistent with the existing literature. However, this effect was not robust to unobserved firm fixed effects, which may indicate that some other latent quality of the firms may be the underlying driver of this effect. Furthermore, there is some, but inconclusive, evidence to suggest that complexity is more pivotal in competitive environments. By contrast, the predictions regarding the curvilinear relationship between repertoire consistency and performance were largely unsupported at typical levels of competitive pressure. In fact, in the case of market share the relationship may be U-shaped, rather than the hypothesized inverted U relationship. However, the data suggest that the second order effect of repertoire consistency on performance may be moderated by competitive pressure, but the results are also not conclusive.

CHAPTER 2 – COMPETITIVE REPERTOIRES: A LITERATURE REVIEW

The competitive repertoire as a lens

Several authors have identified the promise of competitive repertoires as a way to understand the overall pattern of firm actions over time, and their performance consequences in competitive settings (e.g., Lamberg et al., 2009; Miller & Chen, 1996a). A competitive repertoire is defined as "the set of market actions used by an organization during a given year to attract, serve, and keep customers, [which is] composed of concrete market decisions such as price changes, product line or service alterations, and changes in the scope of operations" (Miller & Chen, 1996: 420) and "is made up of the entire range of the firm's competitive moves" (see Chen & Miller, 2012: 145). So conceived, competitive repertoires are an observable artifact that records the decisions made by the firm for a certain period of time, including those actions that are responses to competitive activity.

In line with Mintzberg's (1973) conceptualization of strategy as a pattern of action and Chen and Miller's (2012: 138) notion of thematic consistency, aggregating a set of actions that a firm takes for a specific period of time allows researchers to distill a general pattern of activity and deduce the overall aggressiveness, non-conformity, and strategic direction of an organization. Consistent with logic of revealed preference (Varian, 2006), patterns of action allow researchers to more closely examine regularities in decision making, and describe the behavior of the firm more accurately than isolating particular activities or routines (Pentland & Rueter, 1994).

Moreover, examining collections of actions and the aggregate level of competitive response can provide a lens to view how the performance effects of firm decisions are influenced by market processes. One can envision how differences in focal and competitor action propensity can influence the stream of Schumpeterian rents accruing to firms possessing valuable but imitable information, affect the ability to capitalize on composite quasi-rents for firms that have made transaction-specific investments, or modify the demand for required resources, increasing factor prices at the margin (Keyhani, Levesque, & Madhok, 2015; Mahoney & Pandian, 1992). Beyond the conceptual insights that repertoires of action can provide, many dimensions relevant to individual actions can also be considered without loss of generality at the aggregate level. This serves to increase the observed effect size, making signals in noisy data easier to detect. As such, the concept of competitive repertories holds more explanatory power than individual actions when predicting firm outcomes – and affords conceptual tools that are not available when studying actions individually.

I conceptualize the competitive repertoire, building on Lamberg et al.'s (2009) work, as a vector that captures all observable actions taken over the course of a year that are situated within a space of possible actions. When the competitive repertoire is conceptualized in this manner, the repertoire provides a link between firm decisions (which are manifest in observable actions) and the implications of those decisions within a competitive environment. In particular, Lamberg and colleagues (2009) provide a critical insight into understanding how the actual actions undertaken by the firm can be mapped onto the performance landscapes described by those authors using NK modeling studies (e.g., Ghemawat & Levinthal, 2008; Levinthal, 1997). In their paper, the authors conceptualize a firm's repertoire as a vector of actions within an underlying decision space, which they project into two dimensions using a principal component analysis (Lamberg et al., 2009: 54). This conceptualization allows for empirically observed actions to be associated with observed performance levels, providing all of the necessary coordinates for mapping action – performance configurations within a given environment of decision. While the overall shape of the decision space and the performance landscape cannot be imputed from these isolated points, this conceptualization allows the results the simulation studies examining these performance landscapes to be drawn upon and applied.

Facets of the competitive repertoire

While the vector representation of the competitive repertoire is not readily amenable to empirical analysis, I consider three key summary statistics, or facets, of this vector: the total number of actions taken by the firm in a given year (known as volume, see Young, Smith, & Grimm, 1996), the stability of the repertoire's position within a space of possible actions over time (termed consistency, see Lamberg et al., 2009), and the variety and relative proportion of different action types performed by the firm in that same period of time (defined as complexity, see e.g., Ferrier, 2001; Miller & Chen, 1996). I argue that these three facets provide a comprehensive summary of the different structural aspects of the competitive repertoire, shedding light on the firm's potential to undertake meaningful action and generate rents, match actions to environmental contingencies, and balance the competing pressures of specialization and flexibility. Beyond the aspects studied here, a repertoire can also be assessed by the characteristics of the actions from which it is comprised – in other words by considering the typical level of significance, noteworthiness and scope (Hambrick, Cho, & Chen, 1996), reaction difficulty (Chen & Miller, 1994) or irreversibility (Chen and MacMillan, 1992). The component aspects of the repertoire can be classified via a number of dimensions, such as entrepreneurial, Ricardian, deterrent, and cooperative actions (Grimm, Lee, & Smith, 2006; Vannoy & Salam, 2010). However, this information takes into consideration aspects of action content – whereas the three facets considered take into consideration structural factors that should be equally relevant across different industry and environmental settings. I provide a summary of prior work related to these repertoire facets below.

Volume: By volume, I refer to the total number of actions taken by a firm in a given year (Ferrier, 2001; Ferrier et al., 1999). The primary drivers of this construct are the number of events that a firm can respond to (quantity of stimuli) and the propensity to act when presented with the opportunity (likelihood of action, see Nokelainen, 2008). Volume is typically conceptualized as a simple measure of total competitive activity (Andrevski et al., 2007; Derfus et al., 2008; Ferrier, Smith, & Grimm, 1999; Young et al., 1996; Young et al., 2000; Zhang, Song, and Qu, 2011) that a firm undertakes in a given period and is also a component of competitive aggressiveness measures (e.g., Andrevski, Richard, Shaw, & Ferrier, 2014). Young and colleagues (1996) articulate the connection of this construct with Schumpeterian rents, arguing that since rents are limited in duration, engaging in more competitive activity should result in higher levels of performance. This logic has been relied upon in later competitive dynamics studies (e.g., Derfus et al., 2008; Ferrier et al., 1999; Hambrick, Cho, & Chen, 1996) and is one of the most commonly studied repertoire variables.

Moreover, repertoire volume can also be considered as a measure of repertoire magnitude, or the potential degrees of freedom available to firms when undertaking actions. Said differently, the potential for changes in other aspects of the competitive repertoire is bounded by the overall magnitude of the repertoire vector. For instance, the level of consistency (or more accurately, the lack thereof) depends upon the distance between the former and current location of the repertoire within the space of actions. As the absolute magnitude of the repertoire vector increases, the possible level of these other variables should increase as well for purely arithmetic reasons. Thus, even though total competitive activity is an important construct to consider in its own right, it is also a critical control when considering more complicated facets of the repertoire such as complexity or consistency. This measure of competitive activity can also be aggregated across competitors. This change in level of aggregation and the removal of the focal firm from the computation is conceptualized as the level of pressure that competing firms place on a focal firm's ability to capture any rents generated (Young et al., 1996; 2000).

Complexity. Repertoire complexity is the variety of actions taken by a firm in a given year (Ferrier, 2001). Existing studies have typically conceptualized the complexity of the repertoire in this manner (Andrevski, Richard, Shaw, & Ferrier, 2014; Basdeo, Smith, Grimm, Rindova, & Derfus, 2006; Larraneta, Zahra, & Gonzalez, 2014; Offstein & Gnyawali, 2005; Smith, Ferrier, & Ndofor, 2001; Yeung and Lau, 2005). Since repertoire complexity is a variable that can only be observed at the repertoire level, it provided one of the first justifications for aggregating competitive actions in this manner. As a result, many of the early studies of competitive repertoire used several variations of the complexity construct, such as the simplicity, range, dominance and concentration of competitive actions (Miller & Chen, 1996a), the non-conformity of a target repertoire with respect to a benchmark (Boyd & Bresser, 2004; Miller & Chen, 1996b; Norman, Artz, & Martinez, 2007), or the level of competitive inertia within a repertoire (Miller & Chen, 1994). The study of complexity also opened the door for considering the antecedents to complexity, such as management team heterogeneity (Hambrick, Cho, & Chen, 1996) and network characteristics (Chi, Ravichandran, and Andrevski, 2010).

Synthesizing these different aspects from prior research, the level of complexity is determined by the number of actions that a firm can and has taken in a year (requisite variety) and the extent to which actions are evenly distributed across different situations (discriminating use). In this study, I conceptualize the complexity of the repertoire as a measure of the firm's behavioral entropy (Langlois, 1986: 7) - and confers the firm with the ability to at least partially match the entropy of its environment. Thus, while there are a number of potential measures used in the literature to measure complexity and its converse - simplicity (Miller and Chen, 1996a; Ferrier et al., 1999; Zhang, Song, & Qu, 2011) - I utilize a Shannon entropy index to capture both the range of potential actions as well as the evenness of distribution among these observed actions.

Such a measure captures two relevant aspects of the complexity construct. First, a higher level of behavioral entropy provides insight into the maximum amount of environmental entropy that can be accommodated by the firm's existing set of capabilities (Langlois, 1986) - meaning that the firm has an appropriate response to a wider number of environmental contingencies. This ability to match varied situations with varied responses corresponds to Ashby's (1956) principle of requisite variety. Further, to the extent that increased repertoire complexity serves as an insurance policy against environmental changes and contingent events, it also serves to frustrate the attempts of competitors to imitate or duplicate the actions of the focal firm (Rivkin, 2001). Indeed, as the number of potential choices increases and the behavioral entropy of the focal firm increases, it becomes more and more difficult to predict what the best competitive response should be, particularly if these selections are made simultaneously. This is a more difficulty task compared to the focal firm's game with the environment, where contingencies can sometimes be observed before acting (Shy, 1999).

Consistency. Repertoire consistency pertains to the stability of the firm’s repertoire trajectory over time, such that a similar pattern of actions is taken from one year to the next (Lamberg et al., 2009). A fully consistent repertoire is one whose proportion of action types does not vary over time (constant direction), while inconsistent repertoires contain variations in strategic direction. Such changes are particularly inconsistent when the proportion of actions taken changes dramatically (magnitude of shift). Unlike the other two constructs, the construct of repertoire consistency is a relatively recent development within the field of competitive dynamics, but offers great promise in articulating the change in the final position of the repertoire vector in the space of potential actions over time.

Repertoire consistency opens the door to considering the effect of specialization and learning economies, integrating the insights of earlier work on the implications of performance feedback on the structure of competitive repertoires (Miller & Chen, 1994). Consistency also provides a window into the ease or difficulty for a firm to grapple with the forces of strategic change - particularly in situations where the basis of competition has shifted within an industry. In this regard, the roles of consistency and complexity are complementary - the former providing an indication of the firm's trajectory or path within the action space (Sydow et al., 2009; Gruber, 2010), while the latter provides an indicator of the range of possible discretion and latitude the firm has at its disposal as it charts this path forward.

Competitive repertoires and firm performance

The notion of competitive repertoires equates decisions made by a firm to observable actions taken in product and factor markets – with all the attendant performance implications. Specifically, competitive actions generate temporary rents by capitalizing on resource or opportunity differentials in economic and social systems (D'Aveni, Dagnino, & Smith, 2010; Winter, 1995). The following section discusses the conceptual basis for how rents are generated and captured through competitive actions, followed by a summary of the empirical evidence to date relating competitive repertoire facets to performance outcomes.

Competition and the market process. There is a critical assumption inherent in most discussions of firm performance. Namely, it is assumed that if there are no isolating mechanisms present (Mahoney & Pandian, 1992), then the competitive market process (Kirzner, 1973) will drive prices towards equilibrium values consistent with the first fundamental theorem of welfare economics (Mahoney & Qian, 2013). Kirzner (1973: 97) perhaps states it best saying, "for us to speak freely of a lack of competitiveness in a market process, we must be able to point to something which *prevents* market participants from competing" (emphasis original). Indeed, the implicit underpinning of the fundamental theorem (Debreu, 1959) is that the market process, driven by entrepreneurial discovery and action, smooths out informational asymmetries (Kirzner, 1973) and brings prices into line with the costs of production – eliminating economic profits in the long term in the absence of structural impediments (Makowski & Ostroy, 2001).

Critically, actions aim to exploit the temporary differences between product and factor market prices, but the very identification of this discrepancy leads to others discovering the existence of these differences at little to no cost (Arrow, 1962), and thus competitors can similarly exploit and compete away the arbitrage opportunity (Kirzner, 1973: 85; see also von Mises, 1949: 288). Yet, the restrictions placed upon the abilities of firms and their competitors by theories of bounded rationality are of vital importance in explaining the means for generating economic profits (i.e., firm capabilities, see Amit & Schoemaker, 1993; Gavetti, 2005; Schoemaker, 1990), the sustainability of profits (i.e., isolating mechanisms, see Mahoney & Pandian, 1992; Rivkin, 2000) , as well as the potential for firms to accrue profits (e.g., complementarity, see Brynjolfsson & Milgrom, 2012; Ghemawat & Levinthal, 2008).

In particular, when firms are placed upon a performance landscape that represents the complexity of the economic system, and parameterized by the manifold decisions to be made (e.g., Levinthal, 1997; Rivkin, 2000; 2001), it becomes clear that the ability of competitors to instantaneously (or perhaps ever) fully match the successful actions of firms may be stymied for several reasons. To be clear, firms are incentivized to replicate the actions of others to the extent that their resource bases allow them to, and that the higher performance of certain firms can be observed by others.

First, since the environment is not a nearly decomposable system, there are several unknown interactions between the various decisions to be made (Simon, 1962). These non-linearities have been captured using NK-models borrowed from ecology (Kauffman, 1993) and more recently through the use of dense adjacency matrices that reflect the interconnections between firm decisions (Ghemawat & Levinthal, 2008). As discussed by Rivkin (2000: 835), when firms are boundedly rational and operating in a decision landscape that exceeds their computational abilities, local search is a primary mode of adaptation – and can result in firms having markedly different portfolios of actions, particularly if they enter the landscape at different starting points. Second, when firms do attempt to replicate the patterns of actions of leading firms, even small perturbations in the replication process may result in markedly different performance outcomes (Rivkin, 2000: 831), limiting the deleterious effect of imitation even if the firm is able to replicate its success internally (Rivkin, 2001). These and other prior simulation studies provide analytical support regarding how behavioral principles such as local search influence the behavior of firms and their competitors along a performance landscape.

Conversely, even though firms may be hamstrung in exactly replicating the repertoire of their competitors because they compete in different aspects of the action space or cannot duplicate the level of complexity achieved by the focal firm, there are multiple means by which competitors are able to successfully meet customer needs and achieve high performance through the use of problemistic search to find acceptable substitutes. In turn, the increased success of competitors drives the focal firm to search for new methods to overcome decrements in their own performance (Derfus et al., 2008). Taken together, these two mechanisms are the prime drivers of the Red Queen effect, in concert with differential selection (Barnett & Pontikes, 2005). The Red Queen model implies that competitors exert pressure on one another and cause them to "run faster and faster to remain in the same place" (Derfus et al., 2008). Prior research has shown that survival rates depend on the ecology of competitors and the recency, variability, and content of prior competitive experience, because firms learn lessons from one another about how to compete more effectively (Barnett & Hansen, 1996; Barnett & McKendrick, 2004). The effect of the Red Queen has also been shown at the action level (Derfus et al., 2008), where the performance effects of particular actions result in increased competitor activity, which subsequently diminishes the efficiency by which focal firm actions translate to increased performance. These studies and many others within the structure-conduct-performance (Scherer & Ross, 1990), new empirical industrial organization (Martin, 2002), multipoint competition (Yu & Cannella, 2013) and sustainable performance (Ghemawat, 1999) paradigms have illustrated how competitive interactions result in a diminishment of the link between competitive activity and firm performance in the absence of barriers to competitive activity.

Existing empirical evidence. The majority of research applying the competitive repertoire construct is situated within the competitive dynamics literature, which seeks to study "interfirm rivalry based on specific competitive actions and reactions, their strategic and organizational contexts, and their drivers and consequences" (Chen & Miller, 2012: 137), with an emphasis on explaining performance differentials common to studies of competitive strategy. Early studies used competitive repertoire volume as a summary statistic to aggregate actions over a specific period of time to observe firm-level performance effects (Ferrier, Smith & Grimm, 1999; Young et al., 1996; Young, Smith, Grimm & Simon, 2000). This method of discerning the performance effect continues to be used, and is it typically captured using a measure of total competitive activity or competitive pressure (Andrevski et al., 2014; Basdeo et al., 2006; Zhang et al., 2011).

From this base, later studies examined the effect of repertoires on performance and have shown that focal firm competitive activity and speed begets increased performance as measured by revenue, profitability or some variation of return on assets (Bridoux, Smith, & Grimm, 2013; Chen & Hambrick, 1995; Derfus et al., 2008; Young et al., 1996). In a comprehensive study of a number of different resource management actions, Bridoux and colleagues (2013) sketched out the estimated performance boosting effect of different actions over time and found that different action types vary in the magnitude and duration of performance benefit. Studies of market share change (Chen & Hambrick, 1995; Hambrick et al., 1996; Ferrier, 2001; Tsai et al., 2011), industry dethronement (Ferrier et al., 1999; Smith et al., 2001), diffusion rate gaps (Zhang et al.,2011) and relative perceptual performance (Lin & Shih, 2008) all provide further evidence that increased competitive aggressiveness is associated with increased relative performance.

Empirically, strong effect sizes have also been reported for increased action repertoire complexity in its various forms (Andrevski, Brass, & Ferrier, 2013; Basdeo et al., 2006; Larraneta, Zahra, & Gonzalez, 2014; Offstein & Gnyawali, 2005; Smith et al., 2001) – although investigations that consider the potential for reverse causality (i.e. strong performance allows for a more robust competitive repertoire) do not appear to have been systematically performed to date. Concordantly, strategic simplicity has been found to have deleterious performance effects (Miller & Chen, 1996). There is evidence of a feedback loop between good performance and strategic simplicity, wherein good performance results in increasing competitive repertoire simplicity, which begets poorer performance in the future after accounting for the tendency for strong past performance to beget future performance (Miller & Chen, 1996a: 434). Others have started to combine the dimensions of total competitive activity as well as the overall complexity, or diversity, of competitive activity into a summary construct of competitive aggressiveness (e.g., Offstein and Gnywali, 2005; Yu, Subramaniam, & Cannella, 2009) or competitive intensity (Andrevski et al., 2014), while others continue to consider volume, complexity and heterogeneity as separate constructs (e.g., Chi et al., 2010). Similarly, repertoire non-conformity and deviance from industry norms typically have positive influences on these same metrics (Ndofor et al., 2011; Norman et al., 2007). Taken in concert, there is solid evidence to support the claim that competitive repertoires have established links to both relative and absolute performance.

However, there remains ambiguity in the existing literature regarding to what extent temporary and structural rents accrue to firm actions, and to what extent observed effects relate to differences in rent generating capabilities versus the ability to capture those rents (for an exception, see Derfus et al., 2008). The theoretical argumentation for why these performance effects are observed often depend upon the reactions of competitors, rather than an argument for why the activity of the focal firm gives rise to superior performance in the first instance (for exceptions, see Chen & Miller, 1994). Thus, our understanding of how competitive repertoires drive performance is incomplete. We only have one theory of firm rents accruing to action – we assume that rents will be generated via actions and also assume that they will be competed away by competitive activity. When arguing for why different facets of the competitive portfolio will generate rents, prior work tends to not articulate how firms generate these rents, but rather how firm activity retards the efficacy of assumed competitive reactions. I attempt to address this limitation of existing work in my performance related hypotheses.

Limitations of the repertoire approach

The repertoire affords a number of conceptual and practical benefits. To begin, the primary strengths of the repertoire approach is that it can show the manifold means by which firms can generate rents through actions, and how certain repertoire configurations may mitigate the effects of environmental and competitive pressures. This core argument is consistent with the earlier insights of Miller and Chen (1994: 7; 1996) who argue that superior performance may be derived not only from unexpected actions but from alternative mechanisms such as the influence of competitive inertia on firm adaptability. Furthermore, the repertoire provides a parsimonious means to aggregate discrete competitive actions, serving as a way to detect patterns in the set of actions that firms perform which could be difficult to uncover if individual actions or discrete sequences of actions are studied.

However, the use of repertoires is not without its costs. In particular, the dimension of time – a critical aspect of both competitive dynamics research and strategic management more generally – is suppressed when using the repertoire construct. In order to unlock these dynamics, competitive dynamics researchers have used alternative means and measures to examine the back and forth dynamics of competitive attacks and retaliations. In a seminal paper, Ferrier (2001: 859) discussed the concept of competitive attack, which he defines as "an ordered, uninterrupted sequence of repeatable competitive action events." This construct sheds light on the process and temporal ordering of competitive actions and responses. Rindova and her colleagues (2010) use a similar conceptualization and examined the gestalt properties of these sequences such as the predictability, grouping, simplicity and motif of the attack. Similarly, Derfus and associates (2008) investigated Red Queen effects related to competitive action and found that as firm actions increase, the number and speed of rival actions increase, leading to countervailing effects on performance.

In order to maintain theoretical parsimony and retain emphasis on the firm-centric decision constructs, I have chosen to not use these more time- and sequence- sensitive measures – although the argumentation should proceed in largely the same manner. However, while I do not examine the discrete competitive interactions that take place, I do consider the collective weight of all competitive responses, or the overall volume or magnitude of competitor activity, on a focal firm's performance in developing my arguments. The construct of overall competitor pressure captures the total amount of competitive activity generated by all other firms within the industry, which should influence the duration a focal firm's rents can be generated before being eroded by competitor imitation or substitution (Derfus et al., 2008; Young et al., 1996).

The antecedents of competitive repertoires

Repertoires are an artifact of the decision making process, and thus their antecedents are typically rooted in explanations of firm and executive decision making. Prior work in the competitive dynamics field indicates that repertoires and the actions that comprise them stem from the confluence of three factors: *awareness, motivation, and capability* (Chen & Miller, 1994; Chen, 1996). Each of these elements operate at the level of the top management team as well as throughout the lower levels of the organization – in line with a distinction between routine and non-routine decision making (Gavetti, 2005). While a wide body of research exists in both areas, I limit my discussion to research that relates management team characteristics to competitive actions and repertoires.

I use the concept of awareness to refer to the organizational and environmental cues that prompt a need or desire by the firm and its decision makers to act, and the means for recognizing these stimuli. There are several studies that focus on how firm leaders selectively attend to and process these cues (e.g., Andrevski et al., 2014; Ferrier, 2001; Hambrick et al., 1996; Offstein, Gnyawali, & Cobb, 2005). In an early study, Hambrick, Cho and Chen (1996) found that increased top management team (TMT) education and tenure heterogeneity were related to increased propensity to take actions of high magnitude. Ferrier (2001) found the heterogeneity of the TMT increases competitive attack complexity, which he attributes the group's increased field of vision and enriched cognitive map. These ideas have continued to be drawn upon and supported in later papers (Andrevski et al., 2014; Lamberg et al., 2009). More recently, cognitive accounts have been put forward to assess how firms may differ in their responsiveness to certain stimuli (Marcel, Barr, & Duhaime, 2010), conceptualizing organizational cognition and attention patterns using constructs such as competitive tension and acumen (Chen et al., 2007; Tsai, Su & Chen, 2011). For example, competitive acumen - or the extent to which a firm is able to replicate the cognitive map of its competitors (for the purpose of predicting potential response), is explained by a firm's structural and relational embeddedness (Tsai et al., 2011). Similarly, Vannoy and Salam (2010) provide a process model of competitive action that incorporates conceiving, enacting and executing competitive actions, and argue that information systems increase the awareness of competitive stimuli.

Beyond awareness, the firm must also be motivated to expend energy and resources in executing firm actions. Two major perspectives concerning the motivations for competitive actions have been discussed in the literature: incentives to pursue or discourage certain firm activity (see e.g., Chen et al., 1992) and the varied motivations of stakeholders that shape the objectives and goal hierarchy of the firm (e.g., Connelly et al., 2010). Given my emphasis on managerial influences, I limit my discussion to the latter. Specifically, prior work has shown that key stakeholders such as the management team have a substantial influence on the amount and type of actions selected. For example, Offstein and Gnywali (2005) found that CEOs who have larger incentive packages engage in more competitive activity, while Connolly and colleagues (2010) found that dedicated institutional fund ownership is positively related to strategic actions, whereas transient ownership is positively associated with tactical actions and negatively associated with strategic actions. Similarly, Karagozoglu and Fuller (2011) demonstrated that the salience of core stakeholders shapes the relationship between prior performance and the propensity to engage in strategic actions, while Halbelian and associates (2012) found that the firm's overall diversification may allow the corporate office to act a shield between shareholders and business units making acquisitions.

Lastly, firm capabilities are the firm and action specific resources and routines necessary to successfully enact intentions to act. Once decision makers have identified an opportunity for action, they must generate sufficient consensus and mobilize the necessary internal resources. Several prior studies in the upper echelons and behavioral theory of the firm have considered the processes and resources that the TMT has at its disposal to initiate a competitive action. Smith and colleagues (1991) considered the role of education and prior experience on the propensity to respond to rival actions as well as the type of response selected. Hambrick and associates (1996) argued that heterogeneity increases the creative capacity of the management team and facilitates more deliberation and thought exchange, albeit with an increased level of conflict. Lin and Shih (2008) demonstrated that TMT social integration was related to action aggressiveness, as a result of increased team flexibility and imagination that stems from social cohesiveness. Finally, in their investigation of strategic consistency over time, Lamberg and colleagues (2009) posited that a resourceful and focused administrative body is more apt to achieve strategic consistency.

The case for this study

Even though prior work has established that both managerial traits and environmental factors have a role to play in shaping the pattern of firm activity, we still do not have a detailed understanding of how the distribution of prior experience within the management team shapes the awareness, motivation, or capabilities of top managers to engage in complex or consistent repertoires (for an initial step towards that end, see Hambrick, Cho, & Chen, 1996). Further, while the combination of managerial background and industry-level factors has been studied to some degree in the competitive dynamics literature (e.g., Nadkarni, Chen, & Chen, 2015) two salient contextual conditions that have not been considered in detail (in spite of their central role in explaining industry growth and change) are the life cycle (Gort & Klepper, 1982) and the level of competitive activity (e.g., Young et al., 1996).

Both of these factors are expected to have systemic implications for how managerial experience is converted into patterns of firm activity, and how firm activity will translate to performance. In the first case, the industry life cycle likely modifies the available stock of managerial knowledge and the extent to which those stocks are utilized. In the second case, while prior research has hinted that competitive pressure is a key boundary condition for the influence of competitive repertoire configurations on performance, this assertion has not fully tested but for Derfus and colleagues' (2008) study. Thus, a model that considers these elements offers a window into these heretofore missed opportunities to examine how industry participants, available knowledge, competitive pressure, and firm action patterns evolve over time. Figure 1 provides a summary of the hypothesized model to which I now turn.

Insert Figure 1 about here

CHAPTER 3 – HYPOTHESES

As a collective of individuals with considerable decision rights and access to a wide range of relevant information, top managers are particularly influential for firm decision making processes since they "structure decision situations to fit their view of the world" (Finkelstein & Hambrick, 1990: 484). In line with prior work in the upper echelons tradition, I argue that top management teams are a key input to the non-routine decision making processes that are central to the execution of novel competitive actions. For the purposes of this dissertation, I conceptually define the top management team as the dominant coalition drawn from the two highest executive levels within the organization (Finkelstein, Hambrick, & Cannella, 2009: 127), since their position confers them with general responsibility for firm functioning.

