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TECHNOLOGICAL OVERLAP, TECHNOLOGICAL CAPABILITIES, AND RESOURCE RECOMBINATION IN TECHNOLOGICAL ACQUISITIONS

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The performance of technological acquisitions depends heavily on the overlap between the knowledge bases of the target and acquirer. We argue that overlap is best viewed as two distinct constructs: target overlap, the proportion of the target's knowledge base that the acquirer already possesses, and acquirer overlap, the proportion of the acquirer's knowledge base duplicated by the target. Each affects the value created from the firms' technological capabilities differently due to absorptive capacity, knowledge redundancy, and organizational disruption. Further, the low quantity of innovations observed in acquisitions with low target overlap may conceal an offsetting increase in their novelty.

INTRODUCTION

Much of the foundational research on technological acquisitions examined the relationship between acquisition performance and the amount of overlap between the technological knowledge bases of the target firm and acquiring firm (Ahuja and Katila, 2001; Graebner, Eisenhardt, and Roundy, 2010; Kapoor and Lim, 2007). More recent research has extended the concept of technological overlap by investigating the effects that technological similarities and complementarities have on acquisition performance (Makri, Hitt, and Lane, 2010). In this study, we further extend the concept of technological overlap along two different dimensions.

First, we extend technological overlap to encompass both target and acquirer overlap, which may be asymmetric. Most empirical constructions of technological overlap have measured what we call 'target overlap,' the portion of the target's knowledge already known by the acquirer (Ahuja and Katila, 2001; Cloodt, Hagedoorn, and Van Kranenburg, 2006; Kapoor and Lim, 2007). However, acquisitions also vary in the degree to which the acquirer's existing knowledge is duplicated by the target's knowledge, what we call 'acquirer overlap.' In addition to identifying target overlap and acquirer overlap as conceptually and empirically distinct, we develop differential hypotheses regarding their effect on the creation or destruction of value.

Second, while previous research has tested the direct effect of either technological overlap (Ahuja and Katila, 2001; Cloodt *et al.*, 2006; Kapoor and Lim, 2007; Makri *et al.*, 2010) or technological resources/capabilities on acquisition performance (King, Slotegraaf, and Kesner, 2008), we examine these factors jointly. By doing so, we are able to show how acquirer and target overlap differentially affect the acquirer's ability to generate value

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post-acquisition from both its own technological capabilities and those it acquires from the target firm.

This study makes four primary contributions to the literature on technological acquisitions. First, it offers a conceptually and empirically more accurate and nuanced measure of technological overlap. Second, it applies that measure to show that target and acquirer overlap have distinct, but interrelated, impacts on the value created from each firm's technological capabilities. Third, it broadens the theoretical explanation of value creation in technological acquisitions by simultaneously incorporating three drivers: the acquirer's absorptive capacity, knowledge redundancy, and exposure to organizational disruption due to conflict between the acquirer's and target's knowledge workers. Lastly, it extends the literature on technological acquisitions by studying the acquirer's shareholder value creation, which has been a neglected dependent variable in the technological acquisitions literature (Graebner *et al.*, 2010).

THEORY AND HYPOTHESES

In innovative industries, technological change is rapid and frequent (Sarkar *et al.*, 2006). While both incumbents and start-ups strive to innovate, past research provides evidence that much of the truly novel innovations originate in start-ups (Abernathy and Utterback, 1978; Pavitt, Robson, and Townsend, 1987). As a result, technological acquisitions have become a popular complement to internal innovation, allowing firms to overcome the time compression diseconomies (Dierickx and Cool, 1989) inherent in the rapid and frequently changing technologies of innovative industries.

Accordingly, technological acquisitions have become an important stream in the broader acquisitions literature (Ahuja and Katila, 2001; Benson and Ziedonis, 2009; Capron and Mitchell, 2009; Graebner, 2004, 2009; Kapoor and Lim, 2007; Makri *et al.*, 2010; Paruchuri *et al.*, 2006; Puranam, Singh, and Chaudhuri, 2009; Puranam, Singh, and Zollo, 2006; Puranam and Srikanth, 2007; Ranft and Lord, 2002; Schweizer, 2005). Work in this stream has focused on the acquisition of small, technology-intensive target firms, as do we. Beyond their managerial importance, such acquisitions allow researchers to focus on the effects of technological synergies by minimizing the impact of potential confounding factors usually present in the acquisition of large and/or nontechnological targets, such as cost (scale) synergies or market power synergies.

Barney (1988) argued that acquirers can capture economic value by creating novel recombinations from their resources and capabilities and those of the target. More recent research provides evidence that the pursuit of such novel recombinations motivates many acquisitions (Karim and Mitchell, 2000; Larsson and Finkelstein, 1999). A consistent finding is that the degree to which the technological knowledge bases of the acquirer and target overlap (i.e., technological overlap) affects the acquirer's ability to generate novel recombinations.

However, the measurement of technological overlap in existing research obscures important contingencies that determine the potential to create or even destroy value post-acquisition. Prior studies have measured technological overlap as the amount of the target's knowledge base that the acquirer already knows (Ahuja and Katila, 2001), the sum of the technological overlap from both firms (Mowery, Oxley, and Silverman, 1996, 1998), or subsumed technological overlap in a more coarse-grained measure of resource overlap represented by product lines and product categories (Karim, 2006; Karim and Mitchell, 2000). Examining target and acquirer overlap separately allows us to explore the possibility that they differentially influence the ability of the firm to create value from its own technological capabilities and those of the target. We focus on technological capabilities as the source of potential value because as Grant (1996: 380) stated, 'the key to sustainable advantage is not proprietary knowledge itself, but the technological capabilities which permit the generation of new knowledge.'

Our research question demands that our hypotheses examine the interaction between overlap and technological capabilities, allowing us to determine how, for example acquirer overlap affects the value created by acquirer technological capabilities, separate from its effect on the value created by target technological capabilities. The resulting hypotheses tell us whether the contribution of a 'unit' of technological capability to value creation increases or decreases as technological overlap increases. That is, they tell us how effectively the firm translates technological capabilities into value. Incorporating both overlaps

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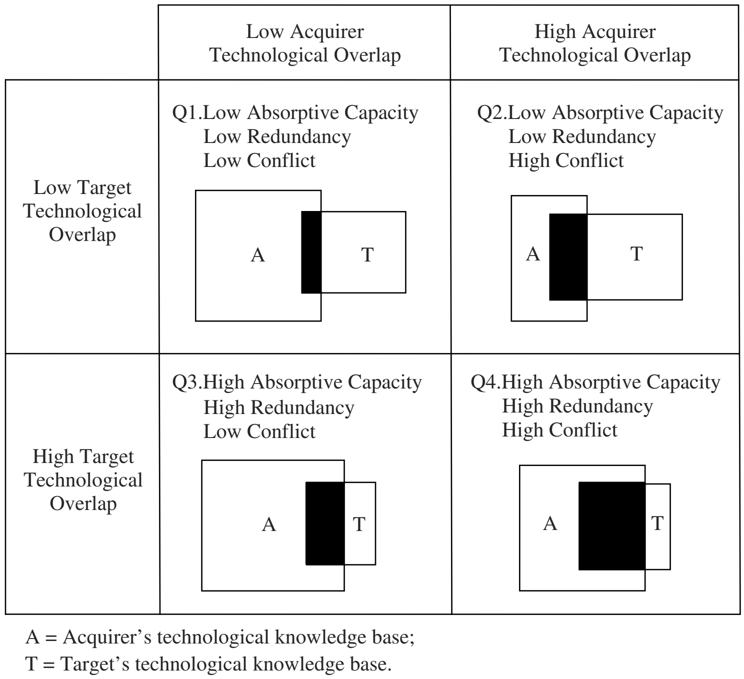

Figure 1. Asymmetries in acquirer and target technological overlap. A = Acquirer's technological knowledge base; T = Target's technological knowledge base

allows us to test simultaneously the effects of absorptive capacity, knowledge redundancy, and post-acquisition conflict in a way prior studies have not been able to accomplish.

