Paper to be presented at the DRUID 2012

on

June 19 to June 21

at

CBS, Copenhagen, Denmark,

Unique synergies in technology acquisitions

George Chondrakis
University of Oxford
Said Business School
g.chondrakis@gmail.com

Abstract
This paper focuses on technology acquisitions to operationalize and test Barney's (1988) unique synergy hypothesis. According to this, acquisitions create value to the acquirer when the resulting synergy cannot be replicated by other bidding firms. Our results provide strong support to this proposition as we find patent portfolio relatedness to have a positive effect on acquirers' performance, but only in industries using complex technologies. These findings emphasize the need to observe synergy potential at a much finer level of analysis, taking the specific nature of resource interdependence into account. This study also explores the determinants of patent acquisitions through corporate takeovers. We find that firms are more likely to buy targets with patents when the threat of patent litigation is high, when they operate across multiple complex technology areas and when their patent productivity is low.
INTRODUCTION

Generating synergies through novel combinations of organizational resources is a key objective in strategic management. To this end, corporate acquisitions provide an important avenue for reconfiguring a firm’s resource portfolio (Capron et al., 1998; Karim et al., 2000). However, it is a well-known fact that acquisitions, be related or not, regularly fail to create value for the acquirer (Moeller et al., 2005; Singh et al., 1987). Barney (1988) offers an explanation for this empirical observation suggesting that acquirers only capture part of the value created if the synergy is bidder-specific. That is, the acquirer must be able to generate unique synergies with the target firm.

Despite the intuitive appeal of this proposition, its empirical verification is limited by the difficulty of operationalizing unique synergies (Harrison et al., 1991; Uhlenbruck et al., 2006). Like other tenets of resource-based theorizing (Hoopes et al., 2003; Priem et al., 2001), the unique synergy hypothesis is vulnerable to the tautology critique: positive acquirers’ returns are attributed to the presence of unique synergies which are in turn observed through positive acquirers’ returns.

However, focusing on technology acquisitions offers a particularly promising setting in order to overcome these concerns. In particular, the transfer of patent rights through technology acquisitions enables the direct measurement of synergy through citation data. Such synergies are by definition unique as patents provide competitive protection to distinct parts of the technology space. Moreover, the difference in patent use across industries – based on the nature of the underlying technology i.e. complex vs. discrete (Cohen et al., 2000; Merges et al., 1990) – allows for the development of competing hypotheses regarding the benefits of patent portfolio relatedness to the acquiring firm.

An analysis of acquisitions made by US public firms in two industries – chemicals and electronics – provides strong support for Barney’s unique synergy hypothesis. Using common citation rate as a proxy for patent portfolio relatedness, we demonstrate that relatedness has a positive effect on acquirers’ returns in industries using complex technologies (i.e. electronics) but no effect in industries using discrete technologies (i.e. chemicals). This is because innovation in complex
technology industries is cumulative and merging related patent portfolios allows the acquiring firm to profit by controlling and (partly) blocking certain parts of the technology space (Merges et al., 1990; Reitzig, 2004; Shapiro, 2001). In contrast, related patent portfolios in discrete technology industries do not allow for such opportunities to emerge as patent rights do not develop such interdependencies, they work more or less alone (Cohen et al., 2000; Merges et al., 1990).

These findings contribute to the study of acquisitions by emphasizing the need to observe synergy potential at a much finer level of analysis and to better understand what resource combinations generate surplus value. A narrow focus on resource similarity, evident in much of the earlier empirical work, will not necessarily translate into higher acquisition performance. As Kim et al. (2009) point out, just because two firms are the same on some dimension does not mean that their strategies, or resources, necessarily fit together in some value-creating manner. Instead, researchers should identify the underlying mechanisms of value creation by carefully observing the nature and characteristics of resource interdependence.

We also explore the technology resource acquisition strategies of firms. Building on the literature exploring the characteristics of technology acquirers (Hitt et al., 1991; Zhao, 2009), we extend this inquiry into the specific nature and selection of technology resources. Of particularly interest is the question of whether acquirers select target with patents (as opposed to targets without patents). We find that firms are more likely to buy targets with patents when the threat of patent litigation is high, when they operate across multiple technology areas in complex technology industries and when their patent productivity is low. These results provide more clarity to the motives of technology acquirers and emphasize their diverse motives.

In fact, this is the first study to demonstrate that technology acquisitions can be a strategic response to the threat of patent litigation. The majority of patent litigation models focus on firm characteristics that increase litigation hazard, treating firm scope as largely exogenous. In contrast, we explicitly hypothesize and provide evidence that changes in firm scope are central means with which firms manage observable or latent patent disputes. Google’s takeover of Motorola Mobility (August 2011) is a case in point. With patent wars in the smartphone
industry raging and after failing to successfully win the bid for Nortel’s patent portfolio, Google spent $12.5 billion largely for access to Motorola’s 17,000-strong patent portfolio. As Larry Page, Google’s CEO, put it: “Our acquisition of Motorola will increase competition by strengthening Google’s patent portfolio, which will enable us to better protect Android from anticompetitive threats from Microsoft, Apple and other companies”.

THEORY AND HYPOTHESES

Economists have traditionally seen corporate acquisitions as motivated by economies of scale and scope and the transfer of management practices (Jensen et al., 1983; Shleifer et al., 1988). Strategy scholars adopt a broader perspective, emphasizing the benefits of resource redeployment following an acquisition (Capron, 1999; Capron et al., 1998). According to this view, value is created through the combination of resources that were previously deployed separately and are subject to market failure (Capron et al., 1998). Indeed, acquisition activity is a key mechanism by which firms change and reconfigure their resource portfolio (Karim et al., 2000).

The resource redeployment perspective of acquisitions largely rests on the premise that resource value is endogenous, that is resource value is a function of other resources in a firm’s portfolio. A number of mechanisms have been proposed in support of this view. For example, firms increase resource productivity through the development of idiosyncratic capabilities (Makadok, 2001). Alternatively, resources can exhibit complementarity allowing for value-enhancing redeployment (Kim et al., 2009; Milgrom et al., 1995). In this context, complementarity is present when a combination of resources leads to the creation of surplus value over and above the sum of the amounts of value the resources could create independently (Adegbesan, 2009:463). Resource orchestration and co-specialization are similar concepts to that of complementarity and have been used to describe interdependencies among resources (Adner et al., 2003; Sirmon et al., 2009; Teece, 1986).

It is interesting to note that Barney (1988) was careful to avoid focusing on the sources of surplus value in his original formulation of a theory of value distribution
in acquisitions. His framework uses the net present value of ‘synergistic cash flows’ to identify the surplus value resulting from acquisitions but remains essentially agnostic about the underlying mechanism generating the synergy. In this paper, we similarly concentrate on the distribution of surplus value. Hence, we define synergy as any value-enhancing opportunity resulting from resource redeployment. This includes notions of market power, economies of scale/scope, complementarity etc.

**Value capture in acquisitions**

Although it is often hard to disentangle the different sources of surplus value creation, e.g. resource divesture versus resource redeployment (Capron, 1999), empirical evidence is broadly supportive of the generation of synergistic gains from acquisitions (Moeller et al., 2005; Mulherin et al., 2000). Nevertheless, these gains are not equally distributed between the merged entities. A number of studies demonstrate that bidding firms regularly fail to capture any value from the acquisition (Fuller et al., 2002; Moeller et al., 2005). Synergistic gains are, to a large extent, captured by the shareholders of the target firm.

Barney (1988) suggests that this observation can be explained by the competitive nature of markets for corporate control. Corporate takeovers are similar to auctions, with bidding firms competing on the basis of their respective valuations. If the target is equally valuable to the bidding firms, the competitive bidding process will result in zero returns for the acquiring firm. Acquisitions then create value to the acquirer when the resulting synergies cannot be replicated by other bidding firms, that is when inimitable and uniquely valuable synergies exist between the target and bidding firm (Barney, 1988:74).

Barney’s (1988) thesis can explain the lack of support for the ‘relatedness’ view of acquisition performance. According to this, acquirers will profit more when buying a target with resources similar to those of the acquirer. Empirical evidence is hardly consistent with this proposition though (Lubatkin, 1987; Singh et al., 1987). Barney (1988) explains that even when related acquisitions create synergies, these are unlikely to be unique amongst bidding firms. Thus, most of the surplus value still accrues to the shareholders of the target firm.
Nevertheless, empirical tests of the unique synergy hypothesis are much harder to come by. The problem lies in the operationalization of unique synergies. Essentially, it is difficult to avoid the tautology trap of identifying unique synergies through acquirers’ returns and vice versa. This point is part of a broader discussion centering on the explanatory power of resource-based theorizing. Its critics suggest that the resource-based view of the firm often defines what it attempts to explain, thus rendering the empirical falsification of its propositions almost impossible (Hoopes et al., 2003; Priem et al., 2001).

