Article

Acquisition target selection and technological relatedness: The moderating role of Top Management Team demographic faultlines

Korcan Kavuşan (iD)
Rotterdam School of Management, Erasmus University, The Netherlands

Nüfer Yasin Ateş
Sabanci Business School, Sabanci University, Turkey

Anna Nadolska (iD)
Rotterdam School of Management, Erasmus University, The Netherlands

Abstract

We investigate why some acquirers value targets' technological relatedness (i.e. similarity and complementarity) more than others. We propose that the importance of technological related-ness as a target selection criterion is influenced by the extent to which an acquirer Top Man-agement Team is divided into subgroups based on managers' demographic characteristics (i.e. faultlines). That is because an acquirer Top Management Team's understanding of technological relatedness depends on the team's information processing capabilities, driven primarily by Top Management Team faultlines. Our analysis of 94 realized acquisitions among 2082 potential acquisition matches in high-technology industries shows that while both technological similarity and complementarity increase the likelihood of an acquisition match, only the impact of techno-logical complementarity is affected by Top Management Team faultlines. Specifically, we find that Top Management Teams with moderately strong divisions between subgroups pay more attention to technological complementarities between their firm and potential acquisition targets than Top Management Teams with very strong or weak divisions.

Keywords

acquisition target selection, demographic faultlines, technological complementarity, technological similarity, technology acquisitions, top management teams

Corresponding author:
Nüfer Yasin Ateş, Sabanci University, Tuzla, 34956, Istanbul, Turkey.
Email: nufer.ates@sabanciuniv.edu

Introduction

In high-technology industries, firms increasingly engage in acquisitions to expand their technological capabilities and enhance their innovation performance (Cassiman et al., 2005; Hagedoorn and Wang, 2012; Stiebale, 2013; Villalonga and McGahan, 2005). Prior research on technology acquisitions have suggested that the relatedness of the acquirer's and target's technological knowledge—that is, technological relatedness—is an important predictor of post-acquisition innovation performance (Ahuja and Katila, 2001; Cassiman et al., 2005; Cloodt et al., 2006; Ornaghi, 2009). To date, this research stream has focused on understanding whether and to what extent similarity and complementarity, the two forms of technological relatedness, are beneficial for future synergy creation (Bena and Li, 2014; Makri et al., 2010; Rao et al., 2016; Sears and Hoetker, 2014; Yu et al., 2016). The findings suggest that acquiring technologically similar targets leads to lower research and development (R&D) expenditures and more incremental innovations, while acquiring targets with complementary (i.e. distinct yet related) technological capabilities leads to improved R&D efficiency, increased innovation quality, and more discontinuous innovations (Cassiman et al., 2005; Makri et al., 2010).

Although we would expect acquirers to choose targets that help them innovate and realize synergies, this is not always the case for two interrelated reasons. First, firms often overlook key sources of synergy, pay attention to the wrong sources, or fail to avoid sources of synergy dilution (Rao et al., 2016). Second, acquirers need to absorb novel information about potential targets of varying relatedness. The less related a potential acquisition target is to a firm's existing business portfolio, the more complexity it adds to the selection decision, the less applicable pre-existing information is, and the more difficult it is to absorb new information about the potential target technology (cf. Cohen and Levinthal, 1990). Therefore, the decision to select a target in a technology acquisition depends not only on the characteristics of the acquiring or target companies—as has been suggested so far (Capron and Shen, 2007; Shen and Reuer, 2005)—but also on acquirers' ability to cope with the information processing demands associated with the assessment of potential targets' technologies and their fit with the acquirer's existing technologies.

This poses the following question: When are some firms better than others at identifying similarities and complementarities in technology acquisitions? To answer this question, we focus on acquirer Top Management Teams (TMTs)—the ultimate decision makers for acquisition target selection (Nadolska and Barkema, 2014; Parola et al., 2015). Following research that emphasized the pivotal role of TMT composition for important acquisition decisions, such as acquisition frequency (Nadolska and Barkema, 2014), geographic location (Barkema and Shvyrkov, 2007), and integration (Parola et al., 2015), we propose that firms' target selection decisions are driven by the extent to which acquirer TMTs recognize a potential target's technological similarity and complementarity. The extent of this recognition, in turn, is determined by the TMT information processing capability, depending on the TMT composition in general (Amason, 1996; Hutzschenreuter and Horstkotte, 2013; Sanders and Carpenter, 1998) and on demographic faultlines in particular (Bezrukova et al., 2007; Meyer and Glenz, 2013; Van Knippenberg et al., 2011). Faultlines refer to the extent that a team has conceptual subgroups based on members' background characteristics (Lau and Murnighan, 1998) and provide a more comprehensive explanation of team cognitive and social processes than diversity indices based on single attributes (Bezrukova et al., 2007; Meyer and Glenz, 2013; Van Knippenberg et al., 2011).

The crux of our argument is that TMTs with moderately strong faultlines are better able to identify and value technological relatedness than TMTs with either weak or very strong faultlines. That is because the positive cognitive effects of faultlines (e.g. benefiting from diverse perspectives with the social support in the subgroups) do not materialize at low values of faultline strength, and the negative

social effects of faultlines (e.g. social categorization preventing teams from having healthy intra-team dynamics) outweigh positive effects at high levels of faultline strength. Our empirical analyses of 94 acquisitions from 2322 potential acquisition targets of 66 technology firms support these predictions.

Our study makes two contributions. First, we add to the acquisition target selection literature (Bena and Li, 2014; Makri et al., 2010; Rao et al., 2016; Sears and Hoetker, 2014; Yu et al., 2016) by showing evidence that the ability of an acquirer to assess a potential target's technological relatedness depends on how well its TMT members jointly process relevant information to identify potential synergistic recombinations between acquirer and target technologies, as well as the commercial value of such recombinations. In doing so, we extend this literature by introducing a critical boundary condition based on insights from upper echelons research. Second, we contribute to the upper echelons theory by offering a positive view regarding TMT faultlines. Upper echelons research almost[1] exclusively studied TMT faultlines as a hindrance to TMT processes (e.g. Barkema and Shvyrkov, 2007; Li and Hambrick, 2005; Ndofor et al., 2015; Tuggle et al., 2010) and firm performance (e.g. Cooper et al., 2013; Van Knippenberg et al., 2011). However, extant theory in small teams faultlines literature (Thatcher and Patel, 2012 for a review) suggests that faultlines may lead to healthy divides in certain contexts, and empirically demonstrates their positive effects (e.g. Bezrukova et al., 2009; Gibson and Vermeulen, 2003). Our finding regarding the inverted U-shaped moderating effect of faultlines on the relationship between technological relatedness and target selection demonstrates the benefit of TMT faultlines at moderate strengths. Therefore, by identifying a context in which the positive effects of TMT faultlines are manifested, our study bridges upper echelons research with the extant theory in small teams faultline literature.

Theoretical background

Acquisitions are important vehicles to enhance firm competitiveness (Ahuja and Novelli, 2014; Dezi et al., 2018), and selecting an appropriate target is essential for acquisition success (Haspeslagh and Jemison, 1991). Target selection studies in strategy and finance literature show that the acquirer's target choice is determined by whether the target is a private or a public firm (Shen and Reuer, 2005); the overlap between the R&D pipelines and current products of the acquiring and target firms (Yu et al., 2016); their similarity in national culture and technical knowledge (Rao et al., 2016); firm characteristics, such as the target's pre-merger profitability, industry growth, geographical scope, and acquirer's acquisition experience; diversifying search (Capron and Shen, 2007); product market and technological overlap (Bena and Li, 2014); and technological relatedness (e.g. Bena and Li, 2014; Rao et al., 2016; Yu et al., 2016).

Despite high risk of failure, potential financial losses (Dezi et al., 2018), and uncertain innovation outcomes (Haucap and Stiebale, 2016), firms in high-technology industries frequently engage in acquisitions to expand their technological knowledge (Cassiman and Veugelers, 2006; Lee and Kim, 2016; Puranam et al., 2009) and to bridge capability gaps (Capron and Mitchell, 2009). Recognizing the importance of technology sourcing through acquisitions, numerous studies have examined how acquirers can leverage target technological capabilities to enhance post-acquisition innovation performance. Generally, these studies provide evidence that technological relatedness between acquirer and target firms enhances innovation output following an acquisition (e.g. Ahuja and Katila, 2001; Cassiman et al., 2005; Cloodt et al., 2006; Makri et al., 2010; Sears and Hoetker, 2014). Building on this literature, as a baseline hypothesis, we first examine whether and to what extent technological relatedness (i.e. technological similarity and complementarity) between acquirers and potential targets impacts acquisition target selection. Subsequently, we focus on how the direction and magnitude of this relationship changes depending on the strength of acquirer TMT demographic faultlines.

Technological relatedness and target selection

Acquisition target selection is the result of a search process in which an acquirer selects a target firm that best fits its acquisition objectives, compared to the alternatives (Chakrabarti and Mitchell, 2013). Since an important objective in technology acquisitions is to enhance technological competencies (Ahuja and Katila, 2001; Cassiman et al., 2005; Cloodt et al., 2006; Makri et al., 2010), this search focuses on potential targets with technological knowledge that allows acquirers to realize the desired innovation outcomes. This process requires acquirers to identify and evaluate the potential value of technological competencies of alternative targets. Making sense of external technological knowledge and understanding its recombination possibilities with internal knowledge requires some level of familiarity with the associated technological area, or technological relatedness (Cohen and Levinthal, 1990; Lane and Lubatkin, 1998).

Technological relatedness can be assessed along the dimensions of technological similarity and complementarity (Cassiman et al., 2005). *Technological similarity* refers to the extent that two firms' technological capabilities focus on the same narrowly defined areas, while *technological complementarity* refers to the extent that technological capabilities are focused on different narrowly defined areas within the same broadly defined area (Makri et al., 2010). In other words, while technological similarity determines the degree of two firms' shared expertise in the same domain, complementarity determines the degree of their expertise in distinct yet related domains. Accordingly, the acquisition of similar capabilities allows acquirers to scale up their existing technological capabilities (Berchicci et al., 2012; Jovanovic and Rousseau, 2002), whereas the acquisition of complementary capabilities enables them to experiment with novel recombination between existing and newly acquired capabilities (Capron et al., 1998; Graebner, 2004; Kaul and Wu, 2016; Kim and Finkelstein, 2009; Ranft and Lord, 2002; Rhodes-Kropf and Robinson, 2008).

Technological similarity between an acquirer and a potential target increases the accuracy of the acquirer's evaluation of the target's technological capabilities by enhancing the acquirer's ability to recognize, evaluate, and internalize external knowledge, that is, absorptive capacity (Cohen and Levinthal, 1990; Mowery et al., 1998; Rosenkopf and Almeida, 2003; Schildt et al., 2012). A high degree of technological similarity allows the acquirer to better understand the assumptions shaping the target's technology (Lane and Lubatkin, 1998) and possible technological problems that may arise when using that technology (Makri et al., 2010). Thus, the acquirer can assess the technological and commercial value of target competencies more easily as the technological similarity between an acquirer and a potential target increases. This implies that, when screening potential targets for acquisition, targets with technological capabilities that are similar to those of the acquirer entail lower search costs than targets with technological capabilities that are unrelated (Chakrabarti and Mitchell, 2013; Chondrakis, 2016). Therefore, we predict as follows:

> *Hypothesis 1a (H1a)*: The higher the technological similarity between an acquirer and a potential target, the higher the probability of acquiring a focal target.