Our measure of value creation is cumulative abnormal return of the acquirer's stock. This measure has been extensively used to evaluate the value created from an acquisition in the management literature (Arikan and Capron, 2010; Capron and Pistre, 2002; Goranova, Dharwadkar, and Brandes, 2010; Kim and Finkelstein, 2009; McWilliams and Siegel, 1997; Uhlenbruck, Hitt, and Semadeni, 2006). Although used less often in the study of technological acquisitions, it offers a special advantage in this context. It captures investors' perceptions of the acquirer's ability to create future cash flows from unique and potentially inimitable synergies generated by recombining its technological capabilities with those of the target, which Barney (1988) has identified as the source of acquirer value appropriation in acquisitions. Since our interest is in the degree to which overlap shapes the realization of such synergies, cumulative abnormal return (CAR) offers benefits beyond other common measures, such as patent counts, in capturing not only the amount of subsequent inventive activity but also whether that activity represents novel synergies likely to generate value.

Figure 1 illustrates four idealized combinations of target overlap and acquirer overlap. The squares represent each firm's knowledge base, that is, the set of knowledge a firm has 'demonstrated familiarity with, or mastery of,' as described by Ahuja and Katila (2001) in their seminal paper. Citing Kim and Kogut (1996), Ahuja and Katila further describe the knowledge base as 'the distinct elements of knowledge with which the firm has revealed a relationship.' The shaded area represents technological overlap, that is, knowledge common to both target and acquirer. The nonshaded areas represent knowledge unique to the acquirer or target.

We begin by considering the impact of target overlap. When target overlap is low (quadrants 1 and 2), a large proportion of the target's knowledge is new to the acquirer and there are many opportunities for novel combinations of the target's knowledge and the acquirer's knowledge. However, the acquirer may not be able to realize these novel recombinations because it lacks absorptive capacity (Cohen and Levinthal, 1990). Lacking what Zahra and George (2002) call *potential* absorptive capacity, the ability to value and

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acquire external knowledge, and *realized* absorptive capacity, the ability to transform and exploit external knowledge, the acquirer will be unable to extract maximal value from the target's capabilities (cf. Mowery *et al.*, 1998). Poor performance may occur because the acquirer is unable to incorporate and exploit the target's capabilities and/or because the target never possessed the amount or type of capabilities the acquirer believed it did.

When target overlap is high (quadrants 3 and 4), the acquirer has a greater ability to understand and absorb the target's knowledge. However, since much of the target's knowledge is redundant to knowledge the acquirer already possesses, there are fewer possibilities to create novel recombinations of the target and acquirer's knowledge. Indeed, the increase in knowledge redundancy not only decreases the possible number of novel recombinations that can be made using the newly acquired knowledge; it may also decrease the novelty and quality of those recombinations (Makri *et al.*, 2010).

In summary, when target overlap is low, there are many opportunities for novel recombinations, but the acquirer lacks the absorptive capacity to recognize and execute them. The technological resources of the target are largely wasted. When target overlap is high, the acquirer has the necessary absorptive capacity, but knowledge redundancy means there are few novel recombinations available. The target's capabilities offer few opportunities to create value.

If both the positive impact of absorptive capacity and the negative impact of redundancy increase linearly as target overlap increases, their combined effect will, of course, be constant—a given change in target overlap will change the value created by the target's capabilities by the same amount at any level of target overlap. Whether the change is positive or negative depends on whether the impact of absorptive capacity or redundancy changes more quickly with changes in target overlap.

It seems more likely that absorptive capacity increases at a decreasing rate as target overlap increases. The negative impact of redundancy may also increase nonlinearly as target overlap increases, although it is less clear whether it will increase at a decreasing or increasing rate. The combination of these nonlinear effects is likely to be nonlinear as well. However, nonlinearity does not imply that the combined effect will necessarily be nonmonotonic when target overlap is between 0 and 100 percent, as it must be by definition.

Depending on the relative magnitude and curvature of the relationship between (1) value creation and absorptive capacity and (2) value creation and redundancy, their combination could yield three potential outcomes. Theory is uninformative as to the relative magnitude and curvature of these two relationships, so we offer competing hypotheses.

It may be the case that, for any increase in target overlap, the improvement in absorptive capacity increases the ability of the firm to create value from the target's capabilities by more than the increase in redundancy decreases it. Colloquially, familiarity outweighs novelty. The combined effect would be a monotonic, possibly nonlinear, increase in the ability of the acquirer to generate value from the target's capabilities as target overlap increases.

Hypothesis 1a: An increase in target technological overlap will positively affect the impact the target's technological capabilities will have on abnormal returns.

It may rather be the case that, for any given increase in target overlap, the increase in redundancy reduces the ability of the firm to create value from the target's capabilities by more than the improvement in absorptive capacity increases it. Colloquially, novelty outweighs familiarity. The combined effect would be a monotonic, possibly nonlinear, decrease in the ability of the acquirer to generate value from the target's capabilities as target overlap increases.

Hypothesis 1b: An increase in target technological overlap will negatively affect the impact the target's technological capabilities will have on abnormal returns.

The last possibility is that the combined effect is nonmonotonic as target overlap increases, with either a U or an inverted U-shaped relationship. The latter would result if, for a given increase over a low level of target overlap, the improvement in absorptive capacity increases the ability of the firm to create value from the target's capabilities by more than the increase in redundancy decreases it—a relationship that is reversed when starting from a high base.

Hypothesis 1c: An increase in target technological overlap will have a nonmonotonic effect on the impact the target's technological capabilities will have on abnormal returns.

We next consider acquirer overlap, which this study is the first to examine. We hypothesize that acquirer overlap affects the value created by both the acquirer's and the target's capabilities. Increased acquirer overlap is associated with increased routine disruption and conflict between the knowledge workers of the target and acquirer, a recognized source of value destruction in the acquisitions literature (Mirvis, 1985; Paruchuri *et al.*, 2006; Puranam *et al.*, 2006).

When acquirer overlap is low (quadrants 1 and 3), there is little basis for conflict arising post-acquisition. Since the overlapping knowledge represents a small portion of the acquirer's knowledge base, few of the acquiring firm's knowledge workers will find themselves in competition with the target's knowledge workers. Rather, supplementing the acquirer's capabilities with complementary capabilities of the target can generate novel recombinations. Since both workforces can benefit from being associated with these new recombinations, there is incentive for cooperation, setting the stage to increase the value of both the acquirer's and the target's capabilities.

For example, in 2000 MKS Instruments acquired Applied Science and Technology (ASTeX), a supplier to the semiconductor industry that had low acquirer overlap. The Chairman and CEO of MKS Instruments stated that 'ASTeX is an ideal strategic fit for MKS. We serve virtually the same markets with zero product duplication; our product lines are fully complementary . . . The combined technological capabilities of the two companies will enable us to add further value through new innovative product solutions' (*PR Newswire*, 2000b). Because there was no significant corresponding activity preexisting within MKS, ASTeX was integrated as a distinct product group while simultaneously maintaining an effort to identify possibilities for companywide integration for new product development (Business Wire, 2001). The avoidance of reconfiguration and conflict allowed ASTeX to maintain its innovative capability post-acquisition, and it received two Semiconductor International 2002 Editor's Choice Best Product Awards for products developed by members of the ASTeX team at MKS (*PR Newswire*, 2002).