In an attempt to explore unique synergies, Harrison et al. (1991) focused on similarities and differences in capital, administrative, interest and R&D intensity. In another study, Capron and Pistre (2002) used post-acquisition survey data to demonstrate that resource transfer from target to acquirer does not contribute to acquirers’ returns. They explain that when the synergy stems from the transfer of target’s resources, this is unlikely to be unique. In contrast, they find that acquirers’ returns are higher when resources are transferred from the acquirer to the target. More recently, Kim and Finkelstein (2009) identified synergy potential through various measures of complementary differences.

Although these studies have greatly contributed to the elucidation and testing of Barney’s (1988) hypothesis, they have focused less on the micro-mechanisms for generating unique synergies. Yet, these are crucial components of a theory of value distribution. As we will argue below, the transfer of patent rights in technology acquisitions provides an ideal setting to address this concern and allows for a strict test of the unique synergy hypothesis.

**Technology acquisitions**

Technology acquisitions provide technological input to the acquiring firm enabling it to avoid the uncertain process of internal technology development and to leverage the target’s knowledge base and capabilities (Ahuja et al., 2001; Puranam et al., 2007). Indeed, the acquisition of small, technology-intensive firms is a major source of growth and renewal in industries with rapid rates of technological change (Karim et al., 2000).
Most studies of technology acquisitions focus on their impact on the innovative capability of acquiring firms. In one of the first studies in the field, Hitt et al. (1991) found that acquisitions negatively affect R&D investment, providing support for the view that acquisitions are seen by managers as substitutes to innovation. Focusing on the output side, Ahuja et al. (2001) demonstrated that the absolute size of the acquired knowledge base positively affects acquirers’ innovative output while relative size reduces innovative output. Valentini (2012) provided a more fine-grained analysis, finding that acquisitions have a positive effect on patenting output but a negative effect on patent impact, originality and generality.

The decision of whether to integrate the acquired entity into the organizational structure of the acquiring firm or to preserve its organizational autonomy has received a lot of attention in the literature. In particular, this decision imposes an inherent trade-off to the acquiring firm as structural integration enhances its ability to use the target’s knowledge base but reduces its ability to leverage the target’s innovative capabilities (Puranam et al., 2007). In addition, the benefits of structural integration are time-variant, with structural integration being more beneficial when it does not coincide with exploration-intensive phases along the acquired firm’s technological trajectory (Puranam et al., 2006). From a similar standpoint, other scholars have explored acquisitions’ impact on inventors’ productivity and incentives as well as the mediating role of structural integration (Kapoor et al., 2007; Paruchuri et al., 2006).

Evidently, much of the emphasis in the literature is on technology acquisitions’ impact on post-acquisition innovative performance (Cassiman et al., 2005; Desyllas et al., 2010; Zhao, 2009). Yet, the resource redeployment perspective of acquisitions points towards a number of avenues for generating synergistic value. In particular, the value of patents depends on the composition of the assignee firm’s patent portfolio (Grindley et al., 1997; Parchomovsky et al., 2005; Reitzig, 2004). Thus, merging two previously separate patent portfolios can produce, under certain circumstances, surplus value to the new entity. In the following section we explain our methodology for identifying unique synergies using patent citation data.
Operationalizing unique synergies

Patent rights provide competitive protection to distinct parts of the technology space. The extent of this protection is defined by the claims listed on the patent document and citations to other patents. Citations can be used to study technological spillovers or patent quality and value (Jaffe et al., 1993; Trajtenberg, 1990). More importantly for this study though, citations provide detailed information on technological relatedness as they reveal the antecedents of patented inventions. Whereas measures of technological distance across patent classes capture broad technological associations (Jaffe, 1986; Paruchuri et al., 2006), citation data reveal unique links between technologies. Uniqueness results directly from the definition of patents – as multiple patents cannot protect the same invention – and citations’ legal function of delimiting patent scope: the claims of the citing patent are suppressed by those of the cited patent (Hall et al., 2005).

Nevertheless, uniqueness is not enough. It is also important to demonstrate synergy potential. Why would related patent portfolios, as measured by common citations, generate additional value when brought together? In fact, this is not a straightforward matter as the characteristics of the underlying technology need to be considered.

A well-established distinction in the patenting literature is between complex and discrete technologies: the key difference between the two is whether a new, commercializable product or process is comprised of numerous separately patentable elements (complex) versus relatively few (discrete) (Cohen et al., 2000:19; Merges et al., 1990). Typical examples of complex technologies are electronics and semiconductors while examples of discrete technologies include chemicals and drugs (Cohen et al., 2000; Reitzig, 2004).

This distinction is important because it mediates the potential of patent portfolio relatedness to generate synergies. In complex product industries, companies do not have control over all of the patented technologies included in their products. Rather, firms regularly use competitors’ technologies either through cross-licensing agreements or through the threat of litigation (Bessen et al., 2005a; Grindley et al., 1997). As explained by Merges et al. (1990:881), such technologies define a complex
system with many components and existing inventions get incorporated into subsequent inventions. Hence, patents are often labeled as bargaining chips (Hall et al., 2001b).

The combination of patent portfolios then will change the competitive and bargaining dynamics in complex product industries. When the acquirer and target’s patents draw from similar technologies, as measured through common citations to other patents, the combined firm will be able to control and (partly) block certain parts of the technology space (Reitzig, 2004; Shapiro, 2001). This results in increased ability to negotiate, compete and extract licensing fees.

In contrast, patents in discrete technologies work more like exclusion rights. Most products incorporate only a few patented technologies normally held by the same firm (Cohen et al., 2000; Reitzig, 2004). Indeed, discrete inventions do not typically incorporate a large number of interrelated components – they stand more or less alone (Merges et al., 1990:881). Common citations then shouldn’t provide any opportunities for synergy. Given this background, we expect patent portfolio relatedness to differentially affect acquirer’s returns in complex and discrete technology industries:

*Hypothesis 1a*: Acquirer’s returns will be higher when the acquirer and target’s patent portfolios are related (as measured by common citations to other patents) in industries using complex technologies.

*Hypothesis 1b*: Acquirer’s returns will be unaffected when the acquirer and target’s patent portfolios are related (as measured by common citations to other patents) in industries using discrete technologies.

**Selection of target with patents**

The generation of unique synergies through the combination of related patent portfolios requires the target firm to have patent(s). However, this is not a random decision on behalf of the acquirer. Acquirers select between buying targets with or without patents on the basis of their own characteristics.

*Patent productivity*

Technology development is an inherently uncertain and risky process. Even when investment in R&D is high, there is no guarantee of a high-quality patenting output
in Hall et al., 2005; Miller et al., 2004). In essence, the firm-level patent productivity function includes an important stochastic component (Lanjouw et al., 2004a).

Low patent productivity indicates failure to generate patents of increased value and technological importance. Acquirers then will focus on strengthening their patent portfolio in order to ensure their ability to operate. In particular, a high-quality patent portfolio increases the value of other specialized complementary assets (Arora et al., 2006; Teece, 1986), blocks competitors from accessing important technologies (Arora, 1997) and enhance the negotiating power of assignee firms (Grindley et al., 1997; Hall et al., 2001b). Especially in industries where they are important means of competition, patents also provide a reliable stream of licensing revenue (Arora et al., 2001; Arora et al., 2010). We therefore hypothesize that:

*Hypothesis 2: Acquirers are more likely to buy targets with patents when the quality of their patenting output – or patent productivity – is low.*

**Patent portfolio technological concentration**

Besides patent productivity, patent portfolio characteristics influence the propensity of acquirers to buy targets with patents. This is because of the strategies firms adopt in response to the increased uncertainty they face regarding the future value of their technology investments. In particular, patent acquisitions, like any technology investments, can be seen as real options (Bloom et al., 2002; McGrath, 1997; Myers, 1977). According to this logic, technology investment decisions are elements in a sequence of embedded options, with each decision having ramifications on the future options available to the firm (Grenadier et al., 1997:398). A fundamental characteristic of technology real options is that future, but uncertain, profit opportunities are included in their valuation.

For patents, such opportunities include potential synergies (broadly defined) with other patents to be granted in the future. This is because patent value is, to a certain extent, dependent on other related patents and their value changes as technology landscapes evolve (Bessen, 2008, 2009; Parchomovsky et al., 2005). For example, a patent today could be seen as relatively peripheral to the development of a certain production process. However, this could change in the future if an
important subsequent invention builds (at least partly) on this patent. In this case, the value of the patent will increase and will enable the assignee firm to reap additional benefits. Alternatively, a patent could become part of a thicket or pool with other company patents in the future, again resulting in increased negotiating power and ability to extract licensing fees on the part of the assignee firm.

The propensity of acquirers to buy targets with patents then will increase with the value of patent real options. However, real option valuation is not exogenously determined but rather depends on firm characteristics (McGrath, 1997; Miller et al., 2004). As McGrath (1997:980) observes, the value of a particular technology option is deeply embedded in the strategic context of the firm and cannot be considered apart from it. In the case of patent real options, the technological diversity of the acquirer’s patent portfolio is likely to increase their value and, consequently, the probability of acquiring a target with patents.

