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UTILIZING THE FIRM'S RESOURCES: HOW TMT HETEROGENEITY AND RESULTING FAULTLINES AFFECT TMT TASKS

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While theory and evidence show that firms' competitive actions mediate the resource-performance relationship, details of top managements' roles in shaping resource utilization choices have been underemphasized. We address this oversight by integrating top management team heterogeneity and any resulting faultline strength with the resource-action-performance model to investigate how TMT composition differentially affects the model's two linkages. Specifically, we argue that TMT heterogeneity positively affects the resource-action linkage, yet negatively affects the action-performance linkage. Moreover, when heterogeneity begets strong faultlines, all such positive effect is lost. Supportive evidence from the in-vitro medical diagnostic substance manufacturing industry allows us to discuss how our findings contribute to upper echelons theory, as well as the emerging stream on resource utilization.

INTRODUCTION

A central argument in the growing literature on resource utilization (Helfat *et al.*, 2007; Sirmon, Hitt, and Ireland, 2007) is that beyond what resources a firm possesses, how top management utilizes those resources is critical to determining performance outcomes (Mahoney, 1995). In fact, Majumdar (1998) identified significant variation between firms' resource utilization within the same industry, while Adner and Helfat (2003) revealed that such differences matter greatly to firm performance. Next, Peteraf and Reed (2007) demonstrated that resource utilization decisions are critical to a firm attaining fit in rapidly changing markets, while Sirmon, Gove, and Hitt (2008) found that such fit increases a resource's productivity beyond expected levels. More recently, Ndofor and colleagues' (2011) mediated resource-action-performance model suggests that top managements' most crucial roles in resource utilization are found in two primary areas: (1) formulating actions to leverage firm resources, and (2) directing the implementation of those actions to realize performance gains.

However, the treatment of management within this stream has been ambiguous (Sirmon *et al.*, 2011). That is, managements' resource utilization decisions are theorized, but characteristics of the top management teams (TMT), which might influence such actions, have not been investigated in depth. For example, while Sirmon and Hitt (2009)

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discuss how managers need to combine investment and deployment decisions, no attributes of the management team are considered. As Penrose argues, this is problematic because variation in resource utilization is predicated on "working relationship(s) between particular individuals making decisions" (1995:46). Investigating detailed characteristics of the TMT thus overcomes a significant gap in our understanding of why and how firms differ in their resource utilization choices. As such, we integrate upper echelons theory with the resource utilization literature to examine how TMT characteristics affect the conversion of resources to competitive actions (i.e., type of actions designed to leverage the firm's resource base) and the conversion of those actions to performance (i.e., executing those actions).

Specifically, we integrate TMT heterogeneity, which refers to the degree to which TMT members differ (Carpenter, Geletkanycz, and Sanders, 2004), with Ndofor *et al.*'s (2011) mediated resource-action-performance model to investigate how TMT heterogeneity, and any resulting faultlines, that is, potential subgroup schisms within the group reflecting alignment of multiple demographic attributes (Lau and Murnighan, 1998), affect both the type of actions management undertakes to utilize the firm's resources and how well those actions are implemented. Because variation in TMT heterogeneity differentially affects team creativity (Reagans and Zuckerman, 2001) as well as collaboration (Greening and Johnson, 1997), we develop theory that contrasts two opposing moderation hypotheses. First, we investigate how TMT heterogeneity can positively moderate the conversion of resources to competitive actions, and we consider how TMT heterogeneity can negatively moderate the conversion of competitive actions to performance. Furthermore, we expand our treatment of heterogeneity to include any resulting faultlines, which cause deleterious behaviors on executive teams (Li and Hambrick, 2005). We argue that faultlines reduce the positive effects of heterogeneity, while amplifying the negative effects. Thus, using 145 firm-year observations from the in vitro diagnostics manufacturing industry, we model and test how TMT heterogeneity and any resulting faultlines moderate the processes that TMTs engage to effectively utilize firm resources.

Our theory and results contribute to both the emerging resource orchestration (Sirmon *et al.,* 2011) literature as well as the established TMT heterogeneity literature. First, by incorporating detailed characteristics of managers into resource utilization decisions, we contribute to the resource orchestration literature. This increases the efficacy of resource orchestration research by enhancing the limited treatment of management with realities that TMTs must contend with when managing the firm's resources. In fact, our results suggest that TMT heterogeneity and faultline strength helps explain why competitors utilize similar resource portfolios differently. Thus, while management is critical to the realization of resource-based performance gains, ineffective utilization due to heterogeneity, which produces strong faultlines, can undermine the potential of the firm's resources.

Second, we contribute to upper echelons theory by offering more detailed evidence of how TMT heterogeneity affects firm performance. Undoubtedly, the issue of how TMT characteristics affect firm performance has been intensely debated and examined for decades (Finkelstein, Hambrick, and Cannella, 2008). The empirical record is mixed (Carpenter *et al.*, 2004) with some evidence supporting a positive relationship (e.g., Roure and Keeley, 1990; Smith *et al.*, 1994), other evidence supporting a negative relationship (e.g., Simons, Pelled, and Smith, 1999), and still more evidence suggesting no relationship (Joshi and Roh, 2009). By examining how (1) TMT heterogeneity differentially affects two more proximal tasks, (2) incorporating the existence of faultlines within the TMT, and (3) examining the moderating rather than direct effect of TMT characteristics on performance, our results provide greater clarity to the previously mixed empirical record.

In total, then, the research streams on resource utilization and TMT heterogeneity both have gaps, yet like puzzle pieces fitting together, their integration would present a clearer picture by addressing each other's gap. Specifically, TMT heterogeneity provides resource utilization choices with an important treatment of management while resource utilization provides two theoretically and empirically derived tasks of top management to better determine how heterogeneity affects firm performance indirectly via its effect on TMT tasks.

The paper continues with a presentation of our theory and hypotheses. First, we discuss work related to resource utilization and then present hypotheses. The hypotheses are presented in a sequence, and while the main effects are discussed they are not formally hypothesized, as their effects have been previously tested. In total, we build theory to support two-way and three-way interactions in order to examine the role of TMT heterogeneity in resource utilization. The paper closes with the presentation of methods and a discussion of the result's implications.

THEORY AND HYPOTHESES

While the possession of valuable and rare resources provides a firm the potential for competitive advantage, recent criticisms and evidence has focused attention on the variation between firms' ability to realize their resource-based advantages. For example, Priem and Butler argued that the resource-based literature must begin "answering the how questions" (2001: 34). For instance, how are resources transformed into competitive advantage and performance gains? Research with these foci is emerging. For example, broad strokes have been offered by literature concerned with resource utilization (Helfat *et al.*, 2007; Sirmon *et al.*, 2007). These works, having been integrated as resource orchestration (Sirmon *et al.,* 2011), focus on managerial processes needed to support a resource-based competitive advantage and specifically involve the processes of structuring, bundling, and leveraging the firm's resources with the purpose of creating value for customers and competitive advantages for the firm. Their central argument, harkening back to Penrose's original insights, is that several decisions must be synchronized to enable actions to realize any resource-based performance gain.