In contrast, as acquirer overlap increases, represented by a move from the left two quadrants to the right two quadrants in Figure 1, more of the acquirer's knowledge workers are redundant to, rather than complementary to, the target's knowledge workers. Since the target's knowledge duplicates a larger proportion of the acquirer's existing resources, the acquirer is unlikely to maintain two separate bodies of related expertise. Efforts to combine the acquirer's and target's knowledge bases will expose teams from both firms, as well as their respective routines, to disruption. The teams may not work well together due to differences in culture, norms, and routines for communication and problem solving, reducing their performance (Chatterjee *et al.*, 1992). Further, the target's knowledge workers will go from being 'big fish in a small pond' to small fish in the large pond of the acquirer's preexisting capabilities, leading to lost standing and diminished productivity (Kapoor and Lim, 2007; Paruchuri *et al.*, 2006).

Even if teams from the acquirer and target are not actually combined, their similar expertise makes it likely that they will find themselves competing for limited resources related to an already established capability rather than supplementing each other in order to build a new capability. As the firm seeks to resolve this internal competition, it is often the target's workforce that is reconfigured (Capron, Dussauge, and Mitchell, 1998; Capron, Mitchell, and Swaminathan, 2001; Capron and Pistre, 2002; Karim, 2006). The resulting loss of social status and centrality on the part of the target's innovators is one of the most significant drivers of lost technological productivity post-acquisition (Paruchuri *et al.*, 2006). It often leads to increased turnover among the target's workers (Krishnan, Miller, and Judge, 1997), which is highly damaging to knowledge transfer after the acquisition (Ranft and Lord, 2000).

Sometimes, however, it is the acquirer's employees that bear the brunt of post-acquisition reorganization. This is particularly likely to be the case when the acquirer intends to upgrade or substitute their present capabilities with the superior capabilities of the target (Karim, 2006), as would be suggested by a firm acquiring a target that duplicates many of its existing capabilities, rather than relying on internal development to

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expand its capabilities (Capron and Mitchell, 2009; Helfat, 1994; Tripsas and Gavetti, 2000).

Whichever group of employees is ultimately most affected by the acquisition, employees are likely to resist the acquisition for fear of its potential negative effects on their careers (Greenwood, Hinings, and Brown, 1994; Walsh, 1988, 1989). Such resistance is well documented as a source of acquisitions failing to meet their expectations (Blake and Mouton, 1985; Hambrick and Cannella, 1993; Larsson and Finkelstein, 1999). Employee resistance impedes the ease of communication and post-acquisition interaction between the knowledge workers, which is critical for the successful creation of novel recombinations using the acquirer's and target's capabilities.

For example, in 2000 Baxter acquired North American Vaccines (NAV) to enhance its ability to be a leader in the vaccines market where it was at the time a strong regional player. There was significant acquirer overlap, meaning consolidation and reconfiguration were necessary to avoid duplication of activities already existing within Baxter—activities with which the NAV's corresponding activities could be consolidated. The accompanying rationalization of research efforts led to job cuts within former NAV research facilities within two years. Within three years, Baxter terminated independent research within NAV, consolidating efforts within their existing research operation to leverage better the combined proprietary technologies. While initial job cuts were concentrated within NAV, the consolidation exposed both Baxter and NAV's employees to significant disruption (*PR Newswire*, 1999, 2000a; Terry, 2003).

In summary, an increase in acquirer overlap means that more of the acquirer's entrenched knowledge workers face the risk of their knowledge being made redundant by the acquisition and thus have an incentive to resist the integration of the target's knowledge workers. The resulting conflict increases the likelihood of turnover, and the resulting loss of knowledge for both the target and acquirer and makes successful recombination of the acquirer's and target's capabilities more difficult. Thus, we expect greater acquirer overlap to increase conflict leading to a decrease in the acquirer's ability to extract value from the target's and the acquirer's capabilities. This leads to our second and third hypotheses.

Hypothesis 2: An increase in acquirer technological overlap will negatively affect the impact the target's technological capabilities will have on abnormal returns.

Hypothesis 3: An increase in acquirer technological overlap will negatively affect the impact the acquirer's technological capabilities will have on abnormal returns.

We have focused on acquirer overlap as a determinant of conflict. However, target overlap may also affect the degree of disruption experienced. This possibility doesn't affect our understanding of the relationship between *acquirer* overlap and disruption that drives Hypotheses 2 and 3 but may shape our understanding of the results from testing Hypothesis 1, for which we followed the existing literature's focus on absorptive capacity and redundancy. Thus, we briefly explore the potential relationship between target overlap and the degree of disruption experienced.

If disruption and conflict increased with target overlap, it would—like redundancy—have a negative impact as target overlap increased. Disruption and redundancy are therefore complementary explanations, and we cannot rule out that both help drive Hypothesis 1. As we discuss below, the overall pattern of our results is strongly consistent with the extant interpretation that redundancy is a major driving factor behind the negative impact of target overlap on value creation from the target's capabilities.

Further, we believe that the relationship between target overlap and the degree of disruption experienced is significantly weaker than that of acquirer overlap, at least in the setting of technological acquisitions. Larsson *et al.* (2001: 614, emphasis added) described acquisitions as, 'the whole acquired firm being integrated with only the related parts of the acquiring firm. *Being acquired will likely create disruption for all* but those with Transitory career profiles.' That is, *all* target employees, whether or not in the area of overlapping knowledge, will be exposed to disruptions due to changes in culture (Larsson and Finkelstein, 1999), imposition of the acquirer's managerial systems (Capron and Mitchell, 1998), disruption of organizational and social identity (Haunschild, Moreland, and Murrell, 1994), and reduction in high-powered incentives (Kapoor and Lim, 2007).

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In contrast, Larsson *et al.* (2001) describe integration affecting 'only the related parts of the acquiring firm.' Acquirer employees related to the target's knowledge base are much more likely than other acquirer employees to experience disruption and conflict through changed status; disruption of identity as workgroups are shifted, merged, or otherwise reformed; an increase in nonroutine work related to integrating with target-firm employees; and the potential exit of colleagues who are displaced (or fear displacement) by target-firm employees. Life for unrelated acquirer employees will probably continue relatively undisturbed.

Thus, as acquirer overlap varies from low to high, the degree of conflict and disruption will also vary broadly from low to high. However, in light of the substantial, companywide disruption experienced by the target, the additional variation in disruption and conflict caused by the degree of target knowledge overlap is much more constrained.

METHODS

Data and sample

Our sample consists of technological acquisitions obtained from SDC Platinum's Mergers and Acquisitions database from 1995 to 2004. The first year that an acquisition meeting our criteria appears in the SDC database is 1995. Using 2004 as the end date allowed us to construct our patent citation-based independent variables. We initially identified acquisitions as technological acquisitions if both acquirer and target were classified as 'high tech' firms in SDC Platinum's M&A database.

We followed well-established norms in the existing literature on technological acquisitions and constrained the sample in several dimensions to isolate the effect of our theoretical interest, knowledge recombination. Most importantly, we limited the acquisitions to those in which the target had fewer than 500 employees (the U.S. Small Business Administration's definition of a small business) at the time of the acquisition (Granstrand and Sjölander, 1990; Puranam and Srikanth, 2007; Puranam *et al.*, 2006, 2009) and eliminated acquisitions that were clearly not technologically motivated according to a search of news articles and newswires using LexisNexis (Ahuja and Katila, 2001; Ranft and Lord, 2000). This constraint minimizes the impact of potential confounding factors usually present in the acquisition of large and/or nontechnological targets, such as cost (scale) synergies or market power synergies (Graebner and Eisenhardt, 2004; Granstrand, 1999; Puranam *et al.*, 2006; Ranft and Lord, 2002).

