The Impact of Technological Distance on M&A Target Choice and Transaction Value

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ABASTRACT: *Using a sample of 538 M&A transactions covering public and private US firms in a wide range of predominantly high technology industries, I investigate how the innovation characteristics of the target as well as the technological and product market distance between the target and the acquirer affect the acquirer's choice of M&A targets and the transaction price. I match a set of non-chosen alternatives, either based on target sector affiliation and size or randomly, to each acquirer and estimate a conditional logit model. I show that the existence of an inverted U-shape relationship between technological distance and the likelihood of being chosen as a target is not very robust. Overall acquirers appear to prefer technologically close firms as targets. The higher the product market (technological) distance between the acquirer and the target, the more do acquirers prefer firms which are close in technological (product market) space. Regarding the role of acquirer characteristics, I find that the lower the acquirer's return on assets and patenting growth, the more technologically distant firms are chosen. The relationship between technological distance and the transaction price is also investigated parametrically and semi-parametrically, but no statistically robust inverted U-shape relationship is found. I also provide possible explanations for the apparent inconsistency between the evidence found herein and previous studies on the impact of technological distance on post M&A innovation performance. These comprise insufficient robustness checks of the post M&A evidence and management myopia.*

3.1 Introduction

Mergers and acquisitions (M&A) occur for a variety of reasons and these reasons differ significantly between industries and over time. One motivation to engage in M&A transactions, particularly in the most recent M&A wave and in industries such as ICT and pharmaceuticals, is related to technology and innovation (Chakrabarti, Hauschildt & Süverkrüp, 1994; Sleuwaegen & Valentini, 2006). M&A transactions allow companies to source existing technologies, thereby filling gaps in their technology portfolio quicker than is feasible via in-house development and possibly in areas that are too distant for profitable in-house development (Capron & Mitchell, 2009; Schweizer, 2005). Also, it provides a mechanism to learn about the other firm's technologies, to recombine knowledge and technologies residing in different firms and thereby to generate innovations (Kogut & Zander, 1992; Valentini & DiGuardo, 2012). In contrast to other channels for external technology sourcing, such as alliances, licensing or the purchase of patents, M&A provides a high degree of control, thereby alleviating agency and moral hazard problems, combined with the potential to effectively transfer tacit knowledge and complementary resources (Keil, Maula, Schildt & Zahra, 2008; Khanna, Gulati & Nohria, 1998; Ranft & Lord, 2002).

This study focuses predominantly on the role that technological distance plays in the selection of M&A targets and the transaction price.[1] It is built on the assumption that acquirers can successfully outbid other firms that expect fewer synergies from an M&A transaction, which is reflected in successful bids and the level of the transaction value (Barney, 1988; Grimpe & Hussinger, 2013; Hall, 1988a). Hence, I seek to investigate, inter alia, whether the expected synergies are highest when the acquirer and target exhibit a low, intermediate or high level of technological distance.

From a theoretical perspective, technological distance can be beneficial as well as detrimental. Proximity is likely to be associated with higher *contemporary* absorptive capacity, i.e. a higher ability to assimilate and apply the acquired knowledge as well as fewer information asymmetries regarding the assessment and valuation of the technological opportunity that a potential target offers (Cohen & Levinthal, 1990). Economies of scale are also more likely if two companies share the same methods of search, tools and procedures. With patents having strategic value in addition to embodying technological knowledge, acquiring a firm which has patents in technologically close fields may allow the acquirer to conduct its R&D activities in a less constrained manner and possibly to restrain competitors in their innovation efforts by erecting a patent fence (Grimpe & Hussinger, 2008, 2013). However, too much proximity is likely to constrain learning opportunities, gain of new knowledge and the acquisition of *future* absorptive capacity to assimilate and evaluate subsequent opportunities in the target's technology fields (Ahuja & Katila, 2001; Nooteboom, Van Haverbeke, Duysters, Gilsing & Van den Oord, 2007; Sapienza, Parhankangas & Autio, 2004).

[1] Authors have used the terms technological relatedness, technological proximity or technological overlap to refer to the same concept (e.g. Ahuja & Katila, 2001; Grimpe & Hussinger, 2013). Other authors have used the terms complementarity, fit or similarity (e.g. Marki, Hitt & Lane, 2010). As noted by Dehne (2013), there is a high degree of ambiguity in the use of the terms by different authors.