The underlying mechanism here is an increase in the option’s ‘scope of opportunity’, or variance (McGrath et al., 2004). More diverse patent portfolios increase the scope for generating synergies in the future with any given patent because they allow for interdependencies to develop with a wider range of technologies. In contrast, highly concentrated patent portfolios are less likely to exhibit such volatility in synergy potential as there are less technology areas to allow for them to develop. Hence, patent options will exhibit lower variance when combined with highly concentrated patent portfolios and higher variance for less concentrated patent portfolios. Given a fixed price option, higher variance equals higher value in technology options (McGrath et al., 2004; McGrath, 1997).

Of course, this relationship is mediated by the characteristics of the underlying technology. As explained before, the synergy potential described here is primarily a characteristic of industries using complex technologies. Patents develop interdependencies in these settings resulting from the cumulativeness of innovation. In discrete technology industries, such synergies are unlikely to be expected and included in option pricing. Hence, we expect the real options reasoning described above to play a role only in industries using complex technologies.
This logic is evident in the aggressive patenting strategies of firms, often labeled as patent races (Hall et al., 2001b; Lerner, 1997). Hall et al. (2001b:104) demonstrate that the patenting behavior of semiconductor firms is not driven by a desire to win strong legal rights to a standalone technological prize but primarily aims at reducing concerns about being held up by external patent owners and at negotiating access to external technologies on more favorable terms. Ziedonis (2004) similarly points to the forward-looking, strategic motives for patenting by demonstrating that aggressive patenting is increased when ex ante contracting costs are expected to be high.

_Hypothesis 3: Acquirers are less likely to buy target with patents when their patent portfolio is concentrated across few technology areas. However, this relationship holds only in industries using complex technologies._

**Patent litigation threat**

In theory, the patent system grants exclusion rights to patent holders over clearly defined parts of the technology space. In practice, however, patent protection has imperfections and infringement, be that deliberate or not, is not uncommon (Bessen et al., 2006; Choi, 1998). For example, Bessen et al. (2005b) calculate a litigation hazard of 1.18% of lawsuits per patent and Lanjouw et al. (2004b) report a rate of 1.04% lawsuits per patent (both figures based on public firms). Overall, the number of litigation suits has increased substantially after the mid-1980s while the threat of litigation is higher for small firms (Bessen et al., 2005b; Gallini, 2002).

Of course, the observed cases of patent litigation are uncharacteristic of the entire population of patent disputes. This is formally expressed in litigation models where patent disputes are endogenized by allowing for costly monitoring and imitative behavior (Bessen et al., 2006; Crampes et al., 2002). In a series of papers, Bessen and Meurer develop a model that identifies four possible outcomes – acquiesce, settlement, litigation and deterrence – based on the probability of winning an infringement suit (Bessen et al., 2005b; Bessen et al., 2006; Meurer, 1989). Litigation occurs when deterrence is not strong enough or when the costs of
settlement exceed those of litigation. Patent suits then represents a failure of both parties to reach agreement.

Nevertheless, patent litigation is costly and entails significant uncertainty. The American Intellectual Property Law Association estimated in 2007 that the average cost of a patent dispute, including the cost of discovery, is between $3 and $5 million. These costs are substantial and put limits on the patenting behavior of firms. For example, Lerner (1995) found that firms with high litigation costs avoid technology areas where rivals hold patents. Indirect litigation costs, resulting from business disruption or preliminary injunctions, can be even higher. Using an event study, Bessen et al. (2007:4) found that firms lose about half a percentage point of their stock market value upon being sued for patent infringement, corresponding to a mean cost of $28.7 million ($1992). Plaintiffs also report significantly negative returns in some specifications (Bessen et al., 2007). In the presence of multiple infringing technologies, a patent suit risks the disruption of a cooperative equilibrium leading to a series of lengthy and costly suits (Bessen et al., 2005a; Gallini, 2002). Similar conclusions can be reached from theoretical models of litigation: the expected payoffs of either the plaintiff or the defendant are suboptimal in the litigation region. The plaintiff increases her profits by moving to the deterrence (i.e. deterring the competitor from infringing) region while the defendant increases her profits by moving to the settlement (i.e. agreeing on a licensing agreement) region (Bessen et al., 2006; Meurer, 1989).

Given this background it follows that when the threat of litigation is high, firms will try to move away from the litigation region. This can be achieved by increasing the size of their patent portfolio. Firms with large patent portfolios access competitors’ technologies more easily and better negotiate cross-licensing agreements (Grindley et al., 1997; Hall et al., 2001b). In addition, a large patent portfolio deters competitors from suing as the alleged infringer is more likely to retaliate with a countersuit (Bessen et al., 2005a, 2005b). The strategy of amassing patents in order to avoid being threatened by litigation is commonly referred to as ‘defensive patenting’ and has been shown to reduce firm litigation risk in a number of industries (Gallini, 2002; Lanjouw et al., 2001). Since a larger patent portfolio
reduces litigation risk, we expect that acquiring firms are more likely to buy target with patents when the threat of litigation they face is high. Specifically:

_Hypothesis 4: Acquirers are more likely to buy targets with patents when the threat of patent litigation for the acquirer is high._

DATA AND METHODOLOGY

Data

The sample of acquisitions we use to test our hypothesis comes from Securities Data Company’s (SDC) M&A database. We select deals with announcement dates between 1990 and 2002 and where both the target and acquirer are US firms. In addition, the following conditions must be satisfied:

1. The acquirer is a public company and has data in CRSP, Compustat and the NBER patent database (at least one patent granted 10 years prior to the deal).
2. The acquirer bought more than 50% of target’s shares and the target is either a public or private firm (but not a subsidiary). This is to ensure that the ownership of patent rights was transferred along with other corporate resources.
3. The deal was completed and the deal value is equal to or greater than $1 million.
4. The acquirer’s primary SIC code is either in electronics (SIC 36) or chemicals (SIC 28). These two industries are the textbook examples of complex and discrete technology industries so we focused on these ‘clear-cut’ cases (Arora et al., 2003; Cohen et al., 2000).

The final sample consists of 420 unique acquirers making 1,052 successful deals. We then matched our list of acquisitions with stock market data from CRSP, financial data from Compustat and patent data from NBER’s database (Hall et al., 2001a).

Following a number of studies (Bessen et al., 2005b; Lanjouw et al., 2001), we used Derwent’s Litalert database as the primary source of patent litigation data. It is important to note that Litalert has been found to suffer from underreporting (Lanjouw et al., 2001, 2004b). However, this is not a major concern for our study as underreporting is more pronounced prior to the mid-1980s (Hall et al., 2007). In
addition, underreporting does not introduce selection bias to the data (Bessen et al., 2005b; Lanjouw et al., 2004b).

**Dependent variables**

**Acquirer’s returns**

Acquirer’s returns were calculated using standard event study methodology (Brown et al., 1985; Khotari et al., 2007). We calculated cumulative abnormal returns (CAR) over a five-day window surrounding the announcement date [-2,2] using the CRSP value-weighted index as market benchmark. Expected returns were calculated based on firm-specific parameters obtained over a 259-trading day estimation window [-270,-11].

Short-horizon event studies are preferred for measuring acquisition performance given that they minimize the impact of other confounding events and are more robust to different model specifications (MacKinlay, 1997; McWilliams et al., 1997). In addition, several studies have demonstrated that CAR are strongly correlated with other long-term acquisition performance measures (Healy et al., 1992; Kaplan et al., 1992).

**Target with patents**

For the selection model (Hypotheses 2-4) we used a binary variable equal to one when the target firm had at least one patent granted 10 years prior to the announcement date, zero otherwise.

**Independent variables**

**Common citation rate**

We use common citation rate to test Hypothesis 1a and 1b. This is calculated as in Mowery et al. (1998:513), i.e. the ratio of citations in acquirer’s patents to patents cited in target’s patents divided by the number of total citations in acquirer’s patents (and then added to that the equivalent ratio for the target firm). The ratio is calculated for patents granted up to 10 years prior to the announcement date. The only difference in our calculation is that we weigh this ratio with citations received by patents with common cites as follows:
common cit. rate(Acq, Tar) = \frac{\left(\sum_{p_a=1}^{N} citr_{pa} (1 - \delta)^{t-T} / citm_{pa} \right) \left(\sum_{p_a=1}^{N} citr_{pa} (1 - \delta)^{y-T}\right)}{\sum_{p_a=1}^{N} citr_{pa} (1 - \delta)^{y-T}} \\
+ \frac{\left(\sum_{p_t=1}^{N} citr_{pt} (1 - \delta)^{y-T} / citm_{pt} \right) \left(\sum_{p_t=1}^{N} citr_{pt} (1 - \delta)^{y-T}\right)}{\sum_{p_t=1}^{N} citr_{pt} (1 - \delta)^{y-T}}

where \(citr_{pa}\) is the number of citations received by patent \(p\) in acquirer \(a\)’s portfolio, \(citr_{pt}\) is the number of citations received by patent \(p\) in target \(t\)’s portfolio, \(citm_{pa}\) is the number of citations made (to other patents) by patent \(p\) in acquirer \(a\)’s portfolio, \(citm_{pt}\) is the number of citations made (to other patents) by patent \(p\) in target \(t\)’s portfolio, \(y\) is the year the acquisition took place, \(T\) is the year patent \(p\) was granted and \(\delta\) is a depreciation rate set equal to 15% following convention in much of the literature (Hall et al., 2005; Pakes, 1985). Measures of citations received are corrected for truncation as in Hall et al. (2001a).