The role of technological complementarity in acquisition target selection is arguably more nuanced than that of similarity. On the one hand, an acquirer's familiarity with a potential target's broader technological area provides the acquirer with sufficient absorptive capacity to evaluate the usefulness of target technology for its operations (Lane and Lubatkin, 1998), thus lowering the screening costs compared to targets with unrelated technologies. On the other hand, the distinctiveness of the target's narrowly defined technological area facilitates valuable learning opportunities and enables the acquirer to expand its technological expertise to new areas, by experimenting with novel recombination of pre-existing and newly acquired technological capabilities that were not possible prior to acquisition (Makri et al., 2010). Supporting these arguments, Cassiman et al. (2005)

reported that while acquirers of technologically complementary targets have longer time horizons for their R&D projects, they are more active in R&D and have higher R&D efficiency compared to firms acquiring technologically similar targets. Similarly, Makri et al. (2010) found that technological complementarity between acquirer and target firms leads to higher quality and more novel innovations following acquisitions. Accordingly, low screening costs coupled with the potential to develop novel innovations in new technological areas increase the attractiveness of technologically complementary potential targets for acquisition.

> *Hypothesis 1b (H1b)*: The higher the technological complementarity between an acquirer and a potential target, the higher the probability of acquiring a focal target.

The role of TMT in acquisition target selection

Although we predict that, on average, acquirers will be attracted to technologically similar and complementary targets, the importance of technological relatedness as a target selection criterion is likely to differ across acquirers. Technological relatedness merely defines the potential set of valuable recombinations between acquirer and target knowledge elements (e.g. Cassiman et al., 2005; Deng, 2010; Makri et al., 2010), whereas the value attributed to them hinges on acquirers' ability to identify the benefits of such relatedness. Since TMTs are ultimately responsible for evaluating and selecting acquisition targets (Nadolska and Barkema, 2014; Steinbach et al., 2017), we argue that the influence of technological relatedness on target selection is, at least partly, a function of acquirer TMTs' ability to understand the benefits of combining their firms' technological knowledge with that of potential targets.

A TMT consists of the most influential executives in the organization which often includes the chief executive officer (CEO) and his or her direct reports (Carpenter et al., 2004). As they are uncertain and non-routine strategic decisions (Haleblian and Finkelstein, 1999), acquisition target selections require a thorough consideration of alternatives and consequences based on TMT members' knowledge and experience (Nadolska and Barkema, 2014). When considering targets, acquirer TMT members need to not only absorb technically complex information about potential knowledge recombinations but also assess their commercial value. TMT members also need to consider the organizational challenges of realizing innovations because implementation of innovations necessitates a substantial degree of collaboration between acquirer and target employees (Puranam et al., 2009; Puranam and Srikanth, 2007). Due to the cognitively demanding nature of selecting an acquisition target, we argue that TMTs with higher information processing capabilities are better able to identify the technological and commercial implications of acquiring targets with related technologies.

A TMT's information processing capability encompasses its cognitive and social abilities (e.g. Amason, 1996; Hutzschenreuter and Horstkotte, 2013). Assessing potential targets' technological relatedness requires TMT members to elaborate on the different perspectives they provide, which we refer to as their cognitive ability (Fiske and Taylor, 1991; Taylor and Greve, 2006). TMT members also need to freely share their assessments through the lens of their respective areas of expertise, which we refer to as their social ability. The cognitive ability of the TMT goes beyond what each team member knows. It represents the team's collective engagement in idea elaboration. For instance, a diverse TMT where each member possesses unique information may have access to a richer knowledge base (Barkema and Shvyrkov, 2007), yet cognitive ability does not necessarily materialize unless team members engage in a thorough elaboration of this knowledge within the team, meaning that team members collectively hold in-depth discussions and have constructive debates that can reveal unique insights which would not otherwise surface. In this regard, cognitive

ability does not materialize when teams lack social ability (Stasser and Stewart, 1992) because information that is not shared with other members is not discussed within a team (Wittenbaum and Stasser, 1996). Therefore, both the cognitive and social ability of a TMT jointly determine its information processing capability, which is instrumental in identifying the value of targets' technological complementarity and similarity.

An important determinant of information processing capability is the composition of a TMT based on the background characteristics of its members (Carpenter et al., 2004; Dahlin et al., 2005; Hambrick and Mason, 1984; Sanders and Carpenter, 1998), such as age, gender, tenure, and functional background (Thatcher and Patel, 2012). Upper echelons literature views these characteristics as valid proxies of TMT members' cognitive frames, values, and perceptions (Hambrick, 2007) that affect their strategic decisions (Carpenter et al., 2004). Since these attributes are observable, they are also particularly salient for categorizations (Harrison et al., 1998). Earlier strategy research theorized and empirically demonstrated that these attributes influence TMT cognitive and social processes in various strategic contexts (e.g. Barkema and Shvyrkov, 2007; Hutzschenreuter and Horstkotte, 2013; Ndofor et al., 2015).

Recognizing that TMT members may differ or align on more than one diversity attribute, scholars suggested that the joint effects of diversity along multiple attributes should be considered for a thorough assessment of how TMT composition affects information processing (Bezrukova et al., 2007; Meyer and Glenz, 2013; Van Knippenberg et al., 2011). To jointly analyze the effects of multiple background attributes, Lau and Murnighan (1998) developed the *faultlines* perspective. Faultlines are hypothetical dividing lines that split a team into subgroups based on alignment along multiple diversity attributes. By incorporating the combined effects of the diversity characteristics through their alignment with each other, the faultlines perspective provides insights into team processes and outcomes that extend over and beyond explanations based on single diversity attributes alone (Bezrukova et al., 2007; Lau and Murnighan, 2005; Li and Hambrick, 2005; Thatcher et al., 2003). Consider a TMT that consists of two men and two women: one man and one woman who are 30 years old and one man and one woman who are 60 years old. The diversity of this team is the same as that of a TMT consisting of two 60-year-old men and two 30-year-old women. However, the key difference between the two TMTs is the overlap of age and gender in the second team that creates two homogeneous subgroups (i.e. older men and younger women). The split would be even more marked if both women have marketing backgrounds and both men have engineering backgrounds (Lau and Murnighan, 1998).

Building on these insights, the upper echelons literature examined how TMT faultlines affect TMT decision-making in different decision contexts. These studies found that TMT faultlines affect firms' decisions about entering new geographical areas (Barkema and Shvyrkov, 2007), product diversification (Hutzschenreuter and Horstkotte, 2013), resource utilization (Ndofor et al., 2015), and discussion of entrepreneurial issues in board meetings (Tuggle et al., 2010). Drawing on this rich tradition of research, in the next part, we examine how demographic faultlines within a TMT influence the selection of acquisition targets.

TMT faultlines, technological relatedness, and target selection

We expect TMTs with high information processing capabilities to exhibit a greater recognition of the benefits of technological relatedness, thus enhancing the likelihood of selecting targets with similar and complementary technologies. Since demographic faultlines are a primary determinant of TMTs' information processing capability (Amason, 1996; Hutzschenreuter and Horstkotte, 2013; Sanders and Carpenter, 1998), we develop arguments regarding the moderating effect of TMT faultlines for three levels of faultline strength: weak, moderate, and strong.

Weak faultlines. When TMT faultlines are weak—that is, when there are no subgroups within a TMT—there are two possible cases: either (1) team members' background characteristics are highly homogeneous, or (2) they are heterogeneous in the way that they do not divide members into meaningful subgroups. In either case, TMT members would feel comfortable sharing information within the team, implying high social ability. First, when TMT members have highly homogeneous background characteristics, they are not afraid to express ideas (Kramer, 1990) and have a shared language and understanding (e.g. Gibson and Vermeulen, 2003). Second, when there are no subgroups within a TMT due to high heterogeneity of team members, team members share their points of view freely because there would not be any collective opposition from a group of other team members (Asch, 1952). Research shows that highly diverse teams recognize the uniqueness of each team member, are open to hearing different views, and deliberately attempt to comprehend them (Earley and Mosakowski, 2000). This implies "a unity in variety" (Gibson and Vermeulen, 2003: 209) and, despite their individual differences, members would identify with the whole team (Brewer, 1993; Tajfel and Turner, 2004). Therefore, social ability determined by information sharing tendency, albeit through different mechanisms, is high in both cases.

Despite the willingness to share ideas, weak faultlines diminish TMTs' cognitive abilities due to lack of meaningful cohorts—that is, subgroups of team members with similar background characteristics (Gibson and Vermeulen, 2003). First, in the case of homogeneous TMTs, the range and quality of the ideas expressed are constrained because the cognitive base that the TMT can draw on is limited and homogeneous teams are less open to new sources of information (Bantel, 1994). Moreover, members of homogeneous teams expect to agree with one another (Phillips, 2003); hence, any new or unique information is more likely to be disregarded (Bantel, 1994; Phillips et al., 2004). Second, in the case of heterogeneous TMTs without subgroups, despite the fact that these teams have access to a richer cognitive base due to members' diverse characteristics (Van Knippenberg et al., 2004), the joint elaboration of ideas is unlikely to be rigorous. A team member's opinion is more likely to be contemplated by the team when it is supported by at least one other member (Wittenbaum and Stasser, 1996). Lack of meaningful cohorts also hampers team learning (Gibson and Vermeulen, 2003) and impedes creativity (Bezrukova and Uparna, 2009). In summary, a TMT with low faultline strength is characterized by a low degree of cognitive ability.

This line of reasoning suggests that TMTs with weak faultlines enjoy high social skills but suffer from subpar cognitive skills. Therefore, they perform poorly in tasks that necessitate searching and utilizing various information sources (Bowers et al., 2000), such as evaluating the technological and commercial viability of exploiting potential targets' technologies. Due to their impaired information processing capabilities, such TMTs are also not well suited to anticipating the complex challenges of realizing technological synergies. Thus, we argue that weak faultlines constrain a TMT's ability to fully evaluate the technological and commercial implications of potential targets' technological similarity or complementarity with the acquirer.

Moderate faultlines. When TMT faultlines are moderately strong, there are distinct subgroups, yet they are not highly homogeneous with respect to members' background characteristics. Team members may belong to multiple subgroups based on different sets of diversity attributes. Such mild forms of division facilitate a favorable environment for the exchange and evaluation of new ideas within a TMT for several reasons. First, the existence of subgroups increases team members' awareness of their differences, prompting them to actively seek to understand each other (Earley and Mosakowski, 2000). As such, TMT members not only expect to hear diverse opinions but are also better prepared for digesting different viewpoints (Gibson and Vermeulen, 2003). Second, subgroups operate as pockets of social support facilitating idea formulation. Subgroup members are likely to be more willing to engage in a rich exchange of ideas and thorough elaboration of

issues within their own subgroups (Cramton and Hinds, 2004) before sharing their opinions across subgroups. Such in-depth discussion and constructive debate reveal unique insights that would not surface without the presence of subgroups (Azzi, 1993). Consequently, TMTs with moderate levels of faultline strength demonstrate elevated cognitive abilities.