Existing empirical research has resulted in a “puzzle” that I seek to address in this study. On the one hand, abundant research has found that the innovation performance after the acquisition is best when the target and acquirer have an intermediate level of technological distance (Ahuja & Katila, 2001; Cloodt et al., 2006; Prabhu, Chandy & Ellis, 2005). On the other hand, studies that investigate the selection of M&A targets found that technologically close targets are preferred (AlAzzawi, 2008; Bena & Li, in press; Frey & Hussinger, 2012; Hussinger, 2010).[2] However, the post M&A evidence suggests that if increasing innovation performance is the objective of the acquirer, they should opt for firms which are neither too similar nor too distant. Does this imply that decision makers opt for the wrong type of M&A targets? I address this puzzle from an empirical, methodological and theoretical perspective.

For the empirical analysis, I construct a sample of 538 M&A transactions covering public and private US firms in a wide range of predominantly high technology industries. Using a conditional logit model, I find, inter alia, that the existence of an inverted U-shape relationship between technological distance and the likelihood of being chosen as a target is not very robust. The relationship between technological distance and the transaction price is also investigated parametrically and semi-parametrically, as the transaction price – after controlling for characteristics such as size and profitability – reflects the expected synergies from a transaction (Grimpe & Hussinger, 2013). Like for the target choice model, I find no statistically robust inverted U-shape relationship.

This study is structured as follows. Section 3.2 is an extensive review of the literature on the relationship between M&A and innovation. Section 3.3 derives the hypothesis for the empirical analysis. Section 3.4 presents the econometric models, the data, the measures and the descriptive statistics. Section 3.5 presents the results, including robustness checks. In section 3.6, I discuss the findings, point to limitations and provide suggestions for further research.

3.2 The interdependence between innovation and M&A

The interplay between M&A and innovation is a research field that has gained significant momentum recently. The following overview of the research on this relationship is adapted from the author’s Master of Business Research project study (Stellner, forthcoming). The particular focus is on (a) technological motivations of M&A, (b) the innovation characteristics

[22] Frey and Hussinger (2006) and Hussinger (2010) have tested for the existence of an inverted U-shape but did not find supporting evidence.

impacting the likelihood of becoming an acquirer or target in an M&A transaction, (c) the role that technological distance plays in post M&A performance and target choice and (d) the role of technological distance in alliance performance and partner choice.

3.2.1 Motivations to engage in M&A

The industrial organizations, corporate finance and strategic management literatures provide a long list of motivations for firms to engage in M&A transactions. These comprise increasing market power, diversification via entry into new markets (e.g. new countries, new end users or new part of the value chain through vertical transactions), efficiency related reasons such as economies of scale or scope and synergies (e.g. in production, marketing or R&D), exerting corporate control over badly managed targets, empire building, asset and capability sourcing and learning (Andrade, Mitchell & Stafford, 2001; Capron, Dussauge & Mitchell, 1998; Chakrabarti et al., 1994; Haspeslagh & Jemison, 1991; Jensen & Ruback, 1983; Seth, 1990). The industrial organizations literature has focused on a firm's incentives, which are a function of the profit impact (e.g. via economies of scale and scope as well as synergies) of M&A transactions (Berggren, 2003; Seth, 1990), the corporate control and corporate finance literature is concerned with agency issues, behavioral motivations of managers and capital market imperfections (Jensen & Ruback, 1983) while the strategic management literature has focused, inter alia, on core competencies and dynamic capabilities (Barney, 1988; Capron, 1999).

What I am most concerned with in this overview is that some acquirers use M&A for reasons related to technology and innovation, including technological learning, innovation synergies, technology sourcing and strategic aspects relating to technology (Ahuja & Katila, 2001; Bower, 2001; Cantwell & Santangelo, 2006; Chakrabarti et al., 1994; Cohen & Levinthal, 1989; Granstrand, Bohlin, Oskarsson & Sjöberg, 1992; Grimpe & Hussinger, 2008, 2013; Keil, Maula, Schildt & Zahra, 2008; Schweizer, 2005). Several schools of thought provide a theoretical foundation as to why firms engage in M&A for technological motives. For example, the knowledge-based view of the firm regards technological knowledge as an important source of competitive advantage and the dynamic capabilities view has emphasized the importance of learning, which may be achieved by engaging in alliances or through mergers and acquisitions (Conner & Prahalad, 1996; Mowery, Oxley & Silverman, 1996; Teece & Pisano, 1994). Transaction cost economics sees firms weighing the costs and benefits of internal vs. external arrangements (Williamson, 1985). If obtaining the technology by acquiring another company is cheaper than developing the technology in-house, then a company would prefer to engage in M&A rather than spending more on R&D. For example, the incentives to innovate differ between small and large companies, affecting both the productivity and direction of innovation, and it may therefore be optimal for a large established company to buy small innovative start-up companies to source new technologies (Grandstand & Sjölander, 1990).

