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TOP MANAGEMENT TEAM EXPERIENTIAL VARIETY, COMPETITIVE REPERTOIRES, AND FIRM PERFORMANCE: EXAMINING THE LAW OF REQUISITE VARIETY IN THE 3D PRINTING INDUSTRY (1986–2017)

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This study develops and tests a thesis derived from the law of requisite variety. We contend that the greater the experiential variety of a top management team, the more likely it is that the complexity and consistency of the firm's competitive repertoire will be calibrated to relevant external variety. In addition, for firms that achieve such calibrated repertoires, we expect that their financial performance will be superior to that of their peers. We then integrate these arguments and examine whether top management team experiential variety indirectly, through calibrated repertoires, contributes to firm performance. Analyzing hand-collected data for firms operating in the 3D printing industry over the past three decades (1986–2017), we find support for the overall thesis and associated hypotheses. The discussion section elaborates on the study's contributions, limitations, and future research potential.

The law of requisite variety (LRV) often informs the argument that top management teams (TMTs) with greater experiential variety draw upon a rich reserve of cognitive resources and behavioral routines to enact adaptive competitive repertoires that enhance firm performance (Bogner & Barr, 2000; Connelly, Tihanyi, Ketchen, Carnes, & Ferrier, 2017; Ferrier, 2001; Lyon & Ferrier, 2002; Ndofor, Sirmon, & He, 2015). The core logic is that experiential variety within the upper ranks of the firm facilitates efficacious adaptation by enabling a requisite level of variety in competitive repertoires to cope with external variety (Ashby, 1956; Poulis & Poulis, 2016). TMTs equipped with less variety encounter greater difficulty enacting adaptive repertoires, thereby adversely impacting firm performance (Ferrier, 2001; Ketchen, Snow, & Hoover, 2004; Ndofor et al., 2015). So well rehearsed is this logic that it has attained a canon-like status in competitive dynamics and upper-echelons research.

However, past studies have oversimplified and insufficiently elaborated upon the LRV, in three respects. First, prior studies have suggested that TMT experiential variety enables adaptive competitive activity, as embodied by competitive repertoires. But previous studies have overlooked a subtlety when applying the LRV; it is not the *absolute* level of behavioral variety that matters, but, rather, whether the *requisite* level of variety is achieved. Requisite variety occurs when competitive repertoires are *calibrated* with the variety present in the competitive environment (Boisot & McKelvey, 2011; Heiner, 1983; Poulis & Poulis, 2016). In its elemental form, the LRV suggests that a system's performance is dependent on its capacity to match external variety with requisite internal variety (Ashby, 1956; Poulis & Poulis, 2016). Thus, the LRV does not suggest that competitive repertoires are needlessly complex or simple; they need only match—that is, be calibrated to—external variety.

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However, no clear guidance yet exists for assessing the calibration of firm-level competitive repertoires vis-à-vis external variety. If this issue is not addressed, researchers run the risk of drawing erroneous conclusions about the relationships among TMT experiential variety, competitive repertoires, and firm performance because the fulcrum of this set of relationships—competitive repertoires—is not calibrated.

Second, prior applications of the LRV have predominantly focused on the complexity of competitive repertoires as an indicator of requisite variety. However, an equally significant and challenging form of requisite variety is whether the consistency of competitive repertoires is calibrated with external variety. Indeed, a frequently overlooked aspect of LRV applications is that competitive behavior does not remain static amid evolving competitive conditions. Thus, it is necessary to calibrate the level of both repertoire complexity and consistency with changing competitive demands. It then follows that examining both the firm's repertoire complexity (Connelly et al., 2017) and consistency (Lamberg, Tikkanen, Nokelainen, & Suur-Inkeroinen, 2009) may produce a richer insight. Whereas complexity represents contemporaneous variety (i.e., whether a firm's behavior is sufficiently varied at a moment in time), consistency captures temporal variety (i.e., whether the pattern of a firm's behavior varies appropriately over time).

Finally, prior studies have assumed rather than verified that the requisite level of variety of competitive repertoires is the mechanism governing the relationship between TMT experiential variety and firm performance (Poulis & Poulis, 2016). The assumption is particularly prominent among studies that tend to equate TMT experiential variety with requisite internal variety. Even as we join these studies in arguing that experiential variety is essential for a requisite level of cognitive and behavioral variety within TMTs (e.g., Ferrier, 2001), a complete understanding of the LRV's performance thesis necessitates the entire chain to be modeled—that is, experientially varied TMTs giving rise to calibrated repertoires, which in turn impact performance (cf. Andrevski, Richard, Shaw, & Ferrier, 2014).

Accordingly, our intent in this paper is to develop and test a thesis derived from the LRV in a way that addresses the limitations of previous applications. We first argue that TMTs experientially varied with respect to industry backgrounds are more likely to construct competitive repertoires whose complexity and consistency are calibrated to the external variety of the competitive environment. Because the actions of top performers in an industry tend to contemporaneously be in sync with external demands and exert a disproportionate influence on industry-wide competitive dynamics (Lamberg et al., 2009), the variety exhibited by these firms serves as an appropriate standard against which to calibrate competitive repertoires (Boyle & Shapira, 2012; Fredrickson, Davis-Blake, & Sanders, 2010; Moliterno, Beck, Beckman, & Meyer, 2014). For firms that achieve calibrated repertoires, we expect that their financial performance will be higher relative to those that achieve lower levels of calibration. If the firm's actions are overly complex or inconsistent over time, then managerial, financial, and other resources can be misdirected (Connelly et al., 2017). Simultaneously, if competitive actions are too simple or overly consistent, then the firm risks long-run maladaptation (Lamberg et al., 2009; Miller & Chen, 1996). We integrate these arguments to examine the governing role of calibrated repertoires in the relationship between TMT industry experience variety and performance. Because calibrated repertoires optimize resource allocation, mitigate the risk of maladaptation, and address competitive requirements, we predict that TMT industry experience variety, via the mechanism of repertoire calibration, will indirectly impact firm performance.

We test the model and specific hypotheses using hand-collected panel data from the 3D printing industry for a period of three decades (1986–2017). The changes across this evolving industry's life cycle shape the benefits and costs of complex and consistent repertoires and provide the necessary variation in conditions that prompt TMTs to recalibrate repertoires over time. Moreover, the 3D printing industry is a context in which TMT characteristics and firm competitive actions are observable across multiple life cycle stages. The results support the model and hypotheses, which are further reinforced with a set of supplementary analyses that probe the nature of these effects (Certo, Withers, & Semadeni, 2017).

Together, our study contributes to theory and research on the LRV, competitive repertoires, and upper echelons. Our empirical testing answers prior calls to address a key concern about the LRV's use in management theorizing; namely, "empirical substantiation … is strikingly scarce [and] despite its wide appeal, studies that could (dis)confirm the LRV's foundational assumptions are absent from the management literature" (Poulis & Poulis, 2016: 504). We enrich research on competitive repertoires by developing and specifying the construct of calibrated competitive repertoires. In so doing, our study sheds insight and further evidence that the notion of "more is better" may be too simplistic to characterize the relationship between firm performance and repertoire characteristics (Connelly et al., 2017). Additionally, by considering calibration cross-sectionally (complexity) and longitudinally (consistency), we evaluate whether firms calibrate repertoires to enhance performance (Lamberg et al., 2009). For upper echelons researchers, showing that experience variety begets calibration brings key elements of the perspective into sharper focus and introduces a host of new research directions.

THEORETICAL BACKGROUND

Over the past two decades, a growing body of research has examined the relationships among TMT diversity, the characteristics of competitive repertoires, and firm outcomes (Connelly et al., 2017; Ferrier, 2001; Ferrier & Lyon, 2004; Hughes-Morgan, Ferrier, & Labianca, 2011; Lamberg et al., 2009; Miller & Chen, 1996). "Competitive repertoires" are defined as "the set of market actions used by an organization during a given year to attract, serve, and keep customers, [and are] 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). A core argument is that TMTs with higher levels of diversity, particularly experiential variety, can better comprehend the full complexity of the competitive environment and enact adaptive repertoires that increase performance (Andrevski et al., 2014; Ferrier, 2001; Hambrick, Cho, & Chen, 1996; Lyon & Ferrier, 2002). Underpinning many studies is a common thread—a reliance (either explicitly or implicitly) on the LRV to explain why TMT variety shapes competitive repertoires and, in turn, performance (Bell, Villado, Lukasik, Belau, & Briggs, 2011; Bogner & Barr, 2000; Connelly et al., 2017; Ferrier, 2001; Harrison & Klein, 2007; Lyon & Ferrier, 2002; Ndofor et al., 2015). For example, Miller and Chen (1996: 424) wrote that "Ashby's (1956) 'law of requisite variety' … suggests that to be effective a competitive repertoire must be sufficiently comprehensive to address the relevant range of potential customer needs and competitor challenges." Ferrier (2001: 662) was more explicit:

> [TMT] demographic heterogeneity is widely viewed as a proxy for cognitive and experiential heterogeneity. The composition of a TMT shapes the lenslike cognitive structure that defines its members' collective field of vision. By way of greater awareness in sensing strategic problems, heterogeneous teams can match complex competitive challenges and uncertain contexts with a requisite level of cognitive and experiential variety.

Despite its intuitive appeal, however, the LRV's complete logic is often not fully articulated in either competitive dynamics or general management research. Reviewing prior research, Poulis and Poulis (2016: 504) concluded that "management scholars who adopt the law articulate the validity of their arguments based on the premise of its a priori applicability" and often use the law "as a passing reference that solidifies conceptual justifications and hypothesis building related to matching and survival" (Poulis & Poulis, 2016: 506). To wit, a full application of the LRV implies that entities (in our case, firms and their managers) must have sufficient internal variety to both discriminate between stimuli (i.e., to comprehensively envision the competitive environment and select the appropriate response) and to enact a diverse set of responses *calibrated* to external variety (Boisot & McKelvey, 2011; Heiner, 1983; Poulis & Poulis, 2016). Requisite variety does not imply internal variety without bound; rather, it implies sufficient internal variety—that is, no more or no less than what is required by external variety.

To explore the relationship between external and internal variety, Boisot and McKelvey (2011) constructed what they label the "Ashby space," which juxtaposes the variety of stimuli present in the environment (external variety) with the variety of responses enacted by an entity (internal variety). Viewed through this prism, "requisite variety" corresponds to situations when entities successfully match environmental variety with the variety of their actions. However, attaining this level of requisite variety is not always possible because entities are limited by their adaptive frontier. Boisot and McKelvey (2011) identified three ways that entities, such as firms and their managers, respond to external variety. The first is a "calibrated response," which occurs when external variety is matched with sufficient internal variety. This happens when the amount of variety to be detected and responded to is within the adaptive frontier. However, when faced with stimuli whose variety exceeds the entity's current cognitive or behavioral capacity, there are two maladaptive alternatives. One is the "headless chicken response," in which the fidelity of the stimuli is maintained (no cognitive simplifications occur), and unscripted (trial and error) actions are taken until one that works is found. The other is the "routinizing response," where difficult-to-interpret aspects of stimuli are discarded (i.e., cognitive simplifications are made) until an existing set of behaviors deemed to be an appropriate response is selected.

Neither of these maladaptive responses is beneficial. The risks of routinized responses are well documented (e.g., Hambrick, Geletkanycz, & Fredrickson, 1993; Miller & Chen, 1994; Tripsas & Gavetti, 2000). In essence, routinized responses are a failure to acknowledge relevant nuance in the external environment, perhaps manifesting as a tendency to discount and even neglect stimuli that fall outside managers' cognitive structures (Marcel, Barr, & Duhaime, 2011). The increased complexity associated with headless chicken responses is also not necessarily beneficial. Enacting a wide range of actions, especially when such a range of behavior is unnecessary to address the range of stimuli in the external environment or exceeds the adaptive frontier, leads to inefficient resource usage. Together, the "Ashby space" response types provide a holistic approach for understanding whether TMTs with experiential variety can calibrate competitive repertoires to the firm's external variety and whether such calibration subsequently influences firm performance.

Defining Calibrated Competitive Repertoires

Building on Ashby (1956: 206), we conceptualize "external variety" as a temporal sequence of unique stimuli, each of which possesses a best response corresponding to a distinct type of competitive action enacted by a focal firm. A calibrated competitive action repertoire is one where the firm's actions are the same as the best responses for each of these unique stimuli.

Scholars of competitive dynamics (Chen & Miller, 2012; Ferrier, 2001) have identified two properties of competitive repertoires that can provide specific insight into the variety of stimuli that firms face as manifest in their enacted responses to that variety: the (cross-sectional) complexity of repertoires in a given period and their consistency over time (Connelly et al., 2017; Lamberg et al., 2009). The former captures the entropy of actions taken (i.e., their intrinsic variation or uncertainty)—which should correspond to the entropy of stimuli faced. The latter captures the change in the pattern of actions taken over time—which should conform to the changes in the environmental stimuli that induce that behavioral change. The calibration of a firm's competitive repertoire is often difficult to ascertain because both external variety and the specific best responses to stimuli are difficult to observe. Determining whether a focal firm successfully calibrates to the external variety requires an appropriate standard or reference point against which to compare.