Both the upper echelons and strategic cognition literatures indicate that the decision making process generating observed firm actions is constrained by the mental models and knowledge structures of the management team (Walsh, 1995), which themselves may be constrained by the firm's dominant logics (Prahalad & Bettis, 1986) and available social technology (Stinchcombe, 1965). As Walsh and Ungson (1991: 69) noted, "Schemata are formed from past experience to facilitate information processing in information-rich decision environments". Executives' prior experiences thus serve as a perceptual filter for understanding subsequent stimuli (Dearborn & Simon, 1958; Hambrick & Mason, 1984), and provide a schema or frame for understanding means-end relationships and anticipating changes (Cornelissen & Werner, 2014; Simon, 1996; Tripsas & Gavetti, 2000). Moreover, managerial reference points regarding losses and gains (Lant, 1992; March & Shapira, 1992; Miller & Chen, 2004) as well as expectations (i.e., the first and second moments for uncertain outcomes) regarding future performance may also be sensitive to prior experience. For example, recent research has indicated that accurate evaluations of competitive behaviors depends upon the ability for decision makers to “step into the shoes” of their rivals - which could be driven by access to contemporaneous information (Tsai, Su, & Chen, 2011) or could be informed by similar histories. Moreover, prior experiences appear to shape cognitions regarding causal logics and focus attention on different sectors of the environment of decision (Nadkarni & Barr, 2008). Cognitive frameworks also affect the speed and likelihood of challenging the actions of adversaries (Marcel, Barr, & Duhaime, 2010: 129).

Thus, managerial prior experience has several points of contact with strategic decision making processes, making their potential impact critical to uncover. To capture this decisive role of prior managerial experience on competitive actions, I consider a particularly salient type of managerial experience – experiences within and outside the focal industry. These different experiences collectively capture knowledge within two relevant domains of expertise: knowledge related to industry formulae and anticipated outcomes in a given context (total and average focal industry experience), and more general knowledge pertaining to executing different competitive maneuvers (outside experiences and tenure heterogeneity).

Experience, as defined by Merriam-Webster, is “practical knowledge, skill[s], or practice derived from direct observation of or participation in events or in a particular activity.” Bringing this concept into context, prior experience in any industry may provide managers with a reservoir of situated knowledge of customer needs, key industry success factors, potential suppliers, and regulatory conditions (Feeser & Willard, 1990; Kor, 2003). Further, experience can “serve to shape values and beliefs” as well as cognitive models of reality (Finkelstein, Hambrick, & Cannella, 2009: 83). In new venture settings where relevant experience is at a premium, the amount and closeness of prior industry experience to current activities has been shown to enhance the growth rates and survival chances of firms across a number of industries (Bruderl et al., 1992; Colombo & Grilli, 2005; Klepper 2002; Roberts, Klepper, & Hayward, 2011). This is because such experiences allow managers to have causal interactions with their environment of decision (Barnard, 1938), providing private knowledge about what does and does not work (Hayek, 1945). This personal knowledge (Polanyi, 1962) accrues to managers working in any industry and provide a set of data unique to each manager's personal trajectory.

The shaping role of managerial tenure

Tenure within the industry provides a source of valuable, direct experience that enables managers to engage in learning by doing, and confers access to contextual task knowledge in multiple domains. In particular, tenure confers grounded insights regarding competitors, potential customers, and available suppliers (Delmar & Shane, 2006; Feeser & Willard, 1990; Kor, 2003; Roberts, Klepper, & Hayward, 2011). Moreover, prior experience allows managers to develop tacit knowledge and expertise (Reuber & Fischer, 1994) as well as awareness and access to stores of explicit knowledge, such as industry databases or associations. Similarly, industry experience that flows from tenure also confers access to vicarious learning through the formation of ties to industry participants (Geletkanycz & Hambrick, 1997) and increased access to social capital (Hsu, 2007). Further, through the creation of cognitive knowledge structures (Fern, Cardinal, & O'Neill, 2012; Walsh, 1995), managers are more in tune and aware of potential opportunities within their space for rent generating opportunities and how to capture value (Gruber, MacMillan, & Thompson, 2008), and importantly the specific actions (i.e., means-ends relationships) to accomplish these goals.

However, while the foregoing provides a number of reasons why tenure increases the stock of available knowledge available to the focal manager, there are a number of influences that bound and limit the information garnered through these direct and indirect channels.

Importantly, these influences become more prominent at higher levels of tenure. To begin, experience within a focal industry provides access to a group of individuals and institutions that possess industry recipes or other norms that are shared among industry participants (Hambrick, Geletkanycz, & Frederickson, 1993; Spender, 1989). Some scholars define industries as "shared or interlocking metaphors or worldviews" (Huff, 1982: 185). As tenure increases and managers accumulate a large volume of industry relevant knowledge, their knowledge structures become more refined and more tightly align to their repeated prior experience (Finkelstein & Hambrick, 1990; Sutcliffe & Huber, 1998). Evidence suggests that a higher proportion of the learning by managers occurs during the early years of their industry tenure, meaning that learning in this early stage will have an outsized influence on the knowledge structures constructed (Hambrick & Fukutomi, 1991). Further, with increased tenure also comes greater managerial power (Miller, 1991; van Essen, Otten, & Carberry, 2015), increasing the incentive to maintain the course and not introduce disruptive changes. Thus, as tenure increases, information is more tightly processed and filtered through the selective attention to outside sources of information and highly refined knowledge structures. Collectively, these mechanisms result in an increased commitment to the status quo (Hambrick, Geletkanycz, & Frederickson, 1993).

Taken together, the above evidence suggests that as tenure increases from low levels, individual managers will have access to a stock of relevant information that will point them towards a specific subset of actions (Fern, Cardinal, & O'Neill, 2012). This increased awareness of particular courses of actions will channel their attention to known alternatives over more experimental or unproven courses. Furthermore, as tenure levels continue to increase, the effects of status quo biases and restricted information flow will increasingly inhibit individual managers from deviating from established industry recipes (Spender, 1989).

These tendencies are further reinforced as the average level of tenure increases for all members of the management team. Team members tend to focus on common rather than unique knowledge when discussing potential alternatives (Mohammed and Dumville, 2011; Nemeth & Rogers, 1996) and homogenous teams are subject to groupthink (Janis, 1972) and similar biases such as status quo maintenance and cognitive simplification (e.g., Schwenk, 1984). Furthermore, when more individuals within the team are exposed to the same industry, they rely upon the same dominant logics (Prahalad & Bettis, 1986) and draw from similar networks of informants, further restricting information flow and the likelihood of exploring alternative options.

This common worldview and knowledge set will result in the team converging towards a common and unchanging set of actions – as Tripsas and Gavetti (2000) demonstrated in the case of Kodak. While the particular set of activities that the team converges to may be different (e.g., teams with high levels of experience in early life cycle stages may conform to practices from their experiences in related industries such as inkjet printing, while in later stages firms may converge to the emergent body of "best practices"), several mechanisms point towards tenure increasing the firm's level of strategic consistency. While the counterargument can be made that the increased knowledge from tenure may provide the team with a deeper understanding of industry trends and awareness of opportunities, the counteracting effect of shared cognitions and an increased individual commitment to the status quo are expected to overpower these effects.

> *Hypothesis 1: The higher the team's average industry tenure in the focal or highly related industries, the more consistent the firm's competitive repertoire will be from one year to the next.*

The above arguments apply for all industries, not just the focal industry under consideration. This implies that a similar effect is anticipated for tenure gained by managers within any industry that they have prior experience. Importantly, the contextual knowledge gathered in non-related industries will almost surely differ in material ways from that garnered in the focal industry (Beckman, 2006; Fern, Cardinal, & O'Neill, 2012), and the likelihood that information networks are overlapping decreases (Geletkanycz & Hambrick, 1997). Thus, exposure to other industries provides a wider range of insights to be considered and weighed by the team. Indeed, these outside perspectives are often valued, as shown by the hiring of executive team members from other industries to help invigorate discussions. For instance, the trading of executives back and forth from LMVH and Apple (in 2014, Apple hired the VP of sales for Tag Heuer, and in 2015 LMVH hired the chief digital officer from Apple) illustrates how knowledge from different industries can be highly valued, particularly when looking to shift strategic direction (in the case of Apple, making the iWatch, and in the case of LMVH, to build its online businesses).

Therefore, a critical question arises: what is the distribution of inside and outside industry experience in the management team and what effect does it have? As the relative proportion of outside industry experience versus within industry experience increases (holding average tenure constant), two effects should be present. First, the increased variety of perspectives and experience with different action types will increase the team's cognitive complexity allowing for differentiation and integration of insights (Bartunek, Gordon, & Weathersby, 1983) and provide the space for novel recombinations (Baron & Ensley, 2006). Similar to what studies of functional background have reported, variety in industry experience should influence the cues that different managers attend to and bring to the attention of the rest of the team (Dearborn & Simon, 1958; Beyer et al., 1997). While certain firm actions may be dominant under all scenarios, on the margin it is expected that the increased availability of potential actions where team members have prior experience in executing and monitoring will increase the firm's behavioral entropy (Langlois, 1986).

And furthermore, from a process perspective the presence of individuals with perspectives from outside the industry should result in increased debate and dialogue regarding course of action (Simons et al., 1999), generating increased task conflict (Amason, 1996), all of which lead to more comprehensive decision processes (Frederickson, 1984; Forbes, 2007). With increased decision comprehensiveness comes better accuracy in judgments, and often at reduced speed (Wally & Baum, 1994). With a more comprehensive decision making process, "tried and true" actions will not be selected so quickly, and alternative, superior options considered instead. Taken together, social processes that encourage more careful deliberation and increased cognitive diversity should result in a more diverse set of actions.

> *Hypothesis 2: The more heterogeneous the team's industry tenure, the more complex the firm's competitive repertoire will be.*

The conditioning effect of the industry life cycle

The industry life cycle has a substantive influence on the environment of decision that managers face (Gort & Klepper, 1982).[1] A number of different literatures comment on the form of the industry life cycle, including the dominant design paradigm (Utterbeck & Abarnathy, 1975), the Klepperian tradition in evolutionary economics (Agarwal, Sarkar, & Echambadi, 2002; Gort & Klepper, 1982), the organizational ecology school (Baum 1999), and studies of Red Queen competition (Barnett & McKendrick, 2004; Derfus et al., 2008).

Taken together, the insights from these traditions indicate that the life cycle will have an independent effect on the consistency and complexity of actions. Relating to consistency, the evolutionary economics perspective notes that in the first stage of the industry life cycle, a focus on product innovation would limit repertoires to mostly product development actions (Gort &

[1] While there are many definitions of the industry life cycle, I adopt Gort & Klepper's (1982) five stages. In my setting, I can only observe the first three stages of the industry life cycle. Thus, in hypotheses referring to "later stages", this does not include Stage IV and V.

Klepper, 1982). In later stages, companies experiment with a number of alternative business models and process innovation possibilities. Subsequent to this period, repertoire consistency increases again either because a dominant design has been found (Suarez & Utterback, 1995), developing a niche is required to avoid competition for resources (Carroll, 1985), or increased operating barriers necessitates scale, learning, or process innovation economies (Agarwal, Sarkar, & Echambadi, 2002). Similarly, the life cycle should have a direct effect on complexity for several reasons. First, variety may be required in later stages where competitors are fitter on average (Agarwal & Gort, 2002; Barnett & McKendrick, 2004. Second, as the basis of competition shifts from product based to price or other attribute based competition, this necessitates a wider variety of actions in later stages - even though there may be a partial decline in complexity in Stages IV and V in the face of a more concentrated industry with very fit surviving competitors (Karniouchina, Carson, Short, & Ketchen, 2013).

Beyond these direct effects, I argue that the industry life cycle conditions the influence of top management team tenure on competitive repertoire by shaping managerial knowledge and industry competitiveness. To begin, it is important to consider the relative timelines and information content of manager tenure versus the industry age (see Figure 2 for an illustration of these timelines and the stages of the industry life cycle in this context). Essentially, the content of the knowledge that tenure confers is based on the time it which it was learned (Reuber & Fischer, 1999). In later industry cycle stages, managerial tenure covers multiple periods of experience (and the lessons learned therein), whereas in earlier periods the lessons of tenure mostly relate to the “pre-history” of the industry (i.e., knowledge from closely related domains) and the focal industry’s early stages (Helfat & Lieberman, 2002; Klepper & Simons, 2000). Relatedly, the knowledge set of the industry evolves, and the information “learned” in each year of tenure is drawn from this updated set. Since more information is learned in earlier years of executive tenure (Hambrick & Fukatomi, 1991) and this is the filter through which executives process new information, experience in later periods from both direct experience and through social connections may either be discounted, or interpreted and filtered through the lens of prior learning (Ferrier & Lyon, 2004). However, if the difference between prior learning and new information is so distinct that it cannot be related to existing knowledge structures, or if the expected means-end relationships no longer function (i.e., what was once a very profitable strategy now delivers very poor results) managers may update their cognitive structures to adapt to this new reality (Barr, Stimpert, & Huff, 1992).

Insert Figure 2 about here

Based on the above, I argue that the life cycle will weaken the tenure – consistency relationship for two reasons.[2] One, competition in product and factor markets increases due to increased number of competitors (Hannan & Freeman, 1977), and a switch to process innovation and price competition from the product based competition in earlier phases (Gort & Klepper, 1982). Furthermore, the fitness of competitors increases through selection (Nelson & Winter, 1982) and vicarious learning through the Red Queen effect (Barnett & McKendrick, 2004). Given the evolution of best practices, the formulae applied in prior years may no longer be sufficient due to competitor learning – prompting a need to search for new "best responses", particularly as competitor dependence increases (Chen & MacMillan, 1992). Since failing to adjust strategies can impact performance outcomes, problemistic search will cause the management team to collectively reconsider their current strategic trajectory (Boeker, 1997).

[2] To be clear, this prediction holds until Stage IV. During Stage V and later, industry recipes likely become ingrained and competition slackens.

Second, in later life cycle stages, the knowledge encapsulated in managerial tenure will cover a broader cross-section of competitive contexts in comparison to tenure largely learned during the pre-history of the industry.

> *Hypothesis 3: The relationship between average industry tenure and repertoire consistency will be weaker later in the life cycle in comparison to earlier stages.*

Similarly, the life cycle is anticipated to influence the relationship between tenure heterogeneity and repertoire complexity for two reasons. First, knowledge variety is exploited only when it is needed, namely when changes in environmental entropy necessitate an increase in behavioral entropy (Langlois, 1986). In other words, the costs of developing and maintaining capabilities to enact a variety of actions, and determining which action to take are incurred only when the cost of inadequate response is sufficiently high (Heiner, 1983). As discussed above, a wider range of experiences across various industries confers the requisite variety of prior experience and expertise to perform a range of competitive actions (Ashby, 1956). And this increased variety has economic benefit to the management team in later life cycle stages because increased competitiveness demands more numerous and nuanced responses. Indeed, the level of competition increases from practically non-existent (essentially a common struggle for legitimacy) to actively managing competitor responses (Grimm, Lee, & Smith, 2006) and maintaining a sufficient pace of product and process innovation (Klepper & Simons, 2005).

Moreover, as the industry evolves, the knowledge base that industry participants require changes. As the industry develops a number of submarkets (Klepper & Thompson, 2006), the type and quantity of customers in particular segments change. In servicing these various customer groups, the use of product innovation alone becomes insufficient to capture customers in the early and late majority subpopulations due to their lower willingness to pay for a particular performance level (Adner, 2004). This results in process innovations that engender alternative means of doing business, causing a qualitative shift in competition type from entrepreneurial actions to Ricardian and deterrent actions (Grimm, Lee, & Smith, 2006). As a result, the relative value of outside experience should increase as the overlap of outside perspectives with the new competitive reality rises, while the value of earlier industry experiences begins to decline.

> *Hypothesis 4: The relationship between tenure heterogeneity and repertoire complexity will strengthen in later life cycle stages (Stage III) in comparison to earlier stages (Stages I and II).*

Competitive repertoires, competitive pressure, and firm performance

There has been substantial empirical support for the claim that increases in repertoire complexity has a positive influence on absolute (Ndofor et al., 2011) and relative firm performance (Basdeo et al., 2006; Ferrier, 2001), while repertoire simplicity tends to have a negative impact (Miller & Chen, 1996; Ferrier & Lyon, 2004). The received wisdom for this effect is summarized by Basdeo and colleagues (2006: 1208), who state, "diverse actions may achieve superior performance because diverse actions enable [firms] to generate more diverse advantages, which may be more difficult for competitors to imitate and compete away". By contrast, Miller and Chen (1996a: 424) make a more comprehensive argument in discussing the opposite of repertoire complexity (i.e., repertoire simplicity), arguing that: "simplicity allows firms to develop the advantage of focus [and] develop core competencies that attract customers and defy imitation by rivals [… but] a competitive repertoire must be sufficiently comprehensive to address the relevant range of potential customer needs and customer challenges".

Even in the absence of competition, complex repertoires can confer benefits. Profit is generated from the complex interaction between different actions that comprise an underlying activity system (Ghemawat & Levinthal, 2008), resulting in myriad complementarity and substitution effects between different action types which allow replication but not necessarily substitution (Rivkin, 2001: 275). For example, there are natural synergies between pricing actions and promotional activity, such that their simultaneous use in one market should increase revenues more than each activity in isolation. Process improvement capabilities and merger and acquisition activity may have similar synergies, a combination often used by private equity firms. While the additional flexibility and complementarity of such combinations have a positive influence, it is possible for the firm to overextend, impeding the efficiency, repetition, and practice needed to cultivate distinctive capabilities. However, there are several organizational designs that can mitigate these risks (e.g., Simsek et al., 2009). For example, the use of a corporate venturing unit may be an effective way to enact entrepreneurial actions that would otherwise flounder in a bureaucratic setting (Burgelman, 1983).

Beyond these technical complementarities, the temporal order in which actions are executed can be structured to take advantage of temporal complementarities. For instance, a firm operating at capacity using a technology that has increasing returns to scale would do better to execute a capacity increase move prior to a price reduction move than vice versa, since the increased capacity will lower the average cost of production prior to the reduction in price. As Bridoux and colleagues (2013) demonstrated, the period of rent generation differs by action type, and thus balancing the causal cycle (Mitchell & James, 2001) of different action types may smooth performance gains over time as well.

By contrast, if firm activity in concentrated within only a few activity types, initial gains are made from returns to scale and learning advantages, but diminishing returns to those select few actions are likely to set in more rapidly. For example, only so many merger and acquisition deals can be performed in a certain period before the breakeven deal is reached (McNamera, Haleblian, & Dykes, 2008), or only so many price cuts can produce a positive effect.

Furthermore, the actual benefits accrued may differ substantially from expectations when there is a time lag between when actions are planned and when they are executed. One need look no further than the recent mortgage crisis to see an example of bank over-exposure to certain activities that led to detriments in overall performance. By diversifying the firm's portfolio of activity across multiple action types, the probability that any one particular action having deleterious consequences that impact the firm's overall performance is diminished. Taken together, the above arguments collectively suggest:

> *Hypothesis 5: The greater the complexity of competitive actions taken, the higher the firm's performance over the following year.*

In competitive settings, when a firm pursues a complex set of actions, it is more difficult for competitors to fully imitate or otherwise create a substitute environment to mimic the focal firm's value creation capabilities (Ferrier, 2001; Rivkin, 2000). Increasing repertoire complexity makes wholesale copying of the repertoire prohibitively expensive, and when competing on complex performance landscapes, the cost of imperfect imitation can be large as well (Rivkin, 2001b). Moreover, even if the surface characteristics of the action portfolio can be replicated, the underlying pattern of specific activities that is unobservable to competitors is laden with causal ambiguity (Lippman & Rumelt, 1982). This causes further difficulties in matching the value creating capabilities of the focal firm, with the consequent effect that the incremental added value between the focal firm and the imitating competitor is not competed to zero, as would be expected from the competitive process (Kirzner, 1973). Thus, even when competitive activity is very high, if the firm's competitive repertoire is sufficiently complex to avoid substantive imitation, the value-creating nexus of the firm is not in jeopardy (Lenox, Rockhart, & Lewin, 2006). By contrast, at lower levels of complexity, aggressive competitors are able to replicate the "secret sauce" and drive entrepreneurial rents to zero (Keyhani et al., 2015).

Hypothesis 6: As the number of total actions taken by competitors increases, the relationship between repertoire complexity and performance will strengthen.

While the complexity to performance relationship has received empirical attention in the past, investigations of the relationship between repertoire consistency and performance are scarce. The consistency of competitive repertoires was first studied in detail by Lamberg and colleagues (2009) in an effort to reconcile the findings from the competitive dynamics and strategic change literatures that state firms can and must adapt to their environments (e.g., Child, 1972; Porter, 1980) and the evolutionary theory of the firm, which emphasizes the primacy of routines and technological trajectories (e.g., Nelson & Winter, 1982). They argue that firms need to strike a “balance between being fully consistent with the past on the one hand, and being fully adaptive with environmental change on the other” (Lamberg et al., 2009: 49).

On the one hand, strategic consistency allows for economies of scale and scope to develop through learning economies, knowledge reuse, and investments in specialized structures and tools which stem the increasingly fine division of labor and substitution with fixed inputs (Langlois, 1997). Furthermore, consistency provides time for firms to optimize their informational systems, incentive structures, and associated routines (Nelson & Winter, 1982). On the other hand, these structures and other initial conditions can generate inertia that makes it difficult for the firm to react against adaptive pressures that build over time (Simsek et al., 2015). Overly rigid structures with high levels of interdependence between the components make it difficult for the firm to adapt in times of change without altering large swathes of the organizational system simultaneously (Gersick, 1991) with the attendant hazards of organizational failure (Baum, 1999). In the limit, the firm’s structure is totally rigid because of lock-in effects (Sydow, Schreyogg, & Koch, 2009). Even if structural changes are not currently necessary, firms may be loath or cognitively unable to identify and take advantage of new growth opportunities that do not fit the current business model (Christensen & Overdorf, 2000). A prime example of this phenomenon is Polaroid's inability to take advantage of the emerging digital photography market (Tripsas & Gavetti, 2000).

I conclude that these two forces result in a curvilinear relationship between strategic consistency and performance. At low levels of consistency, none of the benefits of complementarity or learning can be realized and the firm cannot establish consistent goals and culture. While the firm is able to freely adapt to changing environmental circumstances, the firm has not invested or developed the necessary capabilities to generate value in excess of its resource inputs (Brandenburger & Stuart, 1996). On the other hand, at high levels of consistency, overly rigid structures make it difficult for the firm to adapt to emerging problems or new opportunities. While the positive effects of complementarity are constant or perhaps have diminishing returns, the magnitude of the negative implications of rigidity increase as the level of strategic consistency rises – resulting in a curvilinear effect. However, at moderate levels of consistency, a balance is struck between these two extremes, allowing for structures and routines to be developed and honed, while providing residual flexibility that avoids the potential for cognitive (Tripsas & Gavetti, 2000) or organizational lock-in (Sydow, Schreyogg, & Koch, 2009).

> *Hypothesis 7: At low and high levels of repertoire consistency, there will be no significant relationship with performance, while at moderate levels, there will be a positive effect on performance in the following year.*

As argued above, the influence of consistency on financial performance is driven by two effects, the positive influence of complementarity and learning effects, and the negative and increasing risks of mal-adaption caused by the structural rigidities. I claim that competitive pressure does not substantively influence the level of complementarity or learning that a firm is able to exploit, because these are aspects of the firm's own production processes and internal capabilities. By contrast, competitive activity has a very substantial effect on the structure of the factor and product markets where the firm buys and sells its goods and services (Chen, 1996). Very active competitors are either the cause, or are at a minimum are reacting to, changes within these marketplaces.

By contrast, lower competitive activity indicates stability within the industry, resulting in a lower industry "clockspeed". In such industries, the value of strategic flexibility (inconsistency) is diminished. This is likely because the gains to flexibility are outweighed by the cost of maintaining the capabilities that confer these degrees of freedom, while the potential for mal-adaption is relatively low (Nadkarni & Narayanan, 2007). Further, these authors found in fast-clockspeed industries the opposite pattern of results was found, which may indicate the risks of mal-adaptation outweigh the gains from stability in this context. As a result, the likelihood that the firm's current strategic direction is mal-adapted to current circumstances increases as the level of competitive activity rises. Thus, only this detrimental effect of strategic consistency is affected by competitor pressure:

> *Hypothesis 8: As the number of total actions taken by competitors increases, the level of repertoire consistency at which performance reaches a maximum will decrease, and the maximum performance achieved at this optimum point is lower.*

A summary of the hypothesized model is available in Figure 1.

CHAPTER 4 – EMPIRICAL SETTING

Appropriateness of setting

I test my proposed model with a longitudinal panel of commercial 3D printer manufacturers (producers are found within NAICS codes 32351, 33271, 33211, 33331, and 33411). The companies within the sample include all publicly traded firms covered by the industry's leading research company (Wohler's Associates) for the period 1988 through 2015 as well as a number of privately held firms where action, management team, and firm performance information is available. Approximately ten years ago, the market for 3D printers bifurcated into two distinct segments: products targeted for commercial use (which had been sold since the 1980s) and products for consumer use (e.g., MakerBot and similar products). I have limited my focus to the professional / consumer market in order to maintain continuity of focus across time, and to ensure that companies in the sampling frame are in competition with each other (cf., Carroll, 1985). Further, a number of firms were acquired during the period of observation, and these firms are treated as separate entities up until the point of acquisition. When selecting the research setting for conducting this study, four key criteria were considered: access to information on the competitive repertoire, sufficient variability in actions taken by industry participants, identification of a near census of firms to capture life cycle and competitive variations, and a range of managerial backgrounds. Taken together, these conditions provide the necessary variance on the variables of interest.

The 3D printing industry scores well on all of the above criteria. First, in order to have observable variation on the competitive repertoire construct using existing methodologies (i.e., the structured content approach, see Chen & Miller, 2012), I needed access to specialty news outlets such as the Wohler's Report, *Econolyst*, 3Ders, and Additive Manufacturing, in addition to major news distributors such as *The New York Times* and *The Economist.* Information from all of these sources was available through the Factiva service provided by LexisNexis. In total, over 100 different sources were drawn from when constructing the database of activities and the full text of 20,179 articles was at risk for being reviewed for competitive action content. A number of blogs and specialty news outlets that provide insight into new trends and activities by 3D printer manufacturers of all sizes was also included in this data collection effort but the full text of these articles could not be recovered (only the leading paragraph). A subset of these articles were in other languages (17,568 in English, 1,575 in German, and 1,036 in Swedish). Only articles written in English were subject to coding.

Second, and related to the first, there must be sufficient variation in competitive actions undertaken in the industry of interest to ensure that observed complexity is a proxy for the potential complexity that a firm's repertoire can exhibit (Langlois, 1986). Because the industry is dynamic and relatively young at 30 years of age and entering into a period of significant growth, it is a testbed for a number of different alternative business models and the competitive actions that are associated with those models. Firms continue to assess their place within the industry vis-à-vis other players, and continue to determine what competitive moves are best suited to capture customers (D'Aveni, 1994). As studies in the organizational ecology and economics literature demonstrate (e.g., Dowell & Swaminithan, 2006; Klepper, 1997; Klepper & Simons, 2005), the period of time from industry founding until the shakeout is a time of many firm foundings and rapid growth within the competitive space. At the same time, the industry is sufficiently developed by 2015 to allow different competitors to undertake a range of competitive maneuvers, such as entrepreneurial, Ricardian, deterrent, and cooperative actions (Grimm, Lee, & Smith, 2006). Industries earlier within their lifecycle may not yet have the requisite financial or cognitive resources to engage in a wide variety of actions, while older industries may have established institutions and well tested business models and cognitive scripts that impede action variety. A review of the descriptive statistics regarding the competitive repertoires of the firms in the sample indicates that this variety is present. In particular, Figure 3 illustrates increasing trends for the typical number of actions taken, as well as higher average levels of repertoire complexity over time. All coded action types (marketing, pricing, capacity, service, and new product) were present within the sample from 1991 forward, with each action type accounting for at least 800 coded actions (the number of actions within each grouping ranges from 893 to 3288). This provides evidence that actions of all types were undertaken by the firms in the sample, and the high average level of complexity (approximately .70 out of a scale from 0-1) indicates that firms exhibit variety in the actions they perform across time.

Insert Figure 3 about here

Third, since I examine the industry life cycle and competitive conditions, a near-census of firms is required for two reasons. First, a census of firms allows me to identify the trends in founding and closures. Second, having both large and small firms allows me to examine the competitive dynamics not only for the dominant players, but for more peripheral competitors as well. Trends in firm entry, exit, and concentration are shown in Figure 4. As the graphic illustrates, the industry has seen a surplus of entries in comparisons to exits (exits include acquisitions) such that the total tally as of 2015 is 62 firms. However, the number of firms with a market share of greater than 1 percent has largely fluctuated between 6 to 14 firms from 1994 until the present. Further, the concentration of the industry has increased from its nadir in 1994. This indicates that while entrants continue to pour into the industry, the majority of these entrants do not have a material effect on the competitive environment within the industry. A tally of the firms in the industry is available in Exhibit A for every year in the sampling frame (based on records of units sold in the Wohler's Report from 1988 – 2015). Firms within the sample vary in size and available resources to engage in competitive activity. On the one hand, several firms have been publicly traded for several years and have sold tens of thousands of units, while other firms remain private and have only sold approximately 100 units since their entry into the market. Thus, a wide range of capabilities are present within the sample. These firms are also geographically diverse, and are located in the United States, Japan, Germany, Israel, and the UK.