Mowery et al. (1998:513) explain that common citation rate measures the degree to which two firms draw from the same external technology pool. Hence, this measure captures the unique technological links and interdependencies developed by patenting firms. However, by using discounted citation-weighted patent counts as opposed to simple patent counts, we are able to account for the relative importance of the common citation pool for the merged entity (Hall et al., 2005; Trajtenberg, 1990).

- Insert Figure 1 around here -

Figure 1 provides a simple example of calculating the common citation rate for the acquiring firm. In this case, the citation-weighted common citation rate is 0.32% while the unweighted common citation rate is 0.22%. The citation-weighted rate is higher because it accounts for the fact that the acquirer’s most important patent, as demonstrated by the high number of citations received, cites a patent also cited by the target’s patents. In addition, this rate is slightly lower compared to the one not accounting for patent age (0.34%), because the patents with common cites are older than the average age of other patents in the portfolio. Clearly, the citation-weighted measure captures additional information related to the technological relationship between the target and acquirer and is thus preferable.
Patent productivity

Patent productivity of the acquiring firm is measured as the natural logarithm of citation-weighted count of patents granted per R&D expenses during a 10-year period prior to the acquisition:

\[
\text{patent productivity}_a = \sum_{pa=1}^{N} \frac{citr_{pa}}{\sum_{t=-10}^{0} R&D_{at}}
\]

where \(citr_{pa}\) is the number of citations received by patent \(p\) in acquirer \(a\)'s portfolio and \(R&D_{at}\) is annual R&D expenses incurred by the acquiring firm \(a\) in year \(t\) prior to the acquisition. Again, the rationale for not using simple patent counts is to account for the quality and importance of patenting output.

Patent technological concentration

To measure the acquirer’s patent technological concentration we use a simple Herfindahl index of the distribution of the acquirer’s patents across US patent classes:

\[
\text{patent technological concentration} = p_a \sum_{j=1}^{f} \left( \frac{p_{aj}}{p_a} \right)^2 - 1 \bigg/ p_a - 1
\]

where \(p_a\) is the number of patents in the acquiring firm’s portfolio and \(p_{aj}\) is the number of patents in US patent class \(j\). This formula is a variation of the standard Herfindahl index used in the literature but adjusted, as suggested by Hall (2002), for producing non-biased estimates when the number of observations is small. See also Ziedonis (2004) and Garcia-Vega (2006) for examples of other studies using this non-biased estimator.

Patent litigation threat

Litigation threat is measured as the number of firms that were either plaintiff or defendant in a case involving patents held by the acquirer and initiated during a 10-year period prior to the deal. This measure is well-placed to reflect litigation threat as the lag between filing a patent suit and reaching a resolution can be considerable, in excess of 5 years in several cases (Hall et al., 2003; Kesan et al., 2006). During this time, the two parties are involved in ongoing negotiations, adjusting their positions according to changes in their patent portfolio. In addition, past litigation is indicative
of a firm’s inability to negotiate a settlement or deter a competitor from suing. Hence, past litigation cases capture some unobservable firm characteristics that increase the litigation hazard faced by the firm.

Although Litalert provides detailed data on litigation, we chose not to count individual cases. This is because litigants usually target each other’s patents in a number of lawsuits while trying to maximize their negotiating power (Bessen et al., 2005a, 2007). Hence, counts of discrete litigants more accurately reflect litigation threat.

**Control variables**

**Acquirer’s returns**

There is a considerable literature, primarily in finance, relating acquirer’s returns with other acquirer, target and deal characteristics. We therefore include a number of control variables in our analysis.

Acquirer characteristics. Financial leverage, calculated here as total liabilities divided by market capitalization, has been shown to have a positive effect on abnormal returns (Maloney et al., 1993). Cash available, here as the percentage of cash out of total assets, proxies agency costs and is found to be negatively correlated with acquirers’ returns (Harford, 1999). Tobin’s Q, here as market capitalization divided by book value of assets, has been shown to be both positively and negatively correlated with abnormal returns (Moeller et al., 2004; Servaes, 1991). We also include a measure of acquisition experience, i.e. a count of acquisitions undertaken by the acquirer in a 5-year period prior to the announcement date. This controls for acquirer’s learning in managing the acquisition process and information revealed about the acquirer’s internal growth opportunities (Fuller et al., 2002; Hayward, 2002). Finally, we include information on operating cash flow divided by assets (Moeller et al., 2004; Moeller et al., 2005), R&D intensity, firm size (natural logarithm of sales), industry (a dummy variable equal to one if the acquirer’s primary SIC code is in electronics, zero otherwise) and patent portfolio (discounted citation-weighted count of patents\(^1\) and technological

---

1 This is calculated as the denominator of the first fraction in the formula for common citation rate.
2 Our results are almost identical when using Heckman’s two-step estimation.
concentration of patents across US patent classes for patents granted up to 10 years prior to the announcement date).

Deal characteristics. There is robust evidence that the method of payment affects abnormal returns in corporate takeovers. For example, Fuller et al. (2002) and Chang (1998) have shown that equity-financed deals yield lower abnormal returns for the acquirer. Here, we include two dummy variables equal to one for deals financed solely either with cash or equity. In addition, we calculate a measure of operational proximity based on SIC codes. This measure is equal to 4 when the target and acquirer are in the same 4-digit SIC code, equal to 3 when target and acquirer are in the same 3-digit SIC code etc. Although some studies use this continuous measure of distance across SIC codes, such an approach has been criticized for assuming that industries equally distant within the SIC hierarchy are equally dissimilar (Lien et al., 2009). Hence, we include instead a set of four dummy variables representing each case. We also include a measure of relative size, here as deal value divided by the acquirer’s market capitalization. This has been shown to affect abnormal returns, although the direction of the relationship is not clear (Asquith et al., 1983; Fuller et al., 2002; Moeller et al., 2004). Finally, a variable equal to one if the acquisition was a tender offer is included (Jarrell et al., 1989).

Target characteristics. We include a dummy variable equal to one if the target firm is public. Several studies have shown a negative correlation between target public status and acquirer’s returns. However, the proposition that markets for private firms are less competitive has not received support (Chang, 1998). To better control for the level of competition in takeover markets we calculate a liquidity index for the target, adapted from Schlingemann et al. (2002), as the number of deals that took place in a particular year and three-digit SIC code. Finally, we calculate measures of patent portfolio quality and concentration (same as acquirer characteristics).

Selection of target with patents

For testing hypotheses 2-4 we include the following control variables: cash available, R&D intensity, firm size, acquirer experience and industry, all defined as above. In addition, we include a measure of profitability, EBITDA divided by sales,
and the percentage of acquisitions (out of the total number of acquisitions 5 years prior to the announcement date) by the acquiring firm where the target had at least one patent in her portfolio.

**Econometric specifications**

Because we operationalize unique synergies through common citations, we are only able to calculate this measure when target firms have patents in their portfolio. However, this is not the case for the majority of targets in our sample. This could introduce sample selection bias to our estimates as we effectively use a nonrandom sample of the population to test Hypotheses 1a and 1b (Heckman, 1979). To correct for this, we used regression analysis with sample selection or, as it is more commonly known, a Heckman selection model. The selection equation models the propensity to acquire a target with patents while the outcome equation estimates a model of abnormal returns while accounting for sample selection. We used full-information maximum likelihood (FIML) estimator, as opposed to Heckman’s two-step method, given that FIML estimator is generally preferable\(^2\) (Kazumitsu, 1994; Manning *et al.*, 1987; Puhani, 2000).

Tables 1 and 2 present descriptive statistics and correlations of the variables included in the selection and outcome equation respectively.

- Insert Table 1 & 2 around here -

**ANALYSIS AND RESULTS**

Table 3 presents the results from the event study. Acquirers’ returns are overall positive and significant while the median is negative. Yet, returns lose significance when we allow for event-induced variance (Boehmer *et al.*, 1991). Consistent with the literature, we find acquirers’ returns are positive for private targets but negative for public targets. In fact, the higher percentage of public targets in chemicals explains the relatively lower abnormal returns as compared to those in electronics. Interestingly, mean dollar returns are negative, indicating that larger acquirers perform worse than smaller ones (Moeller *et al.*, 2004).