While prior LRV studies do not provide substantive guidance regarding how to construct such an external variety reference point, some research streams in management offer guidance and stress the use of other competitors and/or groups of competitors as an appropriate reference point or standard (Buunk & Gibbons, 2007; Moliterno et al., 2014; Panagiotou, 2007). These reference points have been applied to diverse firm-level phenomena across many contexts (Boivie, Bednar, & Barker, 2015; Fredrickson et al., 2010; Kacperczyk, Beckman, & Moliterno, 2015). These research streams suggest that the industry's top performers are of particular salience, influence, and importance for other firms (Boyle & Shapira, 2012; Labianca, Fairbank, Andrevski, & Parzen, 2009; Moliterno et al., 2014). The actions of contemporaneous top performers are the most visible and significant indicator of external variety because they provide a salient social comparison and are likely to be considered by other firms in the industry. Further, irrespective of whether TMTs attend to the actions or aspire to the performance of top competitors per se, the actions of top performers exert a disproportionate influence on industry-wide competitive dynamics (Lamberg et al., 2009)—in part, due to market commonalities and resource similarities with competitors (Baum & Korn, 1996; Chen, 1996). Moreover, top performers likely achieve their position through some combination of temporary and structural advantages. For the former, the leaders' actions will "set the pace" for the industry as a whole and set the bar for any challengers to match (Derfus, Maggitti, Grimm, & Smith, 2008; Ferrier, Smith, & Grimm, 1999). For the latter, the activity required to maintain advantageous structural positions necessitates commitments or actions by competitors to maintain parity (Ghemawat, 1991).[1]

In short, contemporaneous top performers are firms that demonstrate, by their current levels of

[1] We emphasize contemporaneous top performers since this set of firms is constantly updated. To the extent that other firms are better able to capitalize on market trends and ascend to the top of the league tables (displacing existing members), the list of top performers is appropriately updated by the market process to factor in firms whose repertoires meet the current demands of the external environment.

success, an alignment (albeit temporary) with the external environment's demands. Said differently, such firms, by the nature of their position within the market as top performers, have demonstrated an ability to choose a set of actions that are (at least compared to those chosen by their competitors) best responses to environmental stimuli. Moreover, given their relative size and influence on competitive dynamics, the industry's top performers are not passively responding to the environment—they exert material pressures on the industry through their actions. We thus deduce that these top competitors' actions can serve as a de facto standard for the calibrated repertoires of firms within the industry. In the parlance of the LRV, we propose calibrating repertoires by using the competitive repertoires of top performers as a standard. The firm's calibrated repertoire complexity and consistency can be measured against the standard in terms of closeness: more calibrated repertoires should exhibit smaller deviations (in terms of magnitude) from the standard.[2]

HYPOTHESES

In examining TMT experiential variety, we specify and capture it as the variety of industry experiences within and across team members. Compared to other experience characteristics of a TMT, industry experiences are particularly relevant to the pursuit of competitive actions because they bestow managers with blueprints, recipes, and mental models that constitute the cognitive seeds of competitive categorizations, actions, and responses (Carpenter, Geletkanycz, & Sanders, 2004; Crossland, Zyung, Hiller, & Hambrick, 2014; Finkelstein, Hambrick, & Cannella, 2009; Porac & Thomas, 1990; Priem, Lyon, & Dess, 1999). Over time, as managers within an industry observe rivals' competitive actions, they develop mental models of the competitive environment. Since these mental models or recipes differ by industry (Spender, 1989), such experience is pertinent to our specific hypotheses.

Using the terminology developed by Harrison and Klein (2007) and elaborated upon by Bunderson and van der Vegt (2018), we define "TMT industry experience variety" as the number and spread of qualitatively different industry experiences across team members.[3] Specifically, TMT industry experience variety captures the "batches" of information content, knowledge, and unique network ties available within and across team members from accumulated prior work in different industries (Harrison & Klein, 2007: 1204). These experiences broaden the cognitive and behavioral repertoire available to the team members.

TMT Industry Experience Variety and Calibrated Competitive Repertoires

"Competitive repertoire complexity" is the "firm's diversity of competitive actions (i.e., a firm's range of actions and [whether] they are dominated by specific types)" (Connelly et al., 2017: 1153, internal citations removed). "Calibrated repertoire complexity" refers to the extent to which the complexity of a focal firm's competitive repertoire aligns with the level of complexity attained by industry top performers. Deviations in either direction from this standard result in lower calibration levels, since the repertoire complexity of top performers approximates the external variety in the competitive environment.

We argue that TMTs with high levels of industry experience variety deploy their diverse cognitive, sensory, and informational apparatus (Chen, Lin, & Michel, 2010; Ferrier, 2001; Hambrick et al., 1996; Hughes-Morgan, Kolev, & McNamara, 2018) to engage in a larger proportion of *calibrated responses* to external variety (Boone & Hendriks, 2009; Harrison & Klein, 2007). At the limit, if every action selected is a calibrated response, then the repertoire is fully calibrated by aggregation. Core to our argument is the insight that a TMT's industry experience variety lessens its propensity to engage in *routinized* or *headless chicken* responses (Boisot & McKelvey, 2011).

Consider first *routinized responses*. Teams with variegated industry experiences can draw upon an extensive reservoir of competitive actions learned

[2] To be clear, the goal of our analysis is not to ask how close a focal firm's repertoire is to those of top performers. It is to ascertain whether a focal firm's repertoire is calibrated to external variety. We do not claim the repertoires of top performers to be equivalent to external variety—they simply serve as an observable and appropriate proxy to facilitate the testing of our theory.

[3] Historically, the terms "diversity," "variety," and "heterogeneity" have been used interchangeably. We follow Harrison and Klein (2007) and use the term "diversity" to refer to all the dimensions, such as separation, variety, disparity, and skew, along which members of a TMT may differ. We reserve "variety" to capture the number and spread of different experiences among team members.

from contexts with qualitatively different competitive behavior patterns (Gort & Klepper, 1982; Porter, 2008). The presence of varying worldviews, frames of reference, and experiences equip such TMTs with a sufficient breadth of cognitive categories to form appropriate representations of top performers' competitive actions (Gavetti, Levinthal, & Rivkin, 2005). According to the principle of requisite cognitive complexity (Calori, Johnson, & Sarnin, 1994), diverse experiences provide a richer set of cognitive categories and perspectives when attending to competitive stimuli and more alternatives at ready reference when choosing how to respond (Andrevski et al., 2014: 823). Beyond their collection of individual experiences, TMTs with high levels of industry experience variety can draw on wider social networks to search more broadly if firsthand knowledge is lacking (Geletkanycz, Boyd, & Finkelstein, 2001).

Although TMTs lacking industry experience variety may have enough cognitive categories or outside contacts to form accurate representations some of the time (Calori et al., 1994), an overreliance on these limited categories or bridging ties increases the risk of miscalibration, especially as the competitive environment evolves over time (Bogner & Barr, 2000; Henderson, Miller, & Hambrick, 2006). Such teams may oversimplify experiential details into higher-order principles (Finkelstein & Hambrick, 1990; Sutcliffe & Huber, 1998; Tripsas & Gavetti, 2000), and form low-dimensional representations of a higher-dimensional competitive environment (Gavetti & Levinthal, 2000).

Concurrently, industry experience variety allows teams to economize on effort and resources, reducing the number of *headless chicken* responses. Qualitatively different competitive experiences across industries lessen the requirement for trial-and-error learning because the team can draw from "best practices" and analogies learned elsewhere (Gavetti et al., 2005). TMTs with industry experience variety can also correlate their experiences across industries and vicariously identify competitive actions that have failed elsewhere (Kim & Miner, 2007). Furthermore, since experientially varied teams have multiple viewpoints, proposed actions may have to pass through more "stage gates" before ultimate approval, resulting in slower but higher-quality responses (Ferrier, 2001; Hambrick et al., 1996). Additionally, in some cases, the most appropriate action to take is non-action or forbearance (Andrevski & Miller, 2022; Hopkins, 2003); such a reaction to novel stimuli may be easier to justify when multiple alternatives are weighed and all are found wanting. When firms are faced with a competitive threat, there is often a bias toward action and reflexive response (Andrevski & Miller, 2022). It takes an additional understanding and appreciation of the industry context to ascertain that non-action is a more appropriate response. As both Ferrier and Lyon (2004) and Miller and Chen (1996: 420) have argued, if such teams pursue comparatively "simple" repertoires, it may reveal "an active level of decision making, even though actions may be mostly of a single kind." In summary, we expect that, compared to teams with experiences in a more limited set of industry contexts, TMTs with high levels of experience variety are less likely to succumb to the pathologies of over-simplification and over-complexification. Thus, we predict:

Hypothesis 1. TMT industry experience variety will be positively associated with calibrated repertoire complexity.

Beyond complexity, it is also vital for firms to maintain a requisite level of repertoire consistency. "Competitive repertoire consistency" refers to the "year-to-year comparability in the repertoire [of a focal firm] and amount of competitive actions that an organization undertakes when conducting its competitive stance" (Lamberg et al., 2009: 48). An emerging body of work related to temporal issues in strategy (e.g., Granqvist & Gustafsson, 2016; Kaplan & Orlikowski, 2013) has noted how actions and events can be entrained, paced to achieve synchronicity, and undertaken in the context of potential irreversibility. "Calibrated repertoire consistency" occurs when the composition of a firm's competitive repertoire shifts to the same degree as top performers' repertoires over time. Critically, calibrated consistency does *not* capture or assess the conformity of the underlying pattern of actions between a focal firm and top performers. A firm could match the consistency of top performers but do so by utilizing a very different mix of competitive actions (Hughes-Morgan et al., 2011; Ndofor et al., 2015). In practice, calibrated consistency means that, if environmental shifts precipitate changes in top performers' repertoires, a change in consistency of comparable magnitude will be required by other industry participants, even though the underlying composition and content of those actions may differ.[4]

[4] We acknowledge that, compared to top performers, certain firms may be in a comparatively better (or worse) position to respond to changes in environmental conditions at any given time; thus, the absolute magnitude to

For example, for years, Apple has pursued a strategy of increasing the prices of its entry-level phones, and has displayed a high level of consistency in this strategy. However, last year, it significantly lowered the entry-level price. Apple deviated from its earlier strategy in a bid to strengthen its user base, grow its ecosystem of services, and incentivize users to upgrade their devices (Sullivan, 2019). This change reduced the consistency of Apple's competitive repertoire and should portend that the consistency of competitor repertoires would fall as well. However, this does not necessarily imply that competitors need to change the content of their actions to match Apple's specific moves. From an evolutionary perspective, consistency means that a firm's actions conjoin with changes in the competitive environment (Lamberg et al., 2009: 46). In practical terms, this does not mean they merely mimic the content of competitor repertoires, but, rather, seek to maintain evolutionary fitness by adjusting their repertoires, as necessary.

When top-performing firms alter their competitive stance—that is, signal a shift in external variety—those TMTs with varied industry experiences are more likely to detect these shifts by their breadth of cognitive and information-processing resources (Marcel et al., 2011: 128). With this heightened ability to detect changes in the rules of competitive play, they can appropriately draw from their broader repository of acquired industry recipes and competitive playbooks to enact corresponding responses (Mello & Rentsch, 2015: 633–634). These more elaborate strategic schemas and behavioral routines provide the firm with enhanced flexibility to course correct their competitive repertoires as needed (Nadkarni & Narayanan, 2007). In this way, experiential variety serves as an antidote to status quo bias, cognitive or competitive inertia, or routine lock-in that otherwise blind management teams to shifts in the competitive landscape (Hambrick et al., 1993; Miller & Chen, 1994; Tripsas & Gavetti, 2000). This antidote reduces the frequency of *routinized responses.* Additionally, because TMT industry experience variety can also beget decision-making processes that avoid unnecessary trial and error by developing rules optimized to the frequency of specific stimuli (Heiner, 1983), such teams can avoid unnecessary modifications to their repertoires (Ferrier & Lyon, 2004). This helps to maintain the necessary level of longitudinal consonance by avoiding a preponderance of *headless chicken* responses. By contrast, TMTs with little experiential variety lack extensive knowledge of competitive actions across industry contexts and may find it more challenging to maintain the requisite level of repertoire consistency (Lamberg et al., 2009; Nelson & Winter, 1982). They may fall victim to competitive inertia (Miller & Chen, 1994) or be insufficiently mindful of the ramifications of response and thus overly responsive to minor perturbations (Andrevski & Miller, 2022). Thus, we argue:

Hypothesis 2. TMT industry experience variety will be positively associated with calibrated repertoire consistency.

which they must adjust their actions may be less (or more). However, if an environmental shift is strong enough to change the behavior of top performers, it will almost certainly necessitate some level of change in the pattern of activity for all participants in the industry.