The acquisitions of innovative pharmaceutical and biotech companies by large pharmaceutical companies to cope with rising R&D costs via economies of scale and scope and to develop a new generation of drugs or to fill the product pipeline with new drugs developed by another firm to address the "patent cliff" are examples for technologically motivated transactions (Danzon et al., 2007; Higgins & Rodriguez, 2006; Munos, 2009). Schweizer (2005) finds that pharmaceutical companies acquire biotech companies both to obtain existing products as well as to obtain the capabilities to develop new drugs to grow in the future.

In the telecommunications sector, Cisco is frequently cited as a firm that has extensively used acquisitions to obtain existing technologies as well as key personnel such as programmers and engineers (Mayer & Kenney, 2004; Ranft & Lord, 2000). Until 2001, Cisco has acquired 71 companies for over 34.5 billion USD (Mayer & Kenney, 2004). From 2002 to 2013 it has added another 96 acquisitions to this count.[3] Mayer and Kenney (2004) note: "More than any other high-technology firm in history, Cisco has built its dominant market position through acquisition" (p. 299). The authors describe, inter alia, how Cisco reacted to the technological change from routers to switches in the early 1990s by acquiring a company engaged in switches, a technology Cisco was too late in developing internally.

Technological motivations for acquiring another company can come in various forms. The following is a non-exhaustive and non-exclusive list of such motivations:

- **Cost driven motivations** such as economies of scale (spreading fixed costs over more of the same R&D output) or scope (spreading fixed costs over different R&D activities) in R&D activities (Cassiman & Ueda, 2006). Also, an M&A transaction can be used to avoid the duplication of R&D projects (Comanor & Scherer, 2013).
- **Creating synergies** by combining capabilities to create new opportunities. For example a company may acquire a company with complementary technological knowledge with the aim of using the recombined technological competencies to become more

[3] http://www.cisco.com/web/about/doing_business/corporate_development/acquisitions/ac_year/about_cisco_acquisition_years_list.html (last accessed: 23 May 2014)

productive and to develop new and better products (Barney, 1988; Karim & Mitchell, 2000).

- **Strengthening core competencies and restructure existing competencies** (Frey & Hussinger, 2006).
- **Exploring and adapting to a changing environment.** The acquisition of distant technologies may allow a company to adapt to a rapidly changing external environment more quickly than is possible through in-house development, thereby overcoming time compression diseconomies (Dierickx & Cool, 1989; Teece, Pisano & Shuen, 1997). This helps the company to revitalize and overcome the competency trap (Levitt & March, 1988; Vermeulen & Barkema, 2001) and core rigidities (Leonard-Barton, 1995), e.g. by acquiring small innovative firms with the potential for groundbreaking technologies. Obtaining knowledge in new technology fields can also increase the *future* absorptive capacity, thereby enabling companies to better adapt to technological change.
- **Reducing uncertainty and the risk profile** of the company, e.g. via the acquisition of distant technologies so as to diversify and reduce exposure to a particular field. Also, M&A may allow a company to shoulder larger R&D projects that would be too big and risky for each firm standalone. Finally, acquiring a company with a proven technology reduces the uncertainty that risky R&D programs entail.
- **For strategic reasons**, e.g. the acquisition of a company with substitutive technologies with the aim of muting current or future competition or the acquisition of a portfolio of patents for strategic reasons, e.g. to resolve a patent dispute or thicket that is affecting the acquirer or to create a patent fence to block third parties (Gans & Stern, 2000; Grimpe & Hussinger, 2008, 2013; Lerner, Tirole & Strojwas, 2003; Shapiro, 2001).
- **Obtaining access to valuable and scarce resources.** The acquirer may be interested in technological inputs such as key inventors and engineers (Ranft & Lord, 2000) or key patents, as has recently been the case with the 2012 acquisition of Motorola by Google.[4]
- **Internalizing positive or negative knowledge spillovers** between the acquirer and the target (Hart & Holmstrom, 2010; Marco & Rausser, 2011).
- **Providing the right incentives and organizational structure for innovation.** Combining firms to increase the scale of R&D activities can generate economies of

[4] http://www.google.com/press/motorola/ (last accessed on 10 February 2014)

> scale and scope and may allow scientists to specialize and become more productive (Henderson & Cockburn, 1996).[5]

The motivations play a crucial role in assessing the two-way relationship between technological relatedness and M&A transactions. For example, if the main objective is to diversify technologically, then a company is likely to search for companies with a higher technological distance; if the objective is to generate economies of scale and to avoid duplication, the acquired company should be rather close in technology space.