- Insert Table 3 around here -

\(^2\) Our results are almost identical when using Heckman’s two-step estimation.
Table 4 presents the results from the analysis of acquirers’ propensity to buy targets with patents (probit models). We find strong support for Hypotheses 2 and 4. In particular, the marginal effects (at variables’ mean) are positive and significant for litigation threat and negative and significant for patent productivity in all models. Hence, as suggested by Hypothesis 2, acquiring firms with strong internally-generated patenting output are less inclined to buy targets with patents. In addition, litigation threat has a strong positive effect on the probability of acquiring a target with patents (Hypothesis 4). Marginal effects are quite sizeable, with a single-unit increase in the number of litigants resulting in almost 50% higher probability of acquiring a target with patents.

Of course, the significance of marginal effects, albeit informative, is not a definitive test of the hypothesized relationship given that they vary with the value of all model variables. In fact, marginal effects at variables’ mean do not necessarily capture the ‘average’ effect of each variable, especially when mean observations vary across variables (Hoetker, 2007; Train, 1986). We thus followed Hoetker (2007) and Wiersema et al. (2009) and calculated the value and statistical significance of the marginal effects at each observation – see Figure 2. For patent productivity, panel (a), z-statistic values range from -0.17 to -2.1 and the majority of them lie below the -1.96 threshold. Similarly, z-statistic values for the marginal effects of litigation threat, panel (b), range from 0.17 to 7.3 and most of them lie above the 1.96 threshold. This supplementary analysis further supports the robustness of the hypothesized relationships.

For Hypothesis 3, we are interested in evaluating the coefficient of the interaction term between technological concentration and complex industry (=1 if in electronics). However, it is important to avoid modeling interactions in probit

---

3 The solid symbols indicate values of the marginal effect (recorded on the left axis) while the diamond shaped symbols indicate z-statistic values (recorded on the right axis) following Wiersema et al. (2009:684).

4 As Wiersema et al. (2009:684) explain, the lack of significance at extreme probability values is to be expected. It reflects that the slope of the probit cumulative distribution function approaches zero at extreme ends of the distribution.
models as typically done in an OLS framework (Hoetker, 2007; Wiersema et al., 2009). Although we include an interaction term in model 3, this is not necessarily informative neither of the sign, nor of the significance of the hypothesized effect. Instead, a number of approaches have been put forward to test interaction effects in nonlinear models.

First, we split the sample in two along industry membership (Hoetker, 2007:338). We find that the marginal effects of technological concentration are negative and significant in electronics ($p=0.007$) but not in chemicals ($p=0.419$). We also performed Allison’s (1999) test\(^5\) and were able to reject the null hypothesis that the coefficient of technological concentration is the same across the two industries ($p=0.02$). Second, we calculated the ‘true’ marginal effects of the interaction term for each observation (Wiersema et al., 2009:686, eq.5) along with their $z$-statistic. As can be seen from Figure 3, panel (a), $z$-statistic values range from -0.02 to -2.36 and the majority of them are close to or below the -1.96 threshold.

Third, we followed Zelner (2009) and calculated the difference in predicted probabilities of buying a target with patents associated with a complex (versus discrete) technology industry. Panel (b) in Figure 3 maps the difference in predicted probabilities along with the 95 percent confidence intervals surrounding the predicted probabilities. These were produced using King et al.’s (2000) simulation-based approach\(^6\). The figure indicates that as technological concentration increases, the likelihood of buying target with patents decreases in complex technology industries. However, this effect is statistically significant for values of technology concentration higher than (approximately) 0.5, as only in this region the bars do not cross zero. Taken together, these results provide strong support for Hypothesis 3, suggesting that acquirers are less likely to buy a target with patents in complex technology industries when their patent portfolio is concentrated across few technology areas.

- Insert Figure 3 around here -
We now turn to the analysis of acquisition performance. Table 5 presents the results of regression analysis. Model 1 doesn’t account for the differential impact of common citation rate across the two industries. As a result, common citation rate doesn’t seem to affect acquisition performance. However, when we account for differences in technology characteristics we find strong support for our predictions. In particular, common citation rate is positive and significant in industries using complex technologies (Model 2) but negative and not significant in industries using discrete technologies (Model 3). The full model includes all observations and interacts common citation rate with a dummy variable equal to one when the acquirer’s primary SIC code is in electronics. Again, we find that common citation rate increases CAR but only in electronics.

- Insert Table 5 around here -

It is important to note that the negative effect of common citations on acquisition performance in chemicals was not expected. Although the effect is not robust to different specifications (see also robustness checks below), the coefficient is significant at 10% in Model 3. This is likely to be attributed to the correlation between common citation rate and similarity in past or current innovation projects. In particular, a number of studies focusing on the pharmaceutical industry demonstrate that diversification across drug discovery is beneficial (Girotra et al., 2007; Malerba et al., 2002). Hence, the negative effect of common citation rate in chemicals might actually capture the negative effect of reduced diversification in current and future innovation projects.

Other variables are also significant. As expected, acquirer’s returns are reduced when the target firm is public. In addition, Tobin’s Q is negatively correlated with abnormal returns. This result is consistent with the overvaluation hypothesis, i.e. high Q firms provide a negative signal about their true value to the market when announcing an acquisition (Dong et al., 2006). The effect of relative size is also negative and significant. We explained before that there is no consensus in the

---

7 As discussed before, for non-linear models it is important to correctly calculate the marginal effects in order to test the hypothesized effects. However, in the case of the Heckman model, the use of coefficient estimates is not problematic unless the variable appears in both the selection and outcome equation (Vance, 2009). This is not the case for common citation rate so interpretation is not affected by this concern.
literature about the direction of the effect. However, it is reasonable to expect a negative sign in high-tech industries. This is because a number of studies have demonstrated that integrating large knowledge bases entails significant organizational disruption and is likely to negatively affect future inventive performance (Ahuja et al., 2001; Cloodt et al., 2006).

Not surprisingly, we don’t find any significant effects of SIC proximity on acquirers’ returns. None of the dummies enters significantly in the equation. This measure captures broad operational synergies that are unlikely to be unique between the target and bidding firms.

Robustness checks

Table 6 lists different models of acquirer’s returns. In Model 2 we used unweighted common citation rate, as originally in Mowery et al. (1998), while in Model 3 we measure weighted common citation rate but only for patents granted up to 5 years prior to the announcement date. Our results do not change. Results are also robust to different abnormal return specifications. In model 6, abnormal returns are calculated over a 7-day [-3,3] window while in model 7 S&P 500 is used as market benchmark.

It is possible of course that common citation rate captures broad synergies between the acquirer and the target’s innovative capabilities as opposed to unique synergies resulting from common citations. In this case, our model fails to accurately capture unique synergies as hypothesized. To account for this possibility we included in our model two measures of technological distance across patent space between the acquirer and target. Jaffe’s (1986:6) measure, Model 5, uses the uncentered correlation of two vectors including the number of patents in each US patent class for the acquirer and target respectively. Another measure, proposed by Paruchuri et al. (2006:553), measures the Euclidian distance of target and acquirer’s patents across US patent classes. Results remain essentially unchanged.

- Insert Table 6 around here -

Finally, we used alternative measures for Hypotheses 2, 3 and 4. Patent productivity was proxied using simple (as opposed to citation-weighted) patent counts. Patent portfolio technological concentration was calculated without
accounting for small-sample bias (Hall, 2002). Litigation threat was proxied using the number of litigants 5 years prior to the acquisition announcement and also the number of litigation cases 5 and 10 years prior to the acquisition announcement. All results hold.

**DISCUSSION AND CONCLUSION**

This paper contributes to the M&A literature by exploring the conditions under which acquisitions generate value for the acquiring firm. This is a central question for strategy research as acquisitions are some of the most important decisions in corporate history and can inadvertently affect firm survival and profitability (Jensen, 1986; Moeller et al., 2005). Interestingly, the popularity of corporate takeovers doesn’t seem to decline even though it is a well-known fact that acquirers, on average, fail to capture any value. However, the variance of acquirers’ returns is high, suggesting that some acquisitions do generate important benefits for the acquiring firm (Capron et al., 2002; Moeller et al., 2004).

We set out to empirically test Barney’s (1988) unique synergy hypothesis. According to this, acquirers capture part of the synergistic value created only when the resulting synergy cannot be replicated by other bidding firms. Barney’s hypothesis is a corollary of his work on strategic factor markets and profit opportunities under conditions of (near-perfect) competition in resource markets (Barney, 1986; Makadok et al., 2001). However, as with many other facets of resource-based theorizing, the empirical verification of this hypothesis has been problematic (Hoopes et al., 2003; Priem et al., 2001). Basically, it is challenging to *a priori* theorize about the likelihood of generating unique synergies.