Insert Figure 4 about here

Finally, the industry is old enough and has roots in related industries such that a cadre of veterans can be identified through spin-offs and firm dissolutions, as well as new participants because the underlying technological bases of the industry continue to shift. My initial research into the setting indicated that there were a wide variety of managerial backgrounds represented from printing, metals, and other industries (Wohler's Report, 2013). These initial indications have been borne out through the detailed analysis of the data, which indicates a wide range of backgrounds and in many cases the importation of executives from existing companies to new ventures whether through acquisition or through the founding of new firms. However, while there is an overall trend towards higher levels of focal industry experience within the top management team over time, new additions from unrelated industries such as banking, consumer products, and other areas continue to provide a source of external knowledge and insights as the industry matures. Figure 5 provides a summary of the firm genealogies, and a measure of the relative balance between focal and outside industry experience within the management team.

Insert Figure 5 about here

In addition to the above criteria, the 3D printing industry also has the attractive feature of being partially isolated from substitute products and technologies based on subtractive manufacturing methods. This isolation stems from differences in the economic models for subtractive and additive manufacturing products. While subtractive methods have very low variable costs of production, the fixed cost for dies, tools, and other set-up fees are substantial. By contrast, while the variable costs (in terms of both time and materials) for additive manufacturing are significantly higher, the fixed cost of production are often limited to the 3D printer itself (Anderson, 2012). As a result, companies purchasing 3D printers will self-select into using these types of services only when subtractive methods are not cost-effective. As a consequence, 3D printer manufacturers largely compete with one another, rather than with subtractive methods, at a given level of production. And finally, from a managerial standpoint, the 3D printing industry is poised to impact the fates of many different fields, such as medicine, process manufacturing, and small-scale production. As D'Aveni (2015: 48) notes, "thinking about the unfolding revolution in additive manufacturing, it's hard not to reflect on that great transformative technology, the internet."

Dataset construction

Dataset construction proceeded in three steps: the construction of a sampling frame, the procurement of data from a number of sources, and matching of that data to the sampling frame. The sampling frame commences in 1986 because it is the year of founding for the first firm in the industry, and is two years prior to the first recorded 3D printer sale. Several of the major 3D printer technologies were in existence (e.g., stereolithography was already developed and patented in 1986, see Hull, 1986) but others were not developed until later (e.g., selective laser sintering, see Deckard, 1989). Few firms are in the sampling frame until 1994, which "was a pivotal year for the rapid prototyping (RP) industry -- and it was the most progressive year in its history. More systems were sold in '94 than were sold in '92 and '93 combined. Many user companies purchased second and third systems, and a few companies now have as many as a dozen. Tens of thousands of RP jobs were processed last year -- more than ever before. Service providers also experienced a banner year, with record revenues and growth. After-market products and services began popping up regularly, a sure indication that RP is indeed an industry to watch" (Wohler's Report, 1995: 1). Furthermore, Wohler's Reports, the pre-eminent source of knowledge regarding the industry, was first published in 1993. In summary, the choice of 1986 as the start of the sampling frame is appropriate because it is prior to a number of major developments within the industry, and thus the risk of left-truncation is mitigated. The sample is tracked as of 2015 to maximize the number of observations that are admissible into the sample, and captures an increasingly dynamic period within the industry's development. 2016 data has yet to be released for most firms.

In each of these years, the criterion for inclusion of a firm into the sampling frame for a particular year is the recording of at least one 3D printer sale. Using this criteria, a theoretical maximum of 766 firm-years was obtained, summarized in Appendix A. The implication of this approach is that firms that were founded at an earlier point in time, but had yet to sell a unit, are not included in the analysis until sales commence. Data on the top management team, firm actions, and firm performance were constructed from a variety of sources listed in Table 1. Top management team data was collected at the individual executive level, compiled at the executive-firm-year level and aggregated to the firm year level. For example, an executive with 4 years of prior industry experience in an executive position prior to joining a firm, and 3 years of tenure in the management team would have 7 years of focal industry experience. They would have 8 years of experience in the following year if they remained on the team. Action data was similarly aggregated to a firm-year level using the measures described below, while performance data was naturally at a firm-year level of analysis. Figure 6 provides a graphical illustration of how the panel was constructed.

Insert Figure 6 about here

Data was collected for each aspect of the model and matched to the appropriate firm-year. Unfortunately, a number of observations were incomplete, largely due to lack of available return on asset information for small, private firms and the lack of available information for the entire top management team (the operationalization is provided in the next section). As a consequence, and as shown in Appendix A, while there are 273 firm-year observations of competitive repertoires, 303 firm-years of TMT data, and 221 ROA observations, only 165 observations are shared across all data types (the complete dataset drops further due to the presence of leading and lagged variables and "0"s within the ROA source dataset which indicates that the source does not possess the actual value, resulting in the effective sample sizes ranging from 87 to 163 for the tested models). In spite of these data matching challenges, the dataset is still sufficiently robust to generate sufficient power to detect the moderate effect sizes found in prior investigations, as shown in Appendix B.

CHAPTER 5 – METHODS

Variables and measures

All of the dependent and independent variables of interest are listed in Table 1.

Insert Table 1 about here

Dependent Variable - Competitive Repertoires. I synthesize existing conceptualizations to define the competitive repertoire as the entire range of the actual competitive actions used by a firm during a given year to attract, serve, and keep customers. A repertoire is composed of concrete decisions such as price changes, product line or service alterations, and changes in the scope of operations (Miller & Chen, 1996: 420; Chen & Miller, 2012: 145). To be clear, when discussing competitive actions, I refer not only to externally directed actions such as price changes and new product introductions (cf. Smith et al., 2001), but also major internal initiatives to boost the competitive position of the firm such as capacity increases and the like. Therefore, I adopt the inclusive but generalizable approach of Ferrier and Lyon (2004) in coding the actions taken by firms in my sample.

Consistent with prior researchers (e.g., Chen & Miller, 1994; Connolly et al., 2016; Ferrier & Lyon, 2004), I code firm actions through a structured content analysis of press articles and news reports as compiled by Factiva. All articles flagged as pertaining to the firm of interest were included in the initial search, which totaled 20,179 articles. Using the search terms specified by Ferrier and Lyon (2004), articles were coded into one of five distinct action types: product, marketing, capacity, price, and service related (I dropped the sixth classification, signaling, because it represents an intention to act rather than an action in and of itself). Both market facing as well as internal changes were encoded using this approach. Using the count of each action type within a calendar year, I constructed a repertoire vector of the form R = (r_1, r_2, r_i … r_n), where the r_i are equal to the number of actions of type *i*. These repertoire vectors were generated for 184 firm-years with at least one action (and 273 firm-years in total if years when no actions were performed are included). These repertoire vectors are comprised of 11,993 coded actions. Because these articles were coded through the use of computer-aided text analysis, I conducted a random sample of the coded articles to determine whether my own codings were in agreement with that of the computer (with the codings blinded). Overall agreement across all action types was 86%, with 172 agreements out of 200. Interrater agreement (ICC(2,2) =. 58, CI_{95} = [.44, 68]) is sufficiently high to rely upon the results of the coding (Cicchetti, 1994). The majority of the disagreements related to two issues: the miscoding of stock-price related discussions as pricing actions and the lack of coding for certain new product introductions that did not include the required indicator phrases.

The dependent variables (repertoire complexity and consistency) and relevant control variables (repertoire volume) were calculated from these repertoire vectors. Volume is calculated by summing all actions taken by the firm in a given year. This measure captures the overall level of competitive activity undertaken by the firm in a given year. Complexity is measured using a Shannon entropy index, and captures the relative balance of actions across different action types. As would be expected from an entropy index, complexity provides a measure of the difficulty of guessing what action a firm will take next in a given sequence. Conceptually, complexity captures the firm's ability to engage in a broader range of action types (Connolly et al., 2016). Finally, repertoire consistency captures the stability of actions in comparison to the historical trajectory of firm (Lamberg et al., 2009). Consistency is computed using a normalized displacement vector that incorporates information about the magnitude and direction of the year-to-year change in a firm's competitive repertoire (see Lamberg et al., 2009 for further details). In a fully consistent repertoire, the number of actions may change so long as the relative proportion between each action type remains the same. By contrast, a completely inconsistent repertoire is one where the firm performs none of the actions that it performed the prior year, and instead chooses to perform a completely different set of actions in the current year. The typical levels of each of these repertoire facets in each year is shown in Figure 3.

Dependent Variable - Performance. Consistent with prior work, I use market share to measure performance changes (Ferrier, 2001; Ferrier, Smith, & Grimm, 1999). Market share provides an indication of the relative advantage of one firm over its rivals. Even though my definition of the competitive repertoire includes actions that are not exclusively product market facing, changes in internal structures are often made in order to compete more effectively in product markets. The average market share is 4%, but this figure is skewed with the median market share equal to 1% across the entire observation window. I also use return on assets to measure performance changes (e.g., Derfus et al., 2008; Nadkarni et al., 2015; Young et al., 1996). The results regarding ROA were expected to (and indeed did) not align perfectly with those found for market share. This is because ROA is often a benchmark for performance during later stages of the life cycle once industry growth slows and begins to reverse (which increases the salience of profitability and the need to generate free cash flow above and beyond investment needs). However, companies within the earlier life cycle stages may instead prioritize growth (and capturing a share of the market) rather than maximizing returns to available assets. The average return on assets was -2% for the sample, but exhibited high variability (23%) due in part both to quick growth resulting in major returns to small asset bases and major investments that temporarily reduce profitability.

Independent Variables – Managerial Experience. I code the managerial tenure of the top management team through a manual review of executive biographies, CVs, and other literature such as EDGAR 10-K filings and S-1 prospectuses for companies that recently went public. In line with prior work (e.g., Wiersema & Bantel, 1992), I define the top management team as the top two levels of the organizational structure, starting with the level of CEO and other C-suite members. This conceptualization captures those members of the organization that are tasked with major, important, and unstructured decisions. In practice, this typically means that all members of the organization that have either the terms "Chief" or "Executive VP" in their titles were included as part of the top management team. For companies in Japanese and European contexts, this definition also includes managing directors where "Chief" positions are not used. The average size of the TMT was 2.64, due in part to the small size of the TMT during the early years of venture operation prior to later growth. This is evidenced by the median value of 3, which is higher than the mean – indicating a large proportion of solo-founders during the early stages of these firms is bringing down the average.

I measure the distribution of executive tenure within the top management team by computing both the average and the standard deviation of tenure for all TMT members. When determining how much tenure an individual has within the industry, all years of management experience within the 3D printing industry prior to joining the focal firm are considered. Further, every year on the management team is also another year of industry experience, and thus adds to their existing stock of tenure within the industry. While the amount of experience gained by executives may vary from year to year due to different rates of skill and knowledge acquisition (Reuber & Fischer, 1994; Finkelstein et al., 2009), tenure is a commonly used and valid measure for assessing accrued experience within an industry (e.g., Hambrick, Geletkanycz, & Frederickson, 1993). In supplemental testing, I also directly compute the total amount of focal industry experience possessed by the management team as well as the average amount of experience outside of the focal industry through a manual compilation of each executive's prior experiences generated through a triangulation of executive biographies, regulatory filings, and LinkedIn data. While I have tracked industry experience within 3D printing directly, closely related industries (traditional printing and lasers), and somewhat related industries (manufacturing and high-technology), for these reported analyses I have drawn a bright-line distinction between 3D printing industry experience and all other types. Furthermore, in coding executive experience I only coded prior experience as relevant to the extent it is in a senior managerial capacity (i.e., a position of VP or higher). This means, for example, prior work as a low-level employee in an earlier 3D printing firm would not qualify as executive-level prior focal industry experience.

Moderating variables. Since my moderating hypotheses are monotonic with respect to changes in the life cycle, I assess the moderating effect of the industry life cycle changes using the age of the industry. As noted by Gort & Klepper (1982), the industry life cycle is a time path that summarizes the state of the industry's development. The age of the industry provides a smooth measure of change within the market place and preserves variation in the moderating variable, rather than using a discrete measure. However, I also constructed a discrete life cycle stage variable through a cluster analysis of nine different indicators (firm count, entries, exits, net change, industry concentration, sales, cumulative sales, and sales growth rate), consistent with Agarwal & Gort's (2002) generalized discriminant procedure, but for which I make no assumptions regarding the status of the industry life cycle for any observation. Three distinct clusters emerged which were largely consistent with a partitioning of the sampling frame using sales figures alone. Details of these supplemental analyses are available upon request, and the clustering solution and underlying characteristics used for the analysis are available in Figure 7.

Insert Figure 7 about here

By contrast, while the industry life cycle may smoothly unfold over time, the competitive implications of the life cycle can be more erratic and dependent upon interactions between the competitors within the industry (Porter, 1980). As a consequence, I modeled the competitive pressure exerted by competitors more directly through the construction of a competitive pressure measure. This measure is the sum of all of the actions taken within the industry in a given year less the actions of the focal firm. This measure provides an estimate of the number of actions that are either moves or countermoves of rival firms that inhibit the rent generating potential of the firm's actions (Derfus et al., 2008). In other words, the competitive pressure can be considered as a summary of overall competitor activity in a given year (Young et al., 1996).

Control Variables. In the estimation of the repertoire complexity and consistency models, a number of other traits of the TMT, the firm, and the environment may be relevant for ascertaining the effect of TMT tenure. First, the size of the TMT may influence the overall number and diversity of perspectives within the management team, even for two teams with the same tenure distribution. All else equal, larger TMTs have been shown to act and react less frequently (Hambrick, Cho, & Chen, 1996). Second, the age of the TMT members may influence decision making patterns through the channels of risk propensity, cognitive functioning, team cohesion and other factors (Bantel & Jackson, 1989). Thus, both the average age and age heterogeneity are included as control variables. At the firm level, organizational memory has more routines and procedures to perform a wider variety of actions encoded as the firm ages. Moreover, the extent to which a firm is motivated to act likely depends on their current position, available resources and capabilities, and potential threats. Thus, I control for the prior amount of competitive activity performed by the firm, and market share in the prior period to account for available capabilities and prior performance. To control for potential threats, I include the prior level of competitor activity. Firm size is measured using the logarithm of total assets in a given year, and for some models missing values are mean imputed. Finally, public status may influence the amount of press coverage related to the firm (and thus the relative observability of the repertoire) as well as placing pressures on the firm to perform actions beyond what the team would select if they had full control (Connolly et al., 2016).

When estimating the performance models, a lagged performance variable is included in several specifications to account for the potential for reverse causality between actions and performance (i.e., more actions can be taken because the firm was successful in the past) (Miller & Chen, 1996). For both the market share and ROA models, year of firm founding, firm size, and whether the firm is publicly traded are also controlled for. Moreover, since the number of actions taken may have a unique performance effect, I include a control for action volume. To account for industry-level influences on performance, I also include controls for the age of the industry, current levels of concentration, and the sales volume growth rate for the prior period.

Statistical methods and identification strategy

Since all dependent variables are conceptually continuous (performance, consistency), or are arbitrarily scaled to the unit interval (complexity) all models are estimated using least-squares based panel regression methods and with robust standard errors (Greene, 2012). The current repertoire is used to predict performance in the following year to preserve the causal ordering of actions and consequences. I present the descriptive statistics and correlations in Table 1A.

Insert Table 1A about here

For my primary analyses, I estimate the performance and repertoire consistency models separately in order to appropriately select control variables that are pertinent to each construct of interest –and to simplify the methods required to test the hypotheses under consideration. [3] A primary concern in testing models of firm behavior when decision makers anticipate performance consequences is the presence of endogeneity, resulting in inconsistent estimates.

As it relates to the identification of causal effects in my repertoire models, I primarily rely upon the structure of the panel dataset and my research design, using prior year controls in order to isolate the incremental effect of the variables of interest. In particular, I have included a number of explicit controls for prior performance and capabilities in my repertoire models. Further, the volume of actions taken in prior years may influence the available choices in the current year is included as a control to capture the tendency to reuse existing routines. For the assessment of managerial experience on repertoire characteristics, I have not found any convincing instruments that would allow me to perform an instrumental variables analysis as a further safeguard against endogeneity. To be specific, my prior endogeneity concern in the case of the repertoire models instance is one of reverse causality – that in order to support a particularly complex or consistent repertoire, executives are selected on the basis of having that relevant experience. There is some conceptual justification as to why this reverse causality bias may ultimately be minor. Specifically, while it is possible that particular functional experiences correlate with which industries an executive has worked in, it is unlikely that industry

[3] An alternative estimation strategy for the repertoire model is estimating repertoire composition directly. However, this approach will likely a high residual standard error and thus low power to detect changes in repertoire characteristics.

background will be the most salient choice variable for executive selection (self- or otherwise), nor are firms using maximizing or consciously targeting a particular level of complexity or consistency and thus this becomes a primary justification for selection (although the example of Apple and LVMH in the hypotheses section does indicate that the risk is present). To the extent that this potential bias cannot be controlled for, the results should be interpreted accordingly. However, as it related to individuals self-selecting into management teams on the basis of expected future performance, to the extent that this selection is driven by prior success or level of competitive activity, these explanations are partially accounted for by the control variables.

With respect to the potential for endogeneity between repertoire characteristics and subsequent performance, a similar issue of reverse causality may be present, as is the potential for unobserved firm differences that simultaneously affect repertoire formation while also influencing performance (e.g., dynamic capabilities). In an attempt to address the reverse causality issue, as part of my main analyses I also estimate a dynamic panel model with the previous year's performance included to account for reciprocal effects of previous performance on repertoire composition. To account for the potential time-invariant omitted variables such as underlying capabilities or initial resource endowments, I also estimate fixed effects and 3SLS models (using the complexity and consistency models as the first stage) as robustness checks.

Beyond these issues, I consider potential selection effects due to the potentially non-random nature of media coverage, and the implications thereof for estimating the performance equations. In order to account for heteroscedasticity, robust standard errors are employed. Similar results were obtained using yearly cluster-robust standard errors. Interaction terms were mean centered in order to facilitate interpretation and reduce collinearity, and the VIFs for all independent variables were below the recommended value of 10 (Kennedy, 2003).

CHAPTER 6 – RESULTS

Competitive repertoire models

Testing the repertoire complexity model begins with the inclusion of the control variable set. Table 2 provides a summary of the results discussed. In Model 1a, TMT size, prior market share, and status as a public firm were associated with repertoire consistency, with industry age having a positive but insignificant effect on consistency. Model 1b introduces the influence of both average TMT industry tenure and tenure heterogeneity as measured by the standard deviation of TMT industry tenure. Both of these variables have a significant influence on repertoire consistency, with the coefficient of the average tenure variable providing support for Hypothesis 1 ($b = .029$, $se = .006$, $p < .001$). The incremental effect of these additional variables is significant ($\Delta R^2 = .12$, p <. 001). In Model 1c, the moderating effect of the life cycle, as measured by industry age, is introduced. To facilitate interpretation, the time variable is centered near the midpoint of the observation window (i.e., 2007). While the main effect of average TMT tenure is significant and the pattern of interaction is consistent with the predicted effect, there is insufficient evidence to support Hypothesis 3 ($b = .000$, $se = .001$, $p > .10$).

Insert Table 2 about here

Turning to the examination of repertoire complexity, I begin with the control variable model. As shown in Model 2a, prior market share is predictive of repertoire complexity, with industry age having a marginally significant effect. Introducing the main effects of TMT tenure distributions in Model 2b, average TMT industry tenure is associated with more complex repertoires. Furthermore, TMTs with more heterogeneous industry tenures have more complex repertoires, in line with Hypothesis 2 ($b = .052$, $se = .016$, $p < .01$). As Model 2c illustrates, as the industry progresses through its life cycle, tenure heterogeneity appears to result in less complex competitive repertoires, rather than repertoires that are more complex. This pattern of results contrasts to the prediction of Hypothesis 4 – a result that I will examine later in this section ($b = -.005$, $se = .002$, $p < .05$). This interaction effect implies that while complexity tends to increase in the later stages of the industry life cycle, the relative importance of tenure heterogeneity in achieving this complexity is lessened.

Firm performance models

Testing the performance model commences with an analysis of the pooled panel market share model, with Table 3A summarizing the results. In Model 3a, the year of founding is negatively relatively related to market share, as is public status. Firm size is positively related to market share. Model 3b introduces the influence of complexity on market share, which is not significant, failing to support Hypothesis 5 ($b = .043$, $se = .037$, $p > .10$). Model 3c introduces the effect of consistency, for which a negative curvilinear hypothesis was advanced. The data are inconsistent with Hypothesis 7, since the coefficient of the squared consistency term is positive but insignificant, while the linear term is positive and significant. The overall test of the significance of the linear and quadratic terms indicates that they marginally increase the fit of the model ($\Delta R^2 = .04$, $p < .10$). Turning to the moderating effects, Model 3d considers the moderating influence of competitive pressure on the complexity to performance relationship. The coefficient is significant, in support of Hypothesis 6 ($b = 1.4E\text{-}4$, $se = 5.0E\text{-}5$, $p < .01$). Finally, Models 3e and 3f introduce the moderating effect of competitor action volume on the repertoire consistency to market share relationship. There is no significant interaction for the first order term. By contrast, the second order interaction term is negative, but it is insignificant and the overall pattern is different than the predicted effect ($b = -1.9E\text{-}4$, $se = 1.0E\text{-}4$, $p < .10$).

Insert Table 3A about here

Turning to the dynamic panel model, which accounts for the prior level of market share (and essentially is a test of whether repertoire characteristics predict changes in market share), we find that industry age is positively related to share changes, concentration is negatively related to share changes, and the prior year's market share is highly predictive of market share in the following year (i.e., t-1 to t+1) (see model 3g). Model 3h introduces the influence of complexity on market share, which has only a marginal effect ($b = .197$, $se = .108$, $p < .10$). Model 3i introduces the effect of consistency, for which a negative curvilinear hypothesis was advanced. The data are inconsistent with Hypothesis 7, since although the coefficient of the squared consistency term is positive, and nearly significant ($b = .108$, $se = .060$, $p < .10$).

Concluding with the tests of the hypothesized moderating effects, Model 3j considers the moderating influence of competitive pressure on the complexity to performance relationship. The coefficient is not significant nor does the introduction of the moderation increase the predictive power of the model, failing to support Hypothesis 6 ($b = 1.4E\text{-}5$, $se = 3.3E\text{-}5$, $p > .10$). Finally, Models 3e and 3f introduce the moderating effect of competitor action volume on the repertoire consistency to market share relationship. There is no significant interaction for the first order term. The second order interaction term is consistent with the arguments for Hypothesis 8, with the coefficient being negative and significant ($b = .001$, $se = 6.0E\text{-}4$, $p < .01$). This indicates that competitive pressure does appear to induce a dampening effect on performance that increases at higher levels of consistency, but the overall pattern of the interaction differs from what was expected, resulting in a lack of support for H6.

Insert Table 3B about here

Turning to the pooled panel ROA model (Table 3C), Model 3m indicates that the aggregate level of firm actions in the current year is negatively related to subsequent ROA. Industry age is predictive of ROA. Publicly traded firms are associated with a lower level of ROA, which becomes significant in more saturated specifications. Model 3n introduces the influence of complexity on ROA, which has a positive but insignificant effect (b = .197, se = .108, $p < .10$). However, the overall increase in the model R^2 is significant, resulting in partial support of Hypothesis 5. Model 3o introduces the effect of consistency, for which a negative curvilinear hypothesis was advanced. The data are inconsistent with Hypothesis 7, because while the coefficient of the squared consistency term is negative, it is insignificant. By contrast, the linear term is positive and significant (b = .308, se = .114). The overall test of the significance of the linear and quadratic terms indicates that they increase the fit of the model ($\Delta R^2 = .06$, $p <. 05$).

Concluding with the tests of the hypothesized moderating effects, Model 3p considers the moderating influence of competitive pressure on the complexity to performance relationship. While the direction of the interaction term is in line with the predicted effects, the coefficient is not significant nor does predictive power of the model increase, failing to support Hypothesis 6 (b = 1.1E-4, se = 1.6E-4, $p > .10$). Finally, Models 4e and 4f introduce the moderating effect of competitive pressure. There is no significant interaction for the second order term, and the effect is marginal (b = -.001, se = 3.0E-4, $p < .10$). A similar set of results and coefficients are obtained for the dynamic panel model, with the exception that the marginal effect for Hypothesis 5 is no longer present.

Insert Tables 3C and 3D about here

Alternative specifications and further analyses

The preceding models examining the relationship between the competitive repertoire and return on assets only considered cases where at least one action was performed in a given year. However, there are a number of firm-year observations where actions take place in the year before or after, but no actions are observed in that year. In order to increase statistical power, I include these additional cases, increasing the number of observations from 91 to 139. Including these observations is justified since the lack of observed actions does not necessarily constitute the lack of a competitive repertoire, but rather an extended period in which the firm was observed but no actions were undertaken. The results for this alternative specification are provided in Tables 4A and 4B.

Insert Table 4A and 4B about here

As Table 4A indicates, complexity is significantly associated with ROA, providing support for Hypothesis 5 (b = .182, se = .067, $p < .01$). Hypothesis 7 remains unsupported due to a positive and significant linear term (b = .240, se = .093, $p < .05$) but a negative but insignificant quadratic term (b = -.212, se = .242, $p > .10$). Hypothesis 6 now has marginal, but insignificant, levels of support (b = 1.4E-4, se = 7.8E-5, $p < .10$), with only with a marginal increase in the regression R^2. The evidence for Hypothesis 8 is similar to the results already presented (b = 5.1E-4, se = 2.7E=-4, $p < .10$). While neither of these effects are significant at the $p < .05$ level, it is beneficial to show the pattern of interaction of both repertoire characteristics for illustrative purposes. Figure 8 provides a graphical illustration of these interactions, but the reader is cautioned in interpreting them.

Insert Figure 8 about here

With respect to the competitive repertoire composition models, the proposed model was tested using team-wide compositional measures of experience such as the average and the standard deviation of industry tenure. However, the logic of the hypotheses is also consistent with the direct use of overall experience measures rather than group summary statistics. In the alternative specification provided in Table 5, I replace the average tenure variable with a total focal industry experience measure to capture the complete feedstock of relevant insights rather than their distribution across team members. In concert, instead of approximating the presence of outside industry experience through the use of a heterogeneity measure, I explicitly measure the level of outside experience held by the team members. Using these substitutions, I find support for an interaction between average tenure and industry age in predicting repertoire consistency, supporting Hypothesis 3 ($b = -.002$, $se = .000$, $p < .001$). I also continue to find the opposite of the expected effect for Hypothesis 4 ($b = -.001$, $se = .001$, $p = .05$) when substituting outside experience for tenure heterogeneity.

Insert Table 5 about here

In order to better understand the relative importance of focal experience relative to experiences from other industries for repertoire complexity and consistency, I construct a balance variable that takes the difference between the total amount of focal industry experience within the team and the typical amount of outside industry experience. This difference is used because while each year of focal industry experience contributes to the "know-how" and "know-who" of the team, prior experiences garnered in other settings serve primarily as a counterweight for each individual to prevent them from over-relying on specific industry recipes and formulae. The results of this analysis are presented graphically in Figure 9. Specifically, as the industry evolves, the relative balance between inside and outside experience becomes less important over time, in contrast to the logic of Hypothesis 4. Indeed, there appears to be a convergence to an "equilibrium" level of complexity that occurs whether teams are skewed towards either type of experience. This may provide a partial explanation for the unexpected result for Hypothesis 4: while in early life cycle stages the presence of heterogeneity indicates at least someone with prior related experience (and a major boost to the level of complexity) in later stages the presence of variation does not have the same effect. Similarly, the relative balance between inside and outside industry experience becomes less pivotal in explaining variations in repertoire consistency. Furthermore, the more the team's experience is weighted towards the focal industry, the faster this adjustment, consistent with the logic of Hypothesis 3.