When it comes to obtaining new technological capabilities, firms can choose between internal development (e.g. building a new R&D laboratory) and external sourcing (e.g. via alliances or M&A) (Capron & Mitchell, 2009). Potential advantages of external sourcing are that it allows companies to overcome larger capability gaps, to enter a new technology field more quickly and to provide a means for renewal that potentially faces less social rejection (Capron & Mitchell, 2009; Penrose, 1959). Technological distance plays a key role in weighing the costs and benefits of external technology and knowledge sourcing against internal development. With internal generation of knowledge and technology being path dependent, acquisitions of external technology and knowledge may be preferable if a company wants go get access to distant technologies quickly (Capron & Mitchell, 2009; Graebner, Eisenhardt & Roundy, 2010; Kogut & Zander, 1992). Against this, external sourcing is often associated with integration costs, cultural misfit, inability to cherry-pick and ex ante uncertainty as to what exactly is sourced externally.

3.2.2 The impact of innovation characteristics on becoming an M&A acquirer or target

Regarding the causality running from innovation to M&A, researchers have investigated the innovation characteristics of firms that make them more likely to be acquirers or targets and the relationship between the firms (e.g. in the form of similarity in terms of size, innovativeness, technological focus, geographic location, etc.) that makes two firms more likely to merge. Different predictions are given by the literatures. The corporate control literature regards M&A as a means of reallocating resources of inefficiently run companies to a more capable management team (Jensen & Ruback, 1983; Manne, 1965). Hence, it predicts that it is underperformers that are targets of M&A transactions. The resource based view and knowledge based view (Kogut & Zander, 1992; Nelson & Winter, 1982) literatures regard

[5] However, there are also theoretical arguments and empirical evidence, that small firms provide better incentive to innovate (Grandstand & Sjölander, 1990)

M&A as a way to source new competencies and knowledge. Hence, it predicts that target firms must possess valuable resources (e.g. patents, technological capabilities, key technological personnel) in order to attract the interest of possible acquirers. The following is an overview of the empirical literature that investigates the characteristics of acquirer and targets.[6]

Using data on the M&A activity of 217 firms in the US electronics and electrical equipment industry from 1985 to 1993, **Bloningen and Taylor (2000)** find that R&D intensive firms are significantly less likely to engage in M&A activity as an acquirer. Under the assumptions that it is technology that is sourced though the acquisitions, they interpret this finding as support for the conjecture that some firms are using the M&A market to buy technologies while others make the technologies in-house, i.e. M&A and in-house R&D are substitutive.

Desyllas and Hughes (2009) analyze the innovation characteristics of acquired firms in high technology industries to test whether acquirers search for "superiority" as suggested by the resource based view (Penrose, 1959) or "inferiority" as suggested by the market for corporate control theory (Manne, 1965). They find that target firms exhibit a high R&D intensity (R&D/assets) and large patent stock compared to non-acquired firms, but at the same time a lower R&D productivity (successful patent applications/assets) and a weak financial performance. They argue that targets are firms that have been strong innovators in the past but are falling behind in terms of innovation and financial performance recently.

Using data on the M&A activity of 2,500 manufacturing firms over the period 1976-1985, **Hall (1988a)** investigates the selection into M&A based on a matching process in which a firm maximizes the gains from a transaction, taking into account target characteristics and the relatedness between the target and acquirer. She finds that firms are more likely to merge if they are similar in size and R&D intensity. As the R&D conducted by the target was valued relatively higher by the acquiring firm, she argues that targets are successful innovators. Higher value gains were found if both firms have a high R&D intensity. In a subsequent paper, **Hall (1990)** analyzes 2,500 transactions involving US manufacturing firms from 1967 to 1987 and finds that a lower R&D intensity increases the chances of being a target for private and foreign firms and has no impact on being an acquirer.