Having a cohort within the TMT encourages idea sharing through the social support of cohort members (Bandura, 1997). Subgroup members have pleasant interactions (Bezrukova et al., 2010; Stevenson et al., 1985) and strong bonds with each other (Bezrukova et al., 2010; Lau and Murnighan, 2005), leading to high levels of cooperation (Bezrukova et al., 2010; Hart and Van Vugt, 2006; Phillips et al., 2004). Team members feel secure and are less prone to holding back their individual opinions, since they do not fear embarrassment (Bezrukova et al., 2007; Gibson and Vermeulen, 2003). The team is also more receptive to new ideas (Stasser et al., 1989; Wittenbaum and Stasser, 1996) because any idea suggested by a sub-group member might be favored by multiple team members (Azzi, 1993; Stasser et al., 1989). Although not all subgroup members necessarily agree with the proposed idea, the team still benefits from enhanced social ability. Because TMTs with moderate faultlines possess high cognitive and social ability, they can better cope with the information processing demands about the potential benefits arising from exploiting targets' technological relatedness. They can absorb the complex information about technological synergies, assess the commercial value of such synergies more accurately, and generate more realistic expectations about implementation phases. Therefore, targets' relatedness becomes a more prominent criterion in target selection for these TMTs.

Strong faultlines. When faultlines are strong, the team is divided into highly homogeneous sub-groups that are acutely different from each other. In this case, subgroup members are more inclined to be psychologically located within their subgroups, preventing them from exchanging ideas with other subgroup members (Nesdale and Mak, 2003), which impairs TMTs' social and cognitive abilities. TMT members are more likely to be attached to the opinions of their in-group teammates without critical reflection causing polarization (Abrams et al., 1990; Mullen, 1991). Polarized teams discount valuable information due to their distorted perceptions of reality and biased opinions of themselves and other groups (Gibson and Vermeulen, 2003; Tajfel, 1982). The resulting or complementarity with the acquirer.

In all, our reasoning suggests that a TMT's social and cognitive abilities, and therefore its information processing capability is highest at moderate faultline strength. Therefore, we predict an inverted U-shaped relationship between target technological relatedness and target selection as TMT faultline strength increases.

> *Hypothesis 2a (H2a)*: The impact of technological similarity on the probability of acquiring a potential target will first increase and then decrease as the strength of faultlines in an acquirer's TMT increases.
>
> *Hypothesis 2b (H2b)*: The impact of technological complementarity on the probability of acquiring a potential target will first increase and then decrease as the strength of faultlines in an acquirer's TMT increases.

Methods

Sample and data sources

We tested our hypotheses on a sample of acquisitions made by firms operating in five high-technology industries: pharmaceuticals, computer equipment, electronics, telecommunications,

and software.[2] These industries provide an ideal setting for our research, since they are highly R&D intensive and firms in these industries frequently use acquisitions to expand their technological capabilities (Makri et al., 2010). To construct our sample, we first identified acquisitions completed in these industries between 1996 and 2002 according to the Securities Data Company (SDC) Platinum database.[3] We then obtained data on the TMT composition of the acquirer firms from their annual 10K reports filed with the US Securities and Exchange Commission; patent data for acquirer and target firms from the National Bureau of Economic Research (NBER) Patent Data Project (Hall et al., 2001); and financial data from Compustat. Since our theory is based on the premise that expanding technological capabilities is an important motive for acquisitions, we followed the approach of Ahuja and Katila (2001) and limited our sample to acquisitions in which the acquirer successfully applied for at least five patents and the target applied for at least one patent in the 3 years preceding a focal acquisition. In constructing our sample, we excluded acquisitions with missing TMT, financial, or patent data for the acquirer and financial or patent data for the target for the 3 years preceding a focal acquisition. Our final sample included 94 acquisitions by 66 unique acquirers.

Our predictions concern the influence of technological similarity and complementarity on the probability of acquiring a particular target among alternatives. Hence, testing these predictions requires that our sample includes not only actual acquisitions but also alternative acquisition possibilities that could have been realized by the acquirers in our sample. By exploiting the variation between actual and alternative targets, our regression analyses can offer insights into whether and to what extent technological similarity and complementarity influence the selection of actual targets instead of their alternatives. Following existing research on acquisition target selection (Chakrabarti and Mitchell, 2013; Chen et al., 2018), we determined a pool of alternative targets for each focal acquisition, based on two criteria. First, a potential target should have the same four-digit SIC code as the actual target. This criterion ensures that all alternative targets for each focal acquisition primarily operate in the same industry, offering the acquirer similar expansion opportunities through the acquisition. Second, an alternative target should be available for takeover, as it may not be feasible to acquire some firms in the actual target's industry or they may not be worthy of acquiring (Chakrabarti and Mitchell, 2013). To satisfy this criterion, we limited potential targets to firms that were acquired during a 5-year window, starting with the focal acquisition year.[4] As a result, our dataset included 2082 potential acquisition matches, including 94 actual and 1988 alternative targets.

Measures

Dependent variable. Our dependent variable, *Acquisition match*, is a dummy variable representing whether a potential acquisition match has been realized. For each focal acquisition, this variable is coded as 1 for the actual acquirer and target pairing, and 0 for pairings of the acquirer with other alternative targets.

Explanatory variables

Technological similarity. We measured the technological similarity between our acquirers and actual and potential acquisition targets using the distribution of both firms' patents in different technology classes filed 3 years before a focal acquisition.[5] The United States Patent and Trademark Office classifies patents into 417 three-digit classes[6] according to their technological areas. Hall et al. (2001) further aggregated these 417 classes into 37 subcategories and six main categories in the NBER Patent Data Project, where each class belongs to only one subcategory. While patenting in the same three-digit classes represents the development of similar technological

capabilities, patenting in different classes within the same subcategory indicates the development of distinct but related, hence complementary, technological capabilities (Makri et al., 2010).[7] We used the following formula to compute technological similarity (from Schildt et al., 2012)

$$\text{Technological similarity} = \sum_k \frac{\sqrt{P(k,\ A)_{(t-3,\ t-1)} \times P(k,\ T)_{(t-3,\ t-1)}}}{\sqrt{Patents(A)_{(t-3,\ t-1)} \times Patents(T)_{(t-3,\ t-1)}}}$$

In the formula, $P(k, A)$ and $P(k, T)$ denote the number of patents of acquirer and target firms in patent class k, and $Patents(A)$ and $Patents(T)$ denote the total number of their patents. This similarity measure ranges from 0 to 1, with 0 representing complete dissimilarity and 1 representing complete overlap between the two patent portfolios.

Technological complementarity. Following Makri et al. (2010), we measured technological complementarity between acquirer and target firms based on their patents in distinct yet related areas, adjusted for the importance of these areas to the acquirer firm. Accordingly, we used the following formula.

Technological complementarity =

$$\frac{P.Com.Sub(A,\ T)_{(t-3,\ t-1)} - P.Com.Cls(A,\ T)_{(t-3,\ t-1)}}{Patents(A,\ T)_{(t-3,\ t-1)}} \times \frac{P.Com.Sub(A)_{(t-3,\ t-1)}}{Patents(A)_{(t-3,\ t-1)}}$$

In the formula, $P.Com.Sub(A, T)$ denotes the sum of patents successfully applied by acquirer and target firms in common subcategories; $P.Com.Cls(A, T)$ denotes the sum of their patents filed in common classes; $Patents(A, T)$ denotes the sum of all acquirer and target patents; $P.Com.Sub(A)$ denotes the sum of acquirer patents in common subcategories as the target; $Patents(A)$ denotes the sum of all acquirer patents; and t denotes the acquisition year. The value of technological complementarity ranges between 0 and 1, and this increases as acquirer and target firms file more patents in complementary classes relative to common or unrelated classes. We provide an illustrative example of our operationalization of technological complementarity in Table 5 in Appendix 1.

Faultline strength. We used Thatcher et al.'s (2003) measure to operationalize faultline strength. This measure, widely adopted in faultline literature (e.g. Bezrukova et al., 2007; Lau and Murnighan, 2005; Ndofor et al., 2015), captures the percentage of total variation in group attributes accounted for by the strongest group split. TMT members' age, tenure, gender, and functional background are determined as the diversity attributes composing the faultline (Ndofor et al., 2015). We focused on these attributes because not only are they among the most commonly used attributes in faultline composition (Thatcher and Patel, 2012), but they are also observable and impermeable (i.e. they cannot be changed by the member at will). Research has shown that observable characteristics are likely to provoke stereotypes leading to subgroupings (Harrison et al., 1998; Pelled et al., 1999) and that impermeable characteristics are most likely to engender group divisions (Pelled et al., 1999).

To determine the strongest split, we calculated the ratio of the between-group sum of squares to the total sum of squares for each team for all possible subgroup combinations (Thatcher et al., 2003).[8] More formally, for a team of n members with p background attributes, this measure applies the following formula for all possible subgroupings and identifies the strongest one as

$$Fau_g = \left(\frac{\sum_{j=1}^{p}\sum_{k=1}^{2} n_k^g (\bar{x}_{.jk} - \bar{x}_{.j.})^2}{\sum_{j=1}^{p}\sum_{k=1}^{2}\sum_{i=1}^{n_k^g} (x_{ijk} - \bar{x}_{.j.})^2} \right) \qquad g = 1,\ 2,\ \ldots,\ 2^n - 1$$

where x_{ijk} denotes the value of the jth attribute of the ith member of subgroup k; $\bar{x}_{.j.}$ denotes the overall group mean of attribute j; $\bar{x}_{.jk}$ denotes the mean of attribute j in subgroup k; and n_k^g denotes the number of members of the kth subgroup ($k = 1, 2$) under split g. Before we calculated this formula, following Thatcher et al.'s (2003) recommendations, we recoded the categorical variables of gender and functional background into two and eight dummy variables, respectively. Our measure requires a minimum of two team members per subgroup (Thatcher et al., 2003); thus, given the modest sizes of TMTs in our sample, we only considered splits into two subgroups. This measure can range from 0 to 1; the faultline strengths in our sample ranged from 0.13 to 1.00 with a mean of 0.50.

Control variables. We controlled for a range of acquirer, target, and dyadic characteristics to take into account alternative explanations of our results. To account for acquirer-related factors that might affect the selection of acquisition targets, we controlled for acquirers' return on assets (ROA), R&D intensity, acquisition experience, market share, and whether an acquirer had a new CEO in the year preceding a focal acquisition. We also controlled for the composition of the TMT of each acquirer in the year prior to a focal acquisition by including TMT size as well as diversity in terms of age, tenure, gender, and functional background. This allowed us to ensure that we captured the effects of faultlines rather than the team characteristics of acquirer TMTs (Barkema and Shvyrkov, 2007; Nadolska and Barkema, 2014). At the target level, we controlled for ROA and R&D intensity, since these variables may affect firms' attractiveness as acquisition targets. Finally, we included five dyadic characteristics. We controlled for ownership similarity, industry relatedness, and geographic distance between acquirers and targets, as well as the size, in terms of both assets and technological knowledge bases, of actual and alternative targets relative to acquirers. Table 1 presents a summary of our control variables and their measurement.