Insert Figure 9 about here

Robustness tests

To address potential omitted variable bias in the performance analyses, I use a series of fixed effects models to control for time-invariant unobserved firm differences for both the market share as well as the performance model as reported in Models 6a to 6f of Table 6. When accounting for firm fixed effects, changes within the level of complexity within a particular firm are not associated with significant changes in return on assets. By contrast, after controlling for unobserved firm differences, the predicted form of the consistency to ROA relationship becomes very clear, providing support for Hypothesis 7. In Models 6d to 6f, I examine fixed effects models for market share, and find no support for either Hypothesis 5 or 7. Interestingly, over 84% of the variation is explained by the base model (in comparison to 43% in Model 3a), indicating that between firm variation accounts for a large fraction of the overall variability. Since my hypotheses were generated based on a hypothetical comparison across firms, the pooled panel and dynamic analyses were better suited as the primary test of these effects.

Insert Table 6 about here

Second, I wanted to investigate a significant concern, namely that the observability of firm actions is likely non-random. By this I mean that strategic, major, quantum initiatives are more likely to be reported. Also, firms that are larger in size are more likely to have the press capabilities and media coverage to publicize their activity. I used a tobit-2 selection model (Heckman, 1979) to determine whether my market share models are systematically biased by underreporting of firm actions (I cannot do the same for my ROA models because I do not have sufficient instances where ROA is reported but actions are not to obtain reliable estimates). For these analyses, I use total media mentions as an additional exclusion condition since coverage per se should not result in higher financial returns. While the inverse Mills ratio was significant or nearly significant for the models tested, the results for the coefficients of interest were not significantly different than the results reported in the next section (the details of these analyses are available upon request). I also performed a supplemental analysis that directly includes total media mentions to an additional control in a further attempt to isolate the effect of non-random reporting of firm activities. As discussed above, this could be the result of active PR divisions or a preference for or bias against a particular organization held by media outlets. While this variable was significantly related to ROA and market share, no significant differences were found for the coefficients of interest when including this additional control.

Finally, the model proposed is a system of equations. While my proposed approach was to consider each equation separately, I also estimate the overall model using the technique of three stage least squares (3SLS) in order to improve estimation efficiency, account for cross-model correlations, and account for the fact that complexity and consistency are present as both a predictor and a predicted variable (Zellner, 1962). The model is identified through all variables in the first stage (the models that predict repertoire complexity and consistency) being exogenous, while complexity, consistency, and their interaction terms are endogenous to the system. For all models, a separate analysis of the 2SLS estimates indicates that the instruments are strong (see footnotes to tables 7A and 7B). The abridged results of this analysis (I show only the fully saturated models) are reported in Table 7A (where the complexity interaction is tested) and Table 7B (where the consistency interaction is tested), respectively. These models are largely consistent with the results presented up until this point, with Hypotheses 1 and 3 supported. However, after accounting for cross-equation correlations, there is no significant main effect for heterogeneity on complexity in the early stages of the industry life cycle – in contrast to Hypothesis 2. There is marginal evidence for Hypothesis 4 in Model 7d, but not 7h, with this loss in significance likely due to the significant reduction in sample size in comparison to the model that was independently estimated.

In reference to Hypotheses 5 and 6, the individual test of the coefficients is made difficult due to the loss of efficiency by using the first stage projection of their predicted values. However, based on a joint test of these coefficients through a likelihood ratio test, the complexity terms and its interaction with competitive pressure are found to be significant in the case of ROA, but not for market share. For ROA, the pattern is consistent with prior findings. The joint hypotheses 7 and 8 are significant for the both the market share and the ROA model. In the case of ROA, this provides some level of support for a moderated inverted-U relationship, whereas the market share results are more complex as previously discussed.

Insert Tables 7A and 7B about here

CHAPTER 7 – DISCUSSION AND CONCLUSIONS

We know from prior work that both environmental forces and managerial backgrounds influence firm decision making, and we have accumulated evidence to suggest that both forces can influence the competitive repertoires that stem from these decisions. However, until now we did not have direct empirical evidence regarding the influence of the industry life cycle on competitive repertoires, nor did we have any information about how the life cycle shapes (or fails to shape) the influence of managerial experience. Further, while prior research has generated correlations between industry tenure, tenure heterogeneity, and competitive repertoires (see Appendix B for examples), a concerted investigation into the joint effect of focal and outside industry tenure on competitive actions had yet to be performed. Finally, existing research assumes that the primary mechanism by which repertoires influence performance outcomes was through its ability to stymie competition. To address these concerns and limitations, I developed a novel model of the influence of TMT tenure on competitive repertoires. This model also recognized the conditioning effect of the industry life cycle – as manifested by industry age and the level of competitive activity respectively – in shaping both the form and outcomes of competitive repertoires.

Summary of findings

Across a wide variety of model specifications, there was broad support for the assertion that TMT prior industry experience increases the level of consistency in firm competitive repertoires. This represents a large-sample statistical test of the arguments set forth by Lamberg and colleagues (2009). Building from this, I argued that this relationship would weaken over time as the industry developed a more robust set of strategic alternatives and competitive pressures forced firms to modify the scope of actions undertaken. While my initial test did not find evidence of this effect, subsequent examinations using the 3SLS approach and total industry experience found support for this effect. Turning to the influence of tenure heterogeneity and outside experiences on the complexity of the competitive repertoire, a number of significant but un-hypothesized effects were found. I argued that the relationship between tenure heterogeneity and performance would be weak in earlier stages and then strengthen over time as competitive pressures mounted. However, the data strongly suggest (using both a direct measure of outside experience and a measure of tenure heterogeneity) that while outside experiences are associated with more complex repertoires in early life cycle stages, this relationship weakens over time. Digging deeper into this effect, I examined the relative balance between inside and outside industry experience (Figure 9) and uncovered that all firms seemed to be converging to an equilibrium level of complexity regardless of their experience distribution. Put a different way, the data suggests that while in earlier life cycle stages outside experience is necessary to develop a sufficiently complex repertoire, in later stages all firms can develop the necessary capabilities and do not need to rely upon the background of the managers to achieve this end. Furthermore, even if managers could further enhance the complexity of observed repertoires, there appears to be a "pull" towards an equilibrium level of complexity.

As it relates to my hypotheses regarding the effect of the competitive repertoires on firm performance, several specifications indicate that there is a positive main effect between repertoire complexity and firm performance as measured by both market share and return on assets. However, this effect was not robust after accounting for unobserved firm fixed effects, which may indicate that some other latent quality of the firms may be the underlying driver of this significant effect. Furthermore, there is some, but inconclusive, evidence for both market share and return on assets to suggest that repertoire complexity takes on greater importance in increasingly competitive environments (in particular, these results were not robust to controlling for prior levels of the dependent variable in either case). Note that I cannot test my moderating relationships in a fixed effects setting due to the construction of the moderating variable – the fixed effects transformation results in a lack of identification (this is because the mean differences between each firm's number of competitive actions is averaged out).

By contrast, the predictions regarding the curvilinear relationship at average levels of competitive pressure between repertoire consistency and performance were largely unsupported. In fact, in the case of market share there is some evidence to suggest that the relationship is U-shaped, rather than the inverted U-shaped relationship hypothesized. This may be due to the fact that market share is likely maximized using a subset of the overall space of actions (i.e., a focus on price and marketing actions), and thus firms that consistently focus on these activities will gain higher market shares. However, one interesting result is the very strong support for the inverted-U relationship argued for in Hypothesis 6 in the firm fixed-effects model. This result indicates that, holding unobserved firm traits constant, variations in repertoire consistency traces a very distinct curvilinear relationship. This provides an indication that for an individual firm, there may be an optimal level of repertoire consistency, but that this optimum point varies across firms resulting in the lack of support in the models that pool across firms. There are a number of models where there is "marginal" evidence (i.e., insufficient to conclude significance but suggestive) that the second order effect of consistency – which I claim relates to mal-adaption - is increasingly negative as competition increases, and this evidence is consistent across multiple specifications. Table 8 provides a summary of the evidence for each of the tested hypotheses.

Insert Table 8 about here

Theoretical and empirical implications

The results above are consistent with prior work that shows repertoire complexity is influenced by managerial knowledge, and that it has a significant influence on firm performance (e.g., Ferrier, 2001; Ferrier & Lyon, 2004). Moreover, as Appendix B indicates, the observed correlations are generally in line with the correlations found in previous studies. However, the results presented above add to our understanding in three ways. First, while not hypothesized, the results indicate that average industry tenure has an influence on repertoire complexity – which indicates that grounded insights specific to the industry may be important to engage in a broader set of firm activities. Second, while heterogeneity in industry tenure in the earlier phases of the life cycle facilitate the performance of more diverse repertoires, in later life cycle stages high repertoire complexity is achieved across varying levels of heterogeneity. While it may be the case that further complexity is unnecessary, an alternative explanation could be that higher levels of tenure heterogeneity induce process losses from differences in worldviews within the management team. This could result in making decisions only when all parties can agree, reducing the variety of actions undertaken by the team (similar to the findings of Hambrick, Cho, & Chen, 1996). However, such an explanation would not also account for the finding that the overall level of outside experience has a similar effect, nor that the level of complexity in later stages in relatively high in comparison to earlier stages.

Second, this work is the first large-scale quantitative test of the repertoire consistency construct. The results indicate that repertoire consistency is predicted by both the average tenure of the TMT as well as its heterogeneity, and that it is correlated with performance outcomes (in line with to the earlier findings of Lamberg and colleagues). Moreover, the performance analyses provide evidence that the consistency construct has predictive power as it relates to market share and return on assets. The presence of significant findings (although not consistently of the hypothesized functional form) indicates that the repertoire consistency construct can be applied in a different industry and that the construct has predictive validity in a larger setting, as well as a different stage in the industry life cycle. However, variation in the repertoire consistency construct has significant overlap with repertoire complexity, and it may be necessary to perform analyses of discriminant validity using multiple facets to uniquely identify the domain of the construct. What appears to be the case is that the values of consistency and complexity both depend upon the number of free action type parameters – and with a greater number of potential action types at play, the greater the range that both constructs can span.

The findings regarding the effect of consistency on market share were the opposite of the expected pattern of findings. Further investigation into this relationship is required to explain the divergence between the pattern of results for these two performance variables. However, the most likely explanation is the market share does not capture all of the hypothesized aspects of repertoire consistency on performance (Venkatraman & Ramanujam, 1986). Specifically, the performance gains from a high level of consistency could be caused by a relentless focus on marketing and pricing actions, which achieve the goal of growth, but may not be optimal from the standpoint of profitability. Further tests with alternative variables such as Tobin's Q or an intermediate step such as gross profit margins for publicly traded firms may provide further insight into this divergence in the pattern of results.

The inconsistent set of findings regarding the moderating effect of competitive pressure were surprising. Much of the argumentation provided within the competitive dynamics literature regarding the mechanisms by which repertoire characteristics drive performance hinge upon the ability of the repertoire to mitigate the effects of competitive pressure (e.g., Basdeo et al., 2006).

However, in neither the case of repertoire complexity nor the case of repertoire consistency was the moderating influence on competitive pressure persistent or robust. One possible explanation for this is that the market is growing at a rate that allows competitors to take actions with relative independence. Or in other words, the spillover effects of competitive actions during the observed phase of the life cycle are still too small to be significant. A comparative analysis of an industry that has progressed through later stages of the life cycle could be instructive to determine at what point these competitive interactions begin to have a significant effect (Baum, 1999). This could represent a boundary condition in competitive dynamics research, where the regimes of the performance generating mechanisms of competitive repertoires begin to shift from value creation (in earlier life cycle stages) to value capture (in later life cycle stages).

Future testing

These results provide a number of future research directions that follow-on studies using this or similar datasets can tackle in greater detail. First, there is evidence to suggest that firms increasingly cluster around a stable level of complexity as the industry evolves. This may indicate that firms have searched the landscape of possible levels of complexity and arrived at an optimal value. One implication of this is that there could be a curvilinear relationship between the level of complexity and firm performance. This implication could be tested using the existing dataset, and sufficient variation would be present within the panel to undertake this investigation.

Second, the results suggest that managerial background variables have a substantive effect on the pattern of firm activity, but that their influence wanes over time. However, what has yet to be investigated is what specific action types these different experience distributions facilitate or hinder, and how firms are able to develop more complex responses in the absence of managerial backgrounds. One can ask whether vicarious learning is taking place, or whether the type of outside experience is varying over time. For instance, could it be that in earlier stages outside experience was from closely related domains (and thus similar to focal industry experience) whereas in later stages more distal domains are being tapped? Again, finer-grained data regarding the specific relevance of prior managerial backgrounds exists and could be used to model how the overall experience distribution evolves over time.

Third, there are a number of alternative means of capturing the pattern of firm activity over time, such as changes in the pattern of firm investments which can be considered an indicator of strategic change (Wowak, Mannor, Arrfelt, & McNamara, 2016). Future work could combine the approaches of assessing actions via a structured content approach and an alternative measure of strategic change in order to assess the internal consistency and validity not only of the measures, but of the patterns of firm action over time. In other words, are the firm's forward looking investments consistent or inconsistent with the actual actions that they are taking, or are they "building castles upon sand"? In a similar vein, while I conceptualized changes in the competitive environment as the level of actions taken by competitors and the life cycle of the industry as years from founding, conceptually and empirically these measures have a great deal of overlap, and future research can focus on these commonalities and distinctions to determine under which conditions either measure is conceptually and empirically appropriate. In the case of this particular study, the use of competitive pressure allowed for the possibility that strong competitors would experience changes in industry status differently from less active rivals. This may not be as relevant in other contexts. Alternative measures may also exist, such as the overall stock of industry knowledge, which could provide a more direct test of some of the mechanisms discussed in hypotheses 1 – 4.

Finally, through additional data collection (likely involving data on additional industries) it may be possible to explicitly separate the beneficial and harmful aspects of competition in line with work in population ecology (Hannan & Freeman, 1977). There are a number of interesting zero-order correlations between competitive conditions and performance that can be explored in more detail. In particular, there is a positive relationship between competitive pressure and return on assets. While this effect becomes negative once other control variables are entered into the model, it does suggest that competitive activity can be associated with positive returns to the extent that it illustrates a vibrant and growing market. If data is available to compare industries that have similar growth in competitors but vary in the level of competitive actions undertaken, it may be possible to separate the symbiotic aspects of competition from the detrimental "head-on" version.

Limitations

There are a number of limitations to the study that bound the conclusions that can be drawn from this data. First, despite tapping a number of databases and alternative sources of information, the overall sample remains relatively small and thus the power to detect small effects remains relatively low. Fortunately, many of the firms in the sample are still in operation and have not been subject to acquisition, which means that several more observations will be available in the near future. Moreover, while the overall number of firm-year observations is relatively low, both public and private firms, US and international, acquired and free-standing, de novo and de alio firms are within the dataset which mitigates the risk of age, size, and governance related biases. It is important to note that while I was not able to collect managerial and action data for all firms within the industry space, there was significant variability in outcomes (both in terms of performance and survival) among these companies which ameliorates to some degree the risk of selection bias. That said, there remains the risk that were complete data on these very small firms available, the results could differ.

Second, my investigations to date were not able to uncover a sufficiently compelling set of instrumental variables to induce exogenous variation in managerial backgrounds. However, I was able to utilize the first stage predictions of complexity and consistency (with particular emphasis on the interaction between tenure distribution and the life cycle) as a way to induce exogenous variation in the competitive repertoire. Beyond this instrumental variables approach, the fixed effect estimations provide some indication of how robust these effects are to unobserved firm differences (in the case of consistency, the pattern becomes clearer, and in the case of complexity, it provides some evidence to suggest that unobserved variables may be driving both complexity and performance). Further, the Tobit models indicate that the results are not significantly biased by non-random reporting of actions. A review of the data indicates a relatively steep decline in average activity levels and the complexity of firm repertoires immediately in the wake of the financial crisis of 2008 – 2009. This may indicate a potential exogenous shock that induces TMT retirements and / or repertoire shifts in the face of new constraints on firm operations, which can be used for future analyses in this setting.

Third, while I followed established practice in performing the structured content analysis of firm actions, my independent validation of these actions did not result in unanimous agreement. Additional work may need to be done in order to increase the reliability of the coding process – perhaps through the use of multiple dictionary and semantic methods. In addition, while the five action types discussed in Ferrier and Lyon (2004) provide a generalizable and tractable approach for action coding, alternative schemes with greater detail exist such as Nokelainen's (2008) typology or Offstein and Gynawali's (2005) taxonomy. It may be useful to re-perform these analyses with a more fine-grained taxonomy of action to examine repertoire complexity and consistency in more fine grained detail (i.e., both can be measured with greater precision as the number of action types increases). Furthermore, a comparative test between the two approaches may provide a bridge between earlier studies relying on coarse-grained measures in comparison to the fine-grained approach in more recent studies (e.g., Connelly et al., 2016).

Fourth, while my study has attempted to parse out and examine the joint distribution of within and outside industry experience, and explicitly controls for age effects, there are a number of alternative experiences that TMT members accrue over their careers that may result in similar predictions. For example, functional background or educational diversity could be competing explanations for the predicted effects, and would need to be accounted for as alternative explanations (e.g., Hambrick, Cho, & Chen, 1996). Moreover, it could be that there is a more overarching construct such as CEO variety (Crossland, Zyung, Hiller & Hambrick, 2014) which may more parsimoniously explain the distinctions made within this manuscript while also capturing variations in these other, related types of experience.

Conclusions

In summation, this study takes a first step towards understanding the rich and multifaceted interface between management experiences and the environment of decision in which they operate. The competitive repertoire provides a window into how decision making processes unfold within the firm through the observation of an artifact of decisions made in the past. As with many studies, more questions are raised by these results than answered, but it provides a first step towards unpacking the causes and performance consequences of competitive repertoires and the pattern of decisions they represent.

TABLES AND FIGURES

FIGURE 1
Conceptual Model

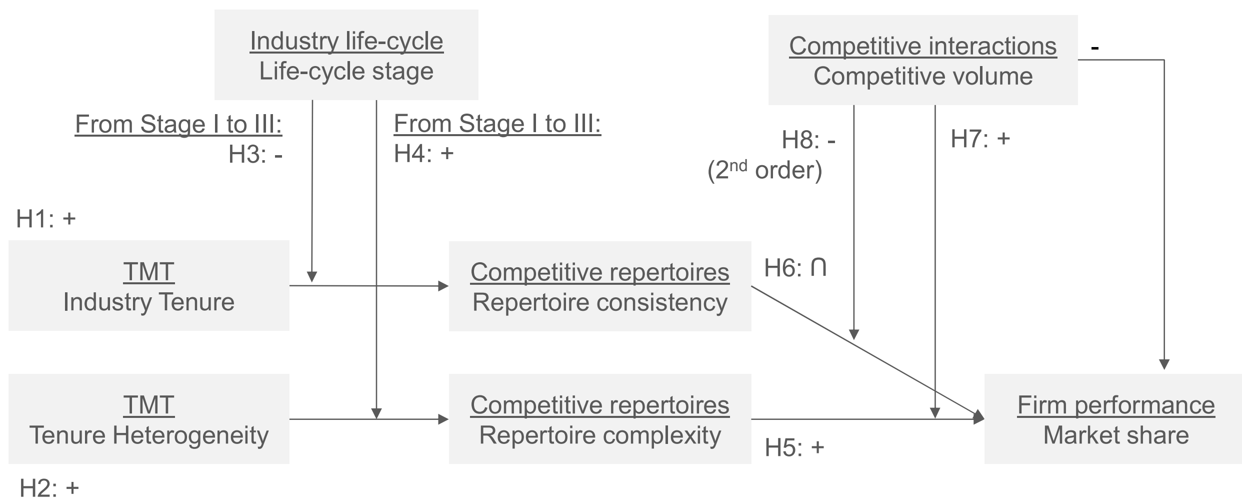
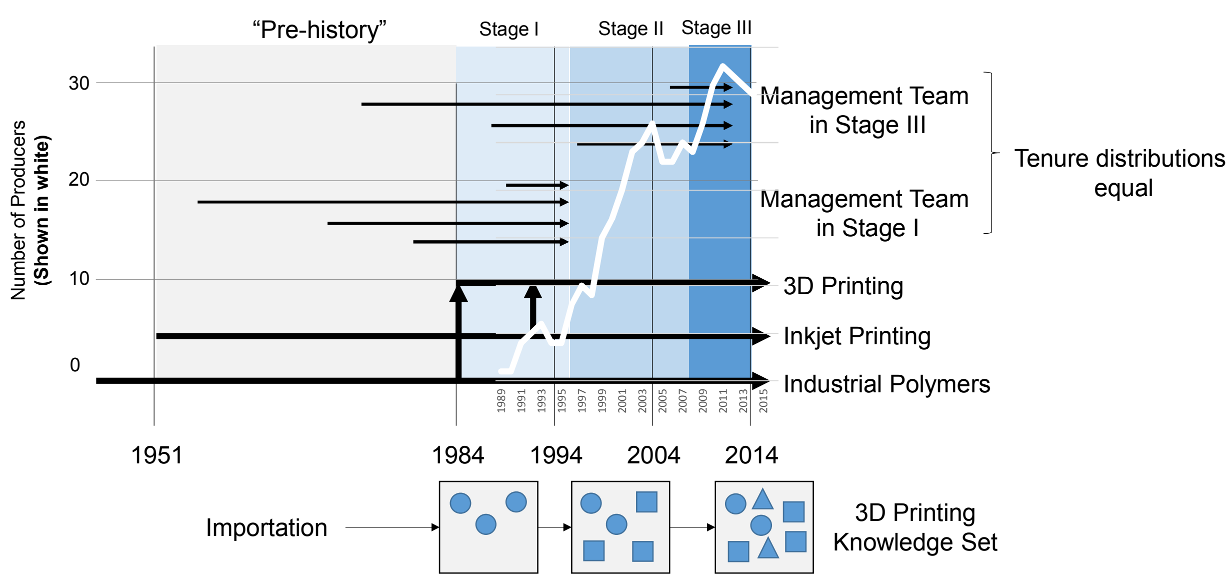


FIGURE 2
Prototypical Timelines of Firm and Industry Experience[4]



[4] Producers shown are those companies with greater than .1% market share at the time of measurement.

FIGURE 3
Repertoire Trends over Time

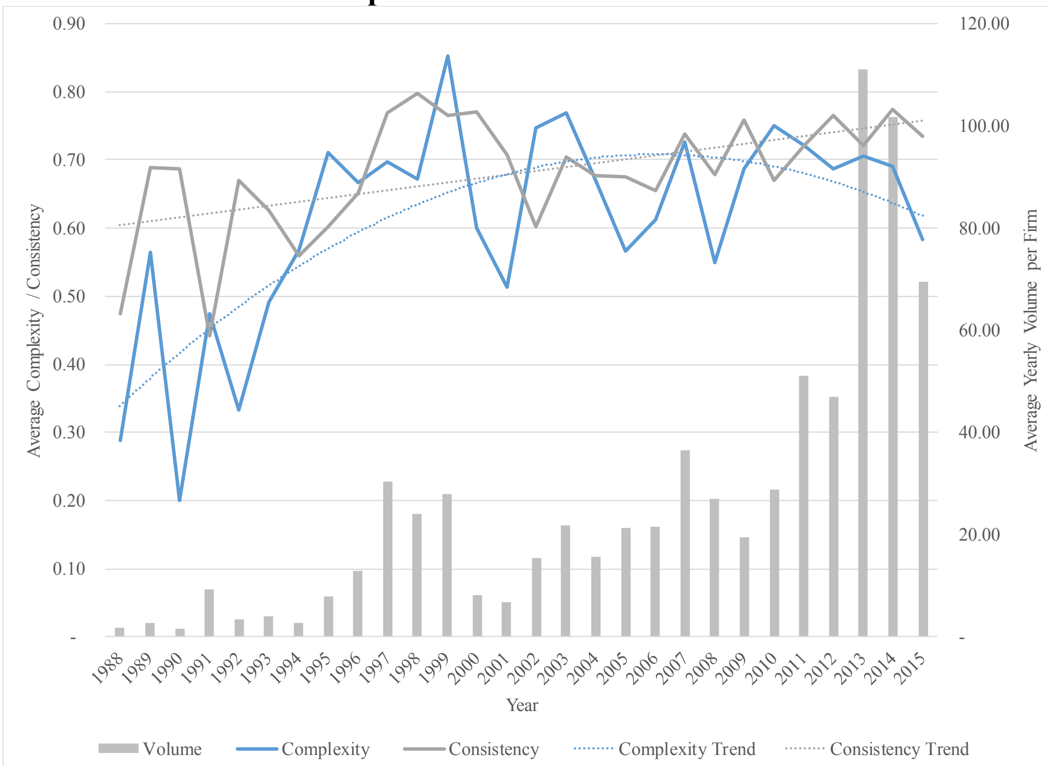


FIGURE 4
Firm Entry, Exit, and Concentration Patterns

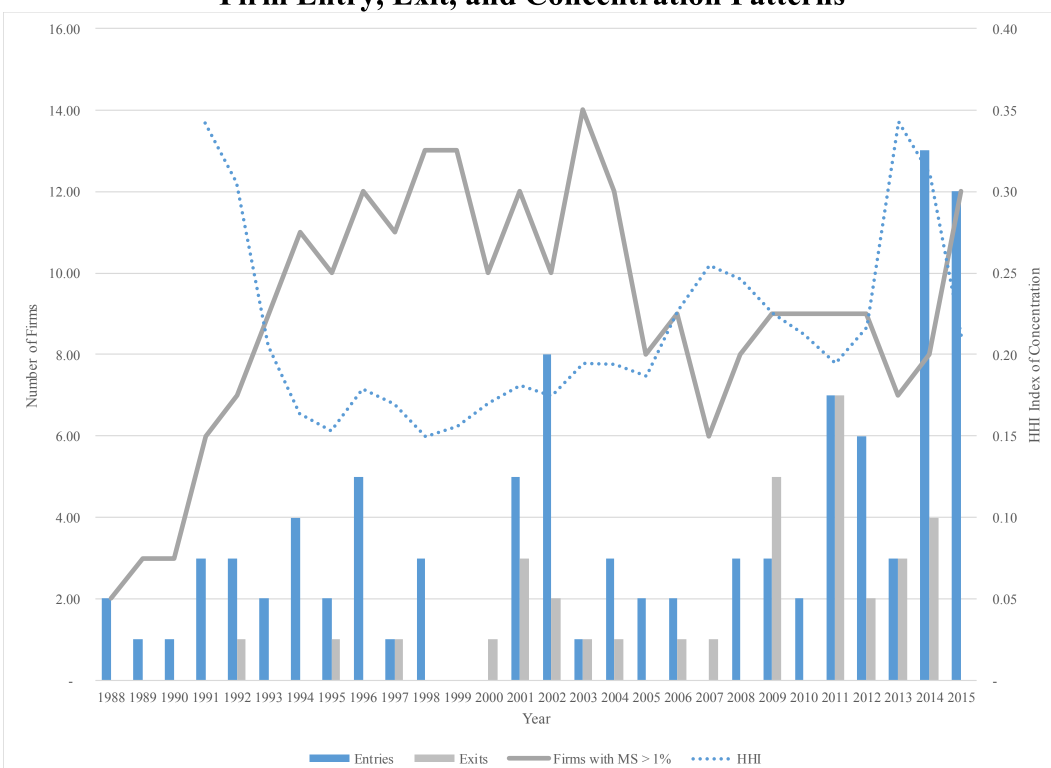
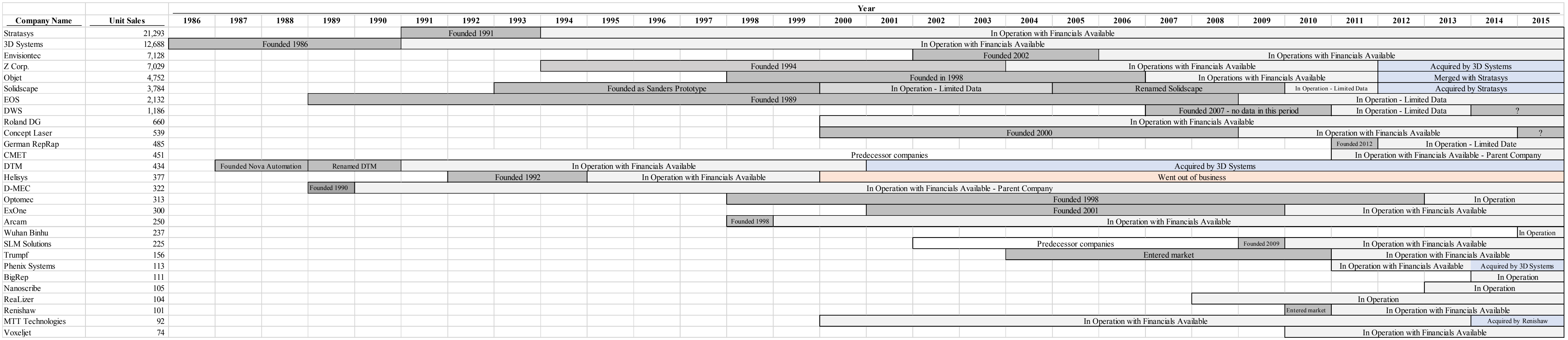


FIGURE 5
Selected Firm Genealogies, Performance Data Availability, and Relative Experience Distributions



Genealogies include all firms that have sold 100 printers or more for which at least some archival information was available for review.