Using case study and survey data on Swedish firms, **Grandstand and Sjölander (1990)** find that large Swedish firms tend to acquire small innovative firms. Their work builds on Williamson (1975) who argued that neither large nor small firms have an advantage in all

[6] The impact of M&A on ex post innovation performance is not discussed in this overview. I refer the reader my related research that discusses this aspect (Stellner, 2014c)

three stages of the innovation process (invention, development and final supply) and that it may be optimal for large firms to acquire small firms at some stage.

Danzon et al. (2007) investigate both the selection into M&A and the impact of M&A transaction on the innovation performance of 383 firms in the pharmaceutical and biotechnology sector from 1988 to 2000. They find that patent expirations and low expected earnings growth (measured by Tobin's q) are a motivation to acquire other companies in the pharmaceutical industry. They regard this as evidence that future excess capacity (e.g. in marketing or production) plays a key role for acquiring firms. Firms in a weak financial position are more likely to be acquired and financially strong firms are more likely not to engage in an M&A transaction.[7] Similarly, investigating 160 M&A transactions from 1994 to 2001, **Higgins and Rodriguez (2006)** find that pharmaceutical firms with a weak innovation pipeline and a high number of patent expiries (which the authors measure with a "Desperation Index") have a higher likelihood to be acquirers.

Zhao (2009) builds on the study by Higgins and Rodriguez (2006) and expands the analysis to a much broader set of industries. He uses data on 1,053 M&A transactions from 1984 to 1997 to assess the two-way relationship between M&A and innovation quantity and quality, the latter being measured in terms of forward patent citations. Regarding the selection into M&A, he finds that bidding firms have fewer forward citations (but not fewer patents) and experience slower growth in citations in the three years prior to the transaction, confirming the results of Higgins and Rodriguez (2006) discussed above. The author sees this as support for the hypothesis that M&A is used for sourcing technologies externally. Compared to unsuccessful bidders (i.e. bidders who did not complete the deal), successful bidders have less forward citations, indicating that technological laggards feel more pressure to finalize a deal.

Gantumur and Stephan (2010) study the telecommunications industry over the period 1988-2004 to investigate the selection into M&A as well as the innovation impact of M&A transactions. Using a multinomial logit model, they find that a higher R&D and patent intensity as well as a lower R&D productivity increase the propensity to acquire. The lower R&D productivity of acquirers suggests that firms acquire to overcome their knowledge inertia. Acquirers as well as targets also have a higher citations based patent stock, which the authors explain with absorptive capacity.

[7] Likewise, in a study on M&A activity in the pharmaceutical industry, Ravenscraft and Long (2000) found that in the 18 months before a transaction, acquired companies had negative stock market performance relative to firms not engaging in M&A transactions.

Using CIS data from 1993 on 269 Belgian firms, **Cassiman and Veugelers (2006)** investigate whether M&A and internal R&D are complementary, i.e. whether one activity increases the marginal return of the other activity. Their results reveal the presence of complementarity between M&A and R&D and that this complementarity is positively mediated by the focus on basic R&D. This basic R&D is presumed to provide the absorptive capacity to make use of the external knowledge obtained through M&A.

3.2.3 The role of technological relatedness

As for the selection of M&A targets as well as the ex post innovation performance, technological relatedness can have a positive as well as negative impact. One core argument is based on absorptive capacity: the higher the similarity of two firms' knowledge bases, the lower are information asymmetries and the easier it is to identify, evaluate and assimilate the acquired knowledge (Cohen & Levinthal, 1990; Haspeslagh & Jemison, 1991; Kogut & Zander, 1992; Lane & Lubatkin, 1998). Zahra and George (2002) distinguish between potential absorptive capacity, which refers to the ability to identify and understand the opportunity before acting, and realized absorptive capacity, which is concerned with the assimilation, transformation and exploitation. Potential absorptive capacity can lower the asymmetric information regarding the outlook and value of an opportunity. While asymmetric information exists as well with regards to product market opportunities, customer relationships and financial data, the high uncertainty of new technological developments and the difficult assessment of tacit knowledge are likely to make asymmetric information particularly pronounced in the technology field (Hussinger, 2010). The absorptive capacity can be positively affected by a high technological proximity between the acquirer and target as well as prior technological relations, e.g. in the form of technology flows or prior technology alliances (Al-Laham, Schweizer & Amburgey, 2010). In addition to aspects pertaining to the companies' knowledge bases, there is a strategic component that has to be taken into account (Grimpe and Hussinger, 2008, 2013). Patents constitute a right to exclude other firms from using the patent owner's technology (also known as the "preemptive power"). By acquiring a company that has patents in technologically close fields, a firm may be able to conduct its R&D activities more freely ex post or to erect a patent fence that restricts competitors in their innovation efforts.