We limited the sample to manufacturing firms, SIC codes 20–39 (Puranam *et al.*, 2006, 2009) and acquisitions in which the acquirer acquired 100 percent of the target, there was no existing toehold, and a divestiture was not involved (Graebner, 2004; Granstrand and Sjölander, 1990; Puranam *et al.*, 2006; Ranft and Lord, 2000). So we could generate our variables, we eliminated acquisitions in which the acquirer was not public or either firm had no patents. Lastly, we limited the sample to deals greater than $50 million, since small deals may have no effect on the acquirer's share price (King *et al.*, 2008; Louis and Sun, 2010; Makri *et al.*, 2010; Wulf and Singh, 2011; Zhao, 2009). After implementing these filters, the final sample consists of 97 acquisitions involving 73 different acquirers.

Measures

Dependent variable

We used the event study method to construct the cumulative abnormal returns (CAR) of the acquirers, that is, acquiring firm's stock market reaction to the announcement of the acquisition (McWilliams and Siegel, 1997). We retrieved daily returns for our acquirers and equally-weighted market returns from the CRSP database (Peterson, 1989). We used an estimation window of 250 days, from 300 to 51 days prior to the announcement, and an event window of 3 days, from 1 day prior to the announcement to 1 day after. A 3-day window allows for differences in the timing of the announcement and the release of the announcement in the press (Peterson, 1989). To ensure that there were no confounding events, we searched LexisNexis for every acquirer and eliminated any acquisitions for which there was a confounding event within a five-day event window. We used Scholes-Williams coefficients to calculate our CARs, which corrects for the bias created from thin and nonsynchronous security trading in the market model (Scholes and Williams, 1977).

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As advocated by McWilliams and Siegel (1997), we first confirmed that the cumulative abnormal returns were significantly different from zero (<0.001) indicating that we captured the stock market's responses to the acquisitions. Of the 97 acquisitions in our sample, 35 have a positive CAR while 62 have a negative CAR.

Independent variables

The variables *acquirer technological overlap* and *target technological overlap* refer to the degree to which the knowledge bases of the two firms overlap. To calculate the overlap measures, we begin by determining each firm's knowledge base. Consistent with definitions of a firm's knowledge base as 'the distinct elements of knowledge with which the firm has revealed a relationship' (Kim and Kogut, 1996) or the set of knowledge with which the firm has 'demonstrated familiarity with, or mastery of' (Ahuja and Katila, 2001), we follow prior work (Ahuja and Katila, 2001; Cloodt *et al.*, 2006; Kapoor and Lim, 2007) and include two components in each firm's knowledge base. First, we include the firm's own patents, since they represent knowledge the firm created. Second, we include patents cited by the firm's patents, since 'By creating a patent that builds on these prior patents, the firm provides evidence that the knowledge contained in those past patents is a part of the firm's knowledge set.' (Ahuja and Katila, 2001: 202). To ensure we were capturing knowledge that was still relevant at the time of the acquisition, we include patents with an application date in the seven years prior to the acquisition announcement, as Jaffe, Trajtenberg and Henderson (1993) found that citations dramatically decrease seven years after the application date.

Combining these two components for the target and eliminating any duplication generates the target's knowledge base. Doing the same for the acquirer generates the acquirer's knowledge base. The technological overlap variables, which range from 0 to 1, are then calculated as follows.

$$\textit{Acquirer technological overlap} = \mathrm{R}/\mathrm{K_a}$$

$$\textit{Target technological overlap} = \mathrm{R}/\mathrm{K_t}$$

where

K_a,= the number of unique patents in the acquirer's knowledge base, which consists of the acquirer's patents and patents cited by the acquirer's patents in the seven years prior to the acquisition announcement date,

K_t,= the number of unique patents in the target's knowledge base, which consists of the target's patents and patents cited by the target's patents in the seven years prior to the acquisition announcement date, and

R, = redundancy in knowledge bases, the number of patents in the intersection of the acquirer and target's knowledge bases.

Technological capabilities refer to the ability of a firm to actually create impactful innovations. We follow an extensive literature and measure technological capabilities using a count of each firm's patents, which each represent a successfully realized innovation, weighted by the number of forward citations each has received to control for quality differences (Hall, Jaffe, and Trajtenberg, 2000; Kalaignanam, Shankar, and Varadarajan, 2007; Trajtenberg, 1990). Doing so for each firm generated *acquirer technological capabilities* and *target technological capabilities*. We dated the patent counts by their application date, which controlled for differences among the patents in the time it took to be granted (Ahuja and Katila, 2001; Henderson and Cockburn, 1996; Trajtenberg, 1990) and chose seven years to be confident that we captured most of the innovative technology that represented the current technological capabilities of the acquirer and the target (Trajtenberg, 1990).

As a robustness check, we also constructed variables for cumulative patents over the prior three, five, and all years. The seven-year measure correlates with the five- and three-year measures for both target and acquirer at the 0.91 level or higher. Thus, we used the seven-year accumulation to be more conservative in making sure we captured all relevant unique technological capabilities a firm possesses. Since event study models ultimately measure investors' perceptions of likely value creation, we note that we do not assume that investors possess full information pertaining to the actual patenting activity of either firm but do understand the outlines of each firm's knowledge base and technological capabilities, based on observing the technological trajectory and cumulative knowledge development of the firms over time (Dosi, 1982; Hoetker and Agarwal, 2007; Nelson, 2000).

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Control variables

We constructed a number of control variables, based on prior studies. Two variables control for acquirer characteristics. First, we constructed the variable *acquisition experience*—which has been found to create benefits (Bruton, Oviatt, and White, 1994; Fowler and Schmidt, 1989; Zollo and Singh, 2004), create a burden (Kusewitt, 1985), and to have no effect (King *et al.*, 2004; Lahey & Conn, 1990)—as the number of acquisitions the acquirer completed in the five years prior to the acquisition. We limited the acquisition experience to five years due to empirical evidence that shows depreciation in the knowledge gained from managerial experience (Sampson, 2005). We also constructed the variable *relative market share* to control for market dominance of the acquirer.

Two variables control for industry differences. *Pharma* is set to one if the acquirer is in the pharmaceutical/biotech industry, since past research has found unique characteristics of the acquisition process between pharmaceutical and biotechnology firms (Kalaitzandonakes, 2000; Schimmelpfennig, King, and Naseem, 2003; Schweizer, 2005). We also used Compustat to construct the *four-firm concentration ratio* at the SIC three-digit classification level.

Two variables control for the size of the two merging firms. To ensure that our results are not driven merely by the relative size of the firm's knowledge bases, we constructed the variable *relative size (knowledge bases)*, which is the number of knowledge elements in the target's knowledge base divided by the number of elements in the acquirer's knowledge base. We also constructed the variable *relative size (employees)* as the log of the relative size of the target to acquirer in terms of their number of employees.

We included two variables to control for transaction specifics. From the SDC Platinum M&A database, we included the percent of the transaction paid in stock, *%stock*. We also included the value of the transaction, *transaction value (100 millions)*, to control for the monetary size of the acquisition.

Finally, we included two dummy variables to control for the timing of the acquisition. The variable *pre-1998* controls for possible differences in shareholder valuation at different stages of the technological acquisition wave that started in the early 1990s. The variable *post-2000* reflects findings by Uhlenbruck *et al.* (2006) that acquirer shareholders valued acquisitions in the internet industry lower after the stock market correction in the year 2000.

Descriptive statistics

Table 1 contains the descriptive statistics and correlations of the variables. The correlation between acquirer overlap and target overlap is only 0.26, supporting our contention that they are separate constructs.

Models

We ran three separate analyses of the data to test our hypotheses. We used OLS regression and estimated robust White-Huber standard errors to correct for potential heteroskedasticity in all three of our analyses. First, we tested the hypotheses by interacting the overlap variables with the capabilities variables. In our second analysis, we avoided interaction terms by splitting the sample by target overlap at the median to test Hypothesis 1 and then splitting the sample by acquirer overlap at the median to test Hypotheses 2 and 3. This allowed for us to test for differences in the capabilities coefficients using a Wald test. In our third analysis, we split the sample at the medians of both target overlap and acquirer overlap, creating four subsamples that correspond to the four quadrants of Figure 1. We then ran separate regressions for each quadrant and tested for differences in the capabilities coefficients using a Wald test.