Company Name	Unit Sales	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Stratasys	21,293									(8)	(6)	(6)	(2)	1	-	7	9	11	13	15	11	14	17	20	23	26	29	(20)	(18)	(21)	(16)
3D Systems	12,688	(21)	(20)	(19)	(18)	(17)	(16)	(15)	(20)	(18)	(16)	(15)	(11)	(7)	(1)	6	10	14	2	(7)	(3)	0	3	9	14	20	25	25	28	44	35
EnvisionTEC	7,128																	(12)	(10)	(8)	(10)	(7)	(4)	(1)	2	5	8	11	14	17	16
Z Corporation	7,029									(19)	(20)	(18)	(16)	(14)	(7)	(2)	2	6	10	14	15	1	(8)	(6)	(4)	(2)	-	(27)			
Objet	4,752													(13)	(14)	(11)	(8)	(5)	(3)	(19)	(18)	(17)	(16)	(15)	(15)	(14)	(16)	(13)			
EOS	2,132				(16)	(15)	(14)	(13)	(12)	(11)	(10)	(9)	(8)	(7)	(6)	(5)	(4)	(3)	(2)	(1)	-	1	2	3	4	5	6	7	3	7	11
Roland DG	660	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(36)	(37)	(38)	(39)	(40)	(40)	(36)	(32)
Concept Laser	539															(10)	(11)	(11)	(8)	(5)	(2)	1	4	7	10	13	16	19	22	25	28
German RepRap	485																											(5)	(6)	(7)	(14)
CMET	451																					(32)	(30)	(28)	(26)	(24)	(30)	(27)	(27)	(24)	(33)
DTM	434					(28)	(29)	(28)	(27)	(22)	(18)	(14)	(11)	(8)	(5)	(2)															
Helisys	377					(11)	(12)	(10)	(8)	(9)	(6)	(14)	(15)	(12)	(9)	(6)															
D-MEC	322																					(35)	(34)	(33)	(30)	(28)	(26)	(24)	(22)	(21)	(18)
Optomec	313														(11)	(10)	(9)	(11)	(10)	(7)	(8)	(4)	3	9	15	21	27	33	39	45	48
ExOne	300																				(29)	(28)	(27)	(33)	(31)	(29)	(27)	(22)	(17)	21	18
Arcam AB	250																(17)	(16)	(15)	(14)	(13)	(12)	(11)	(10)	(9)	(7)	(5)	(6)	(4)	(2)	7
SLM Solutions AG	225																									14	17	20	23	(3)	0
Trumpf	156									(15)	(16)	(17)	(20)	(21)	(22)	(19)	(20)	(21)	(22)	(19)	(16)	(11)	(6)	(1)	4	9	14	19	24	29	34
Renishaw	101									(31)	(32)	(33)	(34)	(35)	(36)	(37)	(33)	(30)	(31)	(30)	(31)	(32)	(33)	(31)	(32)	(33)	(26)	(19)	(12)	(5)	2
MTT Tech	92												(7)	(6)	(5)	(4)	(3)	(2)	(1)	-	1	2	3	4	5	6	(21)	(22)	(23)		
Voxeljet	74														(10)	(11)	(12)	(13)	(14)	(15)	(12)	(9)	(6)	(2)	2	6	10	14	19	25	31
Average Across Companies		(19.00)	(19.00)	(19.00)	(18.00)	(18.40)	(18.60)	(17.80)	(18.20)	(17.59)	(16.64)	(17.04)	(15.37)	(13.83)	(12.10)	(9.79)	(9.90)	(9.00)	(8.94)	(9.43)	(10.14)	(12.06)	(10.70)	(8.50)	(6.20)	(2.81)	(2.16)	(4.06)	0.12	5.88	7.33

Experience Distributions calculated as Total Industry Experience (Measure of Specific Knowledge) – Average Outside Experience (measure of typical outside knowledge).

FIGURE 6
Panel construction example

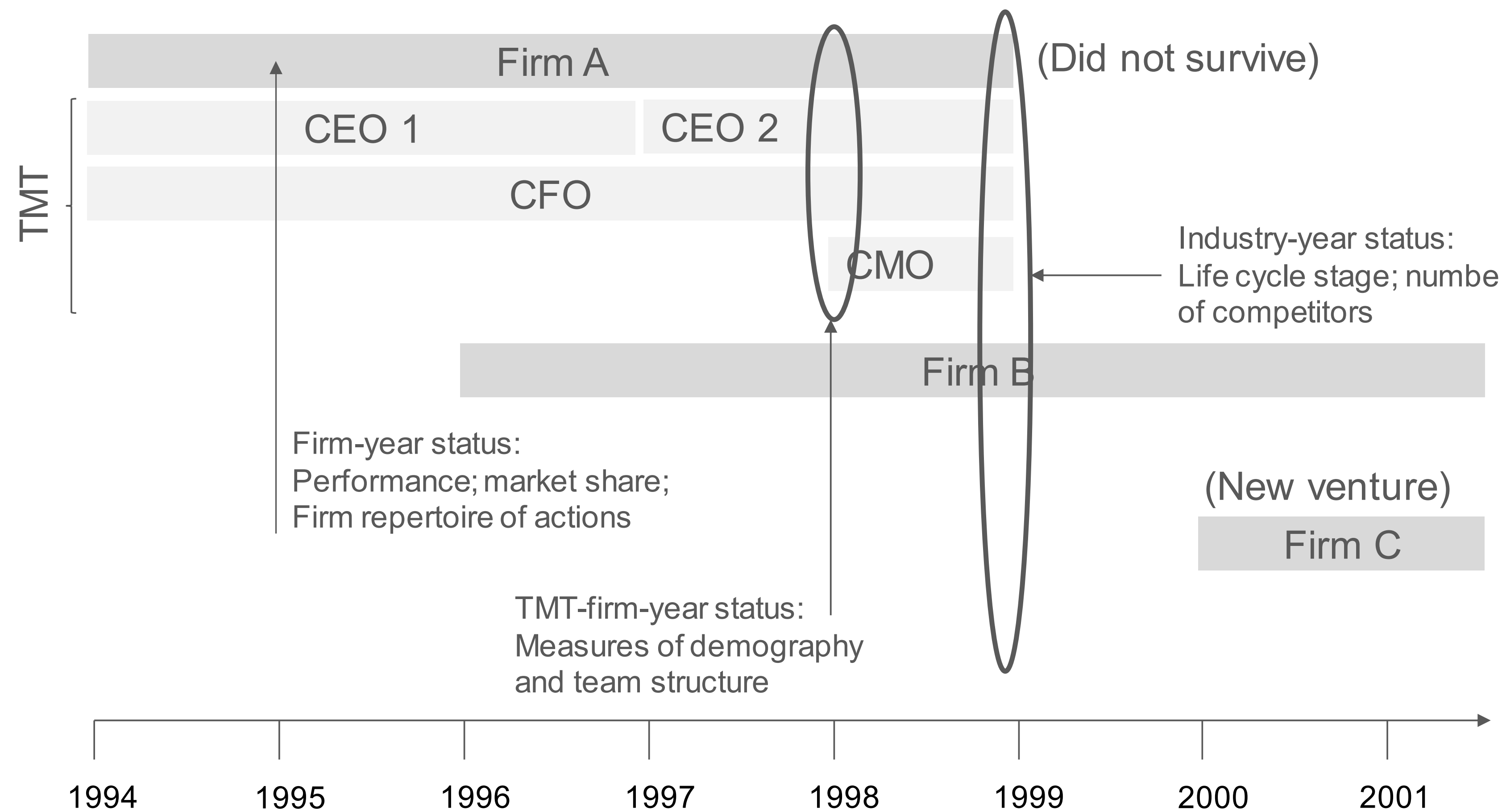
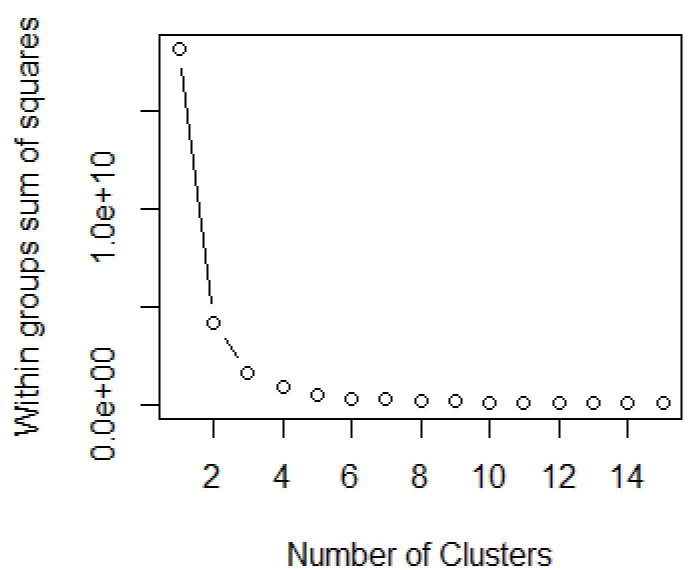
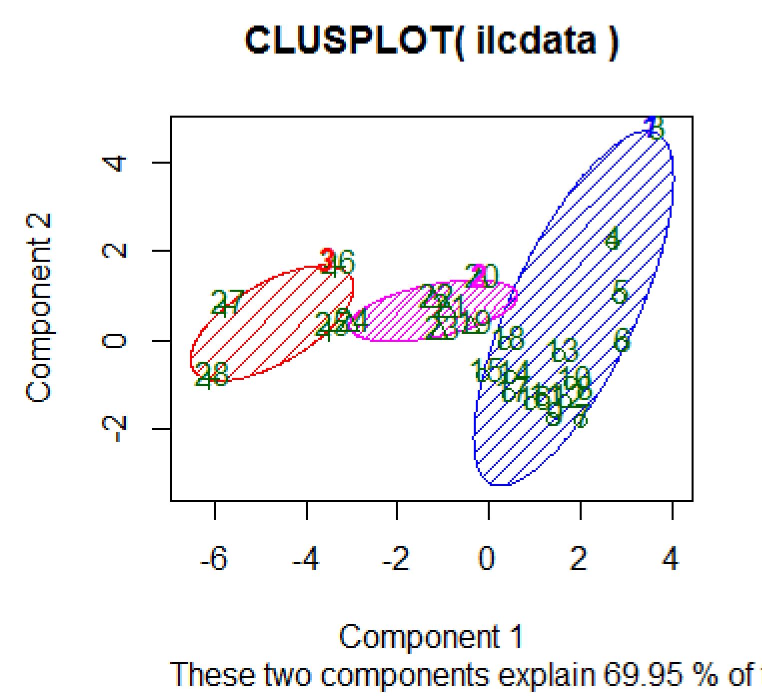


FIGURE 7
Industry Life Cycle Validation

Year	**1988**	**1989**	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**
Firm Count	2	3	4	7	9	11	15	16	21	21	24	24	23	25
Firm Count >1% MS	2	3	3	6	7	9	11	10	12	11	13	13	10	12
Net Change	2	1	1	3	2	2	4	1	5	-	3	-	(1)	2
Firm Entries	2	1	1	3	3	2	4	2	5	1	3	-	-	5
Firm Exits	-	-	-	-	(1)	-	-	(1)	-	(1)	-	-	(1)	(3)
Concentration	0.89	0.82	0.85	0.34	0.31	0.21	0.16	0.15	0.18	0.17	0.15	0.16	0.17	0.18
Sales	34	104	114	82	111	157	320	525	792	1,043	988	1,184	1,319	1,296
Cum Sales	34	138	252	334	445	602	922	1,447	2,239	3,282	4,270	5,454	6,773	8,069
Growth Rate			4%	-10%	7%	8%	18%	14%	12%	8%	-1%	4%	2%	0%
Cluster Analysis Assignment	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Plot ID No.	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*

Year	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Firm Count	31	31	33	35	36	35	38	36	38	38	42	41	50	62
Firm Count >1% MS	10	14	12	8	9	6	8	9	9	9	9	7	8	12
Net Change	6	-	2	2	1	(1)	3	(2)	2	-	4	-	9	12
Firm Entries	8	1	3	2	2	-	3	3	2	7	6	3	13	12
Firm Exits	(2)	(1)	(1)	-	(1)	(1)	-	(5)	-	(7)	(2)	(3)	(4)	-
Concentration	0.17	0.19	0.19	0.19	0.23	0.26	0.25	0.23	0.21	0.19	0.22	0.34	0.31	0.21
Sales	1,468	1,864	2,862	3,533	4,156	4,945	5,019	4,497	6,178	6,530	7,815	9,876	12,859	12,557
Cum Sales	9,537	11,401	14,263	17,796	21,952	26,897	31,916	36,413	42,591	49,121	56,936	66,812	79,671	92,228
Growth Rate	2%	4%	7%	4%	3%	3%	0%	-1%	4%	1%	2%	3%	4%	0%
Cluster Analysis Assignment	1	1	1	1	2	2	2	2	2	2	3	3	3	3
Plot ID No.	*15*	*16*	*17*	*18*	*19*	*20*	*21*	*22*	*23*	*24*	*25*	*26*	*27*	*28*





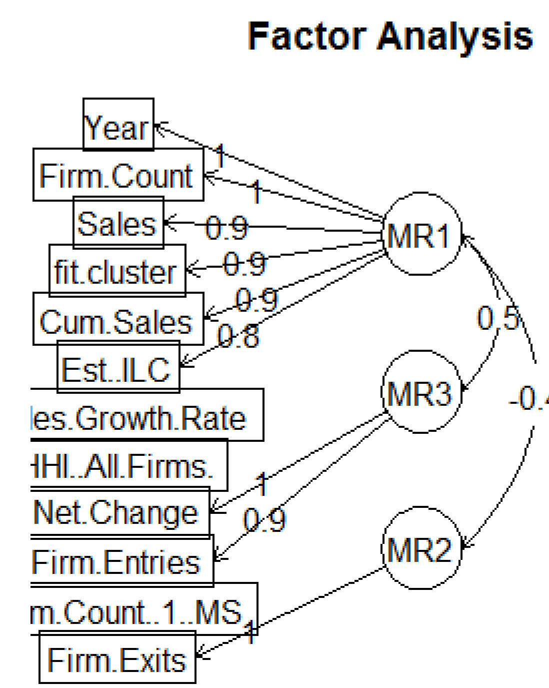
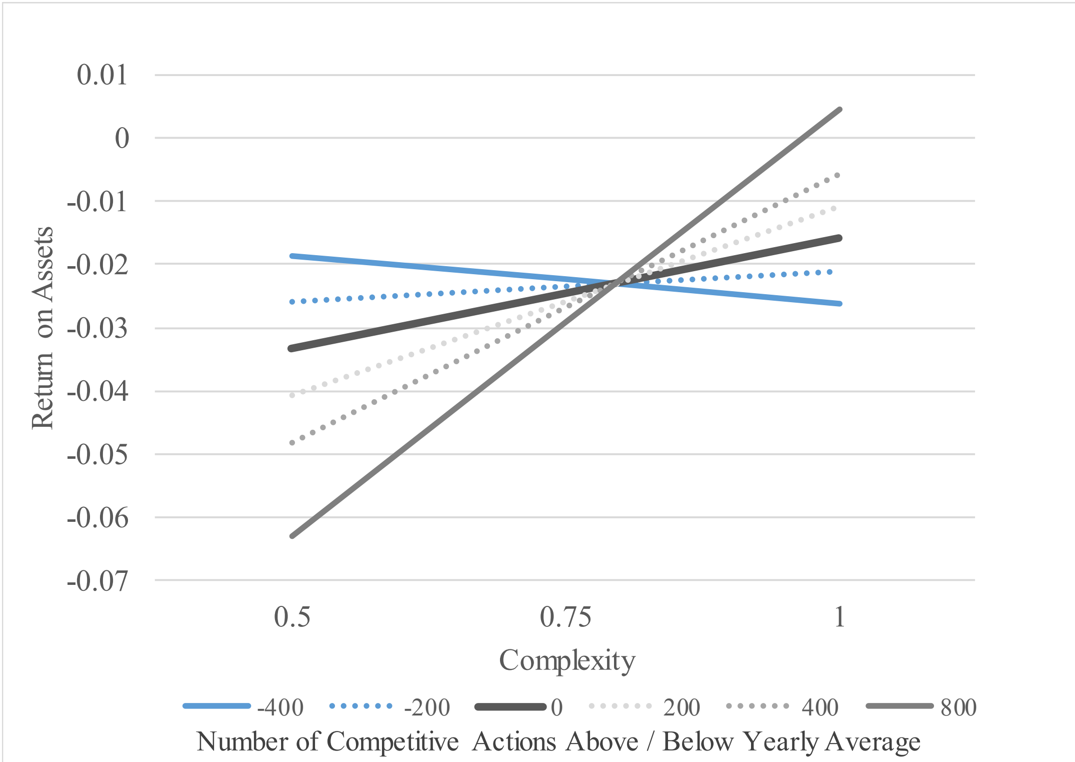


FIGURE 8
The Conditioning Effect of Competitive Pressure on the Repertoire to ROA Relationship



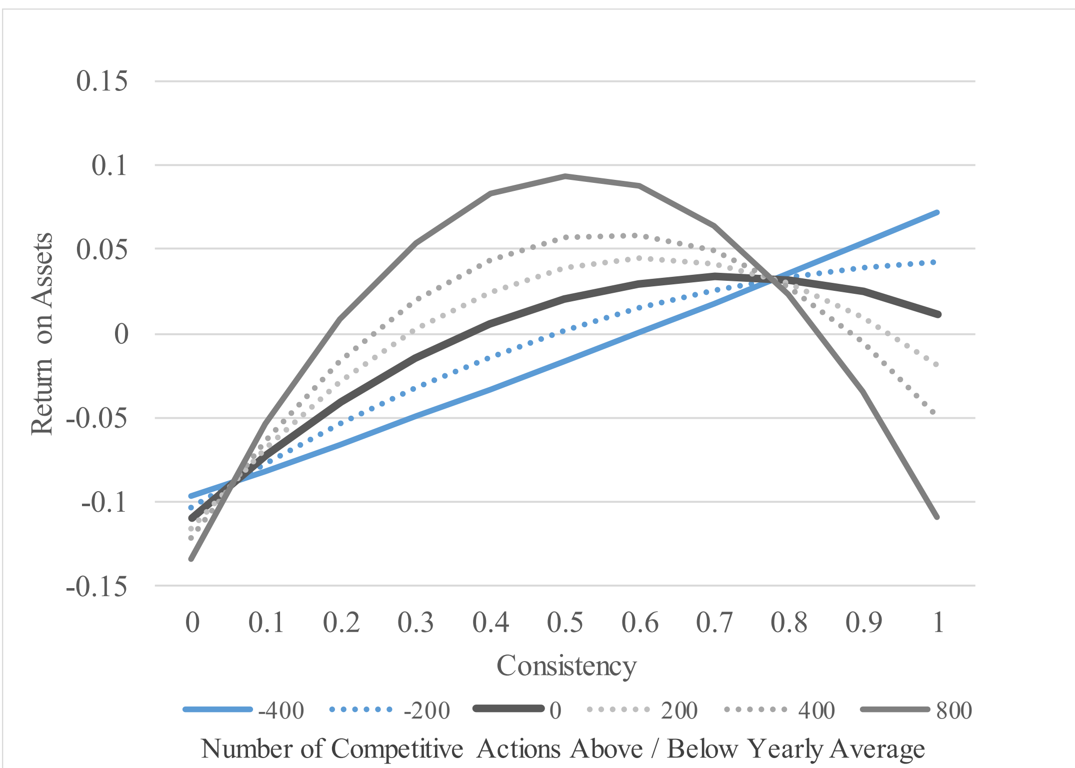
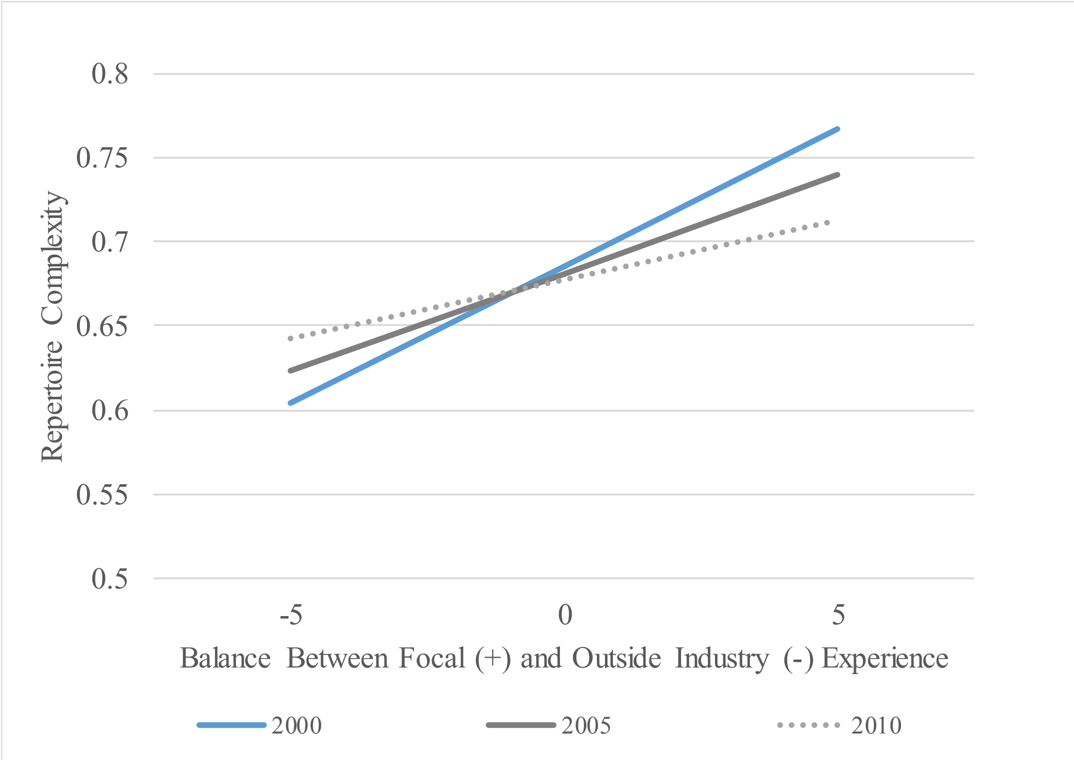


FIGURE 9
The Effect of Industry Experience on Repertoire Complexity and Consistency



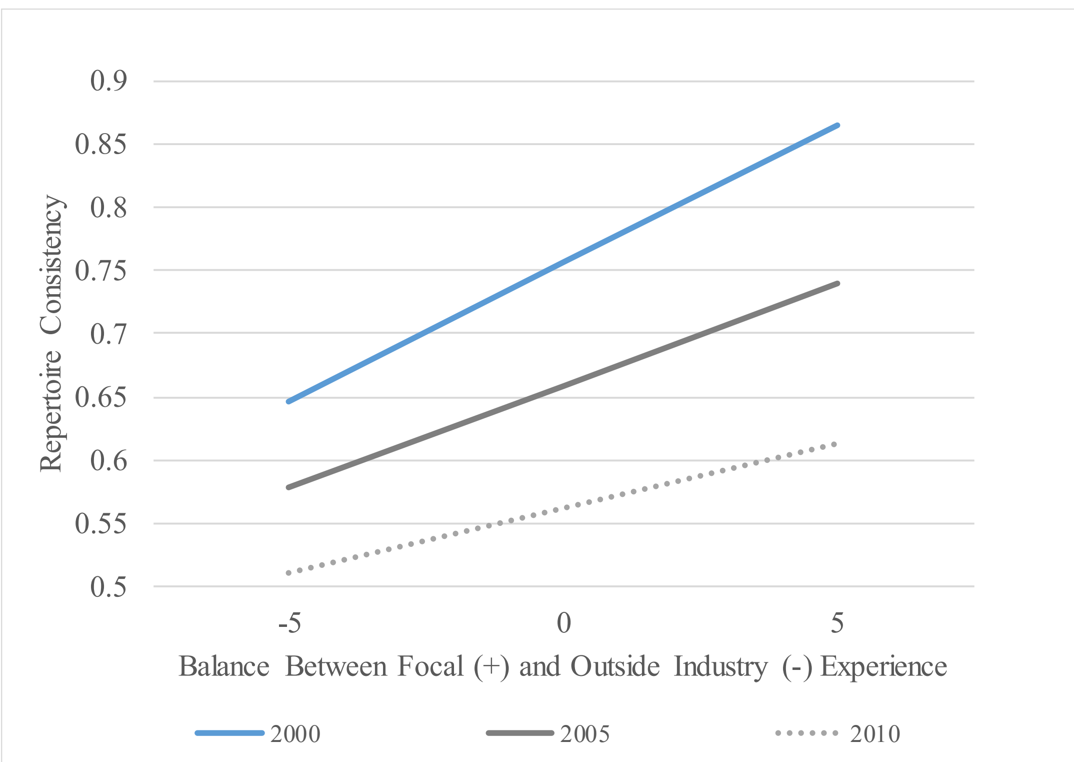


TABLE 1
Variables Investigated

Variable	Construct/Facet	Definition	Operationalization	Data Sources	Coding
Prior Experience					
Prior Industry Tenure	Industry-related experience	Experience acquired in the course of industry tenure (Finkelstein et al., 2009) that provides a set of grounded insights and industry recipes (Spender, 1989)	Average and total number of years current TMT has worked in any of the companies within the industry (multiple versions available, the "strictest" version is used)	Primary: Bloomberg executive biographies Secondary: ThomsonONE Tertiary: Company websites, LinkedIn, EDGAR 10-Ks	Continuous: Number of years of experience computed from stated history, also divided by active members
Outside Industry Tenure	Experience imported from other industries	Experience acquired outside of the focal industry that may or may not be useful in the current context	Average and total number of years that TMT has worked in industries outside of the focal industry		Continuous: Number of years of experience computed from stated history, also divided by active members
Industry Tenure Heterogeneity	Variety in the amount of industry tenure within the team	Separation and variety diversity related to prior experiences, means and mindsets (see e.g., Harrison & Klein, 2007)	Standard deviation of industry tenure within the team		Continuous, computed using data from all members of the team at a given time
Competitive Repertoire					
Consistency	Change in firm position	Actions consistent with external changes and firm history (Lamberg et al., 2009)	Magnitude and direction of change in principal component space	Primary: Factiva; LexisNexis Future Sources: 3Ders	Multinomial: Actions coded to a particular location within a taxonomy, taxonomy elements associated with a repertoire vector and assigned a date stamp Continuous: Taxonomy elements combined to develop measures at left
Complexity	Variety of actions taken	The ability to engage in a broader range of action types (Ferrier et al., 1999)	Entropy index of repertoire components using action taxonomy		
Volume	Number of actions taken	A summary of overall competitive activity by one firm in a year (Young et al., 1996)	Count of all actions taken by firm in a given year		
Performance					
Accounting	Absolute performance	Level of profits holding assets constant, and taking into consideration opportunity costs	Primary: Return on assets (ROA)	Primary: COMPUSTAT Secondary: PrivCo (US Private) Tertiary: LexisNexis	Continuous: ROA as reported in dataset
Market share	Relative performance	Proportion of shipments per year compared to industry total	Primary: Market share	Primary: Wohler's Reports	Continuous: computed using data available from datasets
Moderating Variables					
Industry Age	Progress along industry life cycle	The amount of time that has elapsed since the first firm has entered the new market	Number of years since the first firm was founded (i.e., 3D Systems in 1986)	Primary: Wohler's Reports	Continuous: Computed as Current Year – 1986
Life Cycle Stage	Discrete position in industry life cycle	The regular cycles that industries progress through as they age (Klepper, 1997)	Cluster analysis of several industry level variables	Primary: Wohler's Reports	Discrete (I, II, III)
Competitor Vol.	Amount of competitive activity by other firms	A summary of overall competitive activity in a given year (Young et al., 1996)	Count of all actions taken by all firms in a given year less the actions taken by the focal firm	Primary: Factiva; LexisNexis	Continuous: computed from volume data of all competitors