Results from this literature demonstrate that managers' resource bundling and deployment efforts affect performance and become more important as rivals' resource portfolios approach parity (Sirmon *et al.*, 2008). Additionally, research shows that the fit between separate actions matters. For example, Kor and Leblebici (2005) found that bundling senior partners with less experienced associates in law firms positively affects performance, but that service and geographic diversification influences this relationship. Focusing on resource utilization decisions, Ndofor *et al.* (2011) presented a mediated resource-action-performance model. They argue that firm resources influence performance primarily through the competitive actions they enable management to undertake. Specifically, the breadth of a firm's resource base determines its competitive action repertoire, which in turn affects performance. Essentially, that research suggested strategy is formulated that utilizes firm resources to support specific actions, and performance outcomes are realized when these strategies are effectively implemented.

Like other resource orchestration research, characteristics of the decision makers themselves were absent in Ndofor *et al.'s* works. To effectively understand the utilization of a firm's resources, however, one needs to understand important elements of the TMT (Penrose, 1995). As such, we work to integrate TMT heterogeneity and any resulting faultlines with the Ndofor *et al.* (2011) model to examine how the characteristics of the TMT differentially affect the type of actions a firm's resources enable and the implementation of those actions. Figure 1 presents the conceptual model that guides our theory development and specifies each hypothesis.

TMTs converting resources into actions

A firm is often conceptualized as a portfolio of resources (Penrose, 1995). The salience of certain sets of resources within the portfolio are contextually driven (Brush and Artz, 1999). For any high-technology firm, including this study's sample of in vitro medical diagnostic substance manufacturers, technological resources, defined as the firm's repository of technological knowledge and technological competencies (Miller, 2004), are critical not only to the firm's performance, but also to its long-term viability. Prior research has elucidated that increased breadth in such technological resources are an antecedent to rent generation (Sampson, 2007), research outputs (Durand, Bruyaka, and Mangematin, 2008), breakthrough innovations (Phene, Fladmoe-Lindquist, and Marsh, 2006), and the scope of the firm (Argyres, 1996).

As such, a technology firm's breadth of technological resources identifies the upper bounds of the range of actions managers can formulate. With increased breadth of technological resources, management has the ability to create various technological capabilities (different resource combinations) that enable different competitive actions (Ndofor *et al.*, 2011). That is, increased technological resources provide the firm with more degrees of freedom to produce resource combinations that support more and even uncommon actions

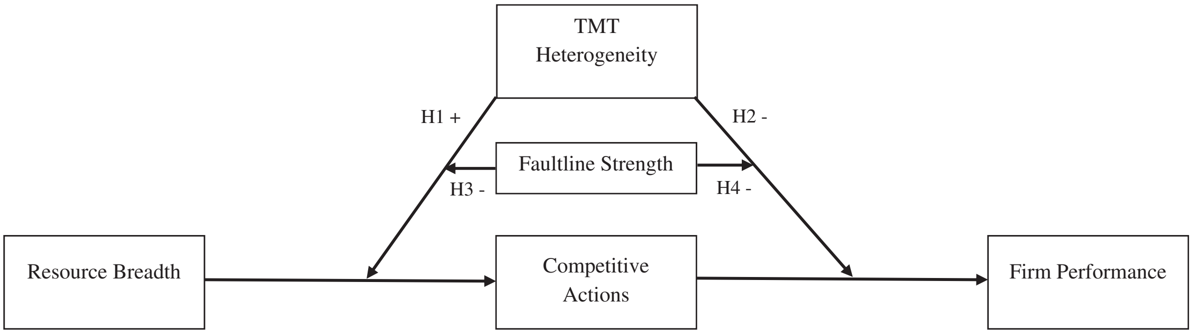

Figure 1. Conceptual model

within its competitive arena—actions that rivals might be incapable of taking. Such actions are often termed deviant actions. Competitive deviance or nonconformity reflects the degree to which a firm's actions differ markedly from industry norms and emphasize a novel mix or sequence of actions not available to competitors (Miller and Chen, 1996). It has also been referred to as action repertoire dissimilarity (Ferrier *et al.*, 1999) or attack heterogeneity (Ferrier and Lee, 2002).

Ndofor *et al.* (2011) argue and show that firms with a wider breadth of technological resources will initiate more deviant competitive actions for several reasons. First, the different resource markets the firm has to compete in to acquire a wider breadth of technological resources exposes it to a greater variety of competitive actions—actions that might be uncommon and thus deviant in its home industry. Next, a wider breadth of technological resources affords the firm the degrees of freedom to experiment with different resources combinations and thus action combinations not available to its competitors. Finally, a wider breadth of technological resources insulates a firm from isomorphic pressures of the industry and thus allows it to initiate more deviant actions, as its breadth of resources makes it less beholden to any particular stakeholder. Too, while the formulation of deviant competitive actions has been found to be promoted by greater breadth in technological resources (the baseline main effect in our model) (Ndofor *et al.,* 2011), the heterogeneity of the TMT is also expected to influence such formulation. We turn our attention to that factor now.

Team researchers have suggested that team tasks can be separated along two dimensions. One dimension is characterized by its behavioral/cognitive element. This dimension addresses the extent to which a task is either conceptual such as generating ideas, planning, or deciding or behavioral, which entails execution. The second dimension is characterized by the level of interdependence within the team (Straus and McGrath, 1994). Task interdependence refers to the extent to which team members need to cooperate and interact to complete tasks (Stewart and Barrick, 2000). It entails collaboration, coordination, and conflict resolution between team members (Straus and McGrath, 1994). For tasks with high interdependence, team members need to interact and communicate closely with each other (Horwitz and Horwitz, 2007). Conversely, for tasks with low interdependence, team members can operate independently with little coordination or collaboration (Stewart, 2006).

When applied to TMT tasks, converting firm resources to competitive actions is a highly conceptual process that entails significant effort in idea generation, planning, and deciding. It requires high cognitive efforts but is not necessarily interdependent. More heterogeneous teams perform better at more cognitive and less interdependent tasks. Specifically, TMT heterogeneity improves team creativity (Reagans and Zuckerman, 2001) and planning openness (Bantel, 1994), necessary prerequisites of effective idea generation. Therefore, it is not surprising that heterogeneous TMTs have been shown to provide more comprehensive strategic alternatives (Finkelstein and Hambrick, 1996). For instance, more heterogeneous TMTs are better equipped to identify and appreciate the deviant competitive actions to which they are exposed in the various resource factor markets the firm engages. Conversely, less heterogeneous teams (i.e., more homogeneity) are less open to new sources of information (Bantel, 1994) and therefore perform poorly on tasks that require seeking and

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utilizing a variety of information sources (Bowers, Pharmer, and Salas, 2000), such as the generation of deviant competitive actions from the breadth of a firm's resources in the resource bundling processes.