RESULTS

Analysis I

In our first analysis of the hypotheses, we tested the moderating effects of target overlap and acquirer overlap by interacting each with acquirer and target capabilities. As reported in Table 2, Model 1 includes all of the variables without any of the interaction variables. Subsequent models add individual interaction terms.

We find support for Hypothesis 1b (a negative relationship between target overlap and the value created by the target's capabilities) over

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Table 1. Descriptive statistics and correlations[a]

Variables	Mean	s.d.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. CAR	−0.03	0.09	−0.34	0.23														
2. Pre-1998	0.06	0.24	0	1	0.04													
3. Post-2000	0.43	0.50	0	1.00	−0.11	−0.22												
4. Transaction value (100 million)	5.11	8.06	0.50	56.58	−0.18	−0.07	−0.06											
5. Pharma	0.37	0.49	0	1	−0.08	−0.20	0.15	0.04										
6. % stock	0.66	0.45	0	1	−0.20	0.01	−0.34	0.20	0.00									
7. Relative size (employees)	−2.95	2.00	−7.32	0.95	−0.30	−0.18	0.07	0.09	−0.03	0.25								
8. Relative size (knowledge bases)	0.58	2.40	0.00	22.90	0.24	−0.05	0.10	−0.06	−0.03	0.02	0.30							
9. Four-firm concentration ratio	0.41	0.10	0.31	0.95	0.17	0.12	−0.14	−0.02	−0.43	−0.06	−0.02	−0.08						
10. Acquisition experience	5.70	8.87	0	53	0.14	−0.04	−0.14	0.25	−0.19	0.07	−0.42	−0.10	0.23					
11. Relative market share	0.06	0.09	0.0001	0.41	0.19	0.13	0.02	−0.12	0.02	−0.20	−0.73	−0.12	−0.09	0.18				
12. Target technological overlap	0.17	0.24	0	1	0.02	−0.09	0.04	0.30	−0.01	−0.13	−0.06	−0.11	−0.01	0.17	0.05			
13. Acquirer technological overlap	0.04	0.08	0	0.4	−0.05	−0.11	0.03	0.06	0.22	0.17	0.33	0.07	−0.15	−0.21	−0.25	0.26		
14. Target technological capabilities	4.92	1.65	0.69	8.94	0.09	0.10	−0.13	0.11	0.04	0.03	−0.10	0.10	−0.23	0.06	0.24	0.19	0.15	
15. Acquirer technological capabilities	7.15	2.25	0	10.43	0.00	0.14	−0.14	0.06	−0.19	−0.22	−0.59	−0.40	−0.04	0.37	0.47	0.23	−0.31	0.33

[a] Correlations equal to or greater than 0.20 are significant at the 0.05 level.

Hypotheses 1a (positive relationship) and 1c (nonmonotonic relationship). The interaction between target capabilities and target overlap is negative and significant in Model 2, supporting Hypothesis 1b over Hypothesis 1a. In Model 3, the interactions of both target overlap and target overlap squared with target capabilities are insignificant. In addition, a likelihood ratio test shows that Model 3 is not a better fit than Model 2 (LR = 0.14; p-value = 0.9328), and Model 2 (−205.69) has a lower AIC than Model 3 (−201.83), indicating that it fits the data better. Thus, there is no evidence of a nonmonotonic relationship and Hypothesis 1b (a monotonic negative relationship) is supported over Hypothesis 1c.

Hypotheses 2 and 3 focus on the effects of acquirer overlap. The interaction between acquirer overlap and target capabilities is negative and significant in Model 4, which supports Hypothesis 2. The interaction between acquirer capabilities and acquirer overlap is negative and significant in Model 5, which supports Hypothesis 3.

Analysis II

Table 3 reports the results of our second analysis, in which we tested the moderating effects of target overlap and acquirer overlap separately. We did so by testing Hypotheses 1a and 1b with the sample split at the target overlap median and then testing Hypotheses 2 and 3 with the sample split at the acquirer overlap median. We omit further consideration of Hypothesis 1c, as Analysis 1 found no evidence of a nonmonotonic relationship.

Models 6 and 7 display the results for our test of Hypotheses 1a and 1b. At low levels of target overlap (Model 6), the coefficient for target capabilities is positive and significant. At high levels of target overlap (Model 7), the coefficient for target capabilities is negative but not significantly different from zero. A Wald test comparing the coefficient for target capabilities across the models confirms that it is significantly greater at low levels of target overlap than at high levels ($p = 0.012$). Confirming the results of our first analysis, Hypothesis 1b is supported over Hypothesis 1a.

Models 8 and 9 report the results of splitting the sample at the median of acquirer overlap to test Hypotheses 2 and 3. Unlike in Analysis I, Hypothesis 2 is not supported. The coefficient for target capabilities is not significant for either low

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Table 2. OLS regression analysis of complete sample

Dependent variable = CAR (three-day window)	(1)	(2)	(3)	(4)	(5)
(H1) Target technological capabilities × target technological overlap	—	−0.037*	−0.056	—	—
	—	(1.67)	(0.08)	—	—
(H1) Target technological capabilities × target technological overlap squared	—	—	0.029	—	—
	—	—	(0.09)	—	—
(H2) Target technological capabilities × acquirer technological overlap	—	—	—	−0.182***	—
	—	—	—	(3.03)	—
(H3) Acquirer technological capabilities × acquirer technological overlap	—	—	—	—	−0.138**
	—	—	—	—	(2.53)
Target technological overlap	0.020	0.204*	0.332	0.017	0.037
	(0.57)	(1.69)	(0.45)	(0.50)	(1.04)
Target technological overlap squared	—	—	−0.180	—	—
	—	—	(0.51)	—	—
Acquirer technological overlap	0.051	0.042	0.024	0.941***	0.665**
	(0.32)	(0.28)	(0.16)	(3.71)	(2.59)
Target technological capabilities	0.008	0.012**	0.013*	0.011**	0.011**
	(1.47)	(2.14)	(0.01)	(2.15)	(2.11)
Acquirer technological capabilities	−0.011**	−0.011**	−0.012**	−0.008	−0.008
	(2.02)	(2.09)	(0.01)	(1.61)	(1.45)
Transaction value (100 million)	−0.131	−0.121	−0.123	−0.138	−0.145
	(0.95)	(0.89)	(0.15)	(0.99)	(1.02)
Pharma	−0.015	−0.013	−0.014	−0.013	−0.012
	(0.81)	(0.71)	(0.02)	(0.69)	(0.65)
% stock	−0.035**	−0.032*	−0.033*	−0.031*	−0.030*
	(2.17)	(1.96)	(0.02)	(1.98)	(1.91)
Relative size (employees)	−0.025***	−0.027***	−0.027***	−0.021***	−0.021***
	(3.74)	(4.04)	(0.01)	(3.25)	(3.27)
Relative size (knowledge bases)	0.011***	0.010***	0.010***	0.010***	0.011***
	(5.84)	(5.64)	(0.00)	(5.70)	(5.85)
Four-firm concentration ratio	0.124	0.128	0.126	0.145	0.145
	(1.24)	(1.27)	(0.10)	(1.46)	(1.46)
Acquisition experience	0.000	0.000	0.000	0.000	0.000
	(0.11)	(0.24)	(0.00)	(0.12)	(0.08)
Relative market share	−0.109	−0.136	−0.136	−0.090	−0.100
	(1.13)	(1.40)	(0.10)	(0.94)	(1.06)
Pre-1998	−0.031	−0.031	−0.030	−0.030	−0.030
	(1.11)	(1.11)	(0.03)	(1.00)	(1.03)
Post-2000	−0.031*	−0.031*	−0.031*	−0.023	−0.026
	(1.82)	(1.82)	(0.02)	(1.42)	(1.59)
Intercept	−0.071	−0.097	−0.097	−0.107*	−0.107*
	(1.09)	(1.36)	(0.07)	(1.72)	(1.68)
Observations	97	97	97	97	97
F-statistic	20.01***	14.47***	13.19***	25.02***	24.26***
R-squared	0.33	0.35	0.35	0.36	0.36

Robust t statistics in parentheses.
*significant at 10%; **significant at 5%; ***significant at 1%.