Calibrated Competitive Repertoires and Firm Performance

Drawing from the LRV, "calibrated repertoire complexity" is achieved when the complexity of a firm's repertoire is commensurate with contemporaneous external variety, as indicated by the repertoire complexity of top performers. The actions of top-performing firms exert a disproportionate influence on industry-wide competitive dynamics and signify salient competitive demands against which a focal firm needs to calibrate its repertoires to improve performance (Barnett & McKendrick, 2004; Derfus et al., 2008; Ferrier et al., 1999; Young, Smith, & Grimm, 1996). The actions of top-performing firms are also more visible and serve as role models for other firms (Burns & Wholey, 1993; Haveman, 1993). Through competitive convergence (Porter, 1996) and mimetic isomorphism (DiMaggio & Powell, 1983), the actions of top-performing rivals influence industry-wide competitive norms (Haveman, 1993).

In the case of a focal firm's repertoire complexity, significantly undershooting top performers' complexity increases the likelihood of being outmaneuvered. Existing research acknowledges that overly simplistic or timid repertoires put the firm at risk of falling behind competitors (Carnes, Xu, Sirmon, & Karadag, 2019; Connelly et al., 2017; Derfus et al., 2008; Ferrier et al., 1999). As leading firms increase the breadth of actions in their repertoire, firms that fail to calibrate to this higher level of complexity face increased pressure of competitive imitation and reduced performance (Ferrier, 2001; Ferrier & Lee, 2002; Hughes-Morgan et al., 2018). A good current example is Spotify's struggle to compete with Apple, Amazon, and Google; each firm offers a greater breadth of services and possesses more degrees of strategic freedom with which to launch attacks than does Spotify. In the context of 3D printing, a similar dynamic can be seen when now-extinct competitors such as Helisys competed against other players such as 3D Systems. For example, contemporaneous industry reports noted the following:

> A staple at the early rapid prototyping shows, Helisys consistently drew large, interested crowds to its LOM [laminated object manufacturing] technology [but] Helisys failed to find a niche and conquer it. The LOM process [Helisys's primary technology] was best suited for thick-walled applications, like patterns for sand or investment casting. However, the market was demanding functional prototypes and prototypes for injection-molded products. Helisys was quick to proclaim "me too" [and] sell[ing] systems into unsuitable environments. (Wohlers Associates, 2001: 81)

Given the higher predictability of simple competitive repertoires, the window for profiting from competitive actions is compressed, since these repertoires are easier to imitate (McGrath, 2013; Young et al., 1996). Even if this limited range of actions is successful, which can be the case in the short run (Miller & Chen, 1996), as Connelly et al. (2017: 1154) argued, relying on a limited range of actions leads to "superstitious learning" that hurts performance "because managers become myopic with respect to their choices of competitive action types."

Excessive complexity may be similarly detrimental, but for different reasons (Heiner, 1983; Langlois, 1986). Connelly and colleagues (2017: 1155) argued and found that "[a] firm will experience a downward performance trend if it enacts a bigger variety of competitive moves than the managerial resources provided by its executives can support." As Ndofor, Sirmon, and He (2011) observed, competitive complexity partially mediates the relationship between resource breadth and subsequent performance. However, from the opposite viewpoint, this suggests that firms attempting to enact action repertoires too complex relative to their resource base may spread managerial capacity and attention too thinly across too many initiatives (Leinwand & Mainardi, 2010; Penrose, 1959). The breadth of capabilities required by overly complex competitive repertoires comes at the cost of operational and asset mass efficiencies accrued from focusing on fewer, best-in-class capabilities (Adler, Goldoftas, & Levine, 1999). Thus, we propose:

Hypothesis 3. Calibrated repertoire complexity will be positively associated with firm performance.

We follow a similar logic in predicting that firms that calibrate their repertoires' consistency with the top-performing firms will likely enjoy higher performance. Top-performing rivals can influence the tempo and rhythm of competitive rivalry (Ferrier et al., 1999; Haleblian, McNamara, Kolev, & Dykes, 2012; Hopkins, 2003). When top firms engage in a new configuration of actions that depart from their historical trajectories, firms employing overly consistent repertoires run a significant risk of being unresponsive to competitive contingencies (Miller & Chen, 1996: 424). When leading firms modify their approaches, firms that fail to adjust may be caught in a "success trap" (Levinthal & March, 1993). They replicate actions that worked well in the past but are now out of kilter with competitive realities (Henderson et al., 2006). Overly consistent repertoires may also indicate routine and resource inertia (Gilbert, 2005) or insufficient exploration (March, 1991; Nicholls-Nixon, Cooper, & Woo, 2000). To wit, firms whose repertoire consistency far exceeds that of top performers are likely pursuing yesterday's actions for today's new demands. Excessive consistency vis-à-vis top performers also increases competitive predictability, enabling competitors to preempt, block, or imitate the firm's competitive actions with ease.

Concurrently, excessively variable and shifting repertoires can result in "an imbalance between organizational capabilities and current competitive actions" (Lamberg et al., 2009: 48). Firms that fail to exhibit sufficient consistency hinder the development of capabilities vital to the generation of economic rents. Bearing the unnecessary costs of adaptation, these firms can enter an endless cycle of failure and unrewarding change (Levinthal & March, 1993). Insufficient consistency may even diminish the firm's legitimacy and increase its cost of capital as investors struggle to make sense of the firm's "headless chicken strategy" (Lamberg et al., 2009; Litov, Moreton, & Zenger, 2012; Rindova, Ferrier, & Wiltbank, 2010). Institutional theory stipulates that firms emulate the actions of firms with high visibility and prestige because stakeholders can look to top performers as a cognitive shortcut when uncertainty is high (Srinivasan, Haunschild, & Grewal, 2007). To the extent that a firm's repertoire consistency is significantly out of line with this standard, performance can be impaired. Thus, we predict the following:

Hypothesis 4. Calibrated repertoire consistency will be positively associated with firm performance.

So far, we have argued that (a) the industry experience variety of a firm's TMT will facilitate calibrated repertoire complexity and consistency and (b) calibrated repertoire complexity and consistency will be positively associated with firm performance. Combining both arguments, we now conclude our theory development by stating the LRV thesis that motivated the study: through calibrated repertoire complexity and consistency, the industry experience variety of a firm's TMT will indirectly shape performance. Considering our prior arguments as a set and given the LRV thesis that a system's performance is dependent on its capacity to match external variety, we expect that this chain of effects will hold. If so, it will provide corroborating evidence that, via the use of internal variety to match external variety, TMT industry experience variety shapes performance (Langlois, 1986), allowing us to provide a test of the LRV. Thus, we expect the following:

Hypothesis 5. Through calibrated repertoire complexity, TMT industry experience variety will have an indirect effect on firm performance.

Hypothesis 6. Through calibrated repertoire consistency, TMT industry experience variety will have an indirect effect on firm performance.

METHODS

Setting and Data

We test our model by using a hand-collected, unbalanced, longitudinal panel of commercial 3D printer manufacturers in operation during from 1986 through 2017. Broadly defined, "3D printing" refers to "additive manufacturing techniques to create objects by printing layers of material based on digital models" (Cohen, Sargeant, & Somers, 2014: 4). Early versions of the technology were introduced during the early 1980s. 3D printing can create objects from various materials, including plastic, metal, ceramics, glass, paper, and even living cells. These materials can come in the form of powders, filaments, liquids, or sheets.

There are five reasons why this setting is appropriate to test our argument and hypotheses. First, the 3D printing industry is covered by several media outlets and publications, such as the annual Wohlers Report and Econolyst research reports, which provide detailed and precise data on firm competitive repertoires. Second, because the industry is dynamic, relatively young, and has transitioned through a period of significant revenue growth, it displays variability in competitive actions and repertoires across industry participants (Grimm, Lee, & Smith, 2006). Third, since the industry has evolved for three decades, firms vary in size and in the available resources required to engage in competitive activity over time. The industry is sufficiently established and has roots in related industries (e.g., inkjet printing, machine tooling) such that a cadre of veterans can be identified through spinouts and firm dissolutions. Moreover, new participants have entered the industry because its underlying technological bases continue to shift (Wohlers Associates, 2013). Fourth, the 3D printing industry is knowledge intensive, and, compared to firms in other, more established sectors, firms in this industry tend to be smaller. Therefore, the influence of managerial experience should be pronounced because these individuals provide a significant fraction of the technological know-how, social connections, and other skills required to initiate competitive actions. Finally, given the distinct value proposition of additive manufacturing compared to traditional subtractive methods (e.g., machine tooling, laser cutting, etc.), the industry's competitive dynamics are primarily governed by the behavior of direct competitors rather than that of indirect competitors or substitutes. As such, the context provides an opportunity for less confounded testing but at the expense of contextual generalizability, which we further discuss in the Limitations section.

Data set construction proceeded in three steps: (1) the development of a sampling frame, (2) the procurement of data from several sources, and (3) the matching of that data to the sampling frame. The sample companies included all publicly traded firms covered by the industry's leading research company (Wohlers Associates) and several privately held firms. The sampling frame spanned from 1986 to 2017, but we only admitted observations into the sample once enough companies were in operation for a sufficient duration to identify top performers (specifically, from 1991 forward). By then, several 3D printer technologies were already in existence and commercialized by multiple firms (e.g., stereolithography and selective laser sintering). In each of these years, the criterion for inclusion of a firm into the sampling frame for a particular year was the recording of at least one commercial 3D printer sale (i.e., units with a price point of $5,000 or greater). Data were collected for each aspect of the model and matched to the appropriate firm-year. As described in the measures section, the data on individual executives, TMT composition, firm actions, firm performance, and industry characteristics were constructed from several sources. Due to the lack of available return on assets (ROA) information for small, private firms, the sample for our performance analyses is smaller in absolute size but contains some data for most of the firms in our sample (specifically, 21 firms vs. 23 firms—albeit with shorter time panels).

Dependent Variables

Calibrated repertoire complexity and consistency. Consistent with prior studies, we consider a firm's competitive repertoire to encompass the actual competitive actions—such as price changes, product line or service alterations, and changes in the scope of operations—taken by a firm during a given year (Chen & Miller, 2012: 145; Miller & Chen, 1996: 420). As with prior studies (e.g., Chen & Miller, 1994; Connelly et al., 2017; Ferrier & Lyon, 2004), we coded competitive actions by using a structured content analysis of press articles and news reports compiled by Factiva, which contains articles from major news outlets, such as Dow Jones, Reuters, *Wall Street Journal*, the Associated Press, and from specialty outlets, such as Econolyst. All articles flagged as pertaining to the firms in our sample were included in the population at risk for coding and totaled over 17,500 articles. Using the search terms and action categories specified by Ferrier and Lyon (2004), Connelly et al. (2017), and other studies with lists of competitive action categories (e.g., Boyd & Bresser, 2008; Derfus et al., 2008; Offstein & Gnyawali, 2005), the articles were coded to track 102 specific actions (e.g., "establish warranty program," "price decrease," "open new plant") across the following 10 categories: pricing, marketing, product, capacity, service, signaling, legal, market expansion, strategic alliances, and acquisitions.

Using the quanteda package in R (Benoit et al., 2018), we classified articles by employing a dictionary of 3-grams (sequences of words of up to three stemmed terms) associated with each action. Following Andrevski et al. (2014), to ensure the reliability of the coding procedure (overall agreement = 98.5%), we validated this automated coding process by manually testing a random sample of 175 articles (1% of the sample). We computed Perreault and Leigh's (1989) reliability index and found that the reliability of the coding was .75, which was above the .70 threshold cited in Andrevski et al. (2014) and above the cutoffs for similar measures of reliability (Ryan & Bernard, 2000). Using the count of each of the 10 action types undertaken within a calendar year, we constructed repertoire vectors of the form $R = (r_1, r_2, r_i \ldots r_n)$, where r_i denotes the number of actions of type i. These repertoire vectors were generated for 245 firm-years and comprised 1,590 coded actions (an average of 6.49 actions per firm-year). Calibrated repertoire complexity, calibrated repertoire consistency, and other control variables were calculated from these vectors.

Our main variables of interest are firm calibrated repertoire complexity and consistency,[5] where both the content of the repertoire and the content of the external variety standard change every year. To construct these two variables, we undertook the following: (1) measured the vector of competitive actions that comprised each firm's repertoire; (2) constructed complexity and consistency measures for each firm; (3) ascertained time-varying external variety measures by using the competitive repertoires of top performers; (4) computed the extent to which a focal firm's repertoire complexity and consistency deviated from these external variety standards each year; and, finally, (5) subtracted this calculated value from 1, because, the smaller the deviation from the standards, the more calibrated the repertoire.