Empirical estimation

Since our dependent variable is dichotomous, taking a value of either 0 or 1, we tested our hypotheses using logistic regression, which models the likelihood of the occurrence of an event as a linear combination of predictor variables. In this study, our logistic regression models predict the likelihood of an acquisition match with the actual acquisition target, rather than with any of the alternative targets, based on our explanatory variables: technological complementarity, technological similarity, and faultline strength in acquirer TMTs (Chakrabarti and Mitchell, 2013). In our models, we clustered observations by unique acquirers to account for possible correlations among acquisitions by the same acquirers.

Results

Table 2 shows the means, standard deviations, and maximum and minimum values separately for actual and alternative acquisitions. These descriptive statistics indicate that, on average, our sample acquirers obtained a 16% return on their assets, spent 29% of their earnings on R&D,

Table 1. Control variables and their measurement.

Acquirer controls	Measurement
Acquirer ROA	Acquirer earnings before interest and taxes divided by its total assets in the year preceding each focal acquisition
Acquirer R&D intensity	Acquirer R&D expenditures divided by its total sales in the year preceding each focal acquisition
CEO change	1 = acquirer had a new CEO in the year preceding each focal acquisition; 0 = otherwise
Market share	Acquirer sales divided by total sales by firms in the same four-digit SIC code as the acquirer in the year preceding each focal acquisition
Acquisition experience	The number of acquisitions made by the acquirer in the 5 years preceding each focal acquisition
TMT size	Number of acquirer TMT members
Age diversity Tenure diversity	Coefficient of variation: the standard deviation divided by the mean (Harrison and Klein, 2007). Tenure refers to the time a TMT member had spent in the organization, since organizational tenure heterogeneity might indicate the extent to which experiences were shared among TMT members within the firm (Marcel, 2009)
Gender diversity Function diversity	Blau's index: $1 - \sum p_i^2$ where p_i is the proportion of a TMT member in the ith category (Blau, 1977). While gender had two categories, we coded functional background in eight categories following previous research (i.e. production operations, R&D and engineering, accounting and finance, management and administration, marketing and sales, law, personnel and labor relations, other; Hambrick et al., 1996; Ndofor et al., 2015)
Target controls	
Target ROA	Target's earnings before interest and taxes divided by its total assets in the year preceding each focal acquisition
Target R&D intensity	Target's R&D expenditures divided by its total sales in the year preceding each focal acquisition
Dyad-level controls	
Industry relatedness	1 = the acquirer and target have the same four-digit main SIC code; 0.5 = the acquirer and target share the same three-digit SIC code; 0.33 = the acquirer and target have the same two-digit SIC code; 0.25 = the acquirer and target have the same first digit in their SIC codes (Schildt et al., 2012)
Relative size (total assets)	Target's total assets divided by acquirer's total assets as of the year preceding each focal acquisition
Relative size (patent stock)	Target's patent stock divided by acquirer's patent stock as of the year preceding each focal acquisition
Geographic distance	Distance in kilometers between headquarter cities of acquirer and target
Ownership similarity	1 = both acquirer and target have institutional investors with greater than 5% ownership, or neither have such investors; 0 = only the acquirer or target has institutional investors greater than 5% ownership (Bettinazzi and Zollo, 2018)

ROA: return on assets; CEO: chief executive officer; SIC: standard industrial classification code; TMT: Top Management Team; R&D: research and development.

undertook 10.5 acquisitions in the 5 years before a focal deal, and have TMTs consisting of 9.89 managers. Correlations between variables for the aggregate sample are presented in Table 3 and include both realized and alternative acquisitions. Although the correlations did not raise any

Table 2. Descriptive statistics.

Variable	Actual acquisitions ($n = 94$)				Alternative acquisitions ($n = 1988$)			
	Mean	Standard deviation	Minimum	Maximum	Mean	Standard deviation	Minimum	Maximum
Technological similarity	0.43	0.24	0.00	0.95	0.28	0.26	0.00	0.28
Technological complementarity	0.16	0.18	0.00	0.84	0.14	0.17	0.00	0.14
Industry relatedness	0.55	0.39	0.00	1.00	0.69	0.39	0.00	0.69
Relative size (total assets)	0.21	0.38	0.00	3.03	2.00	25.34	0.00	2.00
Relative size (patent stock)	0.23	0.37	0.00	1.65	0.19	0.33	0.00	0.19
Geographic distance	1806.50	1878.13	0.00	8962.75	2422.70	2283.39	0.00	2422.70
Ownership similarity	0.53	0.50	0.00	1.00	0.50	0.50	0.00	0.50
Target ROA	−0.06	0.40	−2.07	0.40	−0.25	0.90	−12.09	−0.25
Target R&D intensity	0.58	1.06	0.01	6.68	5.08	74.71	0.00	5.08
Faultline strength	0.50	0.13	0.32	1.00				
Acquirer R&D intensity	0.29	0.48	0.02	3.62				
Acquirer ROA	0.16	0.15	−0.34	0.45				
Acquirer acquisition experience	10.49	14.15	0.00	86.00				
TMT size	9.89	3.80	2.00	20.00				
Age diversity	0.12	0.04	0.03	0.27				
Tenure diversity	1.06	0.46	0.00	2.31				
Gender diversity	0.13	0.13	0.00	0.44				
Function diversity	0.70	0.10	0.45	0.84				
CEO change	0.10	0.30	0.00	1.00				
Market share	0.09	0.13	0.00	0.54				

ROA: return on assets; TMT: Top Management Team; CEO: chief executive officer.

concerns regarding multicollinearity, we checked the variance inflation factors (VIFs) of our variables. The VIFs of our key variables were well below the commonly used threshold of 10, suggesting that our results are not affected by multicollinearity.

Table 4 presents the logistic regression results.[9] Model 1 included only dyadic variables and target firm characteristics, while Model 2 added acquirer characteristics. The results in Model 2 indicate that, on average, the acquirer firms in our sample preferred targets that are profitable ($p = 0.001$), geographically close ($p = 0.024$), operate outside their own main industries ($p = 0.000$), relatively small in terms of asset size ($p = 0.002$), but large in terms of knowledge base ($p = 0.031$). The effects and significance levels of these control variables remained unchanged in subsequent models.

The results in Model 2 provide support to H1a and H1b. Both technological similarity and complementarity have positive and significant coefficients in Model 2 ($p = 0.000$ and $p = 0.010$, respectively). This shows that both technological similarity and complementarity are significant predictors of target selection, in line with our argument that acquirers' familiarity with target technologies increases the likelihood of their acquisition. The effect size of technological

Table 3. Correlations between variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(1) Acquisition match	1.00																				
(2) Technological complementarity	0.03	1.00																			
(3) Faultline strength	−0.02	0.10	1.00																		
(4) Technological similarity	0.12	0.03	0.08	1.00																	
(5) Industry relatedness	−0.07	0.08	0.20	0.09	1.00																
(6) Relative size (total assets)	−0.02	0.08	0.03	0.04	−0.02	1.00															
(7) Relative size (patent stock)	0.03	0.03	0.24	0.09	0.06	0.11	1.00														
(8) Target ROA	0.04	0.04	0.04	−0.00	−0.01	0.03	0.04	1.00													
(9) Target R&D intensity	−0.01	−0.00	0.01	−0.00	−0.06	−0.00	0.00	−0.19	1.00												
(10) Acquirer R&D intensity	−0.03	0.14	0.24	0.22	0.04	0.29	0.34	−0.05	0.02	1.00											
(11) Acquirer ROA	0.04	−0.14	−0.23	−0.14	0.04	−0.17	−0.16	0.06	−0.01	−0.68	1.00										
(12) Acquisition experience	0.03	−0.10	−0.17	−0.05	−0.12	−0.05	−0.23	−0.00	−0.01	−0.23	0.43	1.00									
(13) TMT size	0.03	−0.05	−0.41	0.11	0.09	−0.06	0.18	0.01	0.00	−0.20	0.35	0.13	1.00								
(14) Age diversity	0.00	0.07	0.33	−0.00	0.23	0.01	0.34	0.05	−0.02	0.15	−0.03	−0.04	0.19	1.00							
(15) Tenure diversity	0.00	0.01	−0.20	−0.10	0.12	−0.04	−0.04	0.02	−0.00	−0.18	0.32	0.18	0.28	0.12	1.00						
(16) Gender diversity	−0.01	−0.05	−0.35	0.02	−0.15	0.05	−0.04	−0.06	0.02	0.18	−0.10	−0.02	0.01	−0.38	−0.17	1.00					
(17) Function diversity	0.00	0.03	−0.16	−0.06	−0.01	−0.08	−0.16	0.00	−0.01	−0.36	0.24	0.03	0.09	0.18	0.34	−0.31	1.00				
(18) Geographic distance	−0.06	0.09	−0.01	0.02	−0.02	0.02	0.04	0.01	−0.00	0.03	0.00	−0.05	0.04	0.01	0.02	0.04	−0.02	1.00			
(19) Ownership similarity	0.01	−0.02	−0.03	−0.00	0.01	0.01	0.00	−0.02	−0.03	−0.02	−0.01	−0.00	−0.02	−0.05	−0.03	0.01	−0.02	−0.01	1.00		
(20) CEO change	−0.03	0.06	−0.07	−0.01	0.07	−0.03	−0.05	−0.02	−0.01	−0.08	−0.04	−0.10	−0.19	−0.05	0.06	−0.31	0.24	−0.02	−0.02	1.00	
(21) Market share	0.05	−0.08	−0.28	0.05	−0.20	−0.04	−0.14	0.02	−0.01	−0.23	0.46	0.65	0.22	−0.15	0.12	−0.02	0.02	−0.01	0.02	−0.06	1.00

ROA: return on assets; TMT: Top Management Team; CEO: chief executive officer.

Table 4. Logistic regression results with acquisition match as the dependent variable.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Technological similarity	3.406***	3.839***	3.851***	3.561***	3.841***	4.024***	3.750***
	[0.628]	[0.631]	[0.636]	[0.653]	[0.629]	[0.652]	[0.651]
Technological complementarity	1.682**	1.905**	1.933***	2.051***	1.901***	2.956***	2.812***
	[0.730]	[0.741]	[0.748]	[0.750]	[0.730]	[0.782]	[0.759]
Faultline strength		-2.805*	-3.096*	-4.645***	-2.813*	-5.561***	-4.950***
		[1.515]	[1.622]	[1.510]	[1.575]	[1.408]	[1.523]
Faultline strength^2				8.408		11.663**	7.734
				[7.105]		[4.865]	[6.820]
Technological similarity × Faultline strength			1.800	-4.015			-4.265
			[5.871]	[5.142]			[5.353]
Technological similarity × faultline strength^2				24.514			17.479
				[16.106]			[16.150]
Technological complementarity × faultline strength					0.339	12.866	12.984
					[7.031]	[9.825]	[10.044]
Technological complementarity × faultline strength^2						-81.922**	-77.951**
						[32.579]	[33.391]
Industry relatedness	-1.394***	-1.375***	-1.356***	-1.315***	-1.375***	-1.318***	-1.393***
	[0.238]	[0.309]	[0.325]	[0.305]	[0.310]	[0.314]	[0.319]
Relative size (total assets)	-0.452**	-0.538***	-0.536***	-0.596***	-0.538***	-0.575***	-0.567***
	[0.177]	[0.177]	[0.173]	[0.170]	[0.177]	[0.188]	[0.182]
Relative size (patent stock)	0.477**	0.568**	0.580**	0.553**	0.569**	0.686***	0.626**
	[0.233]	[0.264]	[0.274]	[0.266]	[0.264]	[0.261]	[0.263]
Target ROA	0.239***	0.208***	0.205**	0.223***	0.208***	0.207***	0.216**
	[0.085]	[0.080]	[0.082]	[0.086]	[0.080]	[0.080]	[0.085]
Target R&D intensity	-0.145*	-0.124	-0.126	-0.133	-0.125	-0.135*	-0.133*
	[0.088]	[0.077]	[0.078]	[0.081]	[0.076]	[0.080]	[0.080]
Geographic distance	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001*	-0.001**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Ownership similarity	0.179	0.158	0.156	0.135	0.158	0.140	0.138
	[0.204]	[0.208]	[0.209]	[0.210]	[0.208]	[0.211]	[0.212]