Table 3. OLS regression analysis of sample split by technological overlap

	Target overlap		Acquirer overlap	
Dependent variable = CAR	Low (6)	High (7)	Low (8)	High (9)
Acquirer technological overlap	0.901	0.205	—	—
	(1.29)	(0.83)	—	—
Target technological overlap	—	—	0.078	0.057
	—	—	(0.30)	(1.59)
Target technological capabilities	0.016**	−0.005	0.013	0.006
	(2.16)	(0.73)	(1.43)	(0.81)
Acquirer technological capabilities	−0.004	−0.020*	−0.004	−0.031***
	(0.68)	(1.79)	(0.60)	(3.24)
Transaction value (100 million)	−0.208	−0.137	−0.300	−0.060
	(0.35)	(1.46)	(0.65)	(0.51)
Pharma	0.020	−0.063*	0.025	−0.057**
	(0.68)	(1.82)	(0.63)	(2.21)
% stock	−0.039*	−0.018	−0.030	−0.019
	(1.77)	(0.72)	(1.22)	(0.75)
Relative size (employees)	−0.032***	−0.027**	−0.027**	−0.024**
	(2.91)	(2.40)	(2.23)	(2.13)
Relative size (knowledge bases)	0.013***	−0.050	0.013***	−0.014
	(4.19)	(1.28)	(3.55)	(0.62)
Four-firm concentration ratio	0.333*	−0.220**	0.317*	−0.191
	(1.94)	(2.09)	(1.82)	(1.51)
Acquisition experience	−0.001	0.001	0.000	0.003***
	(0.48)	(0.91)	(0.43)	(2.91)
Relative market share	−0.355	−0.070	−0.309	0.051
	(1.61)	(0.71)	(1.34)	(0.46)
Pre-1998	0.044	−0.042**	−0.008	−0.015
	(1.03)	(2.05)	(0.19)	(0.48)
Post-2000	−0.025	−0.048*	−0.024	−0.037*
	(1.05)	(1.78)	(0.97)	(1.74)
Intercept	−0.255***	0.223**	−0.239**	0.201**
	(2.83)	(2.14)	(2.29)	(2.22)
Observations	48	49	48	49
F-statistic	33.84***	2.97***	25.48***	8.79***
R-squared	0.47	0.42	0.43	0.42

Robust t statistics in parentheses; *p*-values in parentheses for chi-square statistics.
*significant at 10%; **significant at 5%; ***significant at 1%.
H1b: 'An increase in target technological overlap will negatively affect the impact the target's technological capabilities' *supported* (chi-squared = 6.27, p = 0.012).
H2: 'An increase in acquirer technological overlap will negatively affect the impact the target's technological capabilities,' *not supported* (chi-sq = 0.63, p = 0.43).
H3: 'An increase in acquirer technological overlap will negatively affect the impact the acquirer's technological capabilities,' *supported* (chi-sq = 8.25, p < 0.01).

(Model 8; $\beta = 0.013$, $p = 0.227$) or high (Model 9; $\beta = 0.006$, $p = 0.571$) acquirer overlap. Additionally, the coefficients do not differ significantly from each other ($p = 0.428$), although the lower coefficient for high acquirer overlap is consistent with Hypothesis 2. Analysis III provides additional insights into this result.

As predicted by Hypothesis 3, the coefficient for the acquirer's capabilities is significantly less ($p = 0.004$) when acquirer overlap is high (Model 9; $\beta = -0.031$, $p = 0.003$) than when it is low (Model 8; $\beta = -0.004$, $p = 0.552$). An increase in acquirer overlap negatively affects the impact the acquirer's capabilities have on abnormal returns.

Analysis III

For our final test of the hypotheses, we split the sample into the four quadrants of Figure 1. We did

Table 4. OLS regression analysis with sample split according to Figure 1

Quadrant from Figure 1 Target overlap Acquirer overlap Dependent variable = CAR (three-day window)	Q1 Low Low (10)	Q2 Low High (11)	Q3 High Low (12)	Q4 High High (13)
Target technological capabilities	0.025**	0.025	0.008	−0.009
	(2.25)	(1.55)	(0.79)	(0.97)
Acquirer technological capabilities	0.007	−0.028	0.012	−0.034**
	(0.32)	(1.42)	(0.83)	(2.94)
Transaction value (100 million)	−0.341	0.067	−0.174***	−0.340
	(0.35)	(0.60)	(5.49)	(1.15)
Pharma	0.070	−0.012	−0.006	−0.087
	(0.88)	(0.31)	(0.28)	(1.49)
% stock	0.043	0.022	−0.030*	−0.029
	(0.30)	(0.41)	(2.02)	(0.50)
Relative size (employees)	−0.053	−0.012	−0.006	−0.029*
	(1.45)	(0.79)	(0.34)	(1.92)
Relative size (knowledge bases)	0.020	−0.028	0.032	−0.017
	(1.54)	(0.71)	(0.19)	(0.21)
Four-firm concentration ratio	0.574	−0.044	−0.148	−0.487*
	(1.43)	(0.25)	(0.69)	(2.14)
Acquisition experience	0.003	−0.001	0.000	0.004
	(0.48)	(0.25)	(0.25)	(1.43)
Relative market share	−0.713	0.346	−0.370	−0.121
	(0.83)	(1.49)	(1.06)	(0.52)
Pre-1998	0.054	−0.040	−0.031	—
	(0.99)	(1.21)	(1.18)	—
Post-2000	−0.018	−0.030	−0.035	−0.023
	(0.29)	(0.78)	(1.42)	(0.78)
Intercept	−0.610	−0.009	−0.044	0.463**
	(1.25)	(0.05)	(0.50)	(2.26)
Observations	25	24	24	24
F-statistic	10.62***	2.10	5.75***	6.96***
R-squared	0.58	0.40	0.55	0.61

Robust t statistics in parentheses.
*significant at 10%; **significant at 5%; ***significant at 1%.

this by splitting the sample at the medians of the acquirer and target overlaps. The regression results can be found in Table 4 while the Wald test results can be found in Table 5.

Testing Hypotheses 1a and 1b requires two comparisons of the coefficient for target capabilities: quadrant 1 versus quadrant 3 and quadrant 2 versus quadrant 4. A Wald test shows that the coefficient is significantly greater ($p = 0.080$) in quadrant 1 (low target overlap/low acquirer overlap; $\beta = 0.025$, $p = 0.044$) than in quadrant 3 (high target overlap/low acquirer overlap; $\beta = 0.008$, $p = 0.443$). Similarly, the coefficient is significantly greater ($p = 0.008$) in quadrant 2 (low target overlap/high acquirer overlap; $\beta = 0.025$, $p = 0.150$) than in quadrant 4 (high target overlap/high acquirer overlap; $\beta = -0.009$, $p = 0.351$). Thus, regardless of the level of acquirer overlap, the target's capabilities create more value when target overlap is low than when it is high. Consistent with both prior analyses, this result supports Hypothesis 1b.