Repertoire complexity captures the firm's ability to engage in a broader range of action types (Connelly et al., 2017), and was measured using a Shannon entropy index of the action types employed by a particular firm in a specific year. This measure captures the number and distribution of actions across categories and the relative difficulty of guessing what action a firm will take next. Consequently, it is a measure of entropy (Heiner, 1983; Langlois, 1986). This measure was normalized by the theoretical maximum—ln(10), which is the value if actions are

[5] Ideally, when assessing whether a firm's competitive repertoire is calibrated, we would have a tally of all of the stimuli presented to the firm, and the order they were received, the best response to the stimuli, and whether the firm enacted such a response or made another choice. But, in reality, such an assessment is infeasible, for two reasons. First, the complete enumeration of all environmental stimuli is challenging to observe. Instead, firm responses to these unobserved stimuli are more readily captured. Second, while the equivalence of stimuli and response is tenuous at the level of individual action (not all stimuli can or are responded to, nor are the responses selected necessarily optimal), there is a more substantive correspondence between a set of stimuli in a given period and the set of responses they drive. We employ the summary measures of repertoire complexity and consistency to surmount these limitations.

equally distributed across all categories—such that the maximum of this variable is equal to unity.

Repertoire consistency captures the stability of actions in comparison to the historical trajectory of the firm (Lamberg et al., 2009). Consistency was 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 (in 10-dimensional space) versus the actions taken in prior years. In a fully consistent repertoire (in which the measure takes a value of unity), the number of actions may change if the relative proportion between each action type remains the same. By contrast, a completely inconsistent repertoire (one that takes a value of zero) is one in which the firm performs an orthogonal set of actions from prior years.

Once the repertoire complexity and consistency measures were computed for all firm-years, for each year, we then identified the top three firms that currently had the highest sales volumes and identified their repertoire complexity and consistency scores for that year. Given the youth, growth, and relative proportion of private companies in the industry, sales volumes are highly germane to the setting and a readily observable indicator of firm success (and regularly reported in major industry reports). Since top performers' repertoires serve only as an estimate of external variety, we used trend analysis to extract the underlying longitudinal time path of external variety.

To do so, we regressed repertoire complexity and consistency for these top-performing companies against linear, quadratic, and cubic orthogonal polynomial trends. In terms of repertoire complexity, while the linear time trend was positive and significant ($b = 0.02$, $SE = 0.002$, $p < .001$), the higher-order quadratic term was not ($b = -0.03$, $SE = 0.03$, $p > .10$). Thus, we employed the linear trend for our complexity standard. This simple linear time trend explained 65% of the variation in top performers' repertoire complexity, indicating a steadily increasing demand for repertoire complexity as the industry develops. By comparison, the linear ($b = -0.01$, $SE = 0.005$, $p < .05$), quadratic ($b = 0.23$, $SE = 0.04$, $p < .001$), and cubic ($b = 0.11$, $SE = 0.04$, $p < .05$) trend terms were all significant in our repertoire consistency analysis, which explained 70% of the variance in the consistency of the top performers. The inflection points traced by this cubic occurred in approximately 1994 (when the curve trends downward) and 2010 (when the curve reverses). The first inflection point corresponds to the rapid rise of new competitors emerging after the first wave of commercialization in the mid-1990s. The second inflection point marks a period of consolidation where de alio players such as HP began entering and just before major players, such as Objet and Stratasys, merged. Given this evidence and institutional details, we employed all three trend components for the consistency standard.

Once these calibrated standards were constructed, we subtracted the actual levels of firm repertoire complexity and consistency from their respective standards for each year. We partitioned the resultant difference into an absolute magnitude and a signed direction because our hypotheses are agnostic to the direction of the deviation (i.e., above or below the standard value). In supplemental analyses, we explored in more detail factors that may predict the sign of these deviations. Finally, we subtracted the computed deviation magnitude from one to obtain our calibration measure, whose value was maximum when there was no difference between the firm's competitive repertoire and the calibration standard.[6]

Firm performance. Consistent with prior work, we used *return on assets* (ROA) to measure performance (Derfus et al., 2008; Young et al., 1996). ROA is commonly used in studies of competitive dynamics (Carnes et al., 2019; Connelly et al., 2017; Derfus et al., 2008; Ndofor et al., 2011) and is appropriate for measuring overall financial performance because it captures the efficiency by which the firm uses its assets to generate revenues above the costs of operations. Financial performance is a proxy for the firm's successful adaptation since an inability to change behavior in the face of changing external variety should reduce performance. In our performance analyses, we controlled for *return on assets in the prior year* to mitigate the threat of reverse causality. Note that our dependent variable to measure performance differs from the metric used to identify contemporaneous top performers. We did this for two reasons. First, while having the benefit of hindsight to ascertain firm financial performance, many

[6] An example may clarify this process. Firm *j*'s calibrated complexity in year *t* is computed as follows: $1 - \text{ABS}(\text{Complexity}_{jt} - \text{ComplexityStandard}_t)$, where ABS is the absolute value function, and $\text{ComplexityStandard}_t$ is the linear trend of top performer repertoire complexity for year *t*, as described above. Following prior work, Complexity_{jt} is computed as follows: $[-\Sigma_i(\text{r}_i/\Sigma\text{r}_i)\ln(\text{r}_i/\Sigma\text{r}_i)]/\ln(10)$, where r_i are the number of actions of type *i* and ln (10) is a normalizing constant such that the maximum possible value of Complexity_{jt} is 1.

companies in the sample were small, privately held firms; thus, financial performance data were not readily available regarding their competitors. Instead, these firms more readily observed competitors' top-line performance through industry bodies, news reports, and discussions with others. Second, using different performance metrics helped to avoid potential circularity in our definition of repertoire calibration (i.e., that firms close to the standard, by definition, perform better). In unreported analyses, we found that controlling for a firm's status as one of the top three performers in a particular year had no impact on our reported findings (details are available upon request).

Independent Variables

To assess TMT industry experience variety, we first identified all TMT members (current and past) for our sample firms. We constructed complete career histories for each of those individuals in terms of our focal variable of industry experience and potential confounding diversity variables such as functional background, age, gender, and race. We constructed a database of TMT experiences from college attendance to the present (or retirement) by performing a manual review of executive biographies, LinkedIn profiles, media interviews, CVs, data maintained by BoardEx, and other literature, such as EDGAR 10-K filings and S-1 prospectuses for companies that had recently gone public. In total, 468 individuals were identified; after triangulating information across sources, we determined that 343 of these individuals were TMT members. We were able to locate the career histories of 285 of those individuals (83%). More importantly, for the firms with complete data on all variables, and thus part of our analyses, 136 of the 139 TMT members identified were located (98%).

In line with prior work (e.g., Ferrier, 2001; Wiersema & Bantel, 1992), starting with the level of CEO or senior managing director, we defined the "top management team" as the top two levels of the organizational structure. This conceptualization captures those members of the organization tasked with major, important, and unstructured decisions. In practice, this means that all organization members who have terms such as "chief" or "executive VP" in their titles were included as part of the TMT unless the firm's organizational structure denoted otherwise. The contemporaneous composition of management teams in each year was discerned by triangulating the data available in BoardEx, FactSet, public filings, such as SEC DEF 14As, 10-Ks, and data on firm websites (both current and historical snapshots). The average size of a TMT was 3.78 (*SD* = 2.33, max = 14), which seems reasonable, given that we observed these firms in the early years of operation before their later growth. For each firm-year, we identified the current members of the TMT and collated the necessary information to compute TMT industry experience variety, other experiential diversity measures, and several controls (discussed later in this section).

To measure TMT industry experience variety specifically, we aggregated on a firm-year basis all the identifiable work experiences each member of the current TMT possessed up until that point in their career. We defined industries in terms of generally agreed-upon boundaries encoded by the North American Industry Classification System (NAICS). Using the primary NAICS code for the firm the individual was employed at during that year (or, where available, the firm's division for multi-business firms), we assigned a NAICS code (with a fidelity of up to six digits) to that experience. Using these data, we calculated a Shannon entropy index of the different NAICS codes present. Consistent with prior work (e.g., Andrevski et al., 2014; Aversa, Santoni, & Marino, 2017; Bell et al., 2011; Ferrier, 2001; Harrison & Klein, 2007), this TMT industry experience variety measure effectively captured the number and spread of qualitatively different experiences. There were 249 distinct industries across the entire population of TMT members examined, and, in total, there were 12,385 person-years of experience available for use to construct this measure. This measure was normalized such that a value of one equated to the theoretical maximum of ln(249).

Control Variables

We also measured several control variables, to reduce the chance that factors at the competitive action, TMT, firm, or industry level would confound our results.

Competitive action controls. To account for differences in the overall novelty, aggressiveness, and publicity of the firm's competitive action repertoire, we controlled for *total competitive actions*, the count of *new action types* employed, and the total number of *media mentions* for that firm in each year captured within the Factiva database. These factors can serve as alternative explanations for finding that calibrated repertoires influence performance (see Connelly et al., 2017). The number of actions taken and media mentions in a given year are relevant to consider because a low number of observed actions can serve to limit observed repertoire complexity and because the firm's overall level of competitive activity bestows a stock of routines and recipes to draw upon in selecting appropriate competitive actions.

TMT controls. At the TMT level, we controlled for several alternative diversity types. First, as Bunderson and van der Vegt (2018) discussed, experiential diversity possesses multiple related but distinct dimensions. Beyond variety—this paper's focus—two other diversity dimensions are germane: *TMT industry experience separation* and *TMT industry experience skew*. "Separation" captures interpersonal differences in the number of years of experience in a focal industry across team members (Harrison & Klein, 2007). By contrast, "skew" captures the predominance of experiences within the management team that are similar to or distal from the types of knowledge pertinent to the firm's focal industry (Bunderson & van der Vegt, 2018).

In line with current best practices, TMT industry experience separation was measured using the coefficient of variation of TMT member industry tenure (Bunderson & van der Vegt, 2018; Harrison & Klein, 2007). Higher values of the separation measure indicate a wider spread in tenure across members. TMT industry experience skew was measured by assigning each of the 249 distinct industries to one of three categories: (1) closely related to 3D printing, (2) moderately related to 3D printing, and (3) distally related to 3D printing. Industries that are closely related include the 3D printing industry itself and close relatives, such as die-casting, laser cutting, or inkjet printing. Moderately related industries include sectors with commonalities in terms of customers, technologies, or processes. While we qualitatively coded industries based on underlying technical, competitive, and demand similarities, our relatedness measure was also correlated with a NAICS code distance measure ($r = .65$). We computed the skew of each TMT's relatedness distribution, where a positive skew indicated a concentration of experiences in industries proximal to 3D printing. Statistical skewness is a measure that is consistent with current practice (Bunderson & van der Vegt, 2018). We examine the effect of skew in more detail in our Supplementary Analyses section.

Beyond the different facets of TMT industry experience diversity, we also controlled for *functional background diversity*, *gender diversity*, and *age diversity*, because such factors may influence the selection and execution of competitive actions (e.g., Ferrier, 2001; Hambrick et al., 1996). We sought to include TMT racial diversity, but no variance was observed in our sample. *Average TMT member age*, *TMT size*, *total 3D printing experience*, and *average relatedness of TMT member experiences* (to the 3D printing industry) may also influence the overall number and variety of perspectives within the management team. All else equal, larger TMTs have been shown to act and react less frequently (Hambrick et al., 1996). Through the channels of risk propensity, cognitive functioning, team cohesion, and other factors, differences in TMT members' average age may influence decision-making patterns (Bantel & Jackson, 1989).

Firm controls. At the firm level, we controlled for other pertinent aspects of corporate governance by considering *board size* and *CEO industry tenure*. Controlling for CEO industry tenure helped us to distinguish whether our effects were being driven by TMT dynamics or the CEO's experiences, while the size of the board of directors provided a window into another source of experiential insights beyond the TMT. We also controlled for *firm age* (measured by time since founding), *firm size* (measured by sales), as well as the firm's *public status* (as several firms went public during this sampling window, this measure was time varying). In our performance analyses, we also controlled for *return on assets in the prior year*. We tested and verified that prior ROA was not a significant predictor of calibrated repertoire complexity or consistency.

Industry controls. Finally, competitive activity may be driven by changes in industry structure and firms' conduct within the industry. We included controls for industry concentration, industry sales growth, and accumulated industry experience. Our measure of accumulated industry experience comprised four components: (1) competitive knowledge, or the total number of actions taken by all firms in the sample in a given year; (2) technical knowledge, measured by new patents filed by industry participants; (3) experiential knowledge, captured by the current year sales output of all firms; and (4) congenital knowledge, captured by the number of new firms founded in a given year (Huber, 1991). These measures exhibited convergent validity ($\alpha = .93$) and were consolidated to a single index to avoid collinearity and ill-conditioning issues. Similar results were achieved by employing year dummies to account for these time-varying and firm-invariant industry effects.

Analytical Technique

To test the effect of TMT experience variety on repertoire calibration (Hypotheses 1 and 2), we employed random-effects panel models with robust standard errors to account for unobserved, firm-level idiosyncratic effects, because our hypothesized mechanisms should operate equally when making comparisons within firms over time or across firms (Certo et al., 2017). Later, we employed fixed-effects and hybrid panel models to test whether within-firm changes had a similar effect as between-firm changes and to account for the potential endogeneity caused by firm-specific but time-invariant confounding variables (Greene, 2012). For our analyses of performance (Hypotheses 3 and 4), we likewise employed random effects models with robust standard errors and included the measure of past performance to account for potential reverse causality. We also included the complexity and consistency standards to ascertain the effect of achieving a dynamic fit with external variety contemporaneously and over time. In our supplemental analyses, we examined these models by using the fixed-effects approach. As expected, substantively identical results were also found using hierarchical linear modeling, and these are available upon request (Certo et al., 2017).