(continued)

Table 4. (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Acquirer R&D intensity		-0.226	-0.283	-0.437	-0.227	-0.463	-0.416
		[0.364]	[0.448]	[0.521]	[0.364]	[0.439]	[0.496]
CEO change		-1.395***	-1.407***	-1.443***	-1.396***	-1.464***	-1.464***
		[0.356]	[0.360]	[0.400]	[0.357]	[0.381]	[0.389]
Market share		-0.000	0.104	0.269	0.006	0.781	0.541
		[1.447]	[1.475]	[1.271]	[1.467]	[1.287]	[1.309]
Acquirer ROA		1.487	1.429	1.764*	1.483	1.516	1.676
		[1.060]	[1.098]	[1.024]	[1.066]	[1.022]	[1.075]
Acquisition experience		-0.021**	-0.021**	-0.024***	-0.021**	-0.025***	-0.026***
		[0.010]	[0.010]	[0.009]	[0.010]	[0.009]	[0.009]
TMT size		-0.057	-0.061	-0.074**	-0.057	-0.088**	-0.081**
		[0.035]	[0.039]	[0.038]	[0.036]	[0.036]	[0.038]
Age diversity		5.411	5.718	8.895**	5.394	9.495***	9.729***
		[3.580]	[3.516]	[3.776]	[3.515]	[3.394]	[3.756]
Tenure diversity		0.435*	0.447*	0.525**	0.435*	0.493**	0.521**
		[0.263]	[0.260]	[0.237]	[0.263]	[0.238]	[0.240]
Gender diversity		-0.477	-0.406	0.007	-0.480	-0.068	-0.114
		[1.071]	[1.119]	[1.025]	[1.076]	[1.061]	[1.062]
Function diversity		-3.150***	-3.114***	-2.660**	-3.145***	-2.715**	-2.815**
		[0.960]	[0.998]	[1.094]	[0.970]	[1.128]	[1.109]
Constant	-4.091***	-1.854	-0.712	-1.349	-1.589	-2.044*	-0.994
	[0.666]	[1.217]	[1.182]	[1.210]	[1.208]	[1.233]	[1.211]
Observations	2082	2082	2082	2082	2082	2082	2082
Log-likelihood	-330.7	-323.1	-323.0	-319.5	-323.1	-317.9	-317.4
Prob > χ^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000

ROA: return on assets; CEO: chief executive officer; TMT: Top Management Team; R&D: research and development.

Robust standard errors in brackets.
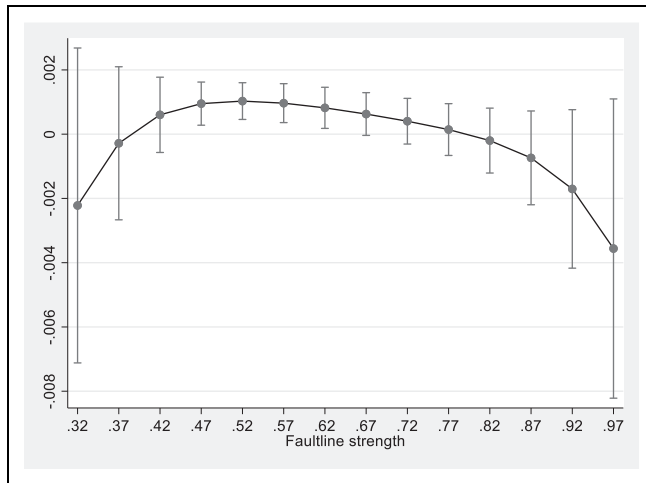
*$p < 0.1$.

**$p < 0.05$.

***$p < 0.01$.

Figure 1. The average effect of a 1% increase in technological complementarity on the probability of an acquisition match with 95% confidence intervals.

similarity is approximately twice that of technological complementarity, and a Wald test indicated that the size difference was marginally significant ($p = 0.056$). Empirical support for H1a and H1b remained robust to the inclusion of interaction terms in subsequent regression models.

We tested H2a with the interaction terms between Technological similarity and Faultline strength and its squared term. We mean centered the variables when constructing their interaction terms (Jaccard et al., 1990). Since we predicted a curvilinear (inverted U-shaped) effect, we interacted technological similarity with both faultline strength, in Model 3, and its quadratic term, in Model 4 (Haans et al., 2016). In Models 3 and 4, the coefficient of the interaction term between technological similarity and faultline strength was statistically insignificant ($p = 0.759$ and $p = 0.237$, respectively). Similarly, in Model 4, the coefficient of the interaction term between technological similarity and the squared term of faultline strength was insignificant ($p = 0.128$). These findings provide no support to H2a.

We tested H2b with the interaction terms between technological complementarity and faultline strength and its squared term in Models 5 and 6. In both models, the coefficient of the interaction term between technological complementarity and faultline strength was statistically insignificant ($p = 0.962$ and $p = 0.190$, respectively), indicating that there is no support for a linear interaction between these variables. In Model 6, the coefficient of the interaction term between technological complementarity and the squared term of faultline strength was negative and significant ($p = 0.012$), supporting H2b. This result shows that the impact of technological complementarity on target selection first increases and then decreases as faultline strength increases. The effect remained robust in Model 7, our full model.

Figure 1 illustrates the marginal effects of technological complementarity on the probability that an acquirer selects a particular target across the sample range of faultline strength. The graph shows that the 95% confidence intervals exclude zero at moderate levels of faultline strength, consistent with H2b. Similarly, Figure 2 depicts the effect of technological complementarity on the probability of selecting a particular target at the sample mean, and two standard deviations below and above the mean of faultline strength. The graph suggests that while at moderate levels of faultline strength, this probability increases as technological complementarity increases, this effect is not observed when faultline strength is at low and high levels, in line with our prediction.
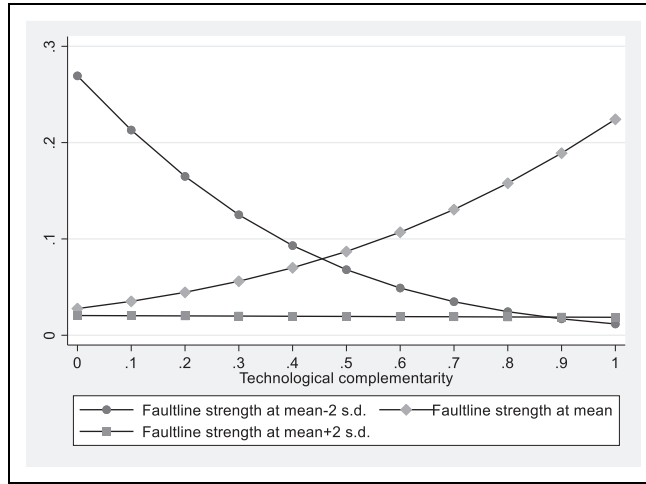
Figure 2. The average predicted probability of an acquisition match at different levels of technological complementarity and faultline strength.

Interpretation of results

Due to the nonlinear nature of logistic regression, the variables' impact on the outcome and their statistical significance should be assessed at meaningful values of explanatory variables, rather than based on regression coefficients (Hoetker, 2007). Thus, for each observation in our sample, we calculated how the probability of selecting a particular acquisition target changed across some meaningful values of technological similarity and complementarity, and reported the average (Hoetker, 2007). Based on Model 2, the average predicted probability of an acquisition match with a given target was 0.040 at the mean value of technological similarity. This probability decreased to 0.016 when technological similarity was one standard deviation below its mean and increased to 0.096 when it increased to one standard deviation above its mean. The average predicted probability of an acquisition match was 0.045 at the mean value of technological complementarity. This probability decreased to 0.034 when technological complementarity was one standard deviation below its mean and increased to 0.059 when it increased to one standard deviation above its mean. All values are precisely estimated with $p = 0.000$ and are based on average sample values.

Beyond this average impact of technological complementarity on acquisition match, our results also show that the impact of technological complementarity hinges on the level of faultline strength. Therefore, we also calculated how this impact changed across different levels of faultline strength based on Model 6. On average, when both technological complementarity and faultline strength were at their sample means, one standard deviation increase in technological complementarity led to a 1.7% ($p = 0.000$) greater probability of an acquisition match. Yet this probability decreased to 0.3% ($p = 0.823$) when faultline strength was one standard deviation below its mean and to 1.2% ($p = 0.008$) when it was one standard deviation above its mean. As a comparison, in our sample, one standard deviation increase in geographic distance (2270 km) led to a 1.2% ($p = 0.010$) lower probability of an acquisition match. Hence, increasing faultline strength by one standard deviation above its mean lowered the impact of technological complementarity on the probability of an acquisition match to the same extent as moving the target firm 946 km further from the acquirer.

An alternative explanation for our findings is that the observed difference in the importance of technological relatedness as a target selection criterion may be determined by the technological backgrounds of TMT members, rather than faultline strength. Specifically, members with

technology backgrounds could lead a TMT to place more emphasis on technological relatedness when selecting acquisition targets. To test this possibility, we performed an additional analysis (Table 6 in Appendix 1) in which the number of TMT members with a technological background replaced TMT faultlines as moderator to technological similarity and complementarity. Neither of the interactions is statistically significant, confirming the robustness of our results.

Discussion

Our results offer several insights into the literature. First, in line with prior research (Bena and Li, 2014; Rao et al., 2016; Yu et al., 2016), we found that both technological similarity and complementarity affect target selection favorably. In addition, we observed that technological similarity has a significantly larger effect on target selection than technological complementarity. This result is in line with Yu et al.'s (2016) finding that acquirers prefer similarity over complementarity in target selection. These findings add to the target selection literature by reinforcing the positive stance toward targets' technological relatedness in general and technological similarity in particular.

Moreover, we established the role of TMT demographic faultlines in the relationship between technological relatedness and target selection. Our results indicate that TMTs with moderately strong faultlines value target technological complementarity the most when selecting targets in technology acquisitions. This finding corroborates our argument that the ability of an acquirer's TMT to cope with the information processing demands associated with the assessment of the target's technological relatedness depends on how well the members of the TMT possess, access, share, and jointly elaborate and reflect on the relevant information to identify potential novel knowledge recombinations between the target's technology base and that of the acquirer. Accordingly, we contribute to the target selection literature (e.g. Bena and Li, 2014; Rao et al., 2016; Yu et al., 2016) by specifying an essential contingency—that is, acquirer TMTs' ability to evaluate targets (characterized by their demographic faultlines)—which grounds strategic management research on realistic psychological assumptions along the lines of behavioral strategy (Powell et al., 2011).