Testing Hypothesis 2, which proposes that an increase in acquirer overlap negatively affects the value created by the target's capabilities, requires two comparisons of the coefficient for target capabilities: quadrant 1 versus quadrant 2 and quadrant 3 versus quadrant 4. A Wald test shows that the coefficient is not significantly greater ($p = 0.991$) in quadrant 1 (low target overlap/low acquirer overlap; $\beta = 0.025$, $p = 0.044$) than in quadrant 2 (low target overlap/high acquirer overlap; $\beta = 0.025$, $p = 0.150$). On the other hand, the coefficient is significantly greater ($p = 0.073$) in

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Table 5. Test of coefficient differences with overlap levels split into four quadrants

	Low acquirer technological overlap	High acquirer technological overlap	H2 and H3
	Q1	Q2	
Low target technological overlap	Target technological capabilities = 0.025**	Target technological capabilities = 0.025	H2 chi-square = 0.00 p-value = 0.9913
	Acquirer technological capabilities = 0.007	Acquirer technological capabilities = −0.028	H3 chi-square = 3.10 p-value = 0.0783
High target technological overlap	Q3	Q4	
	Target technological capabilities = 0.008	Target technological capabilities = −0.009	H2 chi-square = 3.22 p-value = 0.0729
	Acquirer technological capabilities = 0.012	Acquirer technological capabilities = −0.034**	H3 chi-square = 13.23 p-value = 0.0003
H1b	chi-square = 3.06 p-value = 0.0801	chi-square = 7.04 p-value = 0.0080	

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

quadrant 3 (high target overlap/low acquirer overlap; $\beta = 0.008$, $p = 0.443$) than in quadrant 4 (high target overlap/high acquirer overlap; $\beta = -0.009$, $p = 0.351$).

This more fine-grained analysis helps explain the lack of support for Hypothesis 2 in Analysis II. The impact of acquirer overlap on the value created by the target's capabilities is contingent on the level of target overlap. When target overlap is high, there is a negative impact as predicted. When target overlap is low, there is no impact. We discuss this interesting finding in the Discussion section.

Testing Hypothesis 3, which proposes that an increase in acquirer overlap negatively affects the value created by the acquirer's capabilities, also involves comparing quadrant 1 versus quadrant 2 and quadrant 3 versus quadrant 4. A Wald test shows that the coefficient is significantly greater ($p = 0.078$) in quadrant 1 (low target overlap/low acquirer overlap; $\beta = 0.007$, $p = 0.757$) than in quadrant 2 (low target overlap/high acquirer overlap; $\beta = -0.028$, $p = 0.183$). Similarly, the coefficient is significantly greater ($p = 0.000$) in quadrant 3 (high target overlap/low acquirer overlap; $\beta = 0.011$, $p = 0.426$) than in quadrant 4 (high target overlap/high acquirer overlap; $\beta = -0.034$, $p = 0.012$). We thus find strong support for Hypothesis 3. Acquirer capabilities have a more negative impact on value at higher levels of acquirer overlap. This effect exists at both low and high levels of target overlap.

Summary of analyses

Results from the three analyses are consistent. Hypotheses 1b is supported in each case. As target overlap increases, each unit of target capabilities generates less value, suggesting that the negative impact of increased redundancy (and perhaps increased disruption as we discuss below) outweighs the benefits of increased absorptive capacity. Hypothesis 3 was also consistently supported; acquirer overlap negatively affects the value created by the acquirer's capabilities. Only Hypothesis 2 varies across the analyses. In each analysis, the magnitude of the coefficients suggests that, as predicted, an increase in acquirer overlap negatively affects the value created by the target's capabilities. However, the result is statistically insignificant in Analysis II. Collectively, the analyses suggest that the impact of acquirer overlap on the value created by the target's capabilities is contingent on the level of target overlap, a point we address further in the discussion section.

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ADDITIONAL ANALYSIS: POST-ACQUISITION PATENTING

Many prior studies of technological innovations have used post-acquisition patenting as a measure of performance (Ahuja and Katila, 2001; Cloodt *et al.*, 2006; Kapoor and Lim, 2007; Makri *et al.*, 2010). Therefore, we replicated our original Analysis III using the patent counts of the post-acquisition firm for the three years following the acquisition.

In four out of the six tests of our hypotheses, the two measures provide consistent results. Three results (Hypothesis 1 for low acquirer overlap, Hypotheses 2 and 3 for low target overlap) are identical in direction and significance. The test of Hypothesis 3 for high target overlap points in the same direction but loses statistical significance for patents ($p = 0.140$).

The first substantive difference regards Hypothesis 1 (how target overlap affects the contribution of target capabilities) when acquirer overlap is high. We found that an increase in target overlap strengthened the relationship between target capabilities and patenting but weakened the relationship between target capabilities and CAR. This contrast is consistent with the logic we developed for Hypotheses 1a and 1b.

High target overlap indicates that the firm is buying a capability pool it understands well. Per the previous literature and our logic for Hypothesis 1a, this should give the firm the absorptive capacity it needs to identify, value, assimilate, and commercialize successfully the recombinative possibilities of the target's resources (Cohen and Levinthal, 1990). Consistent with this logic, we find that the post-acquisition count of patents as a function of target capabilities increases with greater target overlap.

However, consistent with other previous literature (Ahuja and Katila, 2001; Makri *et al.*, 2010) and our logic for Hypotheses 1b, if high target overlap occurs when acquirer overlap is also high, there are few possibilities to create truly novel recombinations of the target's and acquirer's knowledge. Thus, the innovations occurring in these acquisitions create only marginal added value. Accordingly, the target's capabilities provide less increase in CAR than they would if target overlap were lower and there were more opportunities for novel recombination.

Very similar logic explains the contrasting results for Hypothesis 2 (how acquirer overlap affects the contribution of target capabilities) when target overlap is high. We found that an increase in acquirer overlap increased the relationship between target capabilities and patenting but weakened the relationship between target capabilities and CAR. An increase in acquirer overlap may help target employees identify and execute more opportunities to combine its capabilities with the acquirer's capabilities post-acquisition. This increases the number of patents produced as a function of the target's capabilities. However, an increase in acquirer overlap compounds the redundancy created by high target overlap, meaning there are fewer possibilities to create truly novel recombinations. Thus, the target's capabilities provide less increase in CAR than they would given low acquirer overlap.

Combining the findings for patents and CAR suggests that the *quantity* and *quality* of post-acquisition innovation may be differentially affected by overlap, which echoes the findings of Makri *et al.* (2010) who found different predictors of invention quantity, quality, and novelty. It also illuminates the tension among Hypotheses 1a, 1b, and 1c. Increased target overlap increases the acquirer's absorptive capacity but diminishes the novelty of resulting innovations. Thus, the target's capabilities result in more patents but generate less value. Collectively, these results confirm both the appropriateness and the unique value of the CAR measure in studying technological acquisitions.

ROBUSTNESS TESTS

To ensure that the choice of using the median level of overlap to split the sample was not driving our results, we replicated Analysis II while splitting the sample at the 33rd and 66th percentiles. Consistent with our original results, we find support for Hypothesis 1b when the sample is split at either the 33rd or 66th percentile of target overlap. Results for Hypothesis 2 are consistent with the original analysis: acquirer overlap does not significantly affect the impact that the target capabilities have on value creation at either split. The results for Hypothesis 3 remain substantively robust. Under all three splits, the value created from acquirer capabilities is higher when acquirer overlap is low.

The difference is significant ($p = 0.02$) when the sample is split at the 33rd percentile of acquirer overlap and marginally insignificant when the sample is split at the 66th percentile ($p = 0.11$).

We also ran the analyses with abnormal returns using a five-day event window, which provides the advantage of capturing any value change outside the three-day event window due to information leakage at the cost of more opportunity for confounding events. The results using the five-day window are substantively the same as the three-day window presented in our analyses above.