Finally, we examined our indirect effect hypotheses (Hypotheses 5 and 6) by following Mathieu and Taylor's (2006) recommendations. We first established the indirect effect of industry experience variety on performance and then tested for a direct effect. To triangulate our results, we employed three different techniques. First, we utilized the Monte Carlo method described in Preacher and Selig (2012) using the estimates from the piecewise models used to test Hypotheses 1/3 (the complexity path) and Hypotheses 2/4 (the consistency path). This approach allowed us to take advantage of our consistent estimation of the model's piecewise elements and maximized the available data (as Table 1, below, indicates, ROA data were not available for all firm-years). Second, we constructed an structural equation modeling (SEM) model with the primary variables of interest and employed bootstrapped standard errors to avoid parametric assumptions related to the sampling distribution of the indirect effect (Preacher & Selig, 2012). Third, we constructed an augmented SEM model that incorporated all the control variables and employed cluster-robust standard errors to account for firm-level effects while simultaneously estimating the system.

RESULTS

We present the descriptive statistics and correlations for the study variables in Table 1. For all tested models, multicollinearity does not appear to be a substantive issue, as the variance inflation factors for all variables across all models (but for one) remain below the conventional value of 10. This one exception in our performance models is TMT size, but the results of our analyses are unchanged with or without the inclusion of TMT size in these models.

Hypothesis Tests

Table 2 provides a summary of the results. Model 1 considers the influence of our control variables. In Model 2, we consider whether TMT experiential variety is incrementally predictive of *calibrated repertoire complexity*. We find that new action types and faster industry sales growth are associated with calibrated repertoire complexity. In contrast, high levels of CEO industry tenure, TMT size, and increased accumulated industry experience are negatively associated. As Model 2 indicates, the coefficient for TMT experiential variety is positive and significant ($b = 0.40$, $SE = 0.16$, $p < .05$), supporting Hypothesis 1 that higher levels of TMT experiential variety are positively associated with calibrated repertoire complexity. In terms of economic significance, when moving from one standard deviation below the mean on our TMT industry experience variety measure to one standard deviation above, we find that the magnitude by which firms err in calibrating their repertoire to external variety decreases by approximately 30%. Moreover, we find that the simple effect of experience variety on calibrated complexity is also present without the inclusion of control variables ($b = 0.20$, $SE = 0.06$, $p < .01$).

In Models 3 and 4, we examine whether TMT experiential variety is predictive of *calibrated repertoire consistency*. Model 3 examines the control variables and indicates that TMT gender diversity, new action types, industry concentration, sales growth, and industry experience separation are all associated with calibrated repertoire consistency. In contrast, media mentions and TMT size are negatively associated. In Model 4, supporting Hypothesis 2, we find that the coefficient for TMT experiential variety is positive and significant ($b = 0.83$, $SE = 0.35$, $p < .05$), which corresponds to a 40% reduction in the magnitude of miscalibration when moving from one standard deviation below the mean on our TMT industry experience variety measure to one standard

TABLE 1
Correlations and Descriptive Statistics

	Variable	*n*	*M*	*SD*	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Return on assets (%)	183	(0.17)	25	(106)	37													
2	Calibrated repertoire complexity	245	0.74	0.16	0.44	1.00	.06												
3	Calibrated repertoire consistency	227	0.64	0.26	0.18	1.00	.28	.58											
4	Repertoire complexity standard	245	0.39	0.13	0.07	0.56	.10	(.47)	(.07)										
5	Repertoire consistency standard	245	0.37	0.19	0.18	0.93	(.09)	.18	.12	(.49)									
6	TMT ind. exp. variety	245	0.23	0.12	0.04	0.51	(.36)	.16	.13	.20	(.09)								
7	ROA (prior year) (%)	177	(0.26)	25	(106)	37	.69	.01	.18	.12	(.09)	(.39)							
8	Total competitive actions	245	6.49	12.19	1.00	110	(.11)	.22	.18	.24	.01	.48	(.03)						
9	New action types	245	3.75	2.85	0.00	10.00	.14	.44	.50	.18	(.03)	.36	.16	.57					
10	Media mentions	245	67	124	0	787	(.09)	.25	.23	.24	(.03)	.48	.00	.84	.62				
11	TMT ind. exp. skew	245	0.22	0.20	(0.38)	0.38	(.18)	(.00)	(.04)	.04	(.20)	.23	(.16)	(.05)	.04	(.11)			
12	TMT ind. exp. separation	245	0.09	0.09	0.00	0.46	(.11)	.16	.22	.05	(.14)	.45	(.12)	.17	.29	.16	.26		
13	Average TMT ind. exp. relatedness	245	0.11	0.51	(1.02)	1.39	.34	.09	.03	(.15)	.04	(.63)	.35	(.13)	(.03)	(.19)	(.11)	(.17)	
14	TMT functional background diversity	245	0.93	0.56	0.00	2.20	(.01)	.10	.07	.29	(.18)	.52	(.02)	.36	.45	.40	(.03)	.35	(.32)
15	TMT gender diversity	245	0.11	0.19	0.00	0.50	.02	(.01)	.02	.22	(.23)	.13	(.02)	.10	.04	.06	.07	.02	.18
16	TMT age diversity	245	4.68	3.77	0.00	14.00	(.01)	.14	.14	.21	(.16)	.38	(.08)	.23	.39	.28	(.05)	.45	(.11)
17	TMT average member age	245	51	9	26	71	.40	.07	.30	(.01)	.17	(.25)	.39	.07	.30	.15	(.35)	(.12)	.23
18	TMT size	245	3.78	2.33	1.00	14.00	(.10)	.03	.06	.37	(.11)	.65	(.13)	.62	.45	.62	(.10)	.25	(.34)
19	TMT total 3D printing exp.	245	42	34	1	206	.25	.16	.20	.18	(.03)	(.05)	.27	.25	.54	.30	(.33)	(.01)	.11
20	Board size	245	4.31	5.10	0.00	23.00	.13	(.11)	.31	.29	.02	.10	.14	.27	.27	.35	(.14)	.07	(.17)
21	CEO industry tenure	245	13	6.27	1.00	30.00	.42	.07	.14	(.03)	.05	(.25)	.50	(.08)	.29	(.08)	(.13)	.01	.13
22	Firm age	245	23	21.50	1.00	93.00	.23	.04	.12	(.03)	.12	(.26)	.24	(.05)	.13	(.03)	(.14)	(.02)	.45
23	Firm size	245	335	835	0.00	6,665	(.04)	.20	.17	.21	(.07)	.46	(.02)	.75	.49	.75	(.07)	.23	(.13)
24	Public firm	245	0.47	0.50	0.00	1.00	.24	.06	.33	.03	.19	.14	.24	.27	.30	.39	(.30)	.01	(.30)
25	Industry concentration	245	0.22	0.05	0.15	0.34	.17	(.16)	.09	.46	(.23)	.03	.17	.15	.04	.22	(.04)	.01	(.07)
26	Industry sales growth	245	0.03	0.04	(0.10)	0.18	.05	.22	.06	(.44)	.30	(.09)	(.01)	(.08)	(.10)	(.04)	(.06)	(.10)	.05
27	Accumulated ind. exp.	245	0.18	0.93	(0.89)	1.99	.04	(.42)	.01	.84	.02	.17	.08	.30	.19	.27	(.05)	(.02)	(.13)

TABLE 1
Continued

	Variable	*n*	*M*	*SD*	Min.	Max.	14	15	16	17	18	19	20	21	22	23	24	25	26
1	Return on assets (%)	183	(0.17)	25	(106)	37													
2	Calibrated repertoire complexity	245	0.74	0.16	0.44	1.00													
3	Calibrated repertoire consistency	227	0.64	0.26	0.18	1.00													
4	Repertoire complexity standard	245	0.39	0.13	0.07	0.56													
5	Repertoire consistency standard	245	0.37	0.19	0.18	0.93													
6	TMT ind. exp. variety	245	0.23	0.12	0.04	0.51													
7	ROA (prior year) (%)	177	(0.26)	25	(106)	37													
8	Total competitive actions	245	6.49	12.19	1.00	110													
9	New action types	245	3.75	2.85	0.00	10.00													
10	Media mentions	245	67	124	0	787													
11	TMT ind. exp. skew	245	0.22	0.20	(0.38)	0.38													
12	TMT ind. exp. separation	245	0.09	0.09	0.00	0.46													
13	Average TMT ind. exp. relatedness	245	0.11	0.51	(1.02)	1.39													
14	TMT functional background diversity	245	0.93	0.56	0.00	2.20													
15	TMT gender diversity	245	0.11	0.19	0.00	0.50	.34												
16	TMT age diversity	245	4.68	3.77	0.00	14.00	.62	.35											
17	TMT average member age	245	51	9	26	71	(.03)	(.37)	(.10)										
18	TMT size	245	3.78	2.33	1.00	14.00	.80	.32	.51	.03									
19	TMT total 3D printing exp.	245	42	34	1	206	.50	.04	.31	.48	.46								
20	Board size	245	4.31	5.10	0.00	23.00	.19	.04	.01	.39	.35	.31							
21	CEO industry tenure	245	13	6.27	1.00	30.00	.04	(.25)	(.03)	.35	(.12)	.40	(.03)						
22	Firm age	245	23	21.50	1.00	93.00	.09	.08	.07	.51	.06	.47	.13	0.15					
23	Firm size	245	335	835	0.00	6,665	.22	(.01)	.12	.02	.50	.16	.21	0.04	(0.07)				
24	Public firm	245	0.47	0.50	0.00	1.00	.11	(.24)	(.04)	.47	.22	.19	.65	0.09	(0.13)	0.20			
25	Industry concentration	245	0.22	0.05	0.15	0.34	.15	.13	.06	.01	.21	.10	.18	(0.03)	0.03	0.13	0.03		
26	Industry sales growth	245	0.03	0.04	(0.10)	0.18	(.16)	(.12)	(.13)	.06	(.15)	(.07)	(.10)	0.01	0.02	(0.07)	0.03	(0.15)	
27	Accumulated ind. exp.	245	0.18	0.93	(0.89)	1.99	.23	.13	.15	.07	.36	.19	.34	(0.03)	0.03	0.20	0.14	0.41	(0.32)

Notes: Pairwise correlations reported. Ind. exp., industry experience; ROA, return on assets.