However, this finding indicates that the assessment of target technological complementarity only (not technological similarity) requires further scrutiny from acquirer TMTs. While we initially recognized that identifying the potential novel knowledge recombinations that can emerge from the synergies between the target's and the acquirer's technology bases and judging these synergies' respective commercial values are cognitively demanding tasks, our finding hints that this is primarily the case for assessing technological complementarity. This is arguably due to the fact that the potential benefits of acquiring technologically complementary targets are more uncertain and less obvious (Cassiman et al., 2005). Therefore, accessing their relevance requires TMT members' cognitive focus and more in-depth deliberation about how such complementary capabilities can be combined with those of the acquirer in order to facilitate synergistic gains.

Second, the inverted U-shaped moderating effect of faultlines adds to the strategic decision-making and TMT faultlines literature (e.g. Cooper et al., 2013; Ndofor et al., 2015; Tuggle et al., 2010; Van Knippenberg et al., 2011), as it presents the demonstrates of subgroups within TMTs at moderate faultline strengths. This result implies that moderately strong faultline levels lead TMTs to place more emphasis on technological complementarity when selecting acquisition targets. Theorizing and empirically demonstrating this positive effect is important for a couple of reasons. The faultline is a theoretical construct that upper echelons scholars borrowed from small groups research. These scholars almost exclusively demonstrated the negative effects of faultlines on strategic outcome variables, such as foreign expansions (Barkema and Shvyrkov, 2007), resource utilization (Ndofor et al., 2015), and firm performance (Van Knippenberg et al., 2011). However, these scholars were confined to theorizing about and empirically testing strong faultline cases

where team members identify strongly with their subgroups rather than with the whole TMT—thus the negative effect. However, small groups research moved beyond this negative stance and demonstrated that faultlines may also create healthy divides within a team (Gibson and Vermeulen, 2003) when team members benefit from subgroup support (Asch, 1952; Azzi, 1993). This support particularly matters in settings that necessitate creativity and when novel ideas need to be freely shared and discussed within the group, which makes our strategic decision context (i.e. target selection in technology acquisitions) unique in the study of the potential positive effect of TMT faultlines. This is because when selecting technology acquisition targets, the identification of novel knowledge recombinations and the appraisal of the commercial value of potential synergies require creativity. Our finding adds to the existing debate on upper echelons literature (Carpenter et al., 2004; Hambrick and Mason, 1984) by suggesting a careful consideration of the strategic decision context, and it integrates the theory from small teams faultline literature that highlights the benefits of subgroups and the TMT decision-making literature.

Our results also have implications for literature focusing on the performance effects of technological relatedness (Cassiman et al., 2005; Makri et al., 2010; Sears and Hoetker, 2014). While this literature studied the post-acquisition innovation outcomes of technological relatedness (Ahuja and Katila, 2001; Cassiman et al., 2005; Cloodt et al., 2006; Ornaghi, 2009), we demonstrated its role prior to acquisition, during the target selection process. We provided evidence that acquirers self-select acquisition targets with related technologies, which then leads to novel knowledge recombinations and enhanced innovation performance. Therefore, studies about the performance implications of technological complementarity should consider such endogeneity issues (Certo et al., 2016; Shaver, 1998).

Practical implications

Our research is also relevant from a practical perspective. We highlighted the underlying cognitive and social processes within a TMT when considering potential acquisition targets, and proposed TMT faultlines as a determinant of these processes. While it might be difficult to alter the way in which a TMT functions (i.e. according to its social dynamics and cognitive abilities), our finding regarding TMT composition is instrumental in forming well-functioning executive teams. Specifically, when replacing TMT members, assuring that the new TMT composition has moderate degrees of subgroup divisions would enhance the team's social dynamics and cognitive capacity, leading to greater information processing ability. For instance, if replacing a 67-year-old male engineer with a 35-year-old female MBA creates meaningful subgroups of moderate strength in the TMT, our findings indicate the resulting enhanced information processing capability of the team may help it better consider the synergies from target complementarity in technology acquisitions. Similarly, in strong faultline settings, TMTs may pay attention to appointing new members with cross-cutting background characteristics.

Limitations and future research

Our article is not without limitations. First, TMT demographic characteristics are surface-level diversity attributes (Van Knippenberg et al., 2004) and could be less appropriate as proxies of TMT cognitive bases than deep-level diversity attributes, such as personality, learning orientations, and values. Future research endeavors may consider deep-level characteristics. To this end, we also suggest future research should consider qualitative in-depth case studies that directly observe executives' information processing during TMT strategic decision-making. Second, although patents are an established way to capture firm technological capabilities and are widely used in quantitative studies (e.g. Ahuja and Katila, 2001; Cloodt et al., 2006; Makri et al., 2010; Van de

Vrande, 2013), they are not perfect measures. That is because not all inventions are patented, and patenting rates vary across industries. Also, certain patent classes within a subcategory may be more complementary than others, and complementarities might exist among patent classes across subcategories (Hall et al., 2001). Future research may invest in alternative measures to capture technological capabilities. Third, Ndofor et al. (2015) hinted that the implementation of strategic decisions has different characteristics from their formulation, and thereby the findings of our study may not be valid in an implementation context. Future research may look into post-integration processes and acquisition performance in relation to TMT diversity.

Conclusion

Our research demonstrates the role of a target's technological relatedness in acquisition target selection; both the target's technological similarity and complementarity are positively associated with the acquirer's target choice. More importantly, we establish the role of acquirer TMTs' demographic faultlines in this relationship. TMTs with moderately strong faultlines place more emphasis on target technological complementarity due to their enhanced information processing capabilities than TMTs with weak and strong faultlines. As such, our findings add to the acquisition literature by introducing an important boundary condition on the impact of target technological relatedness on acquisition target selection.

ORCID iDs

Korcan Kavuşan (ID) https://orcid.org/0000-0002-4613-9409
Anna Nadolska (ID) https://orcid.org/0000-0002-2725-775X

Notes

1. Some upper echelons papers hinted that faultlines may enhance feelings of safety within a subgroup (e.g. Barkema and Shvyrkov, 2007; Li and Hambrick, 2005), but none conclusively demonstrated a positive effect empirically. Only Hutzschenreuter and Horstkotte's (2013) study presented some partial support for a positive effect.
2. Standard industrial classification codes (SICs) for these industries are 283×, 357×, 366×, 367×, and 737×.
3. The time frame of our sample is primarily determined by the availability of acquisition and patent data in the SDC database and NBER Patent Data Project, respectively. SDC started to systematically collect acquisition data in the early 1990s, so starting our sample in 1996 enabled us to control for firms' acquisition experiences in the 5 years prior to each focal acquisition, which is a widely acknowledged

determinant of firms' acquisition capabilities (e.g. Haleblian and Finkelstein, 1999; Puranam and Srikanth, 2007). NBER provides information on patents applied for, or granted, before 2006. Because there is typically a grant lag between the application and grant dates of patents, we use patent application rather than grant dates to measure our variables, and we end our sample in 2002 so that there is a 4-year buffer to account for the grant lag, as suggested by Hall et al. (2001).

4. We observed acquisitions of alternative targets by tracking their existence in Compustat. When a firm in the same industry as the actual target of a focal acquisition ceased to exist in Compustat records during a 5-year window starting with the focal acquisition year, we interpreted this to mean that the firm was acquired and so included it in the set of potential targets.

5. We also ran our regression models with patents obtained 4 and 5 years before a focal acquisition; our results were unchanged.

6. While patents may be assigned to multiple classes, we use the main class for each patent in our empirical analyses because this denotes the primary identification of a patent and only the main class is reported in the NBER patent database.

7. For example, patents in the computer graphics class in the computer peripherals subcategory are complimentary to patents in the liquid crystal cells class within the same subcategory, as they can be combined to develop liquid crystal display (LCD) technologies for computer systems.

8. To get a better sense of how subgroups are split and faultlines operationalized, we refer to the examples in Lau and Murnighan's (1998) Table 1 and Thatcher et al.'s (2003) Table 3, respectively. We thank our anonymous reviewer for bringing this point to our attention.

9. In line with the current practice (e.g. Chakrabarti and Mitchell, 2013), to correct for the rare nature of the events, we also estimated our regression models with ReLogit regression. This method was developed by King and Zeng (Tomz et al., 2003), to adapt logistic regression for rare events. The results were consistent with those of conventional logit models reported in this section.

References

Abrams D, Wetherell M, Cochrane S, et al. (1990) Knowing what to think by knowing who you are: Self-categorization and the nature of norm formation, conformity and group polarization. *The British Journal of Social Psychology* 29(2): 97–119.

Ahuja G and Katila R (2001) Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic Management Journal* 22(3): 197–220.

Ahuja G and Novelli E (2014) Mergers and acquisitions and innovation. In: Dodgson M, Gann D and Phillips N (eds) *The Oxford Handbook of Innovation Management*. Oxford: Oxford University Press, pp. 579–599.

Amason AC (1996) Distinguishing the effects of functional and dysfunctional conflict on strategic decision making: Resolving a paradox for top management teams. *The Academy of Management Journal* 39(1): 123–148.

Asch SE (1952) Group forces in the modification and distortion of judgments. In: Asch SE (ed.) *Social Psychology*. Englewood Cliffs, NJ: Prentice Hall, pp. 450–501.

Azzi AE (1993) Implicit and category-based allocations of decision-making power in majority-minority relations. *Journal of Experimental Social Psychology* 29(3): 203–228.

Bandura A (1997) *Self-Efficacy: The Exercise of Control*. New York: W. H. Freeman.

Bantel KA (1994) Strategic planning openness: The role of top team demography. *Group & Organization Management* 19(4): 406–424.

Barkema HG and Shvyrkov O (2007) Does top management team diversity promote or hamper foreign expansion? *Strategic Management Journal* 28(7): 663–680.

Bena J and Li K (2014) Corporate innovations and mergers and acquisitions. *The Journal of Finance* 69(5): 1923–1960.

Berchicci L, Dowell G and King AA (2012) Environmental capabilities and corporate strategy: Exploring acquisitions among U.S. manufacturing firms. *Strategic Management Journal* 33(9): 1053–1071.

Bettinazzi ELM and Zollo M (2018) Stakeholder orientation and acquisition performance. *Strategic Management Journal* 38(12): 2465–2485.

Bezrukova K and Uparna J (2009) Group splits and culture shifts: A new map of the creativity terrain. In: Mannix EA, Neale MA and Goncalo JA (eds) *Research on Managing Groups and Teams: Creativity in Groups*, vol. 12. Bingley: Emerald, pp.163–193.

Bezrukova K, Jehn KA, Zanutto EL, et al. (2009) Do workgroup faultlines help or hurt? A moderated model of faultlines, team identification, and group performance. *Organization Science* 20(1): 35–50.

Bezrukova K, Spell CS and Perry JL (2010) Violent splits or healthy divides? Coping with injustice through faultlines. *Personnel Psychology* 63(3): 719–751.

Bezrukova K, Thatcher SM and Jehn KA (2007) Group heterogeneity and faultlines: Comparing alignment and dispersion theories of group composition. In: Behfar KJ and Thompson LL (eds) *Conflict in Organizational Groups: New Directions in Theory and Practice*. Evanston, IL: Northwestern University Press, pp. 57–92.