TABLE 1A
Descriptive Statistics and Correlations

	Variable	Mean	SD	N	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Average Tenure	5.81	4.62	214													
2	SD Tenure	2.16	2.60	214	0.19												
3	Volume	52.16	110.69	184	(0.01)	0.38											
4	Complexity	0.59	0.35	184	0.23	0.36	0.35										
5	Consistency	0.56	0.34	184	0.26	0.34	0.28	0.63									
6	Market Share (t+1)	0.04	0.14	606	0.13	0.28	0.24	0.13	0.21								
7	ROA (t+1)	(0.02)	0.23	154	0.27	(0.06)	(0.13)	0.13	0.19	0.11							
8	Competitor Pressure	487	602	184	0.18	0.17	0.27	0.18	0.07	(0.15)	0.15						
9	Industry Age	2005	6.82	766	0.23	0.18	0.29	0.28	0.19	(0.22)	0.23	0.73					
10	Market Share (t-1)	0.04	0.16	591	0.09	0.24	0.27	0.12	0.23	0.93	0.00	(0.17)	(0.23)				
11	ROA (t-1)	(0.03)	0.24	153	0.28	0.04	0.15	0.32	0.27	0.22	0.55	0.28	0.32	0.17			
12	No. of Competitors	33.41	9.95	766	0.19	0.20	0.29	0.29	0.22	(0.25)	0.18	0.71	0.94	(0.23)	0.28		
13	Firm Age	6.50	6.45	766	0.46	0.54	0.47	0.27	0.22	0.17	0.19	0.44	0.29	0.16	0.32	0.23	
14	Public Firm	.22	.17	766	(0.13)	0.41	0.31	0.10	0.11	0.43	(0.32)	(0.07)	(0.12)	0.43	(0.31)	(0.13)	0.22
15	Media Mentions	1,251	1,787	298	0.14	0.59	0.41	0.29	0.41	0.68	0.11	(0.11)	(0.14)	0.68	0.22	(0.13)	0.29
16	TMT Size	2.64	1.60	254	(0.06)	0.46	0.28	0.31	0.29	(0.04)	(0.07)	0.49	0.56	(0.02)	(0.01)	0.56	0.21
17	Tenure Distribution	8.22	3.92	214	(0.60)	0.08	0.18	(0.10)	(0.17)	(0.04)	(0.21)	0.11	0.12	(0.00)	(0.16)	0.13	0.15
18	Focal Ind. Tenure	14.96	14.32	254	0.59	0.57	0.26	0.41	0.46	0.12	0.09	0.54	0.57	0.06	0.15	0.55	0.47
19	Outside Ind. Tenure	21.31	6.26	214	(0.34)	0.11	0.21	0.09)	(0.16)	(0.05)	(0.16)	0.22	0.23	(0.01)	0.11)	0.22	0.34
20	HHI	0.22	0.07	766	(0.03)	(0.08)	0.11	(0.05)	(0.06)	0.27	0.08	0.22	0.09	0.23	0.14	0.00	(0.01)
21	Growth Rate	0.03	0.04	766	(0.13)	0.00	(0.06)	(0.14)	(0.15)	0.01	(0.09)	(0.19)	0.42)	0.04	0.16)	0.40)	0.15)
22	Volume (t-1)	43.74	107.07	184	(0.01)	0.39	0.85	0.32	0.35	0.22	(0.18)	0.23	0.28	0.25	0.13	0.35	0.45
23	Comp. Pressure(t-1)	540	699	184	0.13	0.16	0.23	0.19	0.13	(0.14)	0.10	0.86	0.73	(0.14)	0.23	0.84	0.06
24	Average TMT Age	48.82	6.68	214	0.31	0.29	0.25	0.14	0.09	0.17	(0.00)	0.30	0.33	0.17	0.08	0.29	0.64
25	SD TMT Age	8.94	5.20	214	(0.32)	(0.06)	(0.03)	0.03	(0.01)	(0.36)	0.09	0.02	0.04	(0.39)	0.06	0.06	(0.46)

TABLE 1A
Descriptive Statistics and Correlations

	Variable	Mean	SD	N	14	15	16	17	18	19	20	21	22	23	24
1	Average Tenure	5.81	4.62	214											
2	SD Tenure	2.16	2.60	214											
3	Volume	52.16	110.69	184											
4	Complexity	0.59	0.35	184											
5	Consistency	0.56	0.34	184											
6	Market Share (t+1)	0.04	0.14	606											
7	ROA (t+1)	(0.02)	0.23	154											
8	Competitor Pressure	487	602	184											
9	Industry Age	2005	6.82	766											
10	Market Share (t-1)	0.04	0.16	591											
11	ROA (t-1)	(0.03)	0.24	153											
12	No. of Competitors	33.41	9.95	766											
13	Firm Age	6.50	6.45	766											
14	Public Firm	.22	.17	766											
15	Media Mentions	1,251	1,787	298	0.53										
16	TMT Size	2.64	1.60	254	0.11	0.19									
17	Tenure Distribution	8.22	3.92	214	0.36	0.11	0.15								
18	Focal Ind. Tenure	14.96	14.32	254	0.02	0.28	0.72	(0.31)							
19	Outside Ind. Tenure	21.31	6.26	214	0.33	0.17	0.16	0.94	(0.13)						
20	HHI	0.22	0.07	766	0.02	0.18	(0.03)	0.08	0.01	0.09					
21	Growth Rate	0.03	0.04	766	0.07	0.00	(0.15)	0.00	(0.20)	(0.04)	(0.17)				
22	Volume (t-1)	43.74	107.07	184	0.30	0.39	0.36	0.18	0.30	0.19	0.05	(0.11)			
23	Comp. Pressure(t-1)	540	699	184	(0.11)	(0.09)	0.48	0.16	0.50	0.24	0.20	(0.26)	0.30		
24	Average TMT Age	48.82	6.68	214	0.34	0.37	0.11	0.56	0.25	0.78	0.09	(0.10)	0.23	0.30	
25	SD TMT Age	8.94	5.20	214	(0.22)	(0.29)	0.29	(0.31)	(0.01)	(0.48)	(0.17)	0.07	(0.03)	(0.01)	(0.72)

Note: Due to the differences in sample sizes across variables, correlations are pairwise complete.

TABLE 2
Summary of Results – Repertoire Models

	Consistency						Complexity					
	Baseline		Main Effects		Interaction		Baseline		Main Effects		Interaction	
Variables	Model 1a		Model 1b		Model 1c		Model 2a		Model 2b		Model 2c	
Management Team Tenure												
Average TMT Tenure (**H1**)			0.029	***	0.030	**			0.023	**	0.022	**
			(0.006)		(0.010)				(0.007)		(0.007)	
Std. Dev of TMT Tenure (**H2**)			0.041	**	0.041	**			0.052	**	0.077	***
			(0.013)		(0.013)				(0.016)		(0.023)	
Industry Age												
Industry Age	0.002		0.007		0.008		0.016	†	0.023	*	0.032	***
	(0.008)		(0.008)		(0.009)		(0.009)		(0.009)		(0.009)	
Interaction Effects												
Average Tenure x Ind. Age (**H3**)					(0.000)							
					(0.001)							
SD Tenure x Industry Age (**H4**)											(0.005)	*
											(0.002)	
Control Variables												
Team Size	0.065	**	0.049	*	0.049	*	0.030		0.001		(0.006)	
	(0.022)		(0.022)		(0.022)		(0.024)		(0.026)		(0.027)	
Average TMT Age	0.006		0.006		0.006		0.009		0.010		0.010	
	(0.009)		(0.009)		(0.009)		(0.009)		(0.008)		(0.008)	
TMT Age Diversity	0.006		0.005		0.005		0.014		0.009		0.011	
	(0.010)		(0.009)		(0.009)		(0.011)		(0.010)		(0.009)	
Prior Repertoire Volume	0.000		0.001	**	0.001	**	0.000		0.001	*	0.001	**
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Prior Market Share	0.839	***	0.704	**	0.703	**	0.633	*	0.461	†	0.521	*
	(0.234)		(0.218)		(0.217)		(0.258)		(0.256)		(0.259)	
Prior Competitive Activity	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		0.000	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Firm Age	0.005		(0.019)	*	(0.019)	*	0.001		(0.027)	**	(0.025)	**
	(0.005)		(0.008)		(0.008)		(0.005)		(0.009)		(0.009)	
Publicly Traded	(0.169)	†	(0.144)		(0.147)		0.000		(0.004)		(0.055)	
	(0.095)		(0.099)		(0.102)		(0.105)		(0.102)		(0.106)	
Intercept	(0.061)		(0.857)		(0.761)		(0.144)		(1.202)		(1.457)	
	0.478		(0.501)		(0.467)		(0.502)		(0.525)		(0.522)	
n	148		148		148		148		148		148	
R^2	0.24		0.37		0.37		0.20		0.30		0.34	
ΔR^2			0.12	***	0.00				0.10	**	0.04	**
Comparison model			1a		1b				2a		2b	

Robust standard errors are reported in parentheses. Two-tailed tests are used for all hypotheses.
† = p <. 10; * = p <. 05; ** = p <. 01; *** = p <. 001

TABLE 3A
Summary of Results– Market Share Performance Model (Pooled GLS)

	Market Share											
	Baseline		**Complexity Main Effect**		**Consistency Main Effects**		**Complexity Interaction**		**Consistency Interaction**		**Consistency^2 Interaction**	
Variables	**Model 3a**		**Model 3b**		**Model 3c**		**Model 3d**		**Model 3e**		**Model 3f**	
Competitive Repertoire												
Complexity (**H5**)			0.043		0.002		0.006		(0.008)		(0.011)	
			(0.037)		(0.033)		(0.027)		(0.036)		(0.036)	
Consistency					0.075	**	0.064	*	0.094	***	0.090	**
					(0.028)		(0.026)		(0.026)		(0.027)	
Consistency^2 (**H7**)					0.061		0.055		0.056		0.062	
					(0.103)		(0.103)		(0.100)		(0.101)	
Competitive Pressure												
Competitor Pressure	(0.000)		(0.000)		(0.000)		(0.000)	**	(0.000)		(0.000)	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Interaction Effects												
Complexity x							0.000	**				
Comp. Pressure (**H6**)							(0.000)					
Consistency x									(0.000)		0.000	
Comp. Pressure									(0.000)		(0.000)	
Consistency^2 x											(0.000)	†
Comp. Pressure (**H8**)											(0.000)	
Control Variables												
Industry Age	(0.002)		(0.003)		(0.003)		(0.001)		(0.003)		(0.003)	
	(0.003)		(0.003)		(0.003)		(0.004)		(0.003)		(0.003)	
Industry Concentration	0.053		0.145		0.139		0.032		0.123		0.069	
	(0.319)		(0.334)		(0.296)		(0.290)		(0.293)		(0.290)	
Industry Growth Rate	0.026		0.082		0.172		0.055		0.223		0.231	
	(0.266)		(0.270)		(0.254)		(0.255)		(0.248)		(0.253)	
Year Founded	(0.006)	**	(0.006)	*	(0.005)	†	(0.007)	**	(0.004)		(0.004)	
	(0.002)		(0.002)		(0.002)		(0.003)		(0.003)		(0.003)	
Publicly Traded	(0.053)	*	(0.051)	*	(0.057)	**	(0.061)	**	(0.062)	**	(0.059)	**
	(0.021)		(0.021)		(0.020)		(0.018)		(0.022)		(0.022)	
Firm Size	0.025	*	0.025	*	0.021	*	0.028	***	0.021	*	0.022	*
	(0.010)		(0.010)		(0.009)		(0.008)		(0.010)		(0.010)	
Volume	0.000		0.000		0.000		0.000		0.000		0.000	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Intercept	12.571	**	11.110	*	9.667	†	13.652	*	8.441		8.121	
	(4.586)		(4.801)		(4.909)		(5.176)		(5.092)		(5.277)	
n	94		94		94		94		94		94	
R^2	0.43		0.44		0.48	†	0.50	*	0.49		0.49	
ΔR^2			0.010		0.040		0.025		0.006		0.006	
Comparison model			3a		3b		3c		3c		3e	

Robust standard errors are reported in parentheses. Two-tailed tests are used for all hypotheses.
† = p <. 10; * = p <. 05; ** = p <. 01; *** = p <. 001

TABLE 3B
Summary of Results– Market Share Performance Model (Dynamic Panel Model)

Variables	Market Share											
	Baseline		**Complexity Main Effect**		**Consistency Main Effects**		**Complexity Interaction**		**Consistency Interaction**		**Consistency^2 Interaction**	
	Model 3g		**Model 3h**		**Model 3i**		**Model 3j**		**Model 3k**		**Model 3l**	
Competitive Repertoire												
Complexity (**H5**)			0.029	†	0.023		0.019		0.017		0.016	
			(0.017)		(0.016)		(0.016)		(0.018)		(0.018)	
Consistency					(0.011)		(0.011)		0.103	†	(0.007)	
					(0.013)		(0.013)		(0.060)		(0.017)	
Consistency^2 (**H7**)					0.108	†	0.108	†	(0.004)		0.108	†
					(0.060)		(0.060)		(0.017)		(0.057)	
Competitive Pressure												
Competitor Pressure	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		0.000	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Interaction Effects												
Complexity x							(0.000)					
Comp. Pressure (**H6**)							(0.000)					
Consistency x									(0.000)		0.000	
Comp. Pressure									(0.000)		(0.000)	
Consistency^2 x											(0.000)	**
Comp. Pressure (**H8**)											(0.000)	
Control Variables												
Industry Age	0.004	*	0.004	*	0.004	*	0.004	*	0.004	*	0.004	*
	(0.002)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)	
Industry Concentration	(0.283)	*	(0.242)	†	(0.261)	†	(0.252)	†	(0.272)	*	(0.332)	*
	(0.127)		(0.123)		(0.133)		(0.138)		(0.136)		(0.136)	
Industry Growth Rate	0.049		0.099		0.127		0.134		0.143		0.144	
	(0.174)		(0.173)		(0.173)		(0.173)		(0.175)		(0.170)	
Year Founded	(0.001)		(0.000)		(0.000)		(0.000)		(0.000)		0.000	
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
Publicly Traded	(0.011)		(0.007)		(0.010)		(0.011)		(0.014)		(0.009)	
	(0.008)		(0.009)		(0.009)		(0.010)		(0.010)		(0.010)	
Firm Size	(0.002)		(0.005)		(0.008)		(0.007)		(0.006)		(0.006)	
	(0.005)		(0.005)		(0.006)		(0.006)		(0.006)		(0.006)	
Volume	0.000		0.000		0.000		0.000		0.000		0.000	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Prior Market Share	0.928	***	0.940	***	0.938	***	0.939	***	0.929	***	0.932	***
	(0.061)		(0.059)		(0.057)		(0.057)		(0.060)		(0.058)	
Intercept	1.576		0.502		0.330		0.171		0.232		(0.914)	
	(2.460)		(2.529)		(2.706)		(2.867)		(2.699)		(2.825)	
n	90		90		90		90		90		90	
R^2	0.87		0.88		0.88		0.88		0.88		0.89	†
ΔR^2			0.003		0.005		-		0.001		0.006	
Comparison model			3g		3h		3i		3i		3k	

Robust standard errors are reported in parentheses. Two-tailed tests are used for all hypotheses.
† = p <. 10; * = p <. 05; ** = p <. 01; *** = p <. 001

TABLE 3C
Summary of Results – ROA Performance Model (Pooled GLS)

Variables	ROA											
	Baseline		**Complexity Main Effect**		**Consistency Main Effects**		**Complexity Interaction**		**Consistency Interaction**		**Consistency² Interaction**	
Variables	**Model 3m**		**Model 3n**		**Model 3o**		**Model 3p**		**Model 3q**		**Model 3r**	
Competitive Repertoire												
Complexity			0.197	†	0.075		0.083		0.043		0.028	
			(0.108)		(0.105)		(0.101)		(0.103)		(0.101)	
Consistency					0.308	**	0.299	*	0.366	**	0.355	**
					(0.114)		(0.114)		(0.120)		(0.125)	
Consistency²					(0.330)		(0.330)		(0.329)		(0.308)	
					(0.305)		(0.303)		(0.299)		(0.308)	
Competitive Pressure												
Competitor Volume	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		0.000	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Interaction Effects												
Complexity x Competitor Volume							0.000					
							(0.000)					
Consistency x Competitor Volume									(0.000)	†	(0.000)	
									(0.000)		(0.000)	
Consistency² x Competitor Volume											(0.001)	†
											(0.000)	
Control Variables												
Industry Age	0.028	**	0.025	**	0.023	**	0.025	**	0.022	*	0.022	**
	(0.009)		(0.009)		(0.008)		(0.009)		(0.008)		(0.008)	
Industry Concentration	0.317		0.629		0.663		0.587		0.562		0.417	
	(0.837)		(0.847)		(0.776)		(0.770)		(0.743)		(0.711)	
Industry Growth Rate	1.506		1.782		1.927	†	1.838	†	2.122	*	2.178	*
	(1.075)		(1.091)		(1.038)		(1.061)		(1.035)		(1.046)	
Year Founded	(0.009)		(0.006)		(0.004)		(0.006)		(0.002)		(0.002)	
	(0.008)		(0.007)		(0.006)		(0.007)		(0.006)		(0.006)	
Publicly Traded	(0.092)		(0.110)	†	(0.126)	*	(0.130)	*	(0.149)	*	(0.139)	*
	(0.061)		(0.058)		(0.062)		(0.062)		(0.065)		(0.064)	
Volume	(0.001)	**	(0.001)	***	(0.001)	***	(0.001)	***	(0.001)	**	(0.001)	**
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Firm Size	0.037		0.044	†	0.048	*	0.050	*	0.047	*	0.047	*
	(0.027)		(0.024)		(0.021)		(0.023)		(0.021)		(0.021)	
Intercept	17.054		10.714		8.485		12.559		3.253		3.853	
	(15.665)		(14.258)		(12.807)		(14.869)		(12.413)		(11.738)	
n	91		91		91		91		91		91	
R^2	0.29		0.32	*	0.38	*	0.38		0.40		0.42	
ΔR^2			0.032		0.060		0.004		0.020		0.017	
Comparison model			3m		3n		3o		3o		3q	

Robust standard errors are reported in parentheses. Two-tailed tests are used for all hypotheses.
† = p <. 10; * = p <. 05; ** = p <. 01; *** = p <. 001

TABLE 3D
Summary of Results – ROA Performance Model (Dynamic Panel)

	ROA											
	Baseline		**Complexity Main Effect**		**Consistency Main Effects**		**Complexity Interaction**		**Consistency Interaction**		**Consistency^2 Interaction**	
Variables	**Model 3s**		**Model 3t**		**Model 3u**		**Model 3v**		**Model 3w**		**Model 3x**	
Competitive Repertoire												
Complexity			0.097		0.066		0.078		0.026		0.010	
			(0.118)		(0.105)		(0.097)		(0.094)		(0.096)	
Consistency					0.181		0.183		0.229	†	0.231	†
					(0.123)		(0.122)		(0.134)		(0.136)	
Consistency^2					(0.336)		(0.346)		(0.298)		(0.274)	
					(0.294)		(0.294)		(0.281)		(0.292)	
Competitive Pressure												
Competitor Volume	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
	0.000		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Interaction Effects												
Complexity x Competitor Volume							0.000					
							(0.000)					
Consistency x Competitor Volume									(0.000)	†	(0.000)	
									(0.000)		(0.000)	
Consistency^2 x Competitor Volume											(0.000)	†
											(0.000)	
Control Variables												
Industry Age	0.025	**	0.024	**	0.022	**	0.023	**	0.021	**	0.022	**
	0.008		(0.008)		(0.008)		(0.008)		(0.008)		(0.008)	
Industry Concentration	0.529		0.644		0.782		0.781		0.713		0.626	
	0.765		(0.768)		(0.787)		(0.780)		(0.803)		(0.790)	
Industry Growth Rate	1.432		1.582		1.644	†	1.592		1.820	†	1.884	†
	0.916		(0.988)		(0.973)		(0.982)		(0.981)		(0.989)	
Year Founded	(0.006)		(0.004)		(0.004)		(0.005)		(0.003)		(0.003)	
	0.008		(0.007)		(0.007)		(0.007)		(0.007)		(0.006)	
Publicly Traded	(0.023)		(0.039)		(0.053)		(0.058)		(0.076)		(0.076)	
	0.056		(0.062)		(0.065)		(0.063)		(0.070)		(0.071)	
Volume	(0.001)	**	(0.001)	**	(0.001)	**	(0.001)	**	(0.001)	**	(0.001)	**
	0.000		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Firm Size	0.003		0.011		0.021		0.026		0.016		0.016	
	0.023		(0.022)		(0.022)		(0.024)		(0.022)		(0.021)	
Prior ROA	0.542	***	0.497	***	0.435	***	0.424	***	0.436	***	0.419	***
	0.090		(0.100)		(0.115)		(0.115)		(0.112)		(0.113)	
Intercept	11.022		7.964		7.794		9.887		5.128		5.905	
	15.446		(14.106)		(13.550)		(14.721)		(13.211)		(12.707)	
n	87		87		87		87		87		87	
R^2	0.46		0.47		0.48		0.49		0.49		0.50	
ΔR^2			0.007		0.016		0.002		0.011		0.007	
Comparison model			3s		3t		3u		3u		3w	

Robust standard errors are reported in parentheses. Two-tailed tests are used for all hypotheses.
† = p <. 10; * = p <. 05; ** = p <. 01; *** = p <. 001

TABLE 4A
Supplemental Analysis – ROA Model (Pooled GLS) Including Yrs. w/ No Actions

Variables	ROA											
	Baseline		Complexity Main Effect		Consistency Main Effects		Complexity Interaction		Consistency Interaction		Consistency^2 Interaction	
	Model 4a		Model 4b		Model 4c		Model 4d		Model 4e		Model 4f	
Competitive Repertoire												
Complexity			0.182	**	0.040		0.053		0.032		0.027	
			(0.067)		(0.082)		(0.079)		(0.081)		(0.081)	
Consistency					0.240	*	0.242	**	0.249	**	0.243	*
					(0.093)		(0.091)		(0.094)		(0.097)	
Consistency^2					(0.212)		(0.254)		(0.204)		(0.197)	
					(0.242)		(0.244)		(0.240)		(0.243)	
Competitive Pressure												
Competitor Volume	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		0.000	
	0.000		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Interaction Effects												
Complexity x Competitor Volume							0.000	†				
							(0.000)					
Consistency x Competitor Volume									(0.000)		0.000	
									(0.000)		(0.000)	
Consistency^2 x Competitor Volume											(0.001)	†
											(0.000)	
Control Variables												
Industry Age	0.016	**	0.015	**	0.015	**	0.018	***	0.014	**	0.014	**
	0.005		(0.005)		(0.005)		(0.005)		(0.005)		(0.005)	
Industry Concentration	0.274		0.312	†	0.326	†	0.309	†	0.326	†	0.310	†
	0.176		(0.178)		(0.178)		(0.174)		(0.178)		(0.175)	
Industry Growth Rate	0.476		0.634		0.633		0.578		0.648		0.676	
	0.545		(0.563)		(0.556)		(0.555)		(0.563)		(0.569)	
Year Founded	(0.005)		(0.004)		(0.004)		(0.007)		(0.003)		(0.002)	*
	0.005		(0.005)		(0.004)		(0.005)		(0.004)		(0.004)	
Publicly Traded	(0.082)	†	(0.101)	*	(0.104)	*	(0.094)	*	(0.109)	*	(0.095)	*
	0.044		(0.041)		(0.041)		(0.043)		(0.043)		(0.044)	
Volume	(0.001)	*	(0.001)	**	(0.001)	**	(0.001)	***	(0.001)	**	(0.001)	**
	0.000		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Firm Size	0.016		0.031	*	0.036	**	0.034	*	0.038	**	0.039	**
	0.014		(0.014)		(0.013)		(0.014)		(0.013)		(0.013)	
Intercept	10.850		7.628		6.882		14.497		4.925		4.333	
	10.435		(9.126)		(8.347)		(10.383)		(8.433)		(8.270)	
n	139		139		139		139		139		139	
R^2	0.29		0.32	*	0.38	*	0.38		0.40		0.42	
ΔR^2			0.032		0.060		0.004		0.020		0.017	
Comparison model			4a		4b		4c		4c		4e	

Robust standard errors are reported in parentheses. Two-tailed tests are used for all hypotheses.
† = p <. 10; * = p <. 05; ** = p <. 01; *** = p <. 001

TABLE 4B
Supplemental Analysis – ROA Model (Dyn. Panel) Including Yrs. w/ No Actions

	ROA											
	Baseline		Complexity Main Effect		Consistency Main Effects		Complexity Interaction		Consistency Interaction		Consistency^2 Interaction	
Variables	**Model 4g**		**Model 4h**		**Model 4i**		**Model 4j**		**Model 4k**		**Model 4l**	
Competitive Repertoire												
Complexity			0.014	*	0.033		0.047		0.020		0.001	
			(0.007)		(0.088)		(0.084)		(0.083)		(0.084)	
Consistency					0.132		0.139		0.144		0.153	
					(0.108)		(0.107)		(0.114)		(0.114)	
Consistency^2					(0.253)		(0.286)		(0.233)		(0.213)	
					(0.266)		(0.267)		(0.257)		(0.265)	
Competitive Pressure												
Competitor Volume	(0.000)		(0.000)	†	(0.000)		(0.000)		(0.000)		0.000	
	0.000		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Interaction Effects												
Complexity x Competitor Volume							0.000					
							(0.000)					
Consistency x Competitor Volume									(0.000)		0.000	
									(0.000)		(0.000)	
Consistency^2 x Competitor Volume											(0.001)	†
											(0.000)	
Control Variables												
Industry Age	0.014	*	0.000		0.013	*	0.015	*	0.012	*	0.012	*
	0.005		(0.001)		(0.005)		(0.006)		(0.006)		(0.006)	
Industry Concentration	0.268		0.026		0.274		0.270		0.273		0.267	
	0.164		(0.069)		(0.167)		(0.165)		(0.168)		(0.166)	
Industry Growth Rate	0.546		0.055		0.602		0.557		0.631		0.686	
	0.603		(0.091)		(0.641)		(0.635)		(0.654)		(0.652)	
Year Founded	(0.002)		(0.000)		(0.002)		(0.005)		(0.001)		(0.002)	*
	0.005		(0.000)		(0.004)		(0.006)		(0.005)		(0.004)	
Publicly Traded	(0.032)		(0.002)		(0.054)		(0.046)		(0.062)		(0.059)	***
	0.043		(0.004)		(0.050)		(0.052)		(0.056)		(0.057)	
Volume	(0.001)	*	0.000		(0.001)	**	(0.001)	**	(0.001)	*	(0.001)	*
	0.000		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Firm Size	0.002		(0.001)		0.016		0.015		0.016		0.015	
	0.013		(0.002)		(0.015)		(0.015)		(0.015)		(0.015)	
Prior ROA	0.550	***	0.816	***	0.467	***	0.451	***	0.470	***	0.450	***
	0.083		(0.052)		(0.101)		(0.103)		(0.100)		(0.098)	
Intercept	4.260		0.523		3.990		10.725		1.969		2.961	
	9.687		(0.790)		(8.917)		(11.768)		(9.022)		(8.881)	
n	116		116		116		116		116		116	
R^2	0.46		0.47		0.48		0.49		0.49		0.50	
ΔR^2			0.007		0.016		0.002		0.011		0.007	
Comparison model			4a		4b		4c		4c		4e	

Robust standard errors are reported in parentheses. Two-tailed tests are used for all hypotheses.
† = p <. 10; * = p <. 05; ** = p <. 01; *** = p <. 001