TABLE 2
Summary of Hypothesis Testing

	Calibrated repertoire complexity		Calibrated repertoire consistency		Return on assets		
Dependent variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Total competitive actions	0.00	0.00	0.00	0.00	−0.16	−0.15	−0.02
	(0.00)	(0.00)	(0.00)	(0.00)	(0.24)	(0.22)	(0.28)
New action types	0.03***	0.03***	0.05***	0.05***	1.59†	1.26	0.49
	(0.01)	(0.01)	(0.01)	(0.01)	(0.93)	(0.93)	(0.92)
Media mentions	0.00	0.00	−0.00†	−0.00†	−0.07**	−0.07***	−0.08***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.02)	(0.02)
TMT industry experience separation	0.09	0.01	0.49**	0.30	−10.03	−6.26	−10.51
	(0.11)	(0.10)	(0.18)	(0.21)	(14.24)	(14.23)	(15.74)
TMT industry experience skew	−0.05	−0.08	−0.07	−0.12	−5.06	−7.43	−5.24
	(0.06)	(0.06)	(0.10)	(0.09)	(12.58)	(12.12)	(12.02)
TMT functional background	0.03	0.03	−0.08	−0.06	−7.58	−9.23†	−9.78†
Diversity	(0.02)	(0.03)	(0.05)	(0.05)	(5.28)	(5.51)	(5.93)
TMT gender diversity	0.04	0.03	0.31*	0.23*	21.76	20.00	36.59*
	(0.06)	(0.05)	(0.12)	(0.11)	(16.37)	(15.26)	(16.67)
TMT age diversity	−0.00	−0.00	0.00	0.00	1.85*	1.66*	2.31**
	(0.00)	(0.00)	(0.01)	(0.01)	(0.87)	(0.74)	(0.81)
TMT average age	0.00	−0.00	0.00	0.00	0.49	0.34	0.80*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.33)	(0.37)	(0.35)
TMT size	−0.02*	−0.03**	−0.02*	−0.05***	0.64	1.63	0.64
	(0.01)	(0.01)	(0.01)	(0.01)	(1.32)	(1.36)	(1.53)
TMT total 3D printing experience	0.00	0.00	−0.00	0.00	−0.04	−0.09	−0.06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)	(0.06)	(0.07)
Average TMT industry experience	0.01	0.04	−0.06	0.03	4.24	2.22	1.01
Relatedness	(0.02)	(0.03)	(0.04)	(0.06)	(4.51)	(3.92)	(5.49)
Board size	−0.00	−0.00	0.00	0.00	−0.23	−0.34	−0.02
	(0.00)	(0.00)	(0.00)	(0.00)	(0.29)	(0.32)	(0.46)
CEO industry tenure	−0.00***	−0.00**	−0.00	−0.00	0.25	0.36	0.43
	(0.00)	(0.00)	(0.00)	(0.00)	(0.28)	(0.25)	(0.32)
Firm age	−0.00	−0.00	0.00	0.00	−0.05	0.06	−0.15
	(0.00)	(0.00)	(0.00)	(0.00)	(0.14)	(0.14)	(0.18)
Firm size	−0.00	−0.00	0.00	0.00	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Public firm status	0.01	0.01	0.09	0.09†	10.71	12.82†	10.68
	(0.04)	(0.03)	(0.07)	(0.05)	(6.82)	(7.10)	(7.65)
Industry concentration	0.13	0.18	0.91*	1.03**	64.28*	41.94*	60.81**
	(0.17)	(0.16)	(0.36)	(0.35)	(25.14)	(19.59)	(20.94)
Industry sales growth	0.48*	0.49*	0.62†	0.65*	79.70***	99.55*	86.30*
	(0.20)	(0.20)	(0.34)	(0.33)	(24.18)	(46.89)	(38.58)
Accumulated industry experience	−0.07***	−0.08***	−0.03	−0.03	−0.22	−2.78	−0.39
	(0.01)	(0.01)	(0.02)	(0.02)	(1.54)	(2.79)	(1.99)
TMT industry experience variety		0.40*		0.83*	−20.19	−36.20	−35.85
		(0.16)		(0.35)	(33.84)	(33.36)	(36.09)
Return on assets (year prior)					0.52***	0.50***	0.48***
					(0.11)	(0.11)	(0.10)
Calibrated repertoire complexity						25.65*	
						(10.31)	
Repertoire complexity standard						48.55	
						(32.07)	
Calibrated repertoire consistency							11.96*
							(5.19)
Repertoire consistency standard							−10.24
							(11.31)
Constant	0.70***	0.71***	0.12	0.17	−49.24**	−72.75***	−61.81**
	(0.10)	(0.09)	(0.19)	(0.16)	(18.90)	(21.77)	(20.74)

TABLE 2
(Continued)

	Calibrated repertoire complexity		Calibrated repertoire consistency		Return on assets		
Dependent variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Observations	245	245	227	227	175	175	161
R^2 (overall)	0.51	0.53	0.40	0.42	0.61	0.62	0.62
R^2 (within)	0.12	0.11	0.20	0.22	0.33	0.34	0.37
Number of firms	23	23	22	22	21	21	20

Note: Robust standard errors are in parentheses.
† $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

deviation above. The simple effect of experience variety on calibrated consistency is also positive and significant ($b = 0.29$, $SE = 0.13$, $p < .05$).

Turning to our analyses of firm performance, in Model 5, we find that the prior year's return on assets, industry concentration, sales growth, firm size, new action types, and age diversity are associated with increased performance in the current period. Media mentions are associated with decreased performance—perhaps because firms in trouble or growing too rapidly garner more attention. Introducing our effect of interest, in Model 6, we find evidence consistent with Hypothesis 3; calibrated repertoire complexity is associated with higher levels of performance as measured by ROA ($b = 25.65$, $SE = 10.31$, $p < .05$). In terms of economic significance, a one standard deviation increase in complexity calibration translates to a nearly four percentage-point boost on average to ROA. Since the average ROA in our sample is approximately 0% (as would be expected over the lifecycle of a growing industry), this performance advantage is substantial.

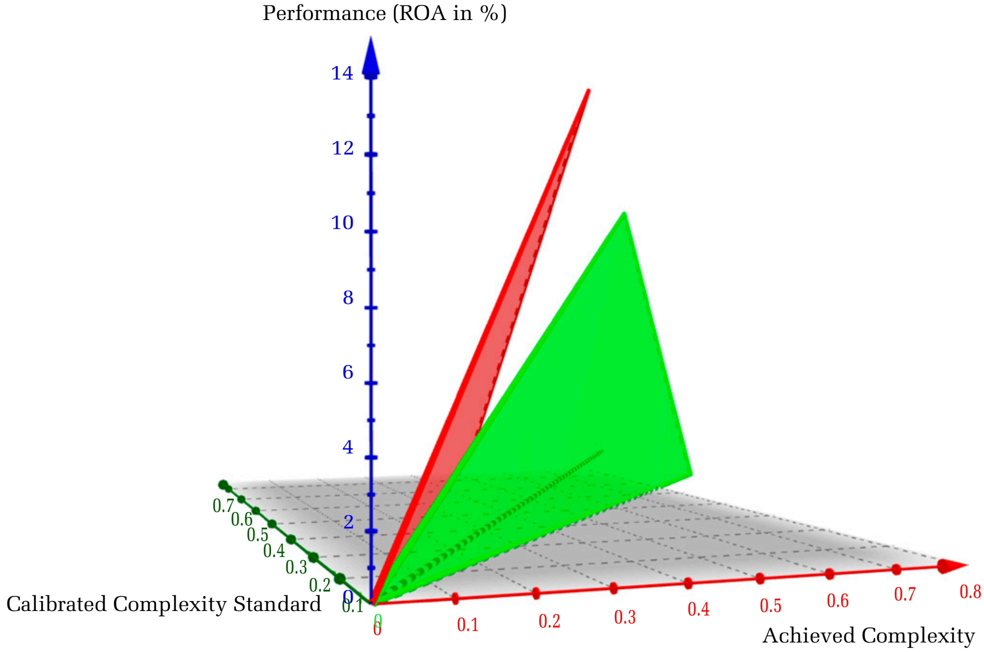
Similarly, in Model 7, we examine the influence of calibrated consistency on performance and find that, consistent with Hypothesis 4, repertoires closer to calibrated consistency levels are likewise beneficial to performance ($b = 11.96$, $SE = 5.19$, $p < .05$).[7]

To verify that this effect is symmetric for deviations both above and below the calibrated standard, we followed Edwards (2002) and tested whether unrestricted piecewise equations for repertoire complexity and consistency correspond to an absolute difference model. We find that calibrated repertoire complexity and consistency have similar effects above and below the calibration point (details available upon request). To visualize these results for calibrated repertoire complexity, we included a rendering of these two unrestricted surfaces for the complexity equations in Figure 1, which illustrates how deviations above and below the calibrated standard have similar effects. The graphic shows three observations: performance increases when a firm's achieved complexity is close to the calibrated level, performance rapidly declines if the level of calibration falls in either direction, and performance tends to be highest in periods in which calibrated complexity is at higher levels and the focal firm's complexity is closely aligned.

With our baseline effects established, we concluded the analysis by examining our indirect effects (Mathieu & Taylor, 2006). First, we tested whether indirect effects were present. As shown in Figure 2, we first report the results of Preacher and Selig's (2012) Monte Carlo estimation method by using 20,000 replications (these results are included in Table 3). Through both calibrated complexity ($b = 9.49$, 95% CI = [0.88, 23.94]) and calibrated

[7] We examine the effect of calibrated repertoire complexity and consistency independently, since they are different facets of the underlying repertoire construct, and we did not seek to test their incremental explanatory power vis-à-vis each other. If both variables are included simultaneously, their effect sizes remain positive but do not meet conventional significance thresholds, due to significant common variance ($r = .58$). A Wald test indicates that the hypothesis that both variables are simultaneously zero is rejected ($c\chi^2(2) = 7.50$, $p = .02$), and orthogonalized versions of the variables are positive and significant. This indicates that the shared variance between the two variables has explanatory power that is discarded when both are entered into the regression simultaneously.

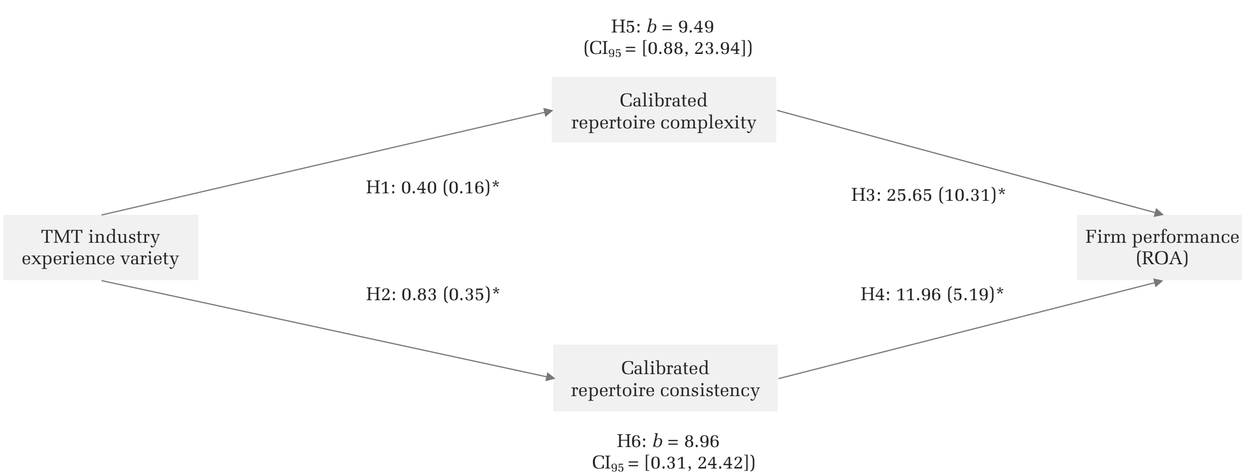
FIGURE 1
The Effect of Deviations from the Calibrated Complexity Standard on Firm Performance



Notes: The green surface corresponds to values wherein achieved complexity is greater than the calibrated complexity standard. The red surface corresponds to values for which achieved complexity is less than the calibrated complexity standard. The dashed line below the surfaces indicates the points in the XY plane where the focal firm's achieved level of complexity matches the calibrated standard.

consistency (b = 8.96, 95% CI = [0.31, 24.42]), there is a positive and significant indirect effect from TMT industry experience variety to ROA. Providing support for Hypotheses 5 and 6, neither of the 95% confidence intervals include zero. These results are largely corroborated by SEM models, including the study control variables and cluster-robust standard errors and simplified SEM models with only the main study variables included and bootstrapped standard errors. The range of the confidence

FIGURE 2
Indirect Effects of TMT Industry Experience Variety on Firm Performance via Repertoire Calibration



Notes: Graphic based on Monte Carlo simulation results (see also Table 3). ROA, return on assets; TMT, top management team.

TABLE 3
The Effects of TMT Industry Experience Variety on Firm Performance

	Experience variety → Calibrated complexity		Calibrated complexity → Performance		Indirect effect		Experience variety → Calibrated consistency		Calibrated consistency → Performance		Indirect effect	
	b	***SE***	***b***	***SE***	***b****	**95% CI [LL, UL]**	***b***	***SE***	***b***	***SE***	***b****	**95% CI [LL, UL]**
Main effects and bootstrapped errors	0.43	0.09	22.64	10.70	9.76	[0.17, 19.35]	0.38	0.20	32.64	7.27	12.42	[−1.33, 26.17]
With controls and cluster-robust errors	0.40	0.15	24.91	9.88	9.96	[−1.14, 21.06]	0.82	0.32	11.52	4.48	9.41	[0.23, 18.58]
Monte Carlo simulation	0.40	0.16	25.65	10.31	9.49	[0.88, 23.94]	0.83	0.35	11.96	5.19	8.96	[0.31, 24.42]

Note: CI, confidence interval; LL, lower limit, UL, upper limit.

intervals and the point estimates of the indirect effects are quite similar across the specifications, particularly for the repertoire complexity path. In all cases, the 90% confidence interval for the indirect effect estimate does not include zero.

Consequently, we then followed the protocol established in Mathieu and Taylor (2006) and proceeded to test whether the direct effect of TMT experience variety on firm performance was present, and found no evidence (Model 5; $b = -20.19$, $SE = 33.84$, $p > .10$). The lack of a significant direct effect is consistent with meta-analytical evidence presented in Bell et al. (2011: 725–727). Together, we thus conclude that, as predicted, the effect of TMT experiential variety on firm performance is indirect. The presence of these indirect effects serves as direct corroboration of the LRV: firms that possess TMT experiential variety can successfully calibrate their internal variety (competitive repertoires) to match the external variety and maintain fit with the environment (resulting in comparatively higher performance).

Supplemental Analyses

Within- versus between-firm effects. We employed a random-effects model for our analyses because our hypothesized mechanisms are agnostic to whether TMT industry experience or calibrated repertoires vary within or between firms (Certo et al., 2017). However, while random effects models allow us to tap into within- and between-firm variance simultaneously, this comes at the price of two risks to our inferences. First, the effects may not be homologous. Second, random effects do not allow us to control for unobserved, time-invariant factors correlated with the error term. To address these issues, we followed the guidance of Certo et al. (2017) to explore the distribution of variance between and within firms and utilize fixed and "hybrid" panel modeling approaches (Allison, 2005); the latter estimates between and within-firm effects (see also Mundlak, 1978). The results are reported in Table 4.