However, too much similarity, like too much distance, constrains the acquirer's opportunities for learning (Sapienza, Parhankangas & Autio, 2004). Acquiring distant technologies allows companies to solve problems in a new way, either standalone or in combination with the acquirer's technologies (Ahuja & Katila, 2001; Cohen & Levinthal, 1990). Also, acquiring distant technologies provides the future absorptive capacity to understand, value and assimilate these technologies going forward (Ahuja & Katila, 2001). This capacity may then be used to make further acquisitions or establish alliances in these technological fields. Finally, acquiring distant technologies constitutes a way to reduce risk via technological diversification.

There are two streams in the literature that I will discuss. First, there is research which investigates the choice of acquisition target, investigating if acquirers search for targets that are close or distant to them in technology space. Second, there is a stream of research which looks at the performance, either in terms of innovation or financials, of the combined entity depending on the ex ante technological distance between the two firms. I begin with the empirical studies that investigate the selection into M&A.

Using data on 242 acquisitions among top patenting firms (predominantly involving US targets), **AlAzzawi (2008)** uses Hall's (1988a) matching model to test the role of actual pre-acquisition knowledge flows (measured by bilateral patent citations) as well as potential knowledge flows (measured by technological distance) on the merger choice decision. The gain of a transaction is a linear function of the technological properties of the target and the distance and knowledge flows between them. She finds that prior knowledge flows as well as technological proximity have a significant positive impact on the merger pairing. Unfortunately, she does not test for a non-linear impact. The size of the patent portfolio of the target has a significant negative impact on being acquired, while the number of global citations and the difference in the number of global citations between target and acquirer have no impact. Finally, firms tend to acquire during times of low patenting output and firms tend to be acquired during times of widely cited patenting output.

Based on a sample of German firms, including many SME, and using Hall's (1988a) matching model, **Hussinger (2010)**, finds that firms which are technologically close are preferred as targets. No indication of a non-linear effect of technological distance on the choice of M&A target is found. She finds that technological proximity is statistically relevant for SME but not for larger firms, the latter possibly being a result of the small sample size. She included geographical and product market proximity as additional explanatory variables, finding that both have a positive impact on the likelihood of being chosen as a target.

Frey and Hussinger (2006) analyze cross-border as well domestic M&A transactions in Europe from 1994 to 2000 and the role that technology plays in these transactions. They also use Hall's (1988) matching model estimated with a nested logit, and find that technological proximity increases the expected benefit.[8] They also find that in cross-border transactions, technological proximity does matter, whereas it does not matter in domestic transactions. This finding is explained with the argument that technological proximity may reduce the uncertainty and risk that cross-border transactions typically involve relative to domestic transactions. Also, it indicates that technology is a motivation for M&A in cross-border transactions.

Marco and Rausser (2011) investigate the role of complementarities and spillovers in the matching of target and acquirer in the plant biotechnology sector from 1984 to 2000. Measuring similarity (and the ensuing complementarity) as citation overlap (citations to same prior art) and spillovers as cross citations, they find that both technological proximity and spillovers increase the likelihood of merging. Technological similarity is found to be more important than direct spillovers in explaining which firms engage in a transaction.

Analyzing a large set of US M&A transactions from 1984 to 2006 in a wide range of industries, **Bena and Li (in press)** investigate the role of innovation characteristics of acquirers and targets and their technological distance in becoming an acquirer or target as well as the post-acquisition performance. They find that more innovative firms, measured by patents or citations weighted patents, are more likely to acquire other firms. After controlling for innovation output, R&D expenditures do not have a significant impact on the probability to acquire. In contrast, less innovative firms with a low level and slow growth rates in innovation output are more likely to become targets. At the same time, target firms are found to invest a lot in R&D, indicating that they have low innovation productivity. Taken together, the results suggest that within the "innovation cycle", acquirers are at the patent output stage while targets are at the R&D investment stage. Measuring innovation complementarity as the angular separation, cross-citations and citations to the same prior art, they find that all overlap measures have a positive impact on merger pair formation. They also tested for the impact of product proximity, finding that it has a positive impact on merger pairing, but that the interaction of product proximity and technological proximity has a negative impact on the likelihood of a merger occurring between two firms. The authors attribute this negative interaction to the presence of rivalry between the firms rather than a desire to merge. Using a control group of planned mergers that were withdrawn for reasons unrelated to innovation activities (so as to control for the selection into M&A), they find that the post transaction innovation performance of mergers (measured as the combined firms' patenting) is higher in