Furthermore, the low task interdependence of the action formulation decision in resource utilization mitigates the key drawback of heterogeneous teams, which is conflict (Greening and Johnson, 1997) that arises due to lack of social closure and group identity. In low interdependent tasks, team member contributions are independent and can be sequenced or aggregated to complete the task (Joshi and Roh, 2009). There is less need for members to interact or rely on each other to complete their task, thus little opportunity for conflict that hinders performance. For example, when an action is identified that might exploit a specific market opportunity, the bundling needs can be isolated in fewer functional areas within the firm. That is, marketing or R&D units might conduct the actual bundling needed to support the action with little interaction with other areas of the firm involved. The wider a firm's technology resource breadth the greater the benefits from having a more heterogeneous TMT, as their varied experiences would lead to even more experimentation and creative ideas on how to utilize the resources and thus more deviant actions. Furthermore, the wider the firm's resource breadth the better placed more heterogeneous TMTs will be to have information about actions commonplace in the various factor markets from which the firm acquires its resources, and thus be able to formulate more deviant competitive actions. Therefore, TMT heterogeneity enhances the formulation of deviant competitive actions based on the firm's wider breadth of resources.

Hypothesis 1: Top management team heterogeneity positively moderates the relationship between the firm's technology resource breadth and its deviant competitive actions.

TMTs converting actions to performance

Moving to the second linkage in the mediated resource-action-performance model, deviant competitive actions were argued to hold great potential to improve performance for several reasons (Ndofor, *et al.*, 2011). First, deviant competitive actions provide firms with performance advantages because it enables firms to leverage distinctive competences (Prahalad and Hamel, 1990) that surprise competitors (Chen and MacMillan, 1992) and are difficult for competitors to anticipate, imitate, or retaliate against (Chen and Miller, 1994). Second, when a firm engages a mix or sequence of actions that deviates from industry norms, it disrupts competition and changes the rules of competition in its favor (D'Aveni, 1994), thus improving performance. Together these effects enable a firm to separate itself from competitors and be better protected from competitors' attempts to replicate or neutralize these advantages.

However, in order to implement deviant competitive actions to realize performance gains, coordination between TMT members is needed (Taylor and Helfat, 2009). Specifically, TMT coordination and information sharing enhance the sequencing and pacing of action deployment. Such synchronization requires both high levels of cognitive/behavior dimension and the interdependence dimension. Yet, highly interdependent and behavioral tasks such as the effective implementation of increasingly deviant competitive actions are hampered by TMT heterogeneity.

First, increased TMT heterogeneity leads to decreased cohesion, coordination, and effective communication among team members, all of which impedes implementation efforts (Milliken and Martins, 1996). For instance, the similarity-attraction paradigm (Byrne, 1971) argues that lack of mutual attraction between team members with dissimilar attributes (i.e., more heterogeneity) leads to less effective communication processes. Without effective communication, the coordination of highly interdependent and behavioral tasks are stymied. Even more, cooperation, which might be mandated in many TMTs and could lead to greater cohesion, is undermined by ineffective communication processes (Wiersema and Bantel, 1992).

Second, social identity theory (Tajfel and Turner, 1979) suggests that TMT heterogeneity leads individuals to categorize other team members into "in-group" and "out-group" categories based on demographic attributes. They identify more with and are attracted to their in-group (i.e., other team members with whom they share similar demographic attributes). This in-group bias leads team members to favor their in-group to the detriment of the out-group. This bias renders increasingly heterogeneous teams less effective in tasks that necessitate cohesion and cooperation between team members.

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In total, multiple theoretical models suggest that increased TMT heterogeneity will inhibit cooperation, cohesion, and coordination among team members. Heterogeneous teams lack mutual attraction and interpersonal connection and thus are more likely to have conflict. This conflict proves especially prevalent and detrimental in tasks that entail interaction, collaboration, and coordination within teams as is required in the implementation of a sequence of deviant actions. The need for collaboration and coordination only increases for TMTs attempting to implement increasingly deviant actions. As such, TMT heterogeneity, which promotes the formulation of deviant competitive actions to leverage the firm's resources, is paradoxically likely to inhibit the requisite coordination for effective implementation of those actions.

Hypothesis 2: Top management team heterogeneity negatively moderates the relationship between deviant competitive actions and firm performance.

TMT heterogeneity and faultline strength

While TMT heterogeneity is often discussed as high and low, all heterogeneity is not the same. Indeed, heterogeneity can be based on several characteristics that allow for various configurations of the underlying characteristics. Lau and Murnighan (1998) propose that, to better understand the effects of group demographics on performance, researchers should proceed beyond an individual's single characteristic and examine the interrelations between multiple characteristics. This is because multiple characteristics are used by team members in the social categorizations that lead to in-/out-group clustering (Webber and Donahue, 2001). Lau and Murnighan (1998) use the concept of faultlines to characterize the hypothetical lines that split a group into subgroups based on multiple demographic attributes. These faultlines reflect potential schisms within a team.

The strength of a faultline depends on (1) the number of salient attributes team members can use in categorizations, (2) how clearly aligned those attributes are across the team members, and (3) the number of potential subgroups that can be formed based on these factors. Stronger faultlines occur when multiple demographic attributes align, thereby creating clear subgroups with high levels of between variance and low levels of within variance.

Research has revealed that faultline strength affects top management team processes above and beyond that provided for by team heterogeneity alone. Li and Hambrick (2005) found faultlines created task conflict, emotional conflict, and behavioral disintegration, thus leading to poor performance. Barkema and Shvyrkov (2007), examining foreign expansion decisions, found strong faultlines in top management teams decreased the novelty of foreign location investments. Similarly, Tuggle, Schnatterly, and Johnson (2010) found boards of directors with strong faultlines spent a lower percentage of board meetings discussing entrepreneurial issues, while those with weak faultlines spent a higher percentage of board meetings discussing entrepreneurial issues.

This evidence clearly suggests TMT faultline strength influences TMT processes and outcome. We propose that TMT faultline strength will also affect both the conversion of resources to actions and the conversion of actions to performance. Specifically, we expect faultline strength to affect how TMT heterogeneity moderates the relationship between the breadth of a firm's technology resources and the deviance of its competitive behavior.

Strong faultlines create increasingly unique subgroups within the TMT that tend to identify more with the subgroup than the TMT (Thatcher, Jehn, and Zanutto, 2003). This leads to behavioral "disintegration" resulting in less interaction between groups, even more strained communications, and as a result less joint decision making (Li and Hambrick, 2005). Again, without communication between subgroups, teams do not fully utilize the cognitive resources of members (Barkema and Shvyrkov, 2007). This restricted use of cognitive resources is detrimental to the performance of a conceptual task such as the formulation of deviant competitive actions designed to leverage the firm's resources.