We first used intraclass correlation coefficients (ICCs) to partition the within- and between-firm variance in TMT industry experience variety, calibrated repertoires, and firm performance, respectively. The majority of the variance in TMT industry experience variety is between firms (ICC(1) = .76). This is not surprising because TMT industry experience variety can only change within firms in two ways: through member additions and departures and the incremental accrual of 3D printing experience by existing

TABLE 4
Hybrid Models of Calibrated Repertoires

	Random effects models		Hybrid effects models	
Dependent variable	**Calibrated complexity Model 8**	**Calibrated consistency Model 9**	**Calibrated complexity Model 10**	**Calibrated consistency Model 11**
New action types[a]	0.03***	0.05***	0.02**	0.05***
	(0.00)	(0.01)	(0.01)	(0.01)
Firm avg (new action types)			0.01	0.02
			(0.01)	(0.02)
Media mentions[a]		−0.00		−0.00
		(0.00)		(0.00)
Firm avg (media mentions)				−0.00
				(0.00)
TMT industry experience skew[a]	−0.09		−0.10	
	(0.05)		(0.08)	
Firm avg (TMT ind. exp. skew)			0.08	
			(0.11)	
TMT gender diversity[a]		0.16*		0.11
		(0.08)		(0.15)
Firm avg (TMT gender diversity)				0.06
				(0.22)
TMT age diversity[a]		0.00		−0.00
		(0.01)		(0.01)
Firm avg (TMT age diversity)				0.00
				(0.01)
TMT size[a]	−0.01*	−0.05***	−0.02**	−0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
Firm avg (TMT size)			0.01	0.00
			(0.01)	(0.02)
TMT ind. exp. relatedness[a]	0.04†		0.04	
	(0.02)		(0.03)	
Firm avg (TMT exp. relatedness)			0.02	
			(0.03)	
CEO industry tenure[a]	−0.00**		−0.00***	
	(0.00)		(0.00)	
Firm avg (CEO industry tenure)			0.01**	
			(0.00)	
Firm age[a]		0.00***		−0.01
		(0.00)		(0.01)
Firm avg (firm age)				0.01†
				(0.01)
Public firm status[a]		0.14***		0.10*
		(0.03)		(0.05)
Firm avg (public firm status)				0.01
				(0.06)
Industry concentration[a]		0.97**		1.21**
		(0.32)		(0.38)
Firm avg (industry concentration)				2.32*
				(0.98)
Industry sales growth[a]	0.49*	0.66†	0.35†	0.13
	(0.20)	(0.35)	(0.18)	(0.34)
Firm avg (industry sales growth)			−2.98*	−7.80†
			(1.36)	(4.47)
Accumulated industry experience[a]	−0.07***	−0.02	−0.05***	0.06
	(0.01)	(0.02)	(0.01)	(0.04)
Firm avg (acc. industry experience)			−0.11**	−0.22**
			(0.04)	(0.08)
TMT industry experience variety[a]	0.35*	0.60***	0.19	0.36
	(0.15)	(0.15)	(0.19)	(0.31)

TABLE 4
(Continued)

Dependent variable	Random effects models: Calibrated complexity Model 8	Random effects models: Calibrated consistency Model 9	Hybrid effects models: Calibrated complexity Model 10	Hybrid effects models: Calibrated consistency Model 11
Firm avg (TMT ind. exp. variety)			0.36	0.64
			(0.22)	(0.44)
Constant	0.72***	0.24**	0.66***	−0.16
	(0.04)	(0.08)	(0.05)	(0.16)
Observations	245	227	245	227
R^2 (overall)	0.50	0.39	0.55	0.45
R^2 (within)	0.07	0.20	0.10	0.24
Number of firms	23	22	23	22

Notes: Robust standard errors are in parentheses. Firm averages may vary for industry-level variables because the panel is unbalanced, differentially exposing firms to factors such as growth rates.

[a] Indicates variables that contain within- and between-firm variance for Models 8 and 9 and within-variance only for Models 10 and 11.

† $p < .10$

* $p < .05$

** $p < .01$

*** $p < .001$

TMT members. In contrast, calibrated complexity (ICC(1) = .56) and consistency (ICC(1) = .26) demonstrate more within-firm variance, as does firm performance (ICC(1) = .56).

We then used fixed effects to test whether our calibrated repertoire results hold. We found that the within-firm effect of TMT experience variety on calibrated complexity was muted and not significant ($b = .05$, $SE = 0.27$, $p > .10$); the within-firm effect on calibrated consistency was similar to the random effects specification but failed to reach conventional significance levels ($b = .90$, $SE = 0.49$, $p < .10$). With this baseline in mind, we employed the hybrid approach. Because the hybrid technique requires each variable (including controls) to be split into between and within components (doubling the parameters to be tested), to avoid unnecessary parameter proliferation, we first eliminated all "impotent controls." For example, when estimating the hybrid complexity deviation model, we omitted TMT experience separation, gender variety, functional background diversity, age diversity, average age, total actions, unit sales, public firm status, board size, and total TMT industry tenure. Linear hypothesis tests that set impotent controls simultaneously to zero were insignificant for both calibrated complexity, $\chi^2(10) = 15.9$, $p > .10$, and consistency, $\chi^2(9) = 14.9$, $p > .10$; this justifies their omission.

As shown in Models 8 and 9, the results of our primary random effects models are replicated after stripping away impotent controls for both complexity ($b = .35$, $SE = 0.15$, $p < .05$) and consistency ($b = .60$, $SE = 0.15$, $p < .01$). In Model 10, we find that there is a difference in the between ($b = .36$, $SE = 0.22$) and within ($b = .19$, $SE = 0.19$) estimates for complexity, but a Wald test indicates that the difference is not significant, $\chi^2(1) = 0.20$, $p > .10$. As Certo et al. (2017) explained, Wald tests serve as a more pointed alternative to the Hausman test. With respect to calibrated consistency, we find, in Model 11, that the between effect is larger ($b = .64$, $SE = 0.44$) than the within effect ($b = .36$, $SE = 0.31$), but the difference is insignificant, $\chi^2(1) = 0.16$, $p > .10$.

In terms of performance effects, we directly tested our results' robustness by employing fixed effects models, since, for calibrated repertoires and performance, a larger fraction of the variance exists within and between firms. As reported in Table 5, we find that within-firm variations in calibrated complexity have a smaller point estimate for performance (Model 12; $b = 9.93$, $SE = 8.26$, $p > .10$). By contrast, for within-firm variations in calibrated consistency, we continue to find a positive and significant effect of the same magnitude as our random-effects estimates (Model 13; $b = 11.28$, $SE = 4.96$, $p < .05$).

Direction of repertoire deviations. Recall that our calibrated repertoire hypotheses are underpinned by predictions regarding the relative proportion of *calibrated*, *routinized*, and *headless chicken* responses. By jointly examining repertoire complexity and repertoire consistency, we can obtain a sense of whether the headless chicken or routinized responses dominate. A repertoire with a surfeit of routinized responses will tend to be more consistent compared

TABLE 5
Fixed Effects Models of Performance

	Return on assets	
Dependent variable	**Model 12**	**Model 13**
Total competitive actions	−0.29	−0.31
	(0.20)	(0.20)
New action types	−0.55	−0.26
	(1.08)	(1.09)
Media mentions	−0.04†	−0.04†
	(0.02)	(0.02)
TMT industry experience separation	−12.81	−5.94
	(8.34)	(8.36)
TMT industry experience skew	−0.18	4.73
	(5.79)	(9.36)
TMT functional background diversity	−10.16	−12.00
	(10.30)	(11.30)
TMT gender diversity	37.70	51.19†
	(28.14)	(25.30)
TMT age diversity	0.87	2.11
	(1.33)	(1.31)
TMT average age	0.88	1.97
	(1.29)	(1.33)
TMT size	3.66†	4.33*
	(1.80)	(1.98)
TMT total 3D printing experience	−0.32	−0.36
	(0.19)	(0.21)
Avg. TMT industry exp. relatedness	3.89	16.91
	(12.38)	(15.26)
Board size	−0.95*	−0.52
	(0.41)	(0.90)
CEO industry tenure	0.40	0.19
	(0.25)	(0.22)
Firm age	0.00	0.96
	(0.00)	(1.24)
Firm size	0.00	0.00
	(0.00)	(0.00)
Public firm status	16.25	11.65
	(9.49)	(9.45)
Industry concentration	47.79*	56.17*
	(18.76)	(19.80)
Industry sales growth	80.43†	86.97†
	(45.70)	(46.79)
Accumulated industry experience	−2.49	−5.99
	(2.80)	(6.28)
TMT industry experience variety	−14.43	5.90
	(56.02)	(77.69)
Return on assets (year prior)	0.29*	0.27†
	(0.14)	(0.14)
Calibrated repertoire complexity	9.93	
	(8.26)	
Repertoire complexity standard	87.35	
	(66.34)	
Calibrated repertoire consistency		11.28*
		(4.96)
Repertoire consistency standard		18.72
		(18.46)
Fixed effects	Yes	Yes
Constant	−97.60†	−155.16*
	(46.91)	(60.19)
Observations	175	161
R^2 (within)	0.40	0.44
Number of firms	21	20

Note: Robust standard errors are in parentheses.
† $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

to the consistency standard (because the same subset of actions is employed even when stimuli change from year to year) and less complex than the complexity standard (since pertinent elements of stimuli are discarded, resulting in a smaller subset of actions being employed in a given period). By comparison, a repertoire containing a surplus of headless chicken responses will have the opposite pattern. Such repertoires will be more complex than the complexity standard (since random, one-off actions are taken to find an appropriate response) and less consistent than the consistency standard (small changes in the pattern of stimuli from year to year evoke more changes in the repertoire than are necessary).

However, while we utilize TMT industry experience variety to predict what proportion of these responses are calibrated, variety alone is insufficient to predict whether routinized or headless chicken responses are more likely. To validate our model, such information would be useful. To that end, we considered the role of experience skew in predicting how firms err when calibrating their repertoires to external variety. Whereas variety captures the TMT's spread of experiences, skew refers to whether these experiences are skewed toward certain categories.

Consider first the situation in which a firm's experience base skews toward the 3D printing industry. We expect that, in proximal settings, such teams will rely more heavily on learned responses because they will substantially influence managerial cognitions and implicit understanding of industry norms, recipes, and institutions (Hambrick et al., 1993; Spender, 1989). Since managers' perceptual foreground narrows with experience concentrated in a particular context (Starbuck & Milliken, 1988), their ability to assimilate and accommodate emerging

TABLE 6
The Influence of TMT Industry Experience Skew

Dependent variable	Signed complexity deviations Model 14	Signed consistency deviations Model 15
Total competitive actions	0.00	−0.01†
	(0.00)	(0.00)
New action types	0.05***	−0.06***
	(0.01)	(0.01)
Media mentions	0.00**	−0.00†
	(0.00)	(0.00)
TMT industry experience separation	0.00	−0.41
	(0.13)	(0.26)
TMT functional background diversity	0.00	0.11
	(0.03)	(0.07)
TMT gender diversity	0.03	−0.39**
	(0.06)	(0.15)
TMT age diversity	−0.01†	0.01
	(0.00)	(0.01)
TMT average age	−0.00	−0.00
	(0.00)	(0.00)
TMT size	−0.01	0.04*
	(0.01)	(0.02)
TMT total 3D printing experience	−0.00	0.00
	(0.00)	(0.00)
Avg. TMT industry exp. relatedness	0.04†	−0.00
	(0.02)	(0.07)
Board size	−0.00	−0.00
	(0.00)	(0.01)
CEO industry tenure	0.00	−0.01*
	(0.00)	(0.00)
Firm age	−0.00	−0.00
	(0.00)	(0.00)
Firm size	−0.00*	0.00**
	(0.00)	(0.00)
Public firm status	0.00	−0.14
	(0.05)	(0.09)
Industry concentration	−0.07	−0.55
	(0.22)	(0.41)
Industry sales growth	0.85**	−2.09***
	(0.29)	(0.54)
Accumulated industry experience	−0.10***	0.02
	(0.02)	(0.03)
TMT industry experience variety	0.36†	−0.76†
	(0.20)	(0.45)
TMT industry experience skew	−0.11*	0.11
	(0.05)	(0.12)
Constant	−0.24*	0.75***
	(0.10)	(0.22)
Observations	245	227
R^2 (overall)	0.67	0.55
R^2 (within)	0.25	0.31
Number of firms	23	22

Note: Robust standard errors are in parentheses.
† $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

competitive phenomena, trends, and stimuli might be constrained. Thus, such firms likely enact a surfeit of routinized responses, resulting in overly consistent and insufficiently complex repertoires. By contrast, if the firm's experience base skews away from the 3D printing industry, TMTs will likely view the competitive environment through a process of trial-and-error experiential learning (Huber, 1991) and analogical reasoning based on their prior experiences elsewhere (Gavetti et al., 2005). The contextual knowledge acquired in distal industries differs in material ways (Beckman, 2006; Fern, Cardinal, & O'Neill, 2012) and has unique and only partially overlapping dimensions (Geletkanycz & Hambrick, 1997). Thus, teams whose experience skews away from the focal industry likely develop needlessly complex and insufficiently consistent responses.