[8] They also test for a curvilinear relationship, but do not find support for it.

the treatment group than in the control group (measured as the patenting of the target and acquirer whose transaction failed) if the companies are technologically close prior to the transaction. The authors argue that the technological overlap is a source of synergies and that this drives the decision which firms to acquire and the post-transaction performance.

In a study covering 1,428 M&A transactions from 1997 to 2010 involving European firms, **Grimpe and Hussinger (2013)** account for the fact that patents not only characterize the knowledge base of companies but also have a preemptive power owing to the legal title that allows the owner to exclude third parties from using the technology. In contrast to the above studies which use the choice of acquiring a firm as the dependent variable, they use the acquisition price as the dependent variable. The study is nevertheless closely related to the target choice studies as both are concerned with the expected synergies from a transaction. Using the information on X or Y citations (indicating conflicting prior art) and A citations (indicating no conflicting prior art) received by the targets patents, the preemptive power of the target is measured by the share of XY-type citations *received* by the target's patents in the target's citation stock. They find that the preemptive power of the target results in higher acquisition prices paid by the acquirer. This relationship is positively mediated by the acquirer's technology intensity as this increases the potential damage that external patents can cause to the firm as well as the potential benefit of owning patents and thereby establishing a patent fence. Regarding the technological relatedness – measured by the angular separation established at the IPC class level – they find an inverted U-shape relationship, i.e. an intermediate level of technological relatedness is found to result in the highest acquisition prices. This is contrary to the above findings that firms choose technologically close targets but fits well with the findings below that an intermediate level of technological relatedness is most conducive to ex post innovation performance. The authors also include two distinct relatedness measures, one between the acquirer's A-cited patents and the target's A-cited patents (thereby measuring the "knowledge base" component of relatedness) as well as the one between the acquirer's A-cited patents and the target's XY-cited patents (thereby measuring the "preemptive" component of relatedness). While the A-cited/A-cited relatedness measure has again an inverted U-shape relationship with acquisition price, the A-cited/XY-cited relatedness measure has a positive relationship with the acquisition price (and an insignificant squared term). Hence, the preemptive value of the target increases with the similarity to the acquirer's technological profile.

As for empirical studies on the impact of technological distance on performance, Ahuja and Katila (2001) and Cloodt et al. (2006) study the relatedness of innovation that the acquirer and the target engage in. **Ahuja and Katila (2001)** investigate the innovation performance impact of 534 M&A transactions made by 72 large firms in the chemicals sector from 1980-1991. They use a Poisson distributed lag model with the innovation performance measured by patent output as the dependent variable. In their model, the innovation performance in one particular year can be affected by the acquisitions in the preceding 4 years. Transactions which are not technologically motivated are found not to have an impact on post-transaction patenting output, thus not providing any evidence of an indirect effect on innovation (e.g. organizational disruptions causing managers to focus on crisis management rather than routine innovation). For technologically motivated transactions, they find that a large absolute size of the acquired technology base increases patenting, which they explain with the economies of scale and scope, the re-combinatory potential and the increased absorptive capacity, while a large relative size of the acquired knowledge base decreases patenting, explained by the difficult absorption of the new knowledge without impairing the R&D processes and existing routines.[9] They measure technological relatedness as the ratio of the patents (including those that are cited by the focal firm) that are both in the acquirer's and target's pool and the total number of patents in the target's pool (including those that are cited).[10] Using this measure of relatedness they find an inverted U-shape relationship between relatedness and innovation output. However, this result is not robust to a relatedness measure based on only the own patents of the firms (rather than also the cited patents). They control, among others, for product market diversification and foreign acquisitions, finding that foreign acquisitions have no impact on innovation output and diversifying transactions having a negative impact.