To this end, we identified a suitable empirical context in technology acquisitions that also involve the transfer of patent rights from the target to the acquirer. The main premise of our analysis is that patent portfolio relatedness (measured through common citations to other patents) generates unique synergies in industries using complex technologies but has no effect in industries using discrete technologies. This claim is backed by an extensive and well-established literature on differences in patent value and use across industries and technologies (Cohen et al., 2000; Levin et al., 1987; Merges et al., 1990). Our results strongly support Barney’s hypothesis and
the notion that acquirers should primarily focus on identifying unique synergies with the target.

In addition, we examine the propensity of technology acquirers to buy targets with patents. Building on previous studies exploring the determinants of technology acquisitions, we extend this inquiry into the specific nature and selection of technology resources. Although there is increased evidence that technology acquirers have low R&D intensity and patent quality (Blonigen et al., 2000; Hitt et al., 1991; Zhao, 2009), we know less about their strategies of selecting targets. Here, we find that acquirers with low patent productivity, low concentration of patents in complex technologies and high threat of litigation are more likely to buy targets with patents. These results provide more clarity to the motives of technology acquirers and emphasize their diverse motives.

**Implications for resource-based theories of acquisitions**

Our results suggest that a theory of surplus value, or synergy, is an important precondition for understanding value capture in acquisitions. Consequently, the resources of merged entities should be compared at a much finer level of analysis, as opposed to simply looking at common SIC codes. This requires an in-depth understanding of the nature and characteristics of resource interdependence. Although theories of similarity, relatedness or complementary differences make intuitive sense, their predictions are unlikely to be true for every kind of acquisition. In some cases, complementary differences contribute to acquisition performance while in others neither similarity nor complementarity seem to matter (Harrison et al., 1991; Kim et al., 2009).

The reason is that each type of resource has a unique ‘production function’ with different parameters coming into play. Hence, a general theory of acquisition performance based on simple resource comparisons is unlikely to emerge. In the case of combining patent rights, we find that citation patterns and the nature of the underlying technology are important determinants of value capture. Had we not accounted for these specific characteristics, this would have been another study disproving the relatedness hypothesis but offering no explanation for the observed heterogeneity in acquisition performance.
At a more general level, these results pertain to strategy’s core interest in understanding performance differences and patterns of firm growth resulting from preferential access to resources (Penrose, 1959; Wernerfelt, 1984). Although theories of superior expectations, idiosyncratic information and capabilities have been instrumental in highlighting the conditions for achieving above average profitability (Barney, 1986; Denrell et al., 2003; Makadok, 2001; Makadok et al., 2001), little effort has been put into identifying what resource combinations generate surplus value. This is despite agreement that resource value is largely dependent on other resources in a firm’s portfolio (Adegbesan, 2009; Ichniowski et al., 1997; Milgrom et al., 1995). Our study provides a methodology for identifying resource synergies that is not subject to the tautology critique and could be used for the valuation of resources other than patent rights.

**Implications for technology strategy**

This paper also contributes to the technology strategy literature by pointing to the importance of M&As as avenues for accessing patented technologies. From the deals in our sample, roughly 38% involve the transfer of patent rights. This corresponds to more than 12,000 patents changing ownership in two industries (SIC36 and SIC28) over a 12-year period⁸. In comparison, the total number of traded patent (i.e. patent assignments) for corporate inventors in the US over a 21.5-year period is 139,432 (Serrano, 2010). This suggests that technology acquisitions are an important, albeit underexplored, component of markets for technology (Arora et al., 2001; Arora et al., 2010). Recognizing technology acquisitions as an alternative channel for technology exchange other than patent trades and technology licensing, would help better understand the function of markets for technology and their apparent lack of development (Arora et al., 2010).

In addition, these findings reinforce the notion that patent value is driven by the characteristics of the assignee firm. Although an extensive literature tackling the problem of measuring patent value has developed (Bessen, 2008; Hall et al., 2005; Jensen et al., 2011; Pakes, 1986), little attention is paid to individual assignee firm

---

⁸ This figure underestimates the total amount of patents due to the sampling criteria of this study and missing values.
characteristics beyond size. Most of the emphasis lies in heterogeneity in patent value across industries. Yet, we demonstrate here that the composition of the patent portfolio and the links between patented technologies can generate important value for the assignee firm. These results echo assertions that patent value is endogenous and that the value of patented technologies lies in their aggregation (Bessen, 2008; Parchomovsky et al., 2005). Management theorists have long acknowledged the importance of access to complementary assets as a mediating factor for capturing value from patented technologies (Arora et al., 2006; Teece, 1986), but it is important to extend this logic to the composition and design of patent portfolios.

Limitations and future avenues for research

Of course, this study is not without limitations. First, as a result of our sampling frame and methodology, we focused only on acquirers’ returns. Unfortunately, it is extremely difficult to come up with acquisition performance measures in the case of private targets. It would be interesting nevertheless to explore overall acquisition performance and measure the total surplus value generated from the transfer of patent rights. This would allow us to better evaluate what combinations of patent rights are profitable and also to explore the distribution of synergistic gains between the target and acquirer.

Second, like any study focusing on specific industries, we cannot be certain about the generalizability of our results. We chose the chemicals and electronics industries because the specific characteristics of patent rights in these two industries enabled us to isolate the effect of interest. We are confident though that the general prescriptions and insights of the paper hold true, at least in industries where patents are important means of competition. Naturally, additional work in different settings would help extend our understanding of resource redeployment and the associated costs and benefits.

Third, this study is less informative about the actual process of resource transfer and redeployment. We essentially assume that this process is automatic and cost-free. This is a reasonable assumption when considering the merge of patent portfolios, given that patent rights primarily function as a deterrent for competitors.
Yet, this is not necessarily true for other types of resources like tacit knowledge, star scientists or marketing experience. Other studies have demonstrated that there are significant costs and challenges involved in these cases that can influence acquisition performance (Capron, 1999; Capron et al., 1998; Paruchuri et al., 2006).

Finally, the literature on technology acquisitions would benefit by further exploring the heterogeneity of target firms. The majority of studies in the field view targets as inputs to the acquirers’ innovation function with little or no consideration for their characteristics. Here, we demonstrate that the ownership (or not) of patents by the target significantly affects acquirers’ selection. Additional characteristics are likely to affect target selection and acquisition performance though. For example, what types of acquirers select targets with diverse patent portfolios? Or, how does the selection of targets with a focus on radical innovations affect acquirers’ subsequent inventive performance?

We believe that this study helps elucidate one of the central questions in strategic management, that of value capture in corporate acquisitions. It is important to further extend this line of inquiry in order to better understand how resource redeployment contributes to acquisition performance.
REFERENCES


Table 1. Summary statistics and pairwise correlations of variables used in selection equation (N=1052).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>St.Dv.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deal with patents</td>
<td>0.38</td>
<td>0.49</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Litigation threat</td>
<td>0.75</td>
<td>2.34</td>
<td>0.40*</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Patent productivity</td>
<td>3.50</td>
<td>1.53</td>
<td>0.03</td>
<td>0.09*</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tech. concentration</td>
<td>0.26</td>
<td>0.29</td>
<td>-0.10*</td>
<td>-0.17*</td>
<td>-0.32*</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cash available</td>
<td>0.66</td>
<td>0.47</td>
<td>-0.05</td>
<td>-0.12*</td>
<td>0.08*</td>
<td>0.06</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Acq. R&amp;D intensity</td>
<td>0.22</td>
<td>0.20</td>
<td>-0.06</td>
<td>-0.11*</td>
<td>-0.15*</td>
<td>0.19*</td>
<td>0.08*</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Acq. sales (log)</td>
<td>0.15</td>
<td>0.19</td>
<td>-0.01</td>
<td>-0.06</td>
<td>-0.27*</td>
<td>0.07*</td>
<td>0.06*</td>
<td>0.40*</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Electronics</td>
<td>6.14</td>
<td>2.31</td>
<td>0.17*</td>
<td>0.41*</td>
<td>0.03</td>
<td>-0.39*</td>
<td>-0.05</td>
<td>-0.38*</td>
<td>-0.28*</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Profitability</td>
<td>0.07</td>
<td>0.32</td>
<td>0.11*</td>
<td>0.16*</td>
<td>0.05</td>
<td>-0.18*</td>
<td>0.13*</td>
<td>-0.34*</td>
<td>-0.44*</td>
<td>0.60*</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Acq. experience</td>
<td>2.43</td>
<td>3.78</td>
<td>0.05</td>
<td>0.37*</td>
<td>0.06</td>
<td>-0.20*</td>
<td>0.05</td>
<td>-0.15*</td>
<td>0.05</td>
<td>0.38*</td>
<td>0.15*</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Acq. past deals with patents (%)</td>
<td>0.31</td>
<td>0.50</td>
<td>0.09*</td>
<td>0.25*</td>
<td>0.05</td>
<td>-0.14*</td>
<td>-0.06*</td>
<td>-0.08*</td>
<td>-0.04</td>
<td>0.23*</td>
<td>0.13*</td>
<td>0.12*</td>
<td>1</td>
</tr>
</tbody>
</table>