TABLE 5
Supplemental Analyses– Alternative Repertoire Models

	Consistency						Complexity					
	Baseline		**Main Effects**		**Interaction**		**Baseline**		**Main Effects**		**Interaction**	
Variables	**Model 5a**		**Model 5b**		**Model 5c**		**Model 5d**		**Model 5e**		**Model 5f**	
Management Team Experience												
Focal Industry Exp. (**H1**)			0.011	***	0.025	***			0.006	**	0.006	**
			(0.002)		(0.003)				(0.002)		(0.002)	
Outside Industry Exp. (**H2**)			0.000		(0.000)				(0.000)		0.001	
			(0.001)		(0.001)				(0.001)		(0.001)	
Industry Age												
Industry Age	0.007		0.000		0.014	†	0.018		0.015	†	0.042	***
	(0.008)		(0.008)		(0.008)		(0.009)		(0.009)		(0.010)	
Interaction Effects												
Focal Ind. Exp. x Ind. Age (**H3**)					(0.002)	***						
					(0.000)							
Outside Exp. x Ind. Age (**H4**)											(0.000)	***
											(0.000)	
Control Variables												
Average TMT Age	0.011		0.007		0.013		0.012		0.013		0.019	*
	(0.009)		(0.010)		(0.009)		(0.009)		(0.010)		(0.010)	
TMT Age Diversity	0.014		0.008		0.012		0.017		0.017		0.020	*
	(0.010)		(0.010)		(0.009)		(0.011)		(0.011)		(0.010)	
Prior Repertoire Volume	0.001	*	0.001	*	0.001	***	0.000		0.000		0.001	*
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Prior Market Share	0.724	**	0.689	**	0.709	***	0.580		0.531	*	0.731	**
	(0.228)		(0.226)		(0.182)		(0.253)		(0.252)		(0.239)	
Prior Competitive Activity	(0.000)		(0.000)		0.000	*	(0.000)		(0.000)		0.000	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Firm Age	0.000		(0.004)		(0.012)	†	(0.002)		(0.006)		(0.013)	
	(0.005)		(0.006)		(0.006)		(0.005)		(0.007)		(0.007)	†
Publicly Traded	(0.113)		(0.120)		(0.209)	*	0.026		0.031		0.019	
	(0.097)		(0.091)		(0.087)		(0.102)		(0.100)		(0.096)	
Intercept	(0.165)		(0.051)		(0.498)		(0.192)		(0.281)		(0.709)	
	(0.495)		(0.498)		(0.479)		(0.508)		(0.528)		(0.513)	
n	148		148		148		148		148		148	
R^2	0.24		0.37	***	0.43	***	0.20		0.29	***	0.31	†
ΔR^2 (Δdf)			0.13 (2)		0.06 (1)				0.09 (2)		0.02 (1)	
Comparison model												

Robust standard errors are reported in parentheses. Two-tailed tests are used for all hypotheses.
† = p <. 10; * = p <. 05; ** = p <. 01; *** = p <. 001

TABLE 6
Robustness Tests – Firm Fixed Effects Models

	ROA						Market Share					
	Baseline		Complexity Main Effect		Consistency Main Effects		Baseline		Complexity Main Effect		Consistency Main Effects	
Variables	**Model 6a**		**Model 6b**		**Model 6c**		**Model 6d**		**Model 6e**		**Model 6f**	
Competitive Repertoire												
Complexity (**H5**)			0.018		(0.082)				0.021		0.011	
			(0.092)		(0.072)				(0.018)		(0.016)	
Consistency					0.659	**					0.032	
					(0.216)						(0.027)	
Consistency^2 (**H7**)					(1.065)	**					(0.012)	
					(0.334)						(0.056)	
Competitive Pressure												
Competitor Pressure	0.000		0.000		0.000		(0.000)		(0.000)		(0.000)	
	0.000		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Control Variables												
Industry Age	0.021	**	0.020	**	0.019	***	(0.002)		(0.003)		(0.003)	
	0.007		(0.006)		(0.005)		(0.003)		(0.003)		(0.003)	
Industry Concentration	0.110		0.129		0.244		0.525	***	0.532	***	0.532	***
	0.529		(0.555)		(0.492)		(0.105)		(0.102)		(0.107)	
Industry Growth Rate	1.262	*	1.288	*	1.201	*	0.137		0.155		0.159	
	0.580		(0.624)		(0.505)		(0.316)		(0.313)		(0.313)	
Firm Age	0.024		0.025		0.027		0.000		0.001		0.002	
	0.026		(0.026)		(0.027)		(0.006)		(0.006)		(0.006)	
Volume	(0.001)	***	(0.001)	***	(0.001)	***	0.000		0.000		0.000	
	0.000		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
n	107		107		107		163		163		163	
R^2	0.58		0.59		0.66	***	0.84		0.84		0.84	
ΔR^2			0.009		0.066				0.002		0.002	
Comparison model			6a		6b				6d		6e	

Robust standard errors are reported in parentheses. Two-tailed tests are used for all hypotheses.
† = p <. 10; * = p <. 05; ** = p <. 01; *** = p <. 001

TABLE 7A
Robustness Tests – Joint 3SLS Estimation – Complexity Interaction

	Mkt. Share		ROA		Consistency		Complexity	
Variables	**Model 7a**		**Model 7b**		**Model 7c**		**Model 7d**	
Management Team Experience								
Average Industry Tenure (**H1**)					0.052	***	0.037	***
					(0.011)		(0.011)	
SD Tenure (**H2**)					(0.016)		(0.020)	
					(0.024)		(0.024)	
Industry Age								
Industry Age					(0.011)		0.005	
					(0.011)		(0.012)	
Interaction Effects								
Average Tenure x Ind. Age (**H3**)					(0.004)	**		
					(0.001)			
SD Tenure x Ind. Age (**H4**)							(0.003)	†
							(0.002)	
Competitive Repertoire								
Complexity (**H5**)	(0.038)		0.039					
	(0.177)		(0.029)					
Consistency								
Consistency^2 (**H7**)								
Competitive Pressure								
Competitor Pressure	(0.001)		(0.001)					
	(0.000)		0.000					
Interaction Effects								
Complexity x Comp. Pressure (**H6**)	(0.001)		0.001					
	(0.000)		(0.000)					
Consistency x Comp. Pressure								
Consistency^2 x Comp. Pressure (**H8**)								
Control Variables	*Same as pooled panel models, with individual action controls*							
LR test – Add H5 and H6 (df)	2.19(2)		8.85(2)	*				
n	88		88		88		88	
R^2	.061		-.126		.507		.397	
Correlations between residuals	*MS*		*ROA*		*Complexity*		*Consistency*	
MS								
ROA	.59							
Consistency	(.22)		(.23)					
Complexity	(.40)		(.50)		.25			

Repertoire variables predicted in first stage, with non-overlapping variables used as instruments. For ROA, the hypothesis of weak instruments is rejected for both the main effect (F(13,66)=3.108, p < .01), and interaction term (F(13,66)=3.800, p <. 01). The Wu-Hausman test is not rejected.

TABLE 7B
Robustness Tests – Joint 3SLS Estimation – Consistency Interaction

	Mkt. Share		**ROA**		**Consistency**		**Complexity**	
Variables	**Model 7e**		**Model 7f**		**Model 7g**		**Model 7h**	
Management Team Experience								
Average Industry Tenure (**H1**)					0.051	***	0.038	**
					(0.011)		(0.012)	
SD Tenure (**H2**)					(0.015)		(0.021)	
					(0.024)		(0.025)	
Industry Age								
Industry Age					(0.001)		0.001	
					(0.011)		(0.012)	
Interaction Effects								
Average Tenure x Ind. Age (**H3**)					(0.003)	*		
					(0.001)			
SD Tenure x Ind. Age (**H4**)							(0.003)	
							(0.002)	
Competitive Repertoire								
Complexity (**H5**)	(0.045)		(1.300)					
	(0.040)		(1.401)					
Consistency (**H7**)	1.155		2.251					
	(1.681)		(2.920)					
Consistency^2 (**H7**)	(0.068)		(1.252)					
	(1.563)		(2.983)					
Competitive Pressure								
Competitor Pressure	0.000		(0.000)					
	(0.000)		(0.000)					
Interaction Effects								
Consistency x Comp. Pressure	(0.001)		0.002					
	(0.001)		(0.004)					
Consistency^2 x Comp. Pressure (**H8**)	0.001		(0.003)					
	(0.002)		(0.005)					
Control Variables	*Same as pooled panel models, with individual action controls*							
LR test – Add H7 and H8 (df)	29.6 (4)	***	18.18(4)	**				
n	88		88		88		88	
R^2	-.57	***	-1.93	***	.505	***	.395	***
Correlations between residuals	*MS*		*ROA*		*Complexity*		*Consistency*	
MS								
ROA	.37							
Consistency	(.45)		(.30)					
Complexity	.33		.49		.26			

Repertoire variables predicted in first stage, with non-overlapping variables used as instruments. For ROA, the hypothesis of weak instruments is rejected for both the main effects and interaction terms (F(13,66)={3.23–5.42, p <.01). The Wu-Hausman test is marginal (F(4,68)=2.32, p < .10).

TABLE 8
Summary of Results

DV:	Consistency	Complexity	MS	ROA	ROA	Multiple	ROA	MS	Multiple	Multiple
Method:	OLS	OLS	OLS / DPD	OLS / DPD	OLS / DPD	OLS	FE	FE	3SLS	3SLS
Independent Variables:	Avg, SD Tenure, Interactions	Avg, SD Tenure, Interactions	Consistency, Complexity, Interactions	Consistency, Complexity, Interactions	Consistency, Complexity, Interactions	Focal and Outside Ind. Experience	Consistency, Complexity	Consistency, Complexity	Avg, SD Tenure, Interactions	Avg, SD Tenure, Interactions
Endogenous Variables:									Consistency, Complexity	Consistency, Complexity
Hypothesis	**Model 1**	**Model 2**	**Model 3a-l**	**Model 3m-x**	**Model 4a-l**	**Model 5**	**Model 6a-c**	**Models 6d-f**	**Model 7A**	**Model 7B**
H1	Yes					Yes			Yes	Yes
H2		Yes				No			No	No
H3	No					Yes			Yes	Yes
H4		Opposite				Opposite			Opposite	No
H5			No, Marginal	Marginal, No	Yes, Yes		No	No		
H6			Yes, No	No, No	Marginal, No				No, Yes	
H7			No, Opposite	No, No	No, No		Yes	No		
H8			Marginal, Yes	Marginal, Marginal	Marginal, No					Opposite, Yes

Notes

For models 3a-x, results reported related to the pooled panel model, and the dynamic panel model, respectively.
For models 4a-l, additional observations were incorporated for firm-years where no actions were observed, but actions were observable (i.e., these firm-year observations occur in periods between available observations and where performance data is available.
For models 7A and 7B, the reported support for H6 and H8 relate to market share and return on assets, respectively. Support for the interaction based on a likelihood ratio test for both coefficients simultaneously, thus support is listed for the interaction hypotheses (H6, H8) only.
In model 7B, the market share results are significant but the second order term is of the opposite sign.
Effects are only considered to be significant if: for Models 1 – 6, the Wald test of their individual coefficient is significant at $p < .05$ or less, and for Models 7AB, if the likelihood ratio test is significant at $p < .05$ or less. To aid the reader, while not considered significant, effects with $p < .10$ are labeled as ‘marginal’. Significant effects of opposite sign (at $p < .10$ or less) are labeled ‘opposite’.

APPENDICES

APPENDIX A – Sampling Frame

ID	Company Name	Year	Actions (> 1 / year)	TMT	ROA	TMT-Action	Action-MS	Action-Perf.	Full Model
Count			**273**	**303**	**221**	**195**	**210**	**192**	**165**
1	3D Systems	1988	x	x		Y	Y	N	N
97	3D Systems	1989	x	x		Y	Y	N	N
193	3D Systems	1990	x	x		Y	Y	N	N
289	3D Systems	1991	x	x	x	Y	Y	Y	Y
385	3D Systems	1992	x	x	x	Y	Y	Y	Y
481	3D Systems	1993	x	x	x	Y	Y	Y	Y
577	3D Systems	1994	x	x	x	Y	Y	Y	Y
673	3D Systems	1995	x	x	x	Y	Y	Y	Y
769	3D Systems	1996	x	x	x	Y	Y	Y	Y
865	3D Systems	1997	x	x	x	Y	Y	Y	Y
961	3D Systems	1998	x	x	x	Y	Y	Y	Y
1057	3D Systems	1999	x	x	x	Y	Y	Y	Y
1153	3D Systems	2000	x	x	x	Y	Y	Y	Y
1249	3D Systems	2001	x	x	x	Y	Y	Y	Y
1345	3D Systems	2002	x	x	x	Y	Y	Y	Y
1441	3D Systems	2003	x	x	x	Y	Y	Y	Y
1537	3D Systems	2004	x	x	x	Y	Y	Y	Y
1633	3D Systems	2005	x	x	x	Y	Y	Y	Y
1729	3D Systems	2006	x	x	x	Y	Y	Y	Y
1825	3D Systems	2007	x	x	x	Y	Y	Y	Y
1921	3D Systems	2008	x	x	x	Y	Y	Y	Y
2017	3D Systems	2009	x	x	x	Y	Y	Y	Y
2113	3D Systems	2010	x	x	x	Y	Y	Y	Y
2209	3D Systems	2011	x	x	x	Y	Y	Y	Y
2305	3D Systems	2012	x	x	x	Y	Y	Y	Y
2401	3D Systems	2013	x	x	x	Y	Y	Y	Y
2497	3D Systems	2014	x	x	x	Y	Y	Y	Y
2593	3D Systems	2015	x	x	x	Y	Y	Y	Y
2498	3DCeram	2014				N	N	N	N
2594	3DCeram	2015				N	N	N	N
1827	Accufusion	2007				N	N	N	N
1923	Accufusion	2008				N	N	N	N
2019	Accufusion	2009				N	N	N	N
2596	Additive Industries	2015				N	N	N	N
2597	Alkimat	2015				N	N	N	N
2502	Arburg	2014				N	N	N	N
2598	Arburg	2015				N	N	N	N
1255	Arcam	2001	x	x	x	Y	Y	Y	Y
1351	Arcam	2002	x	x	x	Y	Y	Y	Y
1447	Arcam	2003	x	x	x	Y	Y	Y	Y
1543	Arcam	2004	x	x	x	Y	Y	Y	Y
1639	Arcam	2005	x	x	x	Y	Y	Y	Y
1735	Arcam	2006	x	x	x	Y	Y	Y	Y
1831	Arcam	2007	x	x	x	Y	Y	Y	Y
1927	Arcam	2008	x	x	x	Y	Y	Y	Y
2023	Arcam	2009	x	x	x	Y	Y	Y	Y
2119	Arcam	2010	x	x	x	Y	Y	Y	Y
2215	Arcam	2011	x	x	x	Y	Y	Y	Y
2311	Arcam	2012	x	x	x	Y	Y	Y	Y
2407	Arcam	2013	x	x	x	Y	Y	Y	Y
2503	Arcam	2014	x	x	x	Y	Y	Y	Y
2599	Arcam	2015	x	x	x	Y	Y	Y	Y
2312	Asiga	2012				N	N	N	N
2408	Asiga	2013				N	N	N	N
2504	Asiga	2014				N	N	N	N
2600	Asiga	2015				N	N	N	N
1737	Aspect	2006				N	N	N	N
1833	Aspect	2007				N	N	N	N
1929	Aspect	2008				N	N	N	N
2025	Aspect	2009				N	N	N	N
2121	Aspect	2010				N	N	N	N

2217	Aspect	2011	N	N	N	N
2313	Aspect	2012	N	N	N	N
2409	Aspect	2013	N	N	N	N
2505	Aspect	2014	N	N	N	N
2601	Aspect	2015	N	N	N	N
970	Autostrade	1998	N	N	N	N
1066	Autostrade	1999	N	N	N	N
1162	Autostrade	2000	N	N	N	N
1258	Autostrade	2001	N	N	N	N
1354	Autostrade	2002	N	N	N	N
1450	Autostrade	2003	N	N	N	N
1546	Autostrade	2004	N	N	N	N
1642	Autostrade	2005	N	N	N	N
1738	Autostrade	2006	N	N	N	N
1834	Autostrade	2007	N	N	N	N
1930	Autostrade	2008	N	N	N	N
2027	BeAM	2009	N	N	N	N
2123	BeAM	2010	N	N	N	N
2219	BeAM	2011	N	N	N	N
2315	BeAM	2012	N	N	N	N
2411	BeAM	2013	N	N	N	N
2507	BeAM	2014	N	N	N	N
2603	BeAM	2015	N	N	N	N
2604	Beijing EPlus 3D	2015	N	N	N	N
781	Beijing Long Yuan	1996	N	N	N	N
877	Beijing Long Yuan	1997	N	N	N	N
973	Beijing Long Yuan	1998	N	N	N	N
1069	Beijing Long Yuan	1999	N	N	N	N
1165	Beijing Long Yuan	2000	N	N	N	N
1261	Beijing Long Yuan	2001	N	N	N	N
1357	Beijing Long Yuan	2002	N	N	N	N
1453	Beijing Long Yuan	2003	N	N	N	N
1549	Beijing Long Yuan	2004	N	N	N	N
1645	Beijing Long Yuan	2005	N	N	N	N
1741	Beijing Long Yuan	2006	N	N	N	N
1837	Beijing Long Yuan	2007	N	N	N	N
1933	Beijing Long Yuan	2008	N	N	N	N
2029	Beijing Long Yuan	2009	N	N	N	N
2125	Beijing Long Yuan	2010	N	N	N	N
2221	Beijing Long Yuan	2011	N	N	N	N
2317	Beijing Long Yuan	2012	N	N	N	N
2413	Beijing Long Yuan	2013	N	N	N	N
2509	Beijing Long Yuan	2014	N	N	N	N
2605	Beijing Long Yuan	2015	N	N	N	N
782	Beijing Tiertime	1996	N	N	N	N
878	Beijing Tiertime	1997	N	N	N	N
974	Beijing Tiertime	1998	N	N	N	N
1070	Beijing Tiertime	1999	N	N	N	N
1166	Beijing Tiertime	2000	N	N	N	N
1262	Beijing Tiertime	2001	N	N	N	N
1358	Beijing Tiertime	2002	N	N	N	N
1454	Beijing Tiertime	2003	N	N	N	N
1550	Beijing Tiertime	2004	N	N	N	N
1646	Beijing Tiertime	2005	N	N	N	N
1742	Beijing Tiertime	2006	N	N	N	N
1838	Beijing Tiertime	2007	N	N	N	N
1934	Beijing Tiertime	2008	N	N	N	N
2030	Beijing Tiertime	2009	N	N	N	N
2126	Beijing Tiertime	2010	N	N	N	N
2222	Beijing Tiertime	2011	N	N	N	N
2318	Beijing Tiertime	2012	N	N	N	N
2414	Beijing Tiertime	2013	N	N	N	N
2510	Beijing Tiertime	2014	N	N	N	N
2606	Beijing Tiertime	2015	N	N	N	N
2415	BigRep	2013	N	N	N	N
2511	BigRep	2014	N	N	N	N
2607	BigRep	2015	N	N	N	N
2416	Blueprinter	2013	N	N	N	N
2512	Blueprinter	2014	N	N	N	N
2608	Blueprinter	2015	N	N	N	N

2033	Carima	2009				N	N	N	N
2129	Carima	2010				N	N	N	N
2225	Carima	2011				N	N	N	N
2321	Carima	2012				N	N	N	N
2417	Carima	2013				N	N	N	N
2513	Carima	2014				N	N	N	N
2609	Carima	2015				N	N	N	N
1458	Chubunippon	2003				N	N	N	N
1554	Chubunippon	2004				N	N	N	N
1650	Chubunippon	2005				N	N	N	N
1746	Chubunippon	2006				N	N	N	N
1842	Chubunippon	2007				N	N	N	N
1938	Chubunippon	2008				N	N	N	N
403	CMET	1992				N	N	N	N
499	CMET	1993				N	N	N	N
595	CMET	1994				N	N	N	N
691	CMET	1995				N	N	N	N
787	CMET	1996				N	N	N	N
883	CMET	1997				N	N	N	N
979	CMET	1998				N	N	N	N
1075	CMET	1999				N	N	N	N
1171	CMET	2000				N	N	N	N
1267	CMET	2001				N	N	N	N
1363	CMET	2002				N	N	N	N
1459	CMET	2003				N	N	N	N
1555	CMET	2004				N	N	N	N
1651	CMET	2005				N	N	N	N
1747	CMET	2006		x		N	N	N	N
1843	CMET	2007		x		N	N	N	N
1939	CMET	2008		x		N	N	N	N
2035	CMET	2009		x		N	N	N	N
2131	CMET	2010		x		N	N	N	N
2227	CMET	2011	x	x	x	Y	Y	Y	Y
2323	CMET	2012	x	x	x	Y	Y	Y	Y
2419	CMET	2013	x	x	x	Y	Y	Y	Y
2515	CMET	2014	x	x	x	Y	Y	Y	Y
2611	CMET	2015	x	x	x	Y	Y	Y	Y
2715	CMET	2015	x			N	Y	N	N
1364	Concept Laser	2002		x		N	N	N	N
1460	Concept Laser	2003		x		N	N	N	N
1556	Concept Laser	2004	x	x		Y	Y	N	N
1652	Concept Laser	2005	x	x		Y	Y	N	N
1748	Concept Laser	2006		x		N	N	N	N
1844	Concept Laser	2007	x	x		Y	Y	N	N
1940	Concept Laser	2008	x	x		Y	Y	N	N
2036	Concept Laser	2009	x	x	x	Y	Y	Y	Y
2132	Concept Laser	2010	x	x	x	Y	Y	Y	Y
2228	Concept Laser	2011	x	x	x	Y	Y	Y	Y
2324	Concept Laser	2012	x	x	x	Y	Y	Y	Y
2420	Concept Laser	2013	x	x	x	Y	Y	Y	Y
2516	Concept Laser	2014	x	x	x	Y	Y	Y	Y
2612	Concept Laser	2015	x	x		Y	Y	N	N
1269	Cubic Technologies	2001				N	N	N	N
1365	Cubic Technologies	2002				N	N	N	N
1461	Cubic Technologies	2003				N	N	N	N
1557	Cubic Technologies	2004				N	N	N	N
1653	Cubic Technologies	2005				N	N	N	N
1749	Cubic Technologies	2006				N	N	N	N
1845	Cubic Technologies	2007				N	N	N	N
310	Cubital	1991				N	N	N	N
406	Cubital	1992				N	N	N	N
502	Cubital	1993				N	N	N	N
598	Cubital	1994				N	N	N	N
694	Cubital	1995				N	N	N	N
790	Cubital	1996				N	N	N	N
886	Cubital	1997				N	N	N	N
982	Cubital	1998				N	N	N	N
407	Denken	1992				N	N	N	N
503	Denken	1993				N	N	N	N
599	Denken	1994				N	N	N	N

695	Denken	1995				N	N	N	N
791	Denken	1996				N	N	N	N
887	Denken	1997				N	N	N	N
983	Denken	1998				N	N	N	N
1079	Denken	1999				N	N	N	N
1175	Denken	2000				N	N	N	N
1271	Denken	2001				N	N	N	N
1367	Denken	2002				N	N	N	N
1463	Denken	2003				N	N	N	N
1559	Denken	2004				N	N	N	N
1655	Denken	2005				N	N	N	N
1751	Denken	2006				N	N	N	N
1847	Denken	2007				N	N	N	N
1943	Denken	2008				N	N	N	N
120	D-MEC	1989				N	N	N	N
216	D-MEC	1990			x	N	N	N	N
312	D-MEC	1991			x	N	N	N	N
408	D-MEC	1992			x	N	N	N	N
504	D-MEC	1993			x	N	N	N	N
600	D-MEC	1994			x	N	N	N	N
696	D-MEC	1995			x	N	N	N	N
792	D-MEC	1996			x	N	N	N	N
888	D-MEC	1997			x	N	N	N	N
984	D-MEC	1998			x	N	N	N	N
1080	D-MEC	1999			x	N	N	N	N
1176	D-MEC	2000			x	N	N	N	N
1272	D-MEC	2001			x	N	N	N	N
1368	D-MEC	2002			x	N	N	N	N
1464	D-MEC	2003			x	N	N	N	N
1560	D-MEC	2004			x	N	N	N	N
1656	D-MEC	2005			x	N	N	N	N
1752	D-MEC	2006			x	N	N	N	N
1848	D-MEC	2007			x	N	N	N	N
1944	D-MEC	2008			x	N	N	N	N
2040	D-MEC	2009			x	N	N	N	N
2136	D-MEC	2010			x	N	N	N	N
2232	D-MEC	2011	x	x	x	Y	Y	Y	Y
2328	D-MEC	2012	x	x	x	Y	Y	Y	Y
2424	D-MEC	2013	x	x	x	Y	Y	Y	Y
2520	D-MEC	2014	x	x	x	Y	Y	Y	Y
2616	D-MEC	2015	x	x	x	Y	Y	Y	Y
2521	DMG Mori Seiki	2014				N	N	N	N
2617	DMG Mori Seiki	2015				N	N	N	N
2522	DO3D	2014				N	N	N	N
2618	DO3D	2015				N	N	N	N
411	DTM	1992	x	x	x	Y	Y	Y	Y
507	DTM	1993	x	x	x	Y	Y	Y	Y
603	DTM	1994	x	x	x	Y	Y	Y	Y
699	DTM	1995	x	x	x	Y	Y	Y	Y
795	DTM	1996	x	x	x	Y	Y	Y	Y
891	DTM	1997	x	x	x	Y	Y	Y	Y
987	DTM	1998	x	x	x	Y	Y	Y	Y
1083	DTM	1999	x	x	x	Y	Y	Y	Y
1179	DTM	2000	x	x	x	Y	Y	Y	Y
1275	DTM	2001	x			N	Y	N	N
1660	DWS	2005				N	N	N	N
1756	DWS	2006				N	N	N	N
1852	DWS	2007				N	N	N	N
1948	DWS	2008				N	N	N	N
2044	DWS	2009				N	N	N	N
2140	DWS	2010				N	N	N	N
2236	DWS	2011			x	N	N	N	N
2332	DWS	2012			x	N	N	N	N
2428	DWS	2013			x	N	N	N	N
2524	DWS	2014	x			N	Y	N	N
2620	DWS	2015	x			N	Y	N	N
1373	Envisiontec	2002		x		N	N	N	N
1469	Envisiontec	2003	x	x		Y	Y	N	N
1565	Envisiontec	2004	x	x		Y	Y	N	N
1661	Envisiontec	2005	x	x		Y	Y	N	N