More specifically, for teams with stronger faultlines, more technology resource breadth means more avenues for and deeper disagreement between subgroups. Strategic actions appealing to one subgroup might be summarily dismissed by other subgroups, leading to action paralysis. Because prior discussion takes place within subgroups, the range of actions potentially available to the TMT is curtailed because only those actions amenable to the subgroup surface for the entire

TMT to consider. Such a TMT will therefore carry out less deviant actions than they might have otherwise. Conversely, TMT heterogeneity that does not support strong faultlines retains open communication, and the full cognitive resources of each member are available to the TMT. For such TMTs, more technology resource breadth provides fuel for richer discussions and more collaboration, and therefore would allow for the formulation of even more deviant actions. Thus, we expect:

> *Hypothesis 3:* *A negative three-way interaction exists between TMT heterogeneity, faultline strength, and the firm's technology resource breadth such that, in combination, these factors lead to less deviant competitive actions.*

Similarly, TMT faultline strength is expected to affect the implementation of actions. Faultline strength is hypothesized to influence how TMT heterogeneity moderates the relationship between the deviant competitive actions and performance. Group research has shown the role of faultline strength in generating both emotional and task conflict within groups (Thatcher *et al.*, 2003). When TMTs with strong faultlines interact more, the in-group/out-group categorizations central to their subgroup identity become accentuated, giving rise to out-group member hostility (Li and Hambrick, 2005). This leads to greater emotional conflict within the team. In addition, task conflict increases as the mental models of the various subgroups diverge with stronger faultlines. Both of these sources of conflict exacerbate the effect of heterogeneity on the implementation of action, further impinging the action/performance relationship.

Therefore, we argue that, as faultlines strength increases, TMT members' collaboration in the implementation of previously formulated actions decreases. In short, the negative moderating effects of TMT heterogeneity are exacerbated by strong faultlines, which increase emotional and task conflict. Formally:

> *Hypothesis 4:* *A negative three-way interaction exists between TMT heterogeneity, faultline strength, and deviant competitive actions such that, in combination, these factors lead to greater negative effects on firm performance.*

METHODS

Sample

Our sample consists of the population of publicly traded firms in the in vitro diagnostic substance manufacturing industry (NAICS: 325413; SIC: 2835). These are technology-intensive pharmaceutical and medical manufacturing firms in the chemical manufacturing subsector (325). The in vitro diagnostics industry specializes in the diagnosis of human and animal disorders and involves extensive genetic research that produces significant technology- and knowledge-intensive resources for the participants. Firms in this industry create chemical, biological, or even radioactive materials used to diagnose or monitor body fluids or tissues for several different maladies. Technological resources are critical to the competitors in this industry.

We created a longitudinal dataset by drawing our sample from this industry over the years 1995–1999. Of the 78 publicly traded firms in the industry during this time frame, 9 did not have any patents and 20 did not have TMT information available. Thus, the final sample consisted of 49 firms. For several reasons (e.g., mergers and/or new entrants), our panel is unbalanced and provided 145 firm-year observations. Because our sample is only a subset of the firms in the industry, primarily due to lack of patenting activity by some firms in the industry, the potential for selection bias exists. We investigated and concluded that selection bias due to patenting, the main exogenous variable, is not present in this sample for two reasons. First, because patenting is an intensive process, firms are unable to "turn it off and on" easily; thus, the choice is time invariant (i.e., constant over time) over the short and midterms. Since our sampling frame addresses five years of activity, this choice is for all intents and purposes time invariant; therefore, any selection bias is empirically addressed or controlled for by analyses' treatment of firm effects (Wooldridge, 2002). Furthermore, we empirically tested for selection bias using Wooldridge's (2002) modified Heckman test (i.e., two-stage approach) for panel datasets. We used the full industry sample (78 firms) in the first stage. The nonsignificant inverse Mills ratio (lambda) coefficient (2.9; $p < 0.59$) indicates that selection bias due to endogeneity of patenting behavior is not a concern for our sample.

Importantly, our sample selection provides several additional attributes of value. First, confounding industry effects are not present because the sample includes data on a single industry. Second, the vast majority of these firms are undiversified, thus ensuring that their resources and competitive activity share a common competitive arena. Forty-six (94%) firms in the sample competed only in this industry. The remaining three (6%) firms competed in two industries, but generated on average 80 percent of their sales from the in vitro diagnostic substance manufacturing industry. Finally, it is necessary for the independent variables to be measured temporally antecedent to any dependent variable(s). As such, technology resource breadth was measured prior to competitive activity in time, which in turn was measured prior to performance. TMT demography was also measured concurrently with competitive activity and prior to performance. Put differently, the sample is lagged such that causality is appropriately addressed to support the testing of our model.

Dependent variables

Performance

A market-based measure of performance is necessary because all benefits of technological resources and competitive actions might not be evident in accounting performance at a specific time or a duration of time. For example, the value of a new product introduction or capacity expansion might not be captured fully by accounting performance for a given year. Similarly, the economic life of a patent, our measure of technological resources, covers 15–20 years. Thus, market-based performance measures, such as Tobin's *q,* are preferable in research studying performance effects spread over time, because they capture both short-term and long-term performance (Lubatkin and Shrieves, 1986). Following Lee and Tompkins (1999), we calculated Tobin's *q* as the sum of market value of equity, preferred stock value, and debt scaled by total assets. To ensure causality, Tobin's *q* is calculated for the subsequent year of competitive actions and TMT. Data for Tobin's *q* calculation were collected from Compustat from 1996 to 2000.

Independent variables

Technology resource breadth

Competition and success within this industry is based primarily on innovative new products that are effective in diagnosing specific ailments. A firm's patent portfolio results from its inventiveness and thus represents its level of technological knowledge (Hall, Jaffe, and Trajtenberg, 2001). Therefore, the breadth of a firm's patent portfolio is utilized as the indicator of the firm's breadth of technological resources (Miller, 2004). As Miller noted, we acknowledge that patents do not "reveal all valuable knowledge of the firm, but that the breadth of knowledge represented by patents is an accurate indicator of the breadth of the firm's technological resources" (2004: 1118).

We obtained patent data from several sources. First, data from the United States Patent and Trademark Office (USPTO) was acquired through Delphion's searchable database. Searching for patents through Delphion is advantageous because corporate trees (prior acquisitions and subsidiaries) have already been mapped onto the parent firm. Each firm was searched individually, with particular attention to variations in firm name. This search yielded 1,420 patents. Next, we matched the patent numbers from Delphion to the National Bureau of Economic Research (NBER) patent data (Hall *et al.*, 2001). We then searched for additional patents using organization numbers assigned to these patents in NBER's database. This step was essential because the Delphion database did not cover patents granted prior to 1990 (used in the control variable discussed below). We obtained 802 additional patents. Next, for firms that had no patents, we searched the USPTO database directly. In total, of our original sample, nine firms held no patent information prior to 2000. In addition, we deleted patents granted prior to 1975 (only seven patents) to keep our patents within their useful economic life (20 years to 1995). The 1,420 patents in our sample were assigned to 67 distinct USPTO patent classes with an average of nine patent classes per firm (maximum 17).