Lastly, prior work, e.g., Ahuja and Katila (2001), has proposed and often found an inverted-U shaped relationship between technological overlap and acquisition performance. While this is a different relationship from the one we study, it provides a useful opportunity to validate our data. We therefore examined whether target overlap exhibits a curvilinear effect on either CAR or post-acquisition patenting.

In results available from the authors, we found evidence for a curvilinear effect in patenting output. This finding validates the consistency of our data with data used in previous work. We do not find a curvilinear effect for CAR, which we believe to be consistent with our logic and earlier results. Absorptive capacity likely increases at a decreasing rate. The negative impact of target overlap on the novelty (and thus value) of innovation likely decreases at a decreasing rate—the impact of additional overlap is fairly small once overlap is already very high. The nonlinearities effectively cancel each other out. As discussed above, the latter effect is not captured to the same degree in the patent measure, explaining the difference in the results.

DISCUSSION AND CONCLUSION

This study advances our understanding of the performance of technological acquisitions by extending the concept of technological overlap and by incorporating the interaction of the level of technological overlap and the amount of technological capabilities possessed by the target and acquirer. In doing so, it makes four primary contributions.

First, it theoretically and empirically advances the concept of technological overlap by demonstrating that target overlap and acquirer overlap are separate constructs and need not be symmetric. Doing so complements other work (Makri *et al.*, 2010) that takes a more multidimensional view of technological overlap. We believe that the idea of asymmetric knowledge overlap across partners is also applicable to alliances, extending insights generated by examining overlap as a symmetric attribute of an alliance (e.g., Mowery *et al.*, 1996, 1998).

Distinguishing target and acquirer overlap enables the paper's second contribution, simultaneously considering the impact of overlap (both target and acquirer) and technological capabilities (again, both target and acquirer) on acquisition performance. This study is the first paper of which we are aware to do so. One of the paper's key insights, that target overlap and acquirer overlap have distinct effects on the acquirer's ability to create value from combining the target's and the acquirer's capabilities, comes directly from this advance.

The study's third contribution is to broaden the theoretical explanation of value creation in technological acquisitions by simultaneously incorporating three drivers: the acquirer's absorptive capacity, knowledge redundancy, and exposure to organizational disruption due to conflict between the acquirer's and target's knowledge workers. Drawing on prior papers that have discussed each driver in isolation, our separate measures of target overlap and acquirer overlap allow us to consider them simultaneously, even though we do not directly observe them.

The paper's fourth contribution is to extend the literature on technological acquisitions by studying both shareholder value creation and post-acquisition invention productivity (patenting) as outcomes. Although relatively neglected as a dependent variable for technological acquisitions, shareholder value creation provides theoretical and managerial insights. It is a direct measure of the degree to which the managers of the acquiring firm accomplish their ultimate goal of generating shareholder value by acquiring small technological firms. Our combined findings complement other studies of post-acquisition invention productivity (Ahuja and Katila, 2001; Cloodt *et al.*, 2006; Kapoor and Lim, 2007; Makri *et al.*, 2010; Paruchuri *et al.*, 2006; Puranam and Srikanth, 2007). In particular, they suggest that the low innovation quantity observed in acquisitions with low target overlap may conceal an offsetting increase in the novelty and quality of innovations

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generated in such acquisitions. In this regard, it helps confirm Makri *et al.*'s (2010) finding that less quantity can be accompanied with greater quality when lower similarity and greater complementarity exists between the acquirer and target.

Three useful insights flow from these contributions. The first insight comes from our finding that, when target overlap is high, knowledge redundancy decreases an acquirer's ability to derive value from a target's capabilities, but when target overlap is low, there does not seem to be a negative impact from a lack of absorptive capacity. This finding suggests that acquiring managers may be better able to recognize what they do not know than recognize what they know too well. Complementing Coff's (2002) finding that potential acquirers are more likely to withdraw an acquisition when there is little knowledge overlap between the target and the acquirer, we expect management to follow through only on acquisitions with foreseen synergies. However, in pursuit of those potential synergies, they may get tunnel vision and not recognize excessive knowledge redundancy and its potential value destroying effects. As noted above, disruption and conflict may also play a role here.

The second insight regards the precedents and consequences of conflict between knowledge workers on value created by the target's capabilities. High acquirer overlap negatively affects the acquirer's ability to extract value from the target's capabilities only when there is simultaneously high target overlap. Even though much of the acquirer's knowledge is redundant, if it can be coupled with nonredundant knowledge from the target, the target's knowledge workers have much to offer the acquirer. This situation allows for synergy realization, which can provide a productive working environment instead of one of conflict and competition. However, when the target brings less new knowledge (high target overlap), there is less chance for complementarities and synergy realization. Without potential for complementarities between the two firms' knowledge workers, redundancies are likely to translate into a more competitive, hostile environment.

The third insight examines the precedents and consequences of conflict on value created from the acquirer's capabilities. Conflict resulting from high acquirer overlap can actually destroy the value of the acquirer's existing capabilities. Indeed, applying the estimates of Table 5 to an acquisition with mean levels of acquirer and target capabilities shows that the destruction of value from the acquirer's capabilities exceeds that created from the target's capabilities whenever acquirer overlap is high (quadrants 2 and 4). Consistent with Capron and Mitchell (2009), firms seem to be more efficient at acquiring technologies that are more dissimilar to their own as conflict arises if the firms possess similar technological capabilities. Managers considering acquiring a company with knowledge overlapping much of their own must recognize that such acquisitions are not only unlikely to generate value, they may reduce the value of the acquirer's preexisting knowledge.

Several alternative explanations merit careful consideration. First, as demonstrated by Google's recent acquisition of Motorola Mobility, an acquirer's interest may be less in using the target's technology directly and more in having it available for licensing out or using in litigation-related negotiations (Boulton, 2011). We suspect that few of the small target firms in our sample offer a rich enough IP portfolio to merit purchasing the entire company merely to out-license the technology. To the degree that it does occur, however, the value of the target's IP for licensing (litigation-related or otherwise) would be determined by its value to potential licensees, rather than the acquirer, meaning that its value should be minimally affected by the overlap between the acquirer and target knowledge bases and thus not interfere with the relationships we hypothesize. Second, while our sample was chosen to limit the impact of factors beyond knowledge recombination, other assets of the target, including geographic reach, alliance networks, etc., can create value. Lastly, investors may be concerned if a low target overlap acquisition seems to signal that a firm is moving away from its core capabilities. Benner (2010) found that investors often take this as a negative signal, which would be an alternative explanation for Hypothesis 1a. However, it would work against finding significance for the competing Hypothesis 1b, which was consistently supported.

Future research on the microfoundations of the relationship between overlap, capabilities, and acquisition performance would help address the primary limitation of our study. While we were able to build upon a large theoretical literature and rich empirical findings in developing our hypotheses, we did not directly observe the underlying

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mechanisms. In particular, it would be helpful to see how the levels of acquirer and target overlap influence the probability of employees departing from the target and, especially, the acquiring firm (cf. Karim, 2006). The same observation could be undertaken for asset divestitures at different levels of acquirer and target overlap. Future research could also generalize our findings to knowledge recombination in acquisitions more generally, although that would require controlling for motives such as market power and cost synergies that may be more prominent.

In conclusion, we have shown that technological overlap in an acquisition is better thought of as two technological overlaps, one describing the knowledge set of the target firm and the other the knowledge set of the acquiring firm. The two overlaps have distinct, but interrelated, effects on the degree to which the acquirer creates (or destroys) value from its own technological capabilities and those of the target. Our findings suggest that the two overlaps drive value creation or destruction through multiple causal mechanisms: the creation of absorptive capacity, knowledge redundancy, and the generation of post-acquisition disruption and conflict. These mechanisms have different theoretical implications and require different managerial responses, which this study has taken the initial steps to explore. We hope others will use this study as a foundation to expand on that exploration.

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