1757	Envisiontec	2006	x	x	x	Y	Y	Y	Y
1853	Envisiontec	2007	x	x	x	Y	Y	Y	Y
1949	Envisiontec	2008	x	x	x	Y	Y	Y	Y
2045	Envisiontec	2009	x	x	x	Y	Y	Y	Y
2141	Envisiontec	2010	x	x	x	Y	Y	Y	Y
2237	Envisiontec	2011	x	x	x	Y	Y	Y	Y
2333	Envisiontec	2012	x	x	x	Y	Y	Y	Y
2429	Envisiontec	2013	x	x	x	Y	Y	Y	Y
2525	Envisiontec	2014	x	x	x	Y	Y	Y	Y
2621	Envisiontec	2015	x	x	x	Y	Y	Y	Y
222	EOS	1990		x		N	N	N	N
318	EOS	1991		x		N	N	N	N
414	EOS	1992		x		N	N	N	N
510	EOS	1993		x		N	N	N	N
606	EOS	1994		x		N	N	N	N
702	EOS	1995		x		N	N	N	N
798	EOS	1996		x		N	N	N	N
894	EOS	1997		x		N	N	N	N
990	EOS	1998		x		N	N	N	N
1086	EOS	1999		x		N	N	N	N
1182	EOS	2000		x		N	N	N	N
1278	EOS	2001		x		N	N	N	N
1374	EOS	2002		x		N	N	N	N
1470	EOS	2003		x		N	N	N	N
1566	EOS	2004		x		N	N	N	N
1662	EOS	2005	x	x		Y	Y	N	N
1758	EOS	2006	x	x		Y	Y	N	N
1854	EOS	2007	x	x		Y	Y	N	N
1950	EOS	2008	x	x	x	Y	Y	Y	Y
2046	EOS	2009	x	x	x	Y	Y	Y	Y
2142	EOS	2010	x	x	x	Y	Y	Y	Y
2238	EOS	2011	x	x	x	Y	Y	Y	Y
2334	EOS	2012	x	x	x	Y	Y	Y	Y
2430	EOS	2013	x	x	x	Y	Y	Y	Y
2526	EOS	2014	x	x	x	Y	Y	Y	Y
2622	EOS	2015	x	x	x	Y	Y	Y	Y
1279	ExOne	2001				N	N	N	N
1375	ExOne	2002				N	N	N	N
1471	ExOne	2003				N	N	N	N
2335	ExOne	2012	x	x	x	Y	Y	Y	Y
2431	ExOne	2013	x	x	x	Y	Y	Y	Y
1567	ExOne	2004				N	N	N	N
2527	ExOne	2014	x	x	x	Y	Y	Y	Y
2623	ExOne	2015	x	x	x	Y	Y	Y	Y
1663	ExOne	2005				N	N	N	N
1759	ExOne	2006				N	N	N	N
1855	ExOne	2007				N	N	N	N
1951	ExOne	2008				N	N	N	N
2047	ExOne	2009				N	N	N	N
2143	ExOne	2010			x	N	N	N	N
2239	ExOne	2011			x	N	N	N	N
608	F&S GmbH	1994				N	N	N	N
704	F&S GmbH	1995				N	N	N	N
800	F&S GmbH	1996				N	N	N	N
896	F&S GmbH	1997				N	N	N	N
992	F&S GmbH	1998				N	N	N	N
1088	F&S GmbH	1999				N	N	N	N
1184	F&S GmbH	2000				N	N	N	N
1280	F&S GmbH	2001				N	N	N	N
1376	F&S GmbH	2002				N	N	N	N
1472	F&S GmbH	2003				N	N	N	N
2241	Fabrisonic	2011				N	N	N	N
2337	Fabrisonic	2012				N	N	N	N
2433	Fabrisonic	2013				N	N	N	N
2529	Fabrisonic	2014				N	N	N	N
2625	Fabrisonic	2015				N	N	N	N
1378	Generis	2002				N	N	N	N
1474	Generis	2003				N	N	N	N
2627	German RepRap	2015	x	x	x	Y	Y	Y	Y
420	Helisys	1992		x		N	N	N	N

516	Helisys	1993		x		N	N	N	N
612	Helisys	1994		x		N	N	N	N
708	Helisys	1995	x	x	x	Y	Y	Y	Y
804	Helisys	1996	x	x	x	Y	Y	Y	Y
900	Helisys	1997	x	x	x	Y	Y	Y	Y
996	Helisys	1998	x	x	x	Y	Y	Y	Y
1092	Helisys	1999	x	x	x	Y	Y	Y	Y
1188	Helisys	2000	x	x		Y	Y	N	N
2341	Hunan Farsoon	2012				N	N	N	N
2437	Hunan Farsoon	2013				N	N	N	N
2533	Hunan Farsoon	2014				N	N	N	N
2629	Hunan Farsoon	2015				N	N	N	N
2054	Huntsman	2009				N	N	N	N
2150	Huntsman	2010				N	N	N	N
2631	Indmatec	2015				N	N	N	N
2344	Innovation MediTech	2012				N	N	N	N
2440	Innovation MediTech	2013				N	N	N	N
2249	InssTek	2011				N	N	N	N
2345	InssTek	2012				N	N	N	N
2441	InssTek	2013				N	N	N	N
2537	InssTek	2014				N	N	N	N
2633	InssTek	2015				N	N	N	N
2346	Keyence	2012				N	N	N	N
2442	Keyence	2013				N	N	N	N
2538	Keyence	2014				N	N	N	N
2634	Keyence	2015				N	N	N	N
715	Kinergy	1995				N	N	N	N
811	Kinergy	1996				N	N	N	N
907	Kinergy	1997				N	N	N	N
1003	Kinergy	1998				N	N	N	N
1099	Kinergy	1999				N	N	N	N
1195	Kinergy	2000				N	N	N	N
1291	Kinergy	2001				N	N	N	N
1387	Kinergy	2002				N	N	N	N
1483	Kinergy	2003				N	N	N	N
620	Kira	1994				N	N	N	N
716	Kira	1995				N	N	N	N
812	Kira	1996				N	N	N	N
908	Kira	1997				N	N	N	N
1004	Kira	1998				N	N	N	N
1100	Kira	1999				N	N	N	N
1196	Kira	2000				N	N	N	N
1292	Kira	2001				N	N	N	N
1388	Kira	2002				N	N	N	N
1484	Kira	2003				N	N	N	N
1580	Kira	2004				N	N	N	N
1676	Kira	2005				N	N	N	N
1772	Kira	2006				N	N	N	N
1868	Kira	2007				N	N	N	N
1964	Kira	2008				N	N	N	N
2060	Kira	2009				N	N	N	N
2156	Kira	2010				N	N	N	N
2253	Lithoz	2011				N	N	N	N
2349	Lithoz	2012				N	N	N	N
2445	Lithoz	2013				N	N	N	N
2541	Lithoz	2014				N	N	N	N
2637	Lithoz	2015				N	N	N	N
2542	MarkForged	2014				N	N	N	N
2638	MarkForged	2015				N	N	N	N
2351	Matsuura	2012				N	N	N	N
2447	Matsuura	2013				N	N	N	N
2543	Matsuura	2014				N	N	N	N
2639	Matsuura	2015				N	N	N	N
1968	Mcor	2008				N	N	N	N
2064	Mcor	2009				N	N	N	N
2160	Mcor	2010				N	N	N	N
2256	Mcor	2011				N	N	N	N
2352	Mcor	2012				N	N	N	N

2448	Mcor	2013				N	N	N	N
2544	Mcor	2014				N	N	N	N
2640	Mcor	2015				N	N	N	N
625	Meiko	1994				N	N	N	N
721	Meiko	1995				N	N	N	N
817	Meiko	1996				N	N	N	N
913	Meiko	1997				N	N	N	N
1009	Meiko	1998				N	N	N	N
1105	Meiko	1999				N	N	N	N
1201	Meiko	2000				N	N	N	N
1297	Meiko	2001				N	N	N	N
1393	Meiko	2002				N	N	N	N
1489	Meiko	2003				N	N	N	N
1585	Meiko	2004				N	N	N	N
1681	Meiko	2005				N	N	N	N
1777	Meiko	2006				N	N	N	N
1394	Menix	2002				N	N	N	N
1490	Menix	2003				N	N	N	N
1586	Menix	2004				N	N	N	N
1682	Menix	2005				N	N	N	N
1778	Menix	2006				N	N	N	N
1874	Menix	2007				N	N	N	N
1970	Menix	2008				N	N	N	N
627	MTT Technologies	1994		x		N	N	N	N
723	MTT Technologies	1995		x		N	N	N	N
819	MTT Technologies	1996		x		N	N	N	N
915	MTT Technologies	1997		x		N	N	N	N
1011	MTT Technologies	1998		x		N	N	N	N
1107	MTT Technologies	1999		x		N	N	N	N
1203	MTT Technologies	2000	x	x	x	Y	Y	Y	Y
1299	MTT Technologies	2001	x	x	x	Y	Y	Y	Y
1395	MTT Technologies	2002	x	x	x	Y	Y	Y	Y
1491	MTT Technologies	2003	x	x	x	Y	Y	Y	Y
1587	MTT Technologies	2004	x	x	x	Y	Y	Y	Y
1683	MTT Technologies	2005	x	x	x	Y	Y	Y	Y
1779	MTT Technologies	2006	x	x	x	Y	Y	Y	Y
1875	MTT Technologies	2007	x	x	x	Y	Y	Y	Y
1971	MTT Technologies	2008	x	x	x	Y	Y	Y	Y
2067	MTT Technologies	2009	x	x	x	Y	Y	Y	Y
2163	MTT Technologies	2010	x	x	x	Y	Y	Y	Y
1972	Nanoscribe	2008				N	N	N	N
2068	Nanoscribe	2009				N	N	N	N
2164	Nanoscribe	2010				N	N	N	N
2260	Nanoscribe	2011				N	N	N	N
2356	Nanoscribe	2012				N	N	N	N
2452	Nanoscribe	2013				N	N	N	N
2548	Nanoscribe	2014				N	N	N	N
2644	Nanoscribe	2015				N	N	N	N
53	NTT Data CMET	1988				N	N	N	N
149	NTT Data CMET	1989				N	N	N	N
245	NTT Data CMET	1990				N	N	N	N
341	NTT Data CMET	1991				N	N	N	N
437	NTT Data CMET	1992				N	N	N	N
533	NTT Data CMET	1993				N	N	N	N
629	NTT Data CMET	1994				N	N	N	N
725	NTT Data CMET	1995				N	N	N	N
821	NTT Data CMET	1996				N	N	N	N
917	NTT Data CMET	1997				N	N	N	N
1013	NTT Data CMET	1998				N	N	N	N
1109	NTT Data CMET	1999				N	N	N	N
1205	NTT Data CMET	2000				N	N	N	N
1206	Objet	2000		x		N	N	N	N
1302	Objet	2001		x		N	N	N	N
1398	Objet	2002		x		N	N	N	N
1494	Objet	2003		x		N	N	N	N
1590	Objet	2004		x		N	N	N	N
1686	Objet	2005		x		N	N	N	N
1782	Objet	2006		x		N	N	N	N
1878	Objet	2007	x	x	x	Y	Y	Y	Y
1974	Objet	2008	x	x	x	Y	Y	Y	Y

2070	Objet	2009	x	x	x	Y	Y	Y	Y
2166	Objet	2010	x	x	x	Y	Y	Y	Y
2262	Objet	2011	x	x	x	Y	Y	Y	Y
2358	Objet	2012	x			N	Y	N	N
2551	OPM Lab	2014				N	N	N	N
2647	OPM Lab	2015				N	N	N	N
1016	Optomec	1998				N	N	N	N
1112	Optomec	1999		x		N	N	N	N
1208	Optomec	2000		x		N	N	N	N
1304	Optomec	2001		x		N	N	N	N
1400	Optomec	2002		x		N	N	N	N
1496	Optomec	2003		x		N	N	N	N
1592	Optomec	2004		x		N	N	N	N
1688	Optomec	2005		x		N	N	N	N
1784	Optomec	2006		x		N	N	N	N
1880	Optomec	2007		x		N	N	N	N
1976	Optomec	2008	x	x		Y	Y	N	N
2072	Optomec	2009	x	x		Y	Y	N	N
2168	Optomec	2010	x	x		Y	Y	N	N
2264	Optomec	2011	x	x		Y	Y	N	N
2360	Optomec	2012	x	x		Y	Y	N	N
2456	Optomec	2013	x	x	x	Y	Y	Y	Y
2552	Optomec	2014	x	x	x	Y	Y	Y	Y
2648	Optomec	2015	x	x	x	Y	Y	Y	Y
345	Other	1991				N	N	N	N
441	Other	1992				N	N	N	N
537	Other	1993				N	N	N	N
633	Other	1994				N	N	N	N
729	Other	1995				N	N	N	N
825	Other	1996				N	N	N	N
921	Other	1997				N	N	N	N
1017	Other	1998				N	N	N	N
1113	Other	1999				N	N	N	N
1209	Other	2000				N	N	N	N
1305	Other	2001				N	N	N	N
1401	Other	2002				N	N	N	N
1402	Phenix Systems	2002				N	N	N	N
1498	Phenix Systems	2003				N	N	N	N
1594	Phenix Systems	2004				N	N	N	N
1690	Phenix Systems	2005				N	N	N	N
1786	Phenix Systems	2006				N	N	N	N
1882	Phenix Systems	2007				N	N	N	N
1978	Phenix Systems	2008				N	N	N	N
2074	Phenix Systems	2009				N	N	N	N
2170	Phenix Systems	2010				N	N	N	N
2266	Phenix Systems	2011			x	N	N	N	N
2362	Phenix Systems	2012	x		x	N	Y	Y	N
2458	Phenix Systems	2013	x		x	N	Y	Y	N
1499	POM	2003				N	N	N	N
1595	POM	2004				N	N	N	N
1691	POM	2005				N	N	N	N
1787	POM	2006				N	N	N	N
1883	POM	2007				N	N	N	N
1979	POM	2008				N	N	N	N
2075	POM	2009				N	N	N	N
2171	POM	2010				N	N	N	N
2172	Prodways	2010				N	N	N	N
2268	Prodways	2011				N	N	N	N
2364	Prodways	2012				N	N	N	N
2460	Prodways	2013				N	N	N	N
2556	Prodways	2014				N	N	N	N
2652	Prodways	2015				N	N	N	N
2269	Rapid Shape	2011				N	N	N	N
2365	Rapid Shape	2012				N	N	N	N
2461	Rapid Shape	2013				N	N	N	N
2557	Rapid Shape	2014				N	N	N	N
2653	Rapid Shape	2015				N	N	N	N
2078	ReaLizer	2009				N	N	N	N
2174	ReaLizer	2010				N	N	N	N
2270	ReaLizer	2011				N	N	N	N

2366	ReaLizer	2012				N	N	N	N
2462	ReaLizer	2013				N	N	N	N
2558	ReaLizer	2014				N	N	N	N
2654	ReaLizer	2015				N	N	N	N
2271	Renishaw	2011	x	x	x	Y	Y	Y	Y
2367	Renishaw	2012	x	x	x	Y	Y	Y	Y
2463	Renishaw	2013	x	x	x	Y	Y	Y	Y
2559	Renishaw	2014	x	x	x	Y	Y	Y	Y
2655	Renishaw	2015	x	x	x	Y	Y	Y	Y
1120	Röders	1999				N	N	N	N
2657	Rokit	2015				N	N	N	N
2562	Roland DG	2014	x	x	x	Y	Y	Y	Y
2658	Roland DG	2015	x	x	x	Y	Y	Y	Y
2659	RPMI	2015				N	N	N	N
1316	Sanders Design Int'l	2001				N	N	N	N
1412	Sanders Design Int'l	2002				N	N	N	N
1508	Sanders Design Int'l	2003				N	N	N	N
1604	Sanders Design Int'l	2004				N	N	N	N
837	Schroff	1996				N	N	N	N
933	Schroff	1997				N	N	N	N
1029	Schroff	1998				N	N	N	N
1125	Schroff	1999				N	N	N	N
1221	Schroff	2000				N	N	N	N
1317	Schroff	2001				N	N	N	N
2278	Sciaky	2011				N	N	N	N
2374	Sciaky	2012				N	N	N	N
2470	Sciaky	2013				N	N	N	N
2566	Sciaky	2014				N	N	N	N
2662	Sciaky	2015				N	N	N	N
2663	Sentrol	2015				N	N	N	N
936	Shaanxi Hengtong	1997				N	N	N	N
1032	Shaanxi Hengtong	1998				N	N	N	N
1128	Shaanxi Hengtong	1999				N	N	N	N
1224	Shaanxi Hengtong	2000				N	N	N	N
1320	Shaanxi Hengtong	2001				N	N	N	N
1416	Shaanxi Hengtong	2002				N	N	N	N
1512	Shaanxi Hengtong	2003				N	N	N	N
1608	Shaanxi Hengtong	2004				N	N	N	N
1704	Shaanxi Hengtong	2005				N	N	N	N
1800	Shaanxi Hengtong	2006				N	N	N	N
1896	Shaanxi Hengtong	2007				N	N	N	N
1992	Shaanxi Hengtong	2008				N	N	N	N
2088	Shaanxi Hengtong	2009				N	N	N	N
2184	Shaanxi Hengtong	2010				N	N	N	N
2280	Shaanxi Hengtong	2011				N	N	N	N
2376	Shaanxi Hengtong	2012				N	N	N	N
2472	Shaanxi Hengtong	2013				N	N	N	N
2568	Shaanxi Hengtong	2014				N	N	N	N
2664	Shaanxi Hengtong	2015				N	N	N	N
1321	Shanghai Union	2001				N	N	N	N
1417	Shanghai Union	2002				N	N	N	N
1513	Shanghai Union	2003				N	N	N	N
1609	Shanghai Union	2004				N	N	N	N
1705	Shanghai Union	2005				N	N	N	N
1801	Shanghai Union	2006				N	N	N	N
1897	Shanghai Union	2007				N	N	N	N
1993	Shanghai Union	2008				N	N	N	N
2089	Shanghai Union	2009				N	N	N	N
2185	Shanghai Union	2010				N	N	N	N
2281	Shanghai Union	2011				N	N	N	N
2377	Shanghai Union	2012				N	N	N	N
2473	Shanghai Union	2013				N	N	N	N
2569	Shanghai Union	2014				N	N	N	N
2665	Shanghai Union	2015				N	N	N	N
2666	Sharebot	2015				N	N	N	N
2667	Sinterit	2015				N	N	N	N
1804	Sintermask	2006				N	N	N	N
1900	Sintermask	2007				N	N	N	N
1996	Sintermask	2008				N	N	N	N
2573	Sisma	2014				N	N	N	N

2669	Sisma	2015				N	N	N	N
2286	SLM Solutions	2011	x	x	x	Y	Y	Y	Y
2382	SLM Solutions	2012	x	x	x	Y	Y	Y	Y
2478	SLM Solutions	2013	x	x	x	Y	Y	Y	Y
2574	SLM Solutions	2014	x	x	x	Y	Y	Y	Y
2670	SLM Solutions	2015	x	x	x	Y	Y	Y	Y
1327	Solidica	2001				N	N	N	N
1423	Solidica	2002				N	N	N	N
1519	Solidica	2003				N	N	N	N
1615	Solidica	2004				N	N	N	N
1711	Solidica	2005				N	N	N	N
1807	Solidica	2006				N	N	N	N
1903	Solidica	2007				N	N	N	N
1999	Solidica	2008				N	N	N	N
2095	Solidica	2009				N	N	N	N
2191	Solidica	2010				N	N	N	N
1616	Solido	2004				N	N	N	N
1712	Solido	2005				N	N	N	N
1808	Solido	2006				N	N	N	N
1904	Solido	2007				N	N	N	N
2000	Solido	2008				N	N	N	N
2096	Solido	2009				N	N	N	N
2192	Solido	2010				N	N	N	N
657	Solidscape	1994				N	N	N	N
753	Solidscape	1995				N	N	N	N
849	Solidscape	1996				N	N	N	N
945	Solidscape	1997	x			N	Y	N	N
1041	Solidscape	1998				N	N	N	N
1137	Solidscape	1999				N	N	N	N
1233	Solidscape	2000	x			N	Y	N	N
1329	Solidscape	2001	x			N	Y	N	N
1425	Solidscape	2002				N	N	N	N
1521	Solidscape	2003				N	N	N	N
1617	Solidscape	2004				N	N	N	N
1713	Solidscape	2005				N	N	N	N
1809	Solidscape	2006				N	N	N	N
1905	Solidscape	2007				N	N	N	N
2001	Solidscape	2008				N	N	N	N
2097	Solidscape	2009	x			N	Y	N	N
2193	Solidscape	2010	x		x	N	Y	Y	N
2289	Solidscape	2011	x		x	N	Y	Y	N
2385	Solidscape	2012	x			N	Y	N	N
370	Stratasys	1991				N	N	N	N
466	Stratasys	1992				N	N	N	N
562	Stratasys	1993				N	N	N	N
658	Stratasys	1994	x	x	x	Y	Y	Y	Y
754	Stratasys	1995	x	x	x	Y	Y	Y	Y
850	Stratasys	1996	x	x	x	Y	Y	Y	Y
946	Stratasys	1997	x	x	x	Y	Y	Y	Y
1042	Stratasys	1998	x	x	x	Y	Y	Y	Y
1138	Stratasys	1999	x	x	x	Y	Y	Y	Y
1234	Stratasys	2000	x	x	x	Y	Y	Y	Y
1330	Stratasys	2001	x	x	x	Y	Y	Y	Y
1426	Stratasys	2002	x	x	x	Y	Y	Y	Y
1522	Stratasys	2003	x	x	x	Y	Y	Y	Y
1618	Stratasys	2004	x	x	x	Y	Y	Y	Y
1714	Stratasys	2005	x	x	x	Y	Y	Y	Y
1810	Stratasys	2006	x	x	x	Y	Y	Y	Y
1906	Stratasys	2007	x	x	x	Y	Y	Y	Y
2002	Stratasys	2008	x	x	x	Y	Y	Y	Y
2098	Stratasys	2009	x	x	x	Y	Y	Y	Y
2194	Stratasys	2010	x	x	x	Y	Y	Y	Y
2290	Stratasys	2011	x	x	x	Y	Y	Y	Y
2386	Stratasys	2012	x	x	x	Y	Y	Y	Y
2482	Stratasys	2013	x	x	x	Y	Y	Y	Y
2578	Stratasys	2014	x	x	x	Y	Y	Y	Y
2674	Stratasys	2015	x	x	x	Y	Y	Y	Y
2483	Stratasys Ltd.	2013				N	N	N	N
2676	Structo	2015				N	N	N	N
2677	Titan Robotics	2015				N	N	N	N

2390	Trump Precision	2012				N	N	N	N
2486	Trump Precision	2013				N	N	N	N
2582	Trump Precision	2014				N	N	N	N
2678	Trump Precision	2015				N	N	N	N
1623	Trumpf	2004	x			N	Y	N	N
1719	Trumpf	2005	x	x		Y	Y	N	N
1815	Trumpf	2006	x	x		Y	Y	N	N
1911	Trumpf	2007	x	x		Y	Y	N	N
2007	Trumpf	2008	x	x		Y	Y	N	N
2103	Trumpf	2009	x	x		Y	Y	N	N
2199	Trumpf	2010	x	x		Y	Y	N	N
2295	Trumpf	2011	x	x	x	Y	Y	Y	Y
2391	Trumpf	2012	x	x	x	Y	Y	Y	Y
2487	Trumpf	2013	x	x	x	Y	Y	Y	Y
2583	Trumpf	2014	x	x	x	Y	Y	Y	Y
2679	Trumpf	2015	x	x	x	Y	Y	Y	Y
760	Unirapid	1995				N	N	N	N
856	Unirapid	1996				N	N	N	N
952	Unirapid	1997				N	N	N	N
1048	Unirapid	1998				N	N	N	N
1144	Unirapid	1999				N	N	N	N
1240	Unirapid	2000				N	N	N	N
1336	Unirapid	2001				N	N	N	N
1432	Unirapid	2002				N	N	N	N
1528	Unirapid	2003				N	N	N	N
1624	Unirapid	2004				N	N	N	N
1720	Unirapid	2005				N	N	N	N
1816	Unirapid	2006				N	N	N	N
1912	Unirapid	2007				N	N	N	N
2008	Unirapid	2008				N	N	N	N
2104	Unirapid	2009				N	N	N	N
2200	Unirapid	2010				N	N	N	N
2681	Viridis3D	2015				N	N	N	N
1722	Voxeljet	2005		x		N	N	N	N
1818	Voxeljet	2006		x		N	N	N	N
1914	Voxeljet	2007		x		N	N	N	N
2010	Voxeljet	2008		x		N	N	N	N
2106	Voxeljet	2009		x		N	N	N	N
2202	Voxeljet	2010	x	x	x	Y	Y	Y	Y
2298	Voxeljet	2011	x	x	x	Y	Y	Y	Y
2394	Voxeljet	2012	x	x	x	Y	Y	Y	Y
2490	Voxeljet	2013	x	x	x	Y	Y	Y	Y
2586	Voxeljet	2014	x	x	x	Y	Y	Y	Y
2682	Voxeljet	2015	x	x	x	Y	Y	Y	Y
1435	Wuhan Binhu	2002				N	N	N	N
1531	Wuhan Binhu	2003				N	N	N	N
1627	Wuhan Binhu	2004				N	N	N	N
1723	Wuhan Binhu	2005				N	N	N	N
1819	Wuhan Binhu	2006				N	N	N	N
1915	Wuhan Binhu	2007				N	N	N	N
2011	Wuhan Binhu	2008				N	N	N	N
2107	Wuhan Binhu	2009				N	N	N	N
2203	Wuhan Binhu	2010				N	N	N	N
2299	Wuhan Binhu	2011				N	N	N	N
2395	Wuhan Binhu	2012				N	N	N	N
2491	Wuhan Binhu	2013				N	N	N	N
2588	Wuhan Huake	2014				N	N	N	N
2684	Wuhan Huake	2015				N	N	N	N
2589	Xery	2014				N	N	N	N
2685	Xery	2015				N	N	N	N
2590	Xi'an Bright Laser	2014				N	N	N	N
2686	Xi'an Bright Laser	2015				N	N	N	N
863	Z Corp.	1996		x		N	N	N	N
959	Z Corp.	1997		x		N	N	N	N
1055	Z Corp.	1998		x		N	N	N	N
1151	Z Corp.	1999		x		N	N	N	N
1247	Z Corp.	2000	x	x		Y	Y	N	N
1343	Z Corp.	2001	x	x		Y	Y	N	N
1439	Z Corp.	2002	x	x		Y	Y	N	N
1535	Z Corp.	2003	x	x		Y	Y	N	N

1631	Z Corp.	2004	x	x	x	Y	Y	Y	Y
1727	Z Corp.	2005	x	x	x	Y	Y	Y	Y
1823	Z Corp.	2006	x	x	x	Y	Y	Y	Y
1919	Z Corp.	2007	x	x	x	Y	Y	Y	Y
2015	Z Corp.	2008	x	x	x	Y	Y	Y	Y
2111	Z Corp.	2009	x	x	x	Y	Y	Y	Y
2207	Z Corp.	2010	x	x	x	Y	Y	Y	Y
2303	Z Corp.	2011	x	x	x	Y	Y	Y	Y

APPENDIX B - Power Analysis

Prior Study Sample Sizes and Variables

DV	Fox (2017)	Ferrier (2001)	Ndofor et al. (2011)	Bridoux et al. (2013)	Rindova et al. (2010)	Miller & Chen (1996)	Nadkarni et al. (2015)	Hambrick et al., (1996)	Derfus et al. (2008)
Perf.	155	224	147	172	262	126	1,186	156	281
Actions	148	224	239	N/A	262	126	1,186	139	N/A

A Priori and Post-Hoc Power Analysis[5,6,7]

…and ΔR^2 (r) equals…		If Sample Size is X% of the Wohler's report N… 25% N = 111	34% N = 155	50% N = 222	100% N = 444	150% N = 667
		… then Power equals				
$R^2 =$ 0.005	r = 0.07	0.11	0.11	0.18	0.32	0.45
0.01	0.10	0.18	0.23	0.32	0.56	0.73
0.02	0.14	0.32	0.42	0.56	0.85	0.95
0.03	0.17	0.45	0.58	0.74	0.95	0.99
0.04	0.20	0.56	0.71	0.86	0.99	0.99
0.05	0.23	0.67	0.81	0.92	0.99	0.99

Representative Study Correlations[8]

Independent Variable	Dependent Variable Performance	Volume	Complexity	Consistency
Volume	.15*, .15^, .22^^, .14^^ , .24(MS), -.13 (ROA)			
Complexity	.26*, .21', .13 (MS), .13 (ROA)	.18'', .35		N/A
Functional Diversity (Tenure Diversity)	-.10^, -.04, .04, .28 (MS), -.06 (ROA)	.07*, .07^, -.13**, .38	.03*, -.02`, .36	
Industry Tenure	.10**, -.06**, .13 (MS), .27 (ROA)	.04**,.12``, .08	.23	

* Ferrier (2001) – performance = MS gain; functional diversity is a composite; complexity = simplicity
** Hambrick et al. (1996) – performance = market share change, profit change; volume = action propensity
^ Nadkarni et al. (2015) – functional diversity is a composite; performance = ROS, ROA
^^ – Derfus et al. (2008) – performance = ROA, ROS
' Miller and Chen (1996) – complexity = concentration
'' Andrevski et al. (2013) – complexity = action variety
` Ferrier and Lyon (2004) – complexity = simplicity
`` Smith et al (1991) = volume = response likelihood; industry tenure = years of experience
Fox (2017)

5 Assumes 30 predictors. Used G-Power 3.1, linear multiple regression, post hoc setting (power given alpha, sample size, and effect size).
6 The sample size from the Wohler's Report information is calculated in Appendix A.
7 Achieved sample size is indicated in red..
8 I have coded also coded repertoire simplicity correlations as complexity.

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