* p ≤ 0.05
<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Liquidity index</td>
<td>0.12*</td>
<td>0.32*</td>
<td>0.13*</td>
<td>0.12*</td>
<td>0.01</td>
<td>0.13*</td>
</tr>
<tr>
<td>SIC proximity</td>
<td>0.05</td>
<td>0.07</td>
<td>0.11</td>
<td>0.05</td>
<td>0.06</td>
<td>0.07</td>
</tr>
<tr>
<td>Relative size</td>
<td>0.11</td>
<td>0.21</td>
<td>0.14</td>
<td>0.21</td>
<td>0.11</td>
<td>0.25*</td>
</tr>
<tr>
<td>Tender</td>
<td>0.53*</td>
<td>0.12*</td>
<td>0.12*</td>
<td>0.54*</td>
<td>0.17*</td>
<td>0.21*</td>
</tr>
<tr>
<td>Equity only</td>
<td>0.15*</td>
<td>0.18*</td>
<td>0.15*</td>
<td>0.35*</td>
<td>0.37*</td>
<td>0.08</td>
</tr>
<tr>
<td>Tobin'Q</td>
<td>0.38*</td>
<td>0.39*</td>
<td>0.10</td>
<td>0.25*</td>
<td>0.33*</td>
<td>0.12*</td>
</tr>
<tr>
<td>Tender</td>
<td>0.53*</td>
<td>0.12*</td>
<td>0.12*</td>
<td>0.54*</td>
<td>0.17*</td>
<td>0.21*</td>
</tr>
<tr>
<td>Equity only</td>
<td>0.15*</td>
<td>0.18*</td>
<td>0.15*</td>
<td>0.35*</td>
<td>0.37*</td>
<td>0.08</td>
</tr>
<tr>
<td>Tobin'Q</td>
<td>0.38*</td>
<td>0.39*</td>
<td>0.10</td>
<td>0.25*</td>
<td>0.33*</td>
<td>0.12*</td>
</tr>
</tbody>
</table>

Table 2: Summary statistics and pairwise correlations of variables used in outcome equation (N=354).
Table 3. Abnormal returns are estimated using the market model with CRSP value weighted index as market benchmark. Dollar returns (in millions) are calculated by multiplying the cumulative abnormal returns by the acquirer’s market capitalization 11 trading days prior to the announcement date. t-statistic calculated as in Brown et al. (1985).

<table>
<thead>
<tr>
<th>Panel A: Acquisitions in Electronics</th>
<th>Observations</th>
<th>Average (median) ( CAR_{(-2,2)} )</th>
<th>Average (median) dollar returns</th>
<th>t-statistic (one-tailed)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Public targets</td>
<td>107</td>
<td>-1.75% (-1.94%)</td>
<td>-572.29 (-5.70)</td>
<td>-3.03**</td>
</tr>
<tr>
<td>Private targets</td>
<td>585</td>
<td>0.81% (0.24%)</td>
<td>-79.56 (0.30)</td>
<td>3.12**</td>
</tr>
<tr>
<td>Total</td>
<td>692</td>
<td>0.41% (-0.06%)</td>
<td>-155.75 (-0.06)</td>
<td>1.75*</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Acquisitions in Chemicals</th>
<th>Observations</th>
<th>Average (median) ( CAR_{(-2,2)} )</th>
<th>Average (median) dollar returns</th>
<th>t-statistic (one-tailed)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Public targets</td>
<td>105</td>
<td>-1.80% (-1.01%)</td>
<td>-514.69 (-19.04)</td>
<td>-4.08**</td>
</tr>
<tr>
<td>Private targets</td>
<td>255</td>
<td>1.14% (0.22%)</td>
<td>-50.52 (0.41)</td>
<td>3.43**</td>
</tr>
<tr>
<td>Total</td>
<td>360</td>
<td>0.28% (-0.11%)</td>
<td>-185.91 (-0.65)</td>
<td>1.06</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C: All acquisitions</th>
<th>Observations</th>
<th>Average (median) ( CAR_{(-2,2)} )</th>
<th>Average (median) dollar returns</th>
<th>t-statistic (one-tailed)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Public targets</td>
<td>212</td>
<td>-1.78% (-1.14%)</td>
<td>-543.76 (-12.55)</td>
<td>-4.87**</td>
</tr>
<tr>
<td>Private targets</td>
<td>840</td>
<td>0.91% (0.23%)</td>
<td>-70.74 (0.35)</td>
<td>4.40**</td>
</tr>
<tr>
<td>Total</td>
<td>1052</td>
<td>0.37% (-0.10%)</td>
<td>-166.07 (-0.21)</td>
<td>2.05*</td>
</tr>
</tbody>
</table>

* \( p \leq 0.10 \)  * \( p \leq 0.05 \)  ** \( p \leq 0.01 \)
Table 4. Probit estimates using a binary variable (=1 if target firm has patents, 0 otherwise) as dependent variable. Estimates of year dummies are suppressed and *p*-values are reported in parentheses. Marginal effects are calculated with the other variables at their mean value. Robust standard errors clustered by acquirer are used in all models.

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficients</td>
<td>Marginal effects</td>
<td>Coefficients</td>
</tr>
<tr>
<td>Litigation threat</td>
<td>1.267***</td>
<td>0.482**</td>
<td>1.289**</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Patent productivity</td>
<td>-0.070*</td>
<td>-0.027*</td>
<td>-0.070*</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.032)</td>
<td>(0.046)</td>
</tr>
<tr>
<td>Tech. concentration</td>
<td>-0.155</td>
<td>-0.058</td>
<td>-0.280</td>
</tr>
<tr>
<td></td>
<td>(0.398)</td>
<td>(0.400)</td>
<td>(0.135)</td>
</tr>
<tr>
<td>Electronics</td>
<td>-0.040</td>
<td>-0.015</td>
<td>-0.070</td>
</tr>
<tr>
<td></td>
<td>(0.705)</td>
<td>(0.704)</td>
<td>(0.517)</td>
</tr>
<tr>
<td>Electronics x Tech.</td>
<td>-0.724*</td>
<td>-0.184**</td>
<td></td>
</tr>
<tr>
<td>concentration</td>
<td>(0.063)</td>
<td>(0.006)</td>
<td></td>
</tr>
<tr>
<td>Cash available</td>
<td>-0.188</td>
<td>-0.071</td>
<td>-0.237</td>
</tr>
<tr>
<td></td>
<td>(0.464)</td>
<td>(0.461)</td>
<td>(0.360)</td>
</tr>
<tr>
<td>R&amp;D intensity</td>
<td>0.287</td>
<td>0.110</td>
<td>0.271</td>
</tr>
<tr>
<td></td>
<td>(0.329)</td>
<td>(0.326)</td>
<td>(0.368)</td>
</tr>
<tr>
<td>Sales (log)</td>
<td>-0.056</td>
<td>-0.021</td>
<td>-0.051</td>
</tr>
<tr>
<td></td>
<td>(0.123)</td>
<td>(0.114)</td>
<td>(0.159)</td>
</tr>
<tr>
<td>Profitability</td>
<td>0.332*</td>
<td>0.127*</td>
<td>0.327*</td>
</tr>
<tr>
<td></td>
<td>(0.089)</td>
<td>(0.085)</td>
<td>(0.094)</td>
</tr>
<tr>
<td>Past deals with</td>
<td>-0.034</td>
<td>-0.013</td>
<td>-0.035</td>
</tr>
<tr>
<td>patents</td>
<td>(0.150)</td>
<td>(0.150)</td>
<td>(0.146)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.202</td>
<td>-0.048</td>
<td>-0.057</td>
</tr>
<tr>
<td></td>
<td>(0.321)</td>
<td>(0.691)</td>
<td>(0.633)</td>
</tr>
<tr>
<td>Year dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Chi²</td>
<td>35.77**</td>
<td>35.74**</td>
<td>40.05**</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-529.9</td>
<td>-523.8</td>
<td>-521.6</td>
</tr>
<tr>
<td>N</td>
<td>1052</td>
<td>1052</td>
<td>1052</td>
</tr>
</tbody>
</table>

*p ≤ 0.10  *p ≤ 0.05  **p ≤ 0.01
Table 5. Regression analysis with selection using cumulative abnormal returns CAR_{[-2,2]} as dependent variable. Selection model as Model 2 in Table 3. Full information maximum likelihood estimation is used. Estimates of year dummies are suppressed and p-values are reported in parentheses. Robust standard errors clustered by acquirer are used in all models.