Technology resource breadth was calculated using a Herfindahl-type index analogous to Hall *et al.*'s (2001) approach:

$$\textit{Technology resource breadth} = 1 - \sum_{i}^{n} S_i^2$$

where S_i is the proportion of n patents in USPTO patent class i. Technology resource breadth within our sample ranged from 0 to 0.91.

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Deviant competitive actions

To calculate competitive actions, we utilized a procedure established in the competitive dynamics literature (Ferrier, 2001; Ferrier and Lyon, 2004; Ferrier, Smith, and Grimm, 1999; Smith, Ferrier, and Ndofor, 2001). First, using newspaper and trade publications identified in LexisNexis, we searched for all news articles pertaining to each sample firm for a given year. We then utilized N*UDIST NVIVO structured content analysis software to categorize each news article into one of several pre-established competitive action categories. These pre-established action categories included new product introductions, capacity actions, acquisitions, alliances and joint ventures, pricing actions, new market entries, legal actions, and financing actions. Examples of action categories and news headlines are listed in Table 1. Two coders first independently read through each article and, using the N*UDIST software, classified it into pre-established action categories. Their intercoder reliability was 0.74. A third coder classified actions on which the two coders did not agree and worked towards agreement. We used this measure to calculate deviant competitive actions.

Deviant competitive actions capture the extent to which a firm's portfolio of actions for a given year differed from those of its competitors. Similar to Ferrier *et al.*'s (1999) calculation of leader-challenger action dissimilarity, deviance is calculated as the sum of squared difference in proportions of categories of competitive action between the focal firm and the industry mean:

$$\textit{action deviance} = \sum_i \left(P_i - \overline{P_i}\right)^2$$

where P_i is the proportion of ith category of competitive action for the focal firm, and $\overline{P_i}$ is the industry mean proportion (excluding focal firm) of ith category of competitive action.

TMT heterogeneity

TMT heterogeneity addresses diversity in top management demographics. TMT heterogeneity is calculated for each management team member's age, tenure, and functional background because the use of composite measures for heterogeneity has been cautioned (Harrison and Sin, 2006). First, heterogeneity in age was "measured using the coefficient of variation, defined as the standard deviation divided by the mean" (Wiersema and Bantel, 1992: 105). TMT tenure heterogeneity measures both TMT organizational tenure and team tenure heterogeneity. Team tenure heterogeneity might indicate the extent of sharing experiences among TMT members within the team, while organizational tenure heterogeneity might indicate the extent of sharing experiences among TMT members within the firm (Marcel, 2009). Both were calculated in the same way as age heterogeneity (Marcel, 2009; Tihanyi *et al.*, 2000; Wiersema and Bantel, 1992). Next, TMT functional heterogeneity indicates the level of having divergent functional backgrounds among TMT members (Finkelstein and Hambrick, 1996; Marcel, 2009). Each top management team member was categorized into one of eight functional backgrounds (production-operations, R&D and engineering, accounting and finance, management and administration, marketing and sales, law, personnel and labor relations, other) (Hambrick, Cho, and Chen, 1996). Then, TMT functional heterogeneity was measured with Blau's (1977) Herfindal-Hirschman index, calculated as $1 - \sum Si^2$, where Si is the proportion of a TMT in the ith category (Wiersema and Bantel, 1992). We utilized each of these three attributes to capture TMT heterogeneity. TMT demographics data were collected from proxy statements filed with the Security Exchange Commission. Officers of the firm listed in proxy statements were identified as TMT members.

Faultline strength

Following Thatcher *et al.* (2003), we operationalized faultline strength as the percentage of total variation in group attributes accounted for by the strongest group split. To compute this measure, we utilized the formula developed by Thatcher *et al.* (2003) and used in faultline research by others (e.g., Lau and Murnighan, 2005). We utilized the same attributes used in calculating the heterogeneity measure. Given the small size of top management teams (4–6 members), we only consider faultlines that split groups into two subgroups, because of the requirement of a minimum two persons per group (Thatcher *et al.*, 2003). For each group, it contains n numbers that are measured on p characteristics and can be split into two subgroups in a total of $S = 2^{n-1} - 1$ ways. We measured faultline strengths by calculating the percent of total variation in

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Table 1. Action classes and headline examples

Action category	Example of headlines
Financing	Matritech executes $30 million equity financing arrangement with Acqua Wellington; covering sale of up to 2.45 million shares
Market entry	Medi-Ject Corporation signs agreement to distribute Vision (TM) Needle-Free Injector in Italy to enter European market
New product introduction	Diagnostic Products Corporation to market new test for pancreatic cancer
Acquisitions	YSIS Inc. acquires TechGen International
Joint venture	Hoechst strengthening the diagnostics business through joint venture with Dade International
New product-market entry	Myriad Genetics, Inc. creates new pharmaceuticals subsidiary; Myriad Pharmaceuticals, Inc. to develop novel oncology compounds
Alliances	Clark Laboratories and Wampole Laboratories establish marketing and manufacturing alliance
Legal action	Home Access Health files countersuit against SALV
Licensing	Diatide licenses new cancer therapy technology based on gene product for metastatic cancer

overall group characteristics accounted for by the strongest group, split by calculating the ratio of the between-group sum of squares to the total sum of squares:

$$Faultline\ strength_g = \left(\frac{\sum_{j=1}^{p} \sum_{k=1}^{2} n_k^g \left(\left(\overline{\mathrm{x}}.jk - \overline{\mathrm{x}}.j \right) 2 \right)}{\sum_{j=1}^{p} \sum_{k=1}^{2} \sum_{i=1}^{n_k^g} \left(\overline{\mathrm{x}}ijk - \overline{\mathrm{x}}.j \right) 2} \right)$$

$$g = 1, 2, \ldots .S.$$

where g is the firm observation, x denotes the value of the jth characteristic of the ith member of subgroup k. Faultline strength values can range from 0 to 1 (0.10–0.99 in our sample) with higher values indicating stronger faultlines.