Blau PM (1977) *Inequality and Heterogeneity: A Primitive Theory of Social Structure*, vol. 7. New York: Free Press.

Bowers CA, Pharmer JA and Salas E (2000) When member homogeneity is needed in work teams: A meta-analysis. *Small Group Research* 31(3): 305–327.

Brewer MB (1993) Social identity, distinctiveness, and in-group homogeneity. *Social Cognition* 11(1): 150–164.

Capron L and Mitchell W (2009) Selection capability: How capability gaps and internal social frictions affect internal and external strategic renewal. *Organization Science* 20(2): 294–312.

Capron L and Shen JC (2007) Acquisitions of private vs. public firms: Private information, target selection, and acquirer returns. *Strategic Management Journal* 28(9): 891–911.

Capron L, Dussauge P and Mitchell W (1998) Resource redeployment following horizontal acquisitions in Europe and North America 1988–1992. *Strategic Management Journal* 19(7): 631–661.

Carpenter MA, Geletkanycz MA and Sanders WG (2004) Upper echelons research revisited: Antecedents, elements, and consequences of top management team composition. *Journal of Management* 30(6): 749–778.

Cassiman B and Veugelers R (2006) In search of complementarity in innovation strategy: Internal R&D and external knowledge acquisition. *Management Science* 52(1): 68–82.

Cassiman B, Colombo MG, Garrone P, et al. (2005) The impact of M&A on the R&D process: An empirical analysis of the role of technological- and market-relatedness. *Research Policy* 34(2): 195–220.

Certo ST, Busenbark JR, Woo H-s, et al. (2016) Sample selection bias and Heckman models in strategic management research. *Strategic Management Journal* 37(13): 2639–2657.

Chakrabarti A and Mitchell W (2013) The persistent effect of geographic distance in acquisition target selection. *Organization Science* 24(6): 1805–1826.

Chen Z, Kale P and Hoskisson RE (2018) Geographic overlap and acquisition pairing. *Strategic Management Journal* 39(2): 329–355.

Chondrakis G (2016) Unique synergies in technology acquisitions. *Research Policy* 45(9): 1873–1889.

Cloodt M, Hagedoorn J and Van Kranenburg H (2006) Mergers and acquisitions: Their effect on the innovative performance of companies in high-tech industries. *Research Policy* 35(5): 642–654.

Cohen WM and Levinthal DA (1990) Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly* 35(1): 128–152.

Cooper D, Patel PC and Thatcher SM (2013) It depends: Environmental context and the effects of faultlines on top management team performance. *Organization Science* 25(2): 633–652.

Cramton CD and Hinds PJ (2004) Subgroup dynamics in internationally distributed teams: Ethnocentrism or cross-national learning? *Research in Organizational Behavior* 26: 231–263.

Dahlin KB, Weingart LR and Hinds PJ (2005) Team diversity and information use. *The Academy of Management Journal* 48(6): 1107–1123.

Deng P (2010) Absorptive capacity and a failed cross-border M&A. *Management Research Review* 33(7): 673–682.

Dezi L, Battisti E, Ferraris A, et al. (2018) The link between mergers and acquisitions and innovation: A systematic literature review. *Management Research Review* 41(6): 716–752.

Earley CP and Mosakowski E (2000) Creating hybrid team cultures: An empirical test of transnational team functioning. *The Academy of Management Journal* 43(1): 26–49.

Fiske ST and Taylor SE (1991) *Social Cognition*, 2nd edn. New York: McGraw Hill.

Gibson C and Vermeulen F (2003) A healthy divide: Subgroups as a stimulus for team learning behavior. *Administrative Science Quarterly* 48(2): 202–239.

Graebner ME (2004) Momentum and serendipity: How acquired leaders create value in the integration of technology firms. *Strategic Management Journal* 25(8–9): 751–777.

Haans RFJ, Pieters C and He Z-L (2016) Thinking about U: Theorizing and testing U- and inverted U-shaped relationships in strategy research. *Strategic Management Journal* 37(7): 1177–1195.

Hagedoorn J and Wang N (2012) Is there complementarity or substitutability between internal and external R&D strategies? *Research Policy* 41(6): 1072–1083.

Haleblian J and Finkelstein S (1999) The influence of organizational acquisition experience on acquisition performance: A behavioral learning perspective. *Administrative Science Quarterly* 44(1): 29–56.

Hall BH, Jaffe A and Trajtenberg M (2001) *The NBER patent citations data file: Lessons, insights and methodological tools*. Discussion Paper No. 3094. London: Centre for Economic Policy Research.

Hambrick DC (2007) Upper echelons theory: An update. *The Academy of Management Review* 32(2): 334–343.

Hambrick DC and Mason PA (1984) Upper echelons: The organization as a reflection of its top managers. *The Academy of Management Review* 9(2): 193–206.

Hambrick DC, Cho TS and Chen MJ (1996) The influence of top management team heterogeneity on firm's competitive moves. *Administrative Science Quarterly* 41(4): 659–684.

Harrison DA and Klein KJ (2007) What's the difference? Diversity constructs as separation, variety, or disparity in organizations. *The Academy of Management Review* 32(4): 1199–1228.

Harrison DA, Price KH and Bell MP (1998) Beyond relational demography: Time and the effects of surface- and deep-level diversity on work group cohesion. *The Academy of Management Journal* 41(1): 96–107.

Hart CM and Van Vugt M (2006) From fault line to group fission: Understanding membership changes in small groups. *Personality and Social Psychology Bulletin* 32(3): 392–404.

Haspeslagh P and Jemison D (1991) *Managing Acquisitions: Creating Value through Corporate Renewal*. New York: Free Press.

Haucap J and Stiebale J (2016) *How mergers affect innovation: Theory and evidence from the pharmaceutical industry. Discussion Paper No. 218*. Düsseldorf: Düsseldorf Institute for Competition Economics.

Hoetker G (2007) The use of logit and probit models in strategic management research: Critical issues. *Strategic Management Journal* 28(4): 331–343.

Hutzschenreuter T and Horstkotte J (2013) Performance effects of top management team demographic faultlines in the process of product diversification. *Strategic Management Journal* 34(6): 704–726.

Jaccard J, Turrisi R and Wan CK (1990) *Interaction Effects in Multiple Regression*. Newbury Park, CA: SAGE.

Jovanovic B and Rousseau PL (2002) The Q-theory of mergers. *American Economic Review* 92(2): 198–204.

Kaul A and Wu B (2016) A capabilities-based perspective on target selection in acquisitions. *Strategic Management Journal* 37(7): 1220–1239.

Kim JY and Finkelstein S (2009) The effects of strategic and market complementary on acquisition performance: Evidence from the U.S. commercial banking industry, 1989–2001. *Strategic Management Journal* 30(6): 617–646.

Kramer RM (1990) The effects of resource scarcity on group conflict and cooperation. In: Lawler EJ (ed.) *Advances in Group Processes*, vol. 7. Bingley: JAI Press, pp. 151–177.

Lane PJ and Lubatkin M (1998) Relative absorptive capacity and interorganizational learning. *Strategic Management Journal* 19(5): 461–477.

Lau DC and Murnighan JK (1998) Demographic diversity and faultlines: The compositional dynamics of organizational groups. *The Academy of Management Review* 23(2): 325–340.

Lau DC and Murnighan JK (2005) Interactions within groups and subgroups: The effects of demographic faultlines. *The Academy of Management Journal* 48(4): 645–659.

Lee J and Kim M (2016) Market-driven technological innovation through acquisitions: The moderating effect of firm size. *Journal of Management* 42(7): 1934–1963.

Li J and Hambrick DC (2005) Factional groups: A new vantage on demographic faultlines, conflict, and disintegration in work teams. *The Academy of Management Journal* 48(5): 794–813.

Makri M, Hitt MA and Lane PJ (2010) Complementary technologies, knowledge relatedness, and invention outcomes in high technology mergers and acquisitions. *Strategic Management Journal* 31(6): 602–628.

Marcel JJ (2009) Why top management team characteristics matter when employing a chief operating officer: A strategic contingency perspective. *Strategic Management Journal* 30(6): 647–658.

Meyer B and Glenz A (2013) Team faultline measures: A computational comparison and a new approach to multiple subgroups. *Organizational Research Methods* 16(3): 393–424.

Mowery DC, Oxley JE and Silverman BS (1998) Technological overlap and interfirm cooperation: implications for the resource-based view of the firm. *Research Policy* 27(5): 507–523.

Mullen B (1991) Group composition, salience, and cognitive representations: The phenomenology of being in a group. *Journal of Experimental Social Psychology* 27(4): 297–323.

Nadolska A and Barkema HG (2014) Good learners: How top management teams affect the success and frequency of acquisitions. *Strategic Management Journal* 35(10): 1483–1507.

Ndofor HA, Sirmon DG and He X (2015) Utilizing the firm's resources: How TMT heterogeneity and resulting faultlines affect TMT tasks. *Strategic Management Journal* 36(11): 1656–1674.

Nesdale D and Mak AS (2003) Ethnic identification, self-esteem and immigrant psychological health. *International Journal of Intercultural Relations* 27(1): 23–40.

Ornaghi C (2009) Mergers and innovation in big pharma. *International Journal of Industrial Organization* 27(1): 70–79.

Parola HR, Ellis KM and Golden P (2015) Performance effects of top management team gender diversity during the merger and acquisition process. *Management Decision* 53(1): 57–74.

Pelled LH, Eisenhardt KM and Xin KR (1999) Exploring the black box: An analysis of work group diversity, conflict and performance. *Administrative Science Quarterly* 44(1): 1–28.

Phillips KW (2003) The effects of categorically based expectations on minority influence: The importance of congruence. *Personality and Social Psychology Bulletin* 29(1): 3–13.

Phillips KW, Mannix EA, Neale MA, et al. (2004) Diverse groups and information sharing: The effects of congruent ties. *Journal of Experimental Social Psychology* 40(4): 497–510.

Powell TC, Lovallo D and Fox CR (2011) Behavioral strategy. *Strategic Management Journal* 32(13): 1369–1386.

Puranam P and Srikanth K (2007) What they know vs. what they do: How acquirers leverage technology acquisitions. *Strategic Management Journal* 28(8): 805–825.

Puranam P, Singh H and Chaudhuri S (2009) Integrating acquired capabilities: When structural integration is (un)necessary. *Organization Science* 20(2): 313–328.

Ranft AL and Lord MD (2002) Acquiring new technologies and capabilities: A grounded model of acquisition implementation. *Organization Science* 13(4): 420–441.

Rao VR, Yu Y and Umashankar N (2016) Anticipated vs. actual synergy in merger partner selection and post-merger innovation. *Marketing Science* 35(6): 934–952.

Rhodes-Kropf M and Robinson DT (2008) The market for mergers and the boundaries of the firm. *The Journal of Finance* 63(3): 1169–1211.

Rosenkopf L and Almeida P (2003) Overcoming local search through alliances and mobility. *Management Science* 49(6): 751–766.

Sanders WG and Carpenter MA (1998) Internationalization and firm governance: The roles of CEO compensation, top team composition, and board structure. *The Academy of Management Journal* 41(2): 158–178.

Schildt H, Keil T and Maula M (2012) The temporal effects of relative and firm-level absorptive capacity on interorganizational learning. *Strategic Management Journal* 33(10): 1154–1173.