<table>
<thead>
<tr>
<th></th>
<th>(1) No interaction</th>
<th>(2) Electronics</th>
<th>(3) Chemicals</th>
<th>(4) Full model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Common citation rate</td>
<td>0.029</td>
<td>0.057*</td>
<td>-0.092</td>
<td>-0.054</td>
</tr>
<tr>
<td></td>
<td>(0.393)</td>
<td>(0.040)</td>
<td>(0.092)</td>
<td>(0.182)</td>
</tr>
<tr>
<td>Common citation rate x</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Electronics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Acquirer Characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Electronics</td>
<td>-0.007</td>
<td>-0.010</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.541)</td>
<td>(0.404)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cash av.</td>
<td>-0.052</td>
<td>-0.125*</td>
<td>0.019</td>
<td>-0.051</td>
</tr>
<tr>
<td></td>
<td>(0.278)</td>
<td>(0.076)</td>
<td>(0.741)</td>
<td>(0.293)</td>
</tr>
<tr>
<td>R&amp;D int.</td>
<td>0.011</td>
<td>0.050</td>
<td>-0.008</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>(0.721)</td>
<td>(0.201)</td>
<td>(0.855)</td>
<td>(0.702)</td>
</tr>
<tr>
<td>Litigation threat</td>
<td>0.000</td>
<td>0.002</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.955)</td>
<td>(0.684)</td>
<td>(0.810)</td>
<td>(0.830)</td>
</tr>
<tr>
<td>Citation-weighted portfolio (log)</td>
<td>-0.003</td>
<td>0.000</td>
<td>-0.008</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.409)</td>
<td>(0.898)</td>
<td>(0.123)</td>
<td>(0.378)</td>
</tr>
<tr>
<td>Tech. concentration</td>
<td>-0.000</td>
<td>-0.037</td>
<td>0.019</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.976)</td>
<td>(0.411)</td>
<td>(0.621)</td>
<td>(0.936)</td>
</tr>
<tr>
<td>Leverage</td>
<td>-0.007</td>
<td>-0.018</td>
<td>0.038</td>
<td>-0.008</td>
</tr>
<tr>
<td></td>
<td>(0.455)</td>
<td>(0.192)</td>
<td>(0.115)</td>
<td>(0.418)</td>
</tr>
<tr>
<td>Sales (log)</td>
<td>0.000</td>
<td>-0.003</td>
<td>0.002</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.982)</td>
<td>(0.633)</td>
<td>(0.695)</td>
<td>(0.956)</td>
</tr>
<tr>
<td>Op. cash flows/Assets</td>
<td>-0.024</td>
<td>-0.021</td>
<td>-0.006</td>
<td>-0.023</td>
</tr>
<tr>
<td></td>
<td>(0.507)</td>
<td>(0.740)</td>
<td>(0.888)</td>
<td>(0.525)</td>
</tr>
<tr>
<td>No past acquisitions</td>
<td>-0.000</td>
<td>-0.003</td>
<td>0.002*</td>
<td>-0.000</td>
</tr>
<tr>
<td></td>
<td>(0.699)</td>
<td>(0.241)</td>
<td>(0.014)</td>
<td>(0.977)</td>
</tr>
<tr>
<td>Tobin’s Q</td>
<td>-0.004*</td>
<td>-0.004</td>
<td>-0.002</td>
<td>-0.004*</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.215)</td>
<td>(0.429)</td>
<td>(0.024)</td>
</tr>
<tr>
<td>Target characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Citation-weighted portfolio (log)</td>
<td>-0.003</td>
<td>-0.000</td>
<td>-0.003</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.440)</td>
<td>(0.876)</td>
<td>(0.476)</td>
<td>(0.449)</td>
</tr>
<tr>
<td>Tech concentration</td>
<td>-0.001</td>
<td>0.025</td>
<td>-0.055*</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.923)</td>
<td>(0.357)</td>
<td>(0.021)</td>
<td>(0.898)</td>
</tr>
<tr>
<td>Public</td>
<td>-0.035*</td>
<td>-0.013</td>
<td>-0.063**</td>
<td>-0.036*</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.558)</td>
<td>(0.002)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Liquidity index</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.004</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.937)</td>
<td>(0.960)</td>
<td>(0.690)</td>
<td>(0.870)</td>
</tr>
<tr>
<td>Deal characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All cash</td>
<td>0.000</td>
<td>0.009</td>
<td>-0.014</td>
<td>0.0012</td>
</tr>
<tr>
<td></td>
<td>(0.968)</td>
<td>(0.685)</td>
<td>(0.485)</td>
<td>(0.943)</td>
</tr>
<tr>
<td>All equity</td>
<td>-0.014</td>
<td>-0.023</td>
<td>0.015</td>
<td>-0.014</td>
</tr>
<tr>
<td></td>
<td>(0.254)</td>
<td>(0.228)</td>
<td>(0.514)</td>
<td>(0.278)</td>
</tr>
<tr>
<td>Tender</td>
<td>0.002</td>
<td>-0.009</td>
<td>0.029*</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.855)</td>
<td>(0.765)</td>
<td>(0.068)</td>
<td>(0.958)</td>
</tr>
<tr>
<td>Relative size</td>
<td>-0.061*</td>
<td>-0.050</td>
<td>-0.075</td>
<td>-0.056*</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.197)</td>
<td>(0.102)</td>
<td>(0.043)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.093*</td>
<td>0.038</td>
<td>0.139*</td>
<td>0.089*</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.555)</td>
<td>(0.014)</td>
<td>(0.045)</td>
</tr>
<tr>
<td>SIC proximity dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Chi^2</td>
<td>77.16**</td>
<td>375.9**</td>
<td>182.4**</td>
<td></td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-137.9</td>
<td>-113.5</td>
<td>21.38</td>
<td>-137.4</td>
</tr>
<tr>
<td>N</td>
<td>304</td>
<td>193</td>
<td>111</td>
<td>304</td>
</tr>
</tbody>
</table>

*p ≤ 0.10  *p ≤ 0.05  **p ≤ .01
Table 6. Robustness checks. Control variables as in Model 4 in Table 4. Model 1 is the baseline model. In Model 2, common citation rate is not weighted by citations received. In Model 3, patents granted up to 5 years prior to the announcement date are used for the calculation of common citation rate. Model 4 and 5 control for Jaffe’s (1986) technological proximity and patent Euclidian distance (Paruchuri et al., 2006) respectively. In model 6 abnormal returns are calculated over a 7-day [-3,3] event window while in model 7 S&P index is used as market benchmark.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Common citation rate</td>
<td>-0.0544</td>
<td>-0.0476</td>
<td>-0.0516</td>
<td>-0.0824*</td>
<td>-0.0670</td>
<td>-0.0781</td>
<td>-0.0530</td>
</tr>
<tr>
<td></td>
<td>(0.182)</td>
<td>(0.210)</td>
<td>(0.191)</td>
<td>(0.076)</td>
<td>(0.109)</td>
<td>(0.119)</td>
<td>(0.204)</td>
</tr>
<tr>
<td>Common citation rate x Electronics</td>
<td>0.110*</td>
<td>0.109**</td>
<td>0.0927*</td>
<td>0.127**</td>
<td>0.106*</td>
<td>0.108*</td>
<td>0.111*</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.009)</td>
<td>(0.042)</td>
<td>(0.008)</td>
<td>(0.019)</td>
<td>(0.048)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Jaffe’s tech. proximity</td>
<td></td>
<td></td>
<td></td>
<td>0.0272</td>
<td></td>
<td></td>
<td>-0.0620</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.139)</td>
<td></td>
<td></td>
<td>(0.105)</td>
</tr>
<tr>
<td>Euclidian distance</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chi²</td>
<td>182.4</td>
<td>217.4</td>
<td>144.8</td>
<td>214.1</td>
<td>210.5</td>
<td>164.1</td>
<td>189.7</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-137.4</td>
<td>-137.3</td>
<td>-127.6</td>
<td>-136.3</td>
<td>-136.0</td>
<td>-160.6</td>
<td>-143.9</td>
</tr>
<tr>
<td>N</td>
<td>304</td>
<td>304</td>
<td>304</td>
<td>304</td>
<td>304</td>
<td>304</td>
<td>304</td>
</tr>
</tbody>
</table>

*p ≤ 0.10  * p ≤ 0.05  ** p ≤ .01
Acquirer*

 Patent space**

\[
\text{common cit. rate}(Acq) = \frac{(2 \times 0.85^5 / 2) + (9 \times 0.85^5 / 2)}{(2 \times 0.85^5) + (3 \times 0.85^4) + (9 \times 0.85^5) + (2 \times 0.85^4)}
\]

* Hexagons symbolize acquirer’s patents as well as the number of citations received by each patent and the number of years granted prior to the acquisition

** Hexagons symbolize different patents in the patent space while shaded hexagons are patents also cited by patents held by the target firm

Figure 1. Example calculation of common citation rate for the acquiring firm
Figure 2. Marginal effects of litigation threat and patent productivity on the probability of buying target with patents.
Figure 3. Interaction effect of complex technology on the relationship between technological concentration and probability of buying target with patents.