Control variables

Next, we measured and included in our analyses seven control variables. First, we controlled for firm size because larger firms might have larger resource portfolios to conduct competitive actions. Firm size was measured as the natural log of number of employees. Second, we controlled for organizational slack because of its influence on the potential for competitive actions (Ferrier, 2001). We focused on a firm's unabsorbed slack, using the firm's current ratio as its proxy (Chen, Su, and Tsai, 2007). Information for these two control variables was collected from Compustat. Third, we controlled for firm age. Age was measured as the number of years since the year of a firm's founding. Because technological resources are path dependent, a firm's longevity will in part determine its opportunity to develop patents. Founding date was collected from Compustat and Mergent Online. Fourth, we controlled for the average age of the firm's patent portfolio. Fifth, we controlled for the number of patents in the firm's patent portfolio. Sixth, we controlled for current investments in technology using R&D intensity. Lastly, we controlled for prior performance as it often influences competitive activity by providing both motivation to act and the capability to act (Smith *et al.*, 2001). Prior performance is calculated as return on assets of the prior year.

Analyses and results

Although we account for changes in a firm's technological resources, TMT, and competitive actions across years, it is quite possible that some firm-specific factors (such as culture) remained constant across the years. This implies firm observations might be correlated across years, thus violating the assumption of independence across observations necessary for ordinary least squares regressions. We therefore used the maximum likelihood estimation of generalized estimating equations (GEE) to estimate the parameters for all our analyses, which address these issues (Liang and Zeger, 1986).

Table 2 lists descriptive statistics and bivariate correlations for the variables used. The results

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of our hypotheses based on GEE analyses are presented in Tables 3 and 4. Table 3 has the results predicting deviant competitive actions, while Table 4 has the results predicting performance. All variables used in interaction terms were mean centered to mitigate unessential multicollinearity (Aiken and West, 1991). Multicollinearity does not present concerns for our analyses, as the variance inflation factor scores are below 1.80. All hypotheses are tested using a two-tailed significance test.

To enhance the clarity of the results, which are discussed next, a brief discussion of how the heterogeneity measures reflect real-life TMTs may prove helpful. Take the age score as an example. The sample's mean TMT age heterogeneity score is 0.24. An actual four-person TMT would arrive at that score if their ages were: 36, 42, 62, 63. Of course many other permutations exist that would convey this score. However, if that four-person team switched the 36-year-old for a 45-year-old, the score would drop to 0.18, while a switch to a 25-year-old would increase the score to 0.27 and a switch to a 40-year-old would yield a 0.21 score. Thus, care is required to conceptualize TMT heterogeneity as "variation in members' factors of interest" and not simply change in membership.

Hypothesis 1 predicts that TMT heterogeneity strengthens the positive relationship between the breadth of a firm's technological resources and deviant actions. Models 2, 5, and 8 of Table 3 have the interaction terms for TMT heterogeneity attributes (age, tenure, and functional background, respectively) and technology resource breadth on deviant competitive actions. The coefficients for age (1.95), tenure (0.24), and functional background (1.31) interactions are all positive and significant at $p < 0.001$ level. Overall, these results establish that greater TMT heterogeneity leads to greater effectiveness in translating broad technology resources into deviant competitive actions. The results support Hypothesis 1.

Hypothesis 2 predicted TMT heterogeneity would interact with deviant competitive actions to negatively affect firm performance. These results are shown on Table 4. Models 2, 5, and 8 of Table 4 list the interaction terms for TMT heterogeneity attributes (age, tenure, and functional background, respectively), as well as deviant competitive actions on firm performance. The coefficients for age (−13.4), tenure (−5.97), and functional background (−11.8) interactions are all negative and significant at $p < 0.05$ levels. Thus, TMTs with high levels of heterogeneity are less able to realize the potential performance gains offered by deviant competitive actions as implementation suffers. The results provide support for Hypothesis 2.

Hypothesis 3 predicted a negative three-way interaction effect between faultline strength, TMT heterogeneity, and technology resource breadth on deviant competitive actions. Models 3, 6, and 9 of Table 3 provide the results for Hypothesis 3. From Model 3, the three-way interaction coefficient for age heterogeneity, faultline strength, and technology resource breadth ($\beta = -5.56$, $p < 0.05$) has a negative and significant effect on deviant competitive actions. From Model 9, the three-way interaction coefficient for functional background heterogeneity, faultline strength, and technology resource breadth ($\beta = -11.59$, $p < 0.01$) has a negative and significant effect on deviant competitive actions. From Model 6, however, the three-way interaction coefficient for tenure heterogeneity, faultline strength, and technology resource breadth ($\beta = 2.31$, $p < 0.001$) has a positive and significant effect, opposite of the prediction, on deviant competitive actions. Therefore, Hypothesis 3 is supported for age and functional heterogeneity but not for tenure heterogeneity.

Hypothesis 4 predicted a negative three-way interaction effect of faultline strength, TMT heterogeneity, and deviant competitive actions on firm performance. Models 3, 6, and 9 of Table 4 provide the results for the testing of Hypothesis 4. From Model 3, the three-way interaction coefficient for age heterogeneity, faultline strength, and deviant competitive actions ($\beta = -33.84$, $p < 0.05$) has a significant negative effect on performance. From Model 6, the three-way interaction coefficient for firm tenure heterogeneity, faultline strength, and deviant competitive actions ($\beta = -29.99$, $p < 0.01$) has a significant negative effect on performance. Finally, from Model 9, the three-way interaction coefficient for functional background heterogeneity, faultline strength, and deviant competitive actions ($\beta = -40.08$, $p < 0.01$) has a significant negative effect on performance. These results support Hypothesis 4 by showing strong faultlines increase negative performance as heterogeneous TMTs work to implement deviant actions.

Table 2. Sample statistics and correlations

Variable	N	Mean	s.d.	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Age	145	14.15	6.86													
2. Firm size	145	10.60	3.44	0.058												
3. Slack	145	5.56	6.39	−0.052	0.213											
4. Average patent age	145	3.38	2.63	0.260	0.154	0.034										
5. Prior performance	139	−0.45	0.92	0.181	0.216	0.148	0.165									
6. R&D intensity	137	0.33	0.37	0.236	−0.230	−0.226	−0.277	−0.275								
7. Technology resource breadth	145	0.43	0.28	0.169	0.039	0.046	0.389	0.201	−0.121							
8. Deviant actions	145	0.43	0.38	0.035	0.171	0.173	0.207	0.241	−0.152	0.207						
9. TMT age heterogeneity	145	0.24	0.16	0.082	0.222	−0.049	0.187	0.142	−0.166	0.105	0.204					
10. TMT tenure heterogeneity	145	1.08	0.75	−0.088	0.140	−0.075	0.121	0.033	−0.064	0.209	0.118	0.399				
11. TMT functional heterogeneity	145	0.54	0.18	0.064	0.424	0.108	0.315	−0.006	−0.235	−0.064	0.146	0.316	0.183			
12. Faultline strength	140	0.56	0.20	−0.014	0.119	0.252	−0.211	0.066	0.067	0.014	0.124	−0.179	−0.242	−0.125		
13. Tobin's q	126	4.14	7.43	−0.010	−0.055	−0.183	−0.230	−0.291	0.394	−0.094	−0.181	0.062	0.219	−0.105	−0.098	
14. Number of patents	145	30.53	51.46	−0.280	−0.114	0.080	0.030	−0.101	0.136	0.341	−0.026	−0.116	0.038	−0.159	0.157	−0.053

Correlations are significant at $p < 0.05$ when coefficients are |0.17|.