Armed with these expectations regarding the *direction* of deviations, in Table 6, we examine the effect of TMT industry experience skew on signed complexity and consistency deviations. In Model 14, we find that teams whose experience set skews toward the focal industry are more likely to have less complex repertoires than the standard ($b = -0.11$, $SE = 0.05$, $p < .05$). However, in Model 15, we find no evidence to suggest that these teams are systematically more consistent than the standard ($b = 0.11$, $SE = 0.12$, $p > .10$).

Interaction of within- versus between-person experiential variety. Our primary analyses examine industry experience variety at the team level. However, teams may achieve this variety in two ways; namely, between individuals (i.e., several specialists working together) and within individuals (i.e., generalists with a variety of experiences). It is also possible that within-person and between-person variety may have interwoven effects because of their differing implications for learning, group interactions, and managerial cognition. We examined whether there was an interaction between within- and between-person variety in predicting calibrated repertoires, but we did not find significant results for either calibrated complexity ($b = -.01$, $SE = 0.01$, $p > .10$) or calibrated consistency ($b = .04$, $SE = 0.03$, $p > .10$).

Calibration time frame. While our calibration measures use top performers' contemporaneous repertoires as the calibration standard, it could be argued that repertoires that anticipate longer time frames may be more adaptive to changing competitive conditions. To explore this further, we considered whether repertoires calibrated against those of top competitors in the future were predictive of firm performance. In unreported analyses,[8] instead of employing the contemporaneous complexity and consistency of top performers, we instead utilized the complexity and consistency of the top performers one, two, three, four, and five years in the future (in all cases, we compared this "leading" value to the current level of repertoire complexity and consistency for the focal firm). The data indicated that calibrating against top performers' current repertoires appeared to have the most poignant effect on performance. It seems that firms able to calibrate their repertoire complexity to future levels enjoy higher performance, but this effect diminishes and becomes insignificant after three years from the current period.

DISCUSSION

Prior studies in upper echelons research (e.g., Hambrick et al., 1996) and competitive dynamics have commonly invoked the LRV to theorize the implications of TMT experiential variety for competitive behavior and firm performance (for reviews, see Chen & Miller, 2012; Ketchen et al., 2004). The canonical logic is that experiential variety equips management teams with the cognitive and sensory apparatus and behavioral routines to enact adaptive competitive repertoires. Although this logic is taken as a core doctrine of competitive dynamics research, it represents what Poulis and Poulis (2016) referred to as a superficial embrace of the law. Researchers in strategy have also tended to widen the scope of the law to suggest that internal variety should be *at least as* great as "the external one so that organizations can cement their adaptability in light of unexpected external variety/complexity" (Poulis & Poulis, 2016: 504).

Leveraging recent advances (Boisot & McKelvey, 2011; Poulis & Poulis, 2016), we proposed a clarification, elaboration, and direct empirical testing of the LRV by advancing the concept of "calibrated competitive repertoires." We theorized and found that, by minimizing the number of competitive misfires—either routinized or headless chicken responses (Boisot & McKelvey, 2011)—management teams with higher levels of experiential variety are better able to calibrate the complexity and consistency of competitive repertoires to external variety, and, in so doing, increase firm performance. Our findings reaffirm one of the core tenets of the LRV in competitive dynamics

[8] Unreported results were provided to the editor and blind reviewers and are available on request.

research; that is, a system can survive only to the extent that the "range of responses it is able to marshal—as it attempts to adapt to imposing tensions—successfully matches the range of situations—threats and opportunities—confronting it" (Ashby, 1956: 207). Critically, our findings regarding calibrated repertoires reaffirm that the concept of "requisite" represents a situation in which the "variety of a system's response matches that of incoming stimuli in an adaptive way" (Boisot & McKelvey, 2011: 284).

Contributions and Future Research

Our study holds implications for research on the LRV, competitive repertoires, and upper echelons theory.

Law of requisite variety. We extend research on the LRV (Ashby, 1956; Boisot & McKelvey, 2011; Poulis & Poulis, 2016) in two ways. First, we introduce the concept of calibrated competitive repertoires as a construct for examining the extent to which a firm's competitive actions match the level of variety demanded by the competitive environment. We propose that a calibrated rather than an absolute level of complexity or consistency represents a more precise approach for applying and testing the LRV. Our empirical investigation suggests that a firm's ability to calibrate the complexity and consistency of its competitive repertoires to that of top-performing competitors pays economic dividends in terms of increased firm performance, at least as measured by ROA. Because the LRV is fundamentally a cybernetic theory of system behavior (Ashby, 1956), calibration is an essential fulcrum by which system stability is attained. Critically, a focus on calibration reorients attention from a lopsided and unduly bright or dark view of complexity to identify the conditions under which complexity is beneficial or not. Furthermore, we believe that the most compelling advance is to redirect attention toward the calibration of system properties with the external environment generally, thereby broadening the applicability of the LRV to other aspects of competitive behavior.

Second, although the LRV has predominantly focused on calibrating complexity with external variety, we extend the theory's conceptual remit to include the consistency of competitive repertoires, recognizing that calibration entails both contemporaneous and temporal components. Critically, it is important to recognize that the level of variety is a moving target. Coming back to the core logic of the LRV as a theory of cybernetics, the most robust empirical test of this theory may be not whether a firm manages to calibrate the level of competitive complexity at a given point in time, but, rather, whether the consistency of competitive repertoires is calibrated; too little consistency may hinder capability development and could indicate a failure trap, and too much consistency may signal inertia and forebode competitive obsolescence.

Calibrating the consistency of repertoires is a far more fundamental challenge for organizations; it involves overcoming multiple sources of inertia, path dependence, and even imprinting effects. Therefore, we would argue that a dual focus on calibrated complexity and consistency presents a more stringent test of the LRV. An important question for future research inspired by this direction is whether there is an inherent trade-off between calibrated complexity and calibrated consistency. For example, calibrating the complexity level could necessarily involve miscalibrating consistency in the short term as the firm seeks to learn through experimentation with different competitive actions. The pertinent question for future research is, if firms are forced into a trade-off, is it better to achieve calibration in complexity or in consistency? In unreported analyses, we found no evidence of substitution effects between complexity and consistency, but it is less clear whether the underlying drivers of complexity and consistency differ and whether trade-offs between these drivers must be made.

Competitive repertoire research. We identify and demonstrate the need to utilize an appropriate reference point when assessing competitive repertoire characteristics. More tangibly, we provide a standard or reference point against which calibration can be evaluated: top-performing competitors. The LRV focuses scholarly attention on external variety, but there are multiple sources of variety. Indeed, a central premise of upper echelons theory (Hambrick & Mason, 1984) and the attention-based view of the firm (Ocasio, 1997) is that, based on functional biases and heuristics, managers may attend to different types or forms of variety (Nisbett & Ross, 1980). Although it may be valid to argue that the focus of competitive attention is on referent others similar in characteristics, capabilities, or positions (Fredrickson et al., 2010), much of the focus of the behavioral theory is on those firms "thought to be slightly better off" (Buunk & Gibbons, 2007: 4).

Indeed, numerous research streams—notably, institutional theory—and the behavioral theory of the firm, have recognized that, whether defined in terms of size or profitability, top performers' actions represent the reference point against which most firms seek to aspire. In essence, when causal ambiguity is high, many firms look to top performers as a cognitive shortcut—a phenomenon known as "outcome-based vicarious learning" (Srinivasan et al., 2007). Therefore, an important contribution of the current study is to shift the reference point for a relevant indicator of external variety from an undefined theoretical maximum level of external variety to top-performing competitors.

Moreover, we enrich the research on competitive repertoires by developing and specifying the multidimensional construct of calibrated competitive repertoires and show their performance implications. In so doing, our study sheds insight and further evidence that the notion of "more is better" may be too simplistic to characterize the relationship between firm performance and repertoire characteristics (Connelly et al., 2017). Additionally, by considering calibration cross-sectionally (complexity) and longitudinally (consistency), we evaluate whether firms calibrate repertoires to enhance performance (Lamberg et al., 2009). Notably, the concept of calibration is not merely another variable of interest—we submit that it represents a fundamental mechanism that provides a more complete and compelling explanation of firms' competitive behavior. One interpretation of our indirect effect analyses is that calibration is the primary mechanism accounting for the relationship between TMT diversity and performance. While it would be imprudent to rule out other possibilities, we believe the most productive focus of inquiry will be to understand how different TMT diversity types result in various forms of miscalibration. Said differently, how firms miscalibrate might be as important as how much they miscalibrate. In this regard, we hope that our study provides a launchpad from which a more focused stream of investigations can be initiated.

Upper-echelons theory. Beyond contributing to the LRV and competitive repertoire research, our theory and findings direct attention to a limitation of upper echelons theorizing and call for a more nuanced approach in two salient respects.

First, the central thrust of upper echelons theorizing has been explaining why an executive or group of executives with a particular set of experiences, values, and personalities engage in certain actions. However, a focus on calibration moves closer to the core logic of the theory. We say this because failures to calibrate occur when managers fail to attend to external variety; this may occur because the field of vision, selective perception, and/or interpretations of executives are limited or biased in some way by the cognitive base or values of executives. Therefore, while the choice of a particular action is an endogenous outcome of a host of considerations, calibration misfires predominantly reside and can be explained with reference to the accuracy of managerial perceptions, which is a core concept of upper echelons theory (Hambrick & Mason, 1984). Therefore, for upper echelons researchers, a focus on the concepts of calibrated competitive complexity and consistency can provide a renewed focus—one that allows for a more stringent and robust test of its underlying mechanisms. While upper echelons theory can offer a compelling account of the cognitive dimensions of calibration, future research that identifies the behavioral routines and rigidities that lead to miscalibrations is a priority.

A second way our results can help advance upper echelons theorizing relates to the conceptualization of top team diversity. Although management scholars have gone to great lengths to clarify and elaborate on the concept of managerial diversity (Bell et al., 2011; Harrison & Klein, 2007), we lack nuanced insights into the additive and combinatorial effects of different types of diversity. In addition to the variety of experiences, it is important to account for whether diverse experiences are skewed in a particular direction. In our supplementary testing, we provide initial evidence that, in management teams, the skew of experience may ignite centrifugal and centripetal forces that regulate the influence of diversity. For example, diverse management teams whose experience is skewed toward the focal industry are found to be less likely to successfully calibrate the complexity of competitive repertoires with top-performing firms; this is likely due to the excessive deference to the critical mass of insiders who can dominate the competitive discourse (i.e., Pitcher & Smith, 2001). We provide upper echelons researchers with evidence that experiential variety appears to mitigate the influence of selective perception and other similar cognitive biases. Although tentative, these findings call for a much more granular approach to theorizing TMT diversity's effects and impact.

Limitations

Several study limitations bound the conclusions that can be drawn from these data. First, despite tapping several databases and alternative sources, the overall sample is relatively small; thus, detecting effects on firm performance could benefit from a larger sample, particularly for industries wherein earlier and later stages of the life cycle can be jointly examined.

Relatedly, while our context provides a lens with which to closely examine our construct of interest in a setting with less confounded testing, it comes at the expense of contextual generalizability that other recent studies, such as Connelly et al. (2017), have achieved by performing cross-industry analyses. Second, while our study attempts to parse out the different aspects of TMT industry experience diversity (namely, variety alongside separation and skew) while also controlling for other types of TMT heterogeneity (gender, functional background, and the like), there are several alternative experiences that TMT members accrue over their careers that may result in similar predictions. Indeed, our study's most potent contribution may not pertain to the specific variables examined, but, rather, to the theoretical development it offers from the perspective of the LRV. For example, functional background or educational diversity could also be theorized to investigate these effects (e.g., Hambrick et al., 1996). Third, while we use a summary measure of financial performance to proxy the firm's ability to adapt to changing competitive circumstances, alternative forward-looking measures, such as market valuations, may provide additional insights (Hughes-Morgan et al., 2018). Finally, we cannot directly observe TMTs discriminating among specific stimuli and constructing their repertoires of actions. Future work can examine decision-making on a more micro level to parse out the processes we allude to in our theory development.

CONCLUSION

We have advanced and tested the thesis that TMT experiential variety of a firm's TMT will influence performance by calibrating competitive repertoires to external variety. After analyzing hand-collected data for firms operating in the 3D printing industry over the past three decades, our results show that the LRV is a plausible explanation for how top teams with greater experiential variety can positively influence the performance of their firms by calibrating competitive repertoires contemporaneously and across evolving competitive conditions.

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