Sears J and Hoetker G (2014) Technological overlap, technological capabilities, and resource recombination in technological acquisitions. *Strategic Management Journal* 35(1): 48–67.

Shaver JM (1998) Accounting for endogeneity when assessing strategy performance: Does entry mode choice affect FDI survival? *Management Science* 44(4): 571–585.

Shen JC and Reuer J (2005) Adverse selection in acquisitions of small manufacturing firms: A comparison of public with private targets. *Small Business Economics* 24(4): 393–407.

Stasser G and Stewart D (1992) Discovery of hidden profiles by decision-making groups: Solving a problem versus making a judgment. *Journal of Personality and Social Psychology* 63(3): 426–434.

Stasser G, Taylor LA and Hanna C (1989) Information sampling in structured and unstructured discussions of three- and six-person groups. *Journal of Personality and Social Psychology* 57(1): 67–78.

Steinbach AL, Holcomb TR, Holmes RM, et al. (2017) Top management team incentive heterogeneity, strategic investment behavior, and performance: A contingency theory of incentive alignment. *Strategic Management Journal* 38(8): 1701–1720.

Stevenson WB, Pearce JL and Porter LW (1985) The concept of "coalition" in organization theory and research. *The Academy of Management Review* 10(2): 256–268.

Stiebale J (2013) The impact of cross-border mergers and acquisitions on the acquirers' R&D—Firm-level evidence. *International Journal of Industrial Organization* 31(4): 307–321.

Tajfel H (1982) Social psychology of intergroup relations. *Annual Review of Psychology* 33(1): 1–39.

Tajfel H and Turner JC (2004) The social identity theory of intergroup behavior. In: Jost JT and Sidanius J (eds) *Political Psychology: Key Readings*. New York: Psychology Press, pp. 276–293.

Taylor A and Greve HR (2006) Superman or the fantastic four? Knowledge combination and experience in innovative teams. *The Academy of Management Journal* 49(4): 723–740.

Thatcher SM and Patel PC (2012) Group faultlines: A review, integration, and guide to future research. *Journal of Management* 38(4): 969–1009.

Thatcher SM, Jehn KA and Zanutto E (2003) Cracks in diversity research: The effects of diversity faultlines on conflict and performance. *Group Decision and Negotiation* 12(3): 217–241.

Tomz M, King G and Zeng L (2003) ReLogit: Rare events logistic regression. *Journal of Statistical Software* 8(i02). Available at: https://www.jstatsoft.org/article/view/v008i02

Tuggle CS, Schnatterly K and Johnson RA (2010) Attention patterns in the boardroom: How board composition and processes affect discussion of entrepreneurial issues. *The Academy of Management Journal* 53(3): 550–571.

Van de Vrande V (2013) Balancing your technology-sourcing portfolio: How sourcing mode diversity enhances innovative performance. *Strategic Management Journal* 34(5): 610–621.

Van Knippenberg D, Dawson JF, West MA, et al. (2011) Diversity faultlines, shared objectives, and top management team performance. *Human Relations* 64(3): 307–336.

Van Knippenberg D, De Dreu CK and Homan AC (2004) Work group diversity and group performance: an integrative model and research agenda. *Journal of Applied Psychology* 89(6): 1008–1022.

Villalonga B and McGahan AM (2005) The choice among acquisitions, alliances, and divestitures. *Strategic Management Journal* 26(13): 1183–1208.

Wittenbaum GM and Stasser G (1996) Management of information in small groups. In: Nye JL and Brower AM (eds) *What's Social about Social Cognition? Research on Socially Shared Cognition in Small Groups*. Thousand Oaks, CA: SAGE, pp. 3–28.

Yu Y, Umashankar N and Rao VR (2016) Choosing the right target: Relative preferences for resource similarity and complementarity in acquisition choice. *Strategic Management Journal* 37(8): 1808–1825.

Author biographies

Korcan Kavuşan is Assistant Professor of Strategy and Entrepreneurship at Rotterdam School of Management, Erasmus University. His research focuses on interfirm relationships such as alliances and acquisitions. He is mainly interested in how companies develop new technological and managerial capabilities through alliances and acquisitions, and how different stakeholders, such as managers and investors, make decisions regarding firms' alliance and acquisition activities. His work is published in the *Strategic Management Journal* and *Research Policy*. Korcan teaches graduate-level courses on strategic management, innovation strategy, and technology-driven interfirm relationships. Prior to earning his doctorate at Tilburg University, he worked as an internal auditor for the UniCredit Group.

Nüfer Yasin Ateş is Assistant Professor of Strategy and Organization at Sabancı Business School, Sabancı University. He received his PhD from the Erasmus Research Institute of Management, Erasmus University Rotterdam. His research revolves around behavioral strategy topics at the intersection of strategic

management and organizational psychology. His research interests include managerial cognition, corporate entrepreneurship, and strategy process, with a special focus on top and middle managers. He is also interested in advancing quantitative research methods. Nüfer's research has appeared in the *Strategic Management Journal* and the *Journal of Management*.

Anna Nadolska is Assistant Professor of Strategic Management at the Department of Strategy and Business Environment at Rotterdam School of Management, Erasmus University. Anna joined the department upon completion of her PhD on internationalization through mergers and acquisitions at Tilburg University. Her research focuses on corporate development activities, capability development, and organizational and individual learning.

Appendix I

In Table 5, the values in the cells represent the number of patents in certain subcategories and classes for the acquirer and the target. The rows show the computation of the technological complementarity measure for both cases. Both the acquirer and target are active in subcategory 1 and in all classes within that subcategory, so there is no basis for complementarity. Both the acquirer and target are also active in subcategory 2, but not in the same classes within that subcategory. Rather, they are active in different classes within the same subcategory, which constitutes a basis for complementarity. Only the acquirer is active in subcategory 3. There is no basis for complementarity. Also, in the first case, the acquirer's patents in subcategory 3, which is not shared with the target, reduce the relative importance to the acquirer of patents in different classes of a subcategory shared with the target.

Table 5. An illustration of the measurement of technological complementarity.

			Case 1		Case 2	
			Acquirer	Target	Acquirer	Target
1	Subcategory 1	Class 11	10	10	10	5
2		Class 12	10	10	20	5
	Subcategory 2	Class 21	40		50	
		Class 22		20		30
3	Subcategory 3	Class 31	20			
4		Class 32				
5	Acquirer + target common subcategory patents		100		120	
6	Acquirer + target common class patents		40		40	
7	Acquirer patents in common subcategory with target		60		80	
8	Acquirer total patents		80		80	
9	Target total patents		40		40	
10	The ratio of acquirer and target complementary patents to all their patents ((5–6) over (8 + 9))		0.5		0.667	
11	The ratio of acquirer patents that are complementary with the target to all its patents ((7) over (8))		0.75		1	
12	Complementarity score adjusted by the importance to the acquirer of patents that are complementary with the target ((10) × (11))		0.375		0.667	

Table 6. Logistic regression results with acquisition match as the dependent variable and the number of TMT members with technological background as moderator.

	(1)	(2)	(3)	(4)	(5)	(6)
Technological similarity	3.406***	3.839***	3.845***	4.003***	3.839***	4.002***
	[0.628]	[0.631]	[0.644]	[0.812]	[0.651]	[0.814]
Technological complementarity	1.682**	1.905**	1.905**	1.889**	1.968**	1.976**
	[0.730]	[0.741]	[0.740]	[0.746]	[0.875]	[0.882]
Number of TMT members with technological background			−0.015	0.109	0.005	0.140
			[0.090]	[0.263]	[0.154]	[0.235]
Technological similarity × number of TMT members with technological background				−0.244		−0.252
				[0.522]		[0.509]
Technological complementarity × number of TMT members with technological background					−0.106	−0.142
					[0.624]	[0.561]
Faultline strength		−2.805*	−2.799*	−2.944*	−2.800*	−2.954*
		[1.515]	[1.518]	[1.582]	[1.520]	[1.587]
Industry relatedness	−1.394***	−1.375***	−1.373***	−1.376***	−1.373***	−1.376***
	[0.238]	[0.309]	[0.308]	[0.310]	[0.309]	[0.311]
Relative size (patent stock)	−0.452**	−0.538***	−0.538***	−0.530***	−0.539***	−0.531***
	[0.177]	[0.177]	[0.176]	[0.172]	[0.176]	[0.172]
Relative size (assets)	0.477**	0.568**	0.564**	0.581**	0.566**	0.585**
	[0.233]	[0.264]	[0.270]	[0.270]	[0.271]	[0.270]
Target ROA	0.239***	0.208***	0.208***	0.209***	0.209***	0.209***
	[0.085]	[0.080]	[0.080]	[0.080]	[0.080]	[0.080]
Target R&D intensity	−0.145*	−0.124	−0.124	−0.123	−0.124	−0.123
	[0.088]	[0.077]	[0.077]	[0.077]	[0.077]	[0.077]
Geographic distance	−0.000**	−0.000**	−0.000**	−0.000**	−0.000**	−0.000**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Ownership similarity	0.179	0.158	0.159	0.157	0.160	0.159
	[0.204]	[0.208]	[0.210]	[0.210]	[0.212]	[0.212]
Acquirer R&D intensity		−0.226	−0.223	−0.229	−0.225	−0.233
		[0.364]	[0.363]	[0.366]	[0.364]	[0.367]
CEO change		−1.395***	−1.391***	−1.387***	−1.390***	−1.385***
		[0.356]	[0.355]	[0.358]	[0.356]	[0.359]
Market share		−0.000	0.046	0.068	0.039	0.058
		[1.447]	[1.545]	[1.534]	[1.548]	[1.537]
Acquirer ROA		1.487	1.472	1.449	1.473	1.443
		[1.060]	[1.093]	[1.088]	[1.093]	[1.089]
Acquisition experience		−0.021**	−0.021*	−0.021*	−0.021*	−0.021*
		[0.010]	[0.011]	[0.011]	[0.011]	[0.011]
TMT size		−0.057	−0.056	−0.058	−0.056	−0.058
		[0.035]	[0.036]	[0.037]	[0.036]	[0.037]
Age diversity		5.411	5.398	5.352	5.391	5.343
		[3.580]	[3.562]	[3.603]	[3.575]	[3.622]
Tenure diversity		0.435*	0.437*	0.435	0.436	0.433
		[0.263]	[0.265]	[0.265]	[0.265]	[0.265]
Gender diversity		−0.477	−0.478	−0.483	−0.475	−0.478
		[1.071]	[1.067]	[1.065]	[1.068]	[1.065]

(continued)

Table 6. (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Function diversity		−3.150***	−3.115***	−3.123***	−3.128***	−3.143***
		[0.960]	[0.993]	[1.001]	[1.002]	[1.010]
Constant	−4.091***	−0.427	−0.452	−0.429	−0.451	−0.423
	[0.666]	[1.398]	[1.433]	[1.434]	[1.434]	[1.440]
Observations	2082	2082	2082	2082	2082	2082
Log-likelihood	−330.7	−323.1	−323.1	−323	−323.1	−323
Prob > χ^2	0000	0000	0000	0000	0000	0000

TMT: Top Management Team; ROA: return on assets; R&D: research and development; CEO: chief executive officer. Robust standard errors in brackets.
*$p < 0.1$.
**$p < 0.05$.
***$p < 0.01$.