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Table 3. Results of GEE regression analysis

Model	1 Main	2 Two-way	3 Three-way	4 Main	5 Two-way	6 Three-way	7 Main	8 Two-way	9 Three-way
Intercept	0.20*	0.10	0.12	0.20*	0.14†	0.11	0.20*	0.16*	0.13
Firm age	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Slack	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
Firm size	0.01	0.01**	0.01*	0.01	0.01†	0.01*	0.01	0.01†	0.01*
Number of patents	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00†	0.00*
Average patent age	0.00	−0.01	−0.01	0.00	0.00	0.01†	0.00	0.00	0.00
Prior performance	0.06***	0.08***	0.08***	0.06***	0.07***	0.06***	0.06***	0.06**	0.06***
R&D intensity	0.00	−0.01	0.00	0.00	0.02	0.05†	0.00	0.00	0.02
Technology resource breadth	0.20***	−0.22***	−0.22***	0.20***	−0.03	0.06	0.20***	−0.53***	−0.66***
TMT age heterogeneity	0.29***	0.28***	0.36***	0.29***	0.29***	0.35***	0.29***	0.32***	0.36***
TMT tenure heterogeneity	−0.01	−0.02	−0.02	−0.01	−0.02	−0.01	−0.01	0.00	0.00
TMT functional heterogeneity	0.11	0.24***	0.21**	0.11	0.16*	0.09	0.11	0.10	0.13
Faultline strength	0.11†	−0.05	0.09	0.11†	0.05	1.20***	0.11	0.15	0.52
Two-way interactions									
Technology resource breadth × TMT age heterogeneity		1.95***	2.26***						
Technology resource breadth × TMT tenure heterogeneity					0.24***	0.17***			
Technology resource breadth × TMT function heterogeneity								1.31***	1.64**
TMT age heterogeneity × faultline strength			0.16						
TMT tenure heterogeneity × faultline strength						−1.34***			
TMT function heterogeneity × faultline strength									−0.51
Technology resource breadth × faultline strength			−1.68*			−2.55***			3.42
Three-way interactions									
Technology resource breadth × faultline strength × TMT age heterogeneity			−5.56*						
Technology resource breadth × faultline strength × TMT tenure heterogeneity						2.31***			
Technology resource breadth × faultline strength × TMT function heterogeneity									−11.5**
Wald chi-square	1,659.1	1,571.2	1,534.7	1,659	1,631	1,555	1,659.1	1,629	1,593.5

†$p < .10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$; all two-tailed tests.
DV = deviant actions.

Table 4. Results of GEE regression analysis

Model	1 Main	2 Two-way	3 Three-way	4 Main	5 Two-way	6 Three-way	7 Main	8 Two-way	9 Three-way
Intercept	−3.33	-3.47^{***}	-2.39^{***}	−3.33	−2.02	−0.71	−3.33	−3.29	1.29^{*}
Firm age	0.21	0.23	0.19^{***}	0.21	0.14^{*}	$0.11^{\dagger}$	0.21	0.22^{***}	$0.03^{\dagger}$
Slack	−0.03	−0.03	−0.01	−0.03	−0.04	−0.02	−0.03	−0.04	-0.14^{***}
Firm size	−0.01	−0.01	-0.09^{*}	−0.01	0.02	−0.04	−0.01	0.01	0.03
Number of patents	-0.02^{*}	-0.02^{*}	-0.02^{***}	-0.02^{*}	-0.02^{**}	-0.02^{**}	-0.02^{*}	-0.01^{*}	0.00
Average patent age	-0.49^{*}	-4.62^{**}	-0.51^{***}	-0.49^{*}	-0.48^{**}	-0.49^{**}	-0.49^{*}	-0.47^{**}	-0.11^{**}
Prior performance	-1.94^{*}	-2.17^{***}	-2.12^{***}	-1.94^{*}	-2.38^{***}	-2.34^{***}	-1.94^{*}	-1.90^{***}	-0.36^{***}
R&D intensity	$9.19^{\dagger}$	9.42^{***}	9.71^{***}	$9.19^{\dagger}$	8.99^{***}	8.44^{***}	$9.19^{\dagger}$	9.16^{***}	0.93^{***}
Technology resource breadth	0.02	0.35	0.98^{**}	0.02	0.81	0.71	0.02	−0.06	-1.04^{***}
TMT age heterogeneity	3.44	6.24^{**}	8.56^{***}	3.44	4.23^{*}	5.05^{*}	3.44	2.96	1.83^{***}
TMT tenure heterogeneity	3.02	2.87^{***}	2.87^{***}	3.02	2.72^{***}	2.42^{***}	3.02	3.04^{***}	0.54^{***}
TMT functional heterogeneity	−1.11	−2.45	-3.00^{***}	−1.11	−1.98	−2.38	−1.11	−1.39	-3.24^{***}
Faultline strength	7.66	7.32	31.14^{***}	7.66	5.11	−7.01	7.66	5.83	-31.7^{***}
Deviant actions	−1.03	2.40	-1.09^{*}	−1.03	5.96^{***}	6.13^{***}	−1.03	$5.70^{\dagger}$	−0.63
Two-way interactions									
TMT age heterogeneity × deviant actions		-13.40^{*}	-75.85^{***}						
TMT tenure heterogeneity × deviant actions					-5.97^{***}	15.52^{*}			
TMT functional heterogeneity × deviant actions								-11.8^{*}	57.8^{***}
Faultline strength × TMT age heterogeneity			0.90						
Faultline strength × TMT tenure heterogeneity						-5.53^{***}			
Faultline strength × TMT functional heterogeneity									1.47
Deviant actions × faultline strength			−5.72			11.97			14.35
Three-way interactions									
Deviant actions × faultline strength × TMT age heterogeneity			-33.84^{*}						
Deviant actions × faultline strength × TMT tenure heterogeneity						-29.90^{*}			
Deviant actions × faultline strength × TMT functional heterogeneity									-40.08^{*}
Wald chi-square	245.0	458.9	413.2	245.6	437.0	430.6	245.0	461.2	347.0

DV = firm performance.
$^{\dagger}p < .10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; all two-tailed tests.

DISCUSSION

A central critique of the resource utilization literature, and resource orchestration more generally, has been its ambiguous treatment of "management" (Sirmon *et al.*, 2011). That is, managements' resource utilization decisions are theorized and measured, but the characteristics of the TMTs that actually formulate and implement those actions are underemphasized. We address this issue by examining the effect of TMT characteristics on resource utilization. Specifically, we argue that TMT heterogeneity, a characteristic suggested to be critical by upper-echelon research, moderates the various processes of resource utilization, but does so differentially. While heterogeneous TMTs enhance the ability of firms with greater breadth of technological resources to initiate more deviant competitive actions, the same characteristic hinders the coordination of deviant actions such that firm performance suffers. Thus, we propose a paradoxical effect of TMT heterogeneity on resource orchestration.

This paradox occurs because the two primary TMT tasks require conflicting attributes for success. Specifically, the coordination and cohesion of homogeneous TMTs necessary for the success of the interdependent and behavioral TMT task of action implementation are deleterious to the independent and creative TMT task of action formulation. Furthermore, we argue that heterogeneity is not all the same. When TMT heterogeneity yields strong faultlines, the positive effect of TMT heterogeneity on converting resources to action is weakened, while the negative effect on converting resources to performance is further strengthened. With the exception of the effect of increasing technology resource breadth for TMTs with high tenure heterogeneity and strong faultlines, the analyses and results support all our hypotheses. The theory and results then provide several contributions to the literature.

First, this work extends resource utilization within the orchestration literature by explicitly incorporating characteristics of the TMT. Until now, the treatment of management was limited and the TMT was not directly addressed at all. The results suggest that, while the processes of resource utilization are shared across firms, characteristics of the TMT can lead to significant differences in resulting actions and performance, even for firms with similar resources. This result confirms prior literature that has argued that how a firm uses its resources is just as, if not more, important as what resources it possesses (Hansen, Perry, and Reese, 2004). The decisions of how to use the firm's resources are made by the TMT; therefore, TMT characteristics influence the performance gains wrought from possessing resources. This is one possible explanation for why organizations possessing similar resources and occupying similar environments experience variations in performance. Indeed, even if resource endowments were identical across firms, performance differences could still arise due to differences in managerial actions such as the timing of resource deployments (Zott, 2003).

Second, this research contributes to the broader literature that examines the relationship between the resources a firm possesses and performance. A central criticism of resource-based research is that the processes through which resources influence performance remain largely unexplained (Priem and Butler, 2001; Sirmon *et al.*, 2007). Recent reviews of the literature have found modest support for the resource-performance link (e.g., Newbert, 2007) with evidence of missing intervening processes that hamper development of the literature (Crook *et al.*, 2008). This paper assuages these criticisms by building on Ndofor *et al.*'s (2011) resource-action-performance model to include the moderating effects of TMT heterogeneity.

Specifically, we add to the Ndofor *et al.*'s (2011) model by incorporating the role of managers in the resource-action-performance relationship and examining the effect of TMT heterogeneity and any resultant faultlines. The results not only confirm the centrality of the TMT, but that TMT characteristics influence the resource utilization process. The Ndofor model extended previous work, and here the inclusion of TMT factors further enriches our understanding of how managers affect the resource-performance relationship.

Third, this research offers insight into the double-edged effect of TMT heterogeneity that is found in upper-echelon research. Specifically, our results suggest that the mixed performance outcomes of TMT heterogeneity are due in part to the different resource utilization tasks the TMT engage. TMT heterogeneity affects team outcomes differentially depending on the task being performed by the team (Hambrick *et al.*, 1996). Our results indicate that prior research findings that propose competing effects of TMT heterogeneity might be a result of the targeted impact of TMT heterogeneity. Without controlling

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for the tasks being performed, TMT research would fail to capture the full and rich effect of TMT heterogeneity on performance. Thus, the mixed empirical record for a TMT heterogeneity/firm performance relationship might be most directly rectified by including intervening constructs, such as we do with the tasks performed by the TMT.

Furthermore, this research reveals that the behavior of a heterogeneous TMT changes significantly depending on whether the heterogeneity creates strong faultlines. Specifically, we found the positive effect of TMT heterogeneity on the resource-action linkage was reduced when faultlines developed. In addition, the negative effect of TMT heterogeneity on the action-performance linkage was exacerbated when strong faultlines developed. In total, these results suggest that, beyond overlooking intervening tasks, it is possible the prior inconclusive findings for the effect of TMT heterogeneity could have also resulted from the failure to model faultlines. This amplifies the need for further incorporating faultlines in research on TMT characteristics.

Contrary to our hypothesis, the three-way interaction of resource breadth, tenure heterogeneity, and faultline strength had a positive and significant effect on deviant competitive actions. Essentially, unlike age and functional background, TMTs with high tenure heterogeneity together with strong faultlines tended to initiate more deviant competitive actions with increasing resources. One possible explanation is that tenure heterogeneity represents cohort effects, which also capture diversity in team commitment (Milliken and Martins, 1996). Diversity in team commitment might serve to also weaken commitment to subgroups that originate due to strong faultlines and, as such, neutralize the deleterious effects of strong faultlines. This result highlights the importance of examining heterogeneity at the attribute level rather than a composite measure. A composite measure of heterogeneity would have masked the conflicting effects of the attributes leading to erroneous conclusions. Future research can examine how and why TMT tenure heterogeneity differs from the other attributes in its effect on some team processes.

Next, a review of our model's equations and statistical outcomes suggests that, in total, greater TMT heterogeneity provides a net positive benefit for the firms in our sample, which are R&D-intensive firms. However, the net positive effect of TMT heterogeneity is lost when faultlines develop. Thus, this research offers insights for practice. Because TMT heterogeneity affects TMT tasks in potentially conflicting ways, the primary tasks to be performed by the TMT should be considered when composing a TMT. Specifically, while TMTs have to both formulate and implement strategy, the salience of each task might vary with industry. In some industries, for example, hypercompetitive or nascent industries with fast-changing environments, action formulation might be more salient as firms have to constantly adjust their strategy to realign with the quickly changing environment. Firms in such industries might fare better with more heterogeneous TMTs. Conversely, in mature or slow-paced industries, action implementation might be more salient as the stable environment reduces the need for firms to constantly formulate new actions. Firms in such industries might fare better with more homogeneous TMTs. This is clearly an avenue ripe for future research.

In addition, consistent with prior literature, we have examined the TMT as one stable group that tackles its various tasks as a singular entity. It is however possible that some TMTs further subdivide into task-based groups. Such a division will clearly influence the relationships hypothesized in this study. For example, some of the negative effects of heterogeneity on implementation could be attenuated by having a more homogeneous sub-TMT group focused on implementation. The effects of such subdivisions might be even more pronounced if conducted along strong faultlines. Future research, therefore, can build on this study by examining how TMT routines could influence these relationships.

Finally, in this paper, we focus only on the TMT. However, some amount of strategy implementation is also carried out at lower levels of management. Future research can examine how the relationships examined in this paper play out when the implementation actions are at lower levels of management. This is consistent with Sirmon *et al.*'s (2011) call that resource orchestration research, in which resource utilization decisions are found, should address levels of management in future work.

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