Cloodt et al. (2006) conduct a study very similar to Ahuja and Katila (2001) using data on 347 firms in four high-tech industries (pharmaceuticals, aerospace and defense, electronics and communications, and computers and office machinery) from 1985 to 1994. They find that non-technological acquisitions have a negative impact on post M&A patent output, which they attribute to organizational disruptions and the reallocation of resources away from innovation activities in the aftermath of a transaction. In contrast to Ahuja and Katila (2001) they find that a higher absolute size of the acquired knowledge increases innovation output in the two years after the transaction and then decreases output. However, the economic significance of this impact is small. They explain this by the focus on high technology industries (rather than the medium technology intensive chemicals industry) where the

[9] Statistical significance is established by the joint significance of the four lagged variables for M&A activity.
[10] Ahuja and Katila (2001) argue that "[b]y 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. Thus, the patents cited by the firm should also be included in its knowledge base" (p. 202).

acquired knowledge becomes obsolete quickly. A larger relative size of the acquired knowledge base has a negative impact on innovation output. Regarding technological relatedness, they find an inverted U-shape relationship, thereby confirming the finding of Ahuja and Katila (2001).

Prabhu et al. (2005) ask the question “Why are some firms better at generating innovations from acquisitions than others?” (p.114) to account for the variability in the innovation impact of M&A transactions. Building on the knowledge-based view of the firm (Nonaka, 1994), the authors argue that a higher breadth and depth of the internal knowledge base positively mediates the impact of M&A on innovations. Regarding technological similarity, they expect an inverted U-shape relationship. They use data on US pharmaceutical companies of various sizes and measure innovation as the number of drugs in Phase 1 trials and similarity as the overlap in patent subclasses divided by the union of subclasses. They find that depth but not breadth of technological knowledge positively interacts with acquisitions in terms of the innovation impact and – like Ahuja and Katila (2001) and Cloodt et al. (2006) – that similarity has an inverted U-shape impact on innovation performance after a transactions. After controlling for the knowledge characteristics of the firms, M&A is found to have no impact on innovation. Hence, it is the knowledge characteristics and their fit that make M&A a “tonic” for innovation.

Ornagi (2009) studies the innovation impact of M&A transactions in the pharmaceutical sector from 1988 to 2004. To account for the possible endogeneity of selection into M&A, she uses control groups based on both the propensity score method (using pre R&D performance and patent expiries as explanatory variables for the propensity to merge) and a matched group of technologically similar firms. In addition, the author used the Heckman two-step procedure to account for the role of relatedness on the selection into M&A. She finds a negative impact of a transaction on innovation performance (i.e. change in R&D, patents and patents/R&D) and stock market performance in the three subsequent years. She also confirms Danzon et al.’s (2007) finding that firms experiencing patent expirations and lacking new products as well as those with weaker stock market performance have a higher propensity to engage in a merger. Technological relatedness (measured by citation overlap, the angular separation and cross-citations) is found to lead to poorer post transaction stock market performance and innovation productivity while product market relatedness results in better performance. Neither technological nor product market relatedness is found to impact R&D expenditures ex post. Despite the comprehensive effort to account for the endogeneity of the decision to merge (in fact, more than any other author discussed in this overview), the author concludes that “[a]

convincing identification of causality will be always hindered by the fact that econometricians cannot observe most of the information that the merging firms employ in their decision" (p. 78). Her research shows that claims of positive impacts of M&A on innovation and research productivity should be taken very cautiously.

Makri, Hitt and Lane (2010) study the impact of technology and science similarity and complementarity on the innovation performance (i.e. quantity, quality and novelty) of firms engaging in M&A transactions. Building on Larsson and Finkelstein (1999), they define technology (science) similarity between firms as the extent to which their technological (scientific) competencies derive from the same specific knowledge field. Technology (science) complementarity between firms is defined as the extent to which their technological (scientific) competencies derive from different specific knowledge within a shared general area of knowledge.[11] Using data on 95 technologically motivated transactions in 1996 involving firms in the drugs, chemicals and electronics industries, they find that technological and scientific knowledge similarities have no impact on innovation quantity and quality, but a negative impact on innovation novelty. Complementarities in technology and science make discontinuous strategic transformations more likely and also have a positive impact on innovation quality. Their findings suggest that knowledge complementarities are crucial for strategic renewal, while knowledge similarities facilitate incremental renewal.

Using data on 97 acquisitions over the period 1995 to 2004 involving US manufacturing firms as well as small technology intensive target firm, **Sears and Hoetker (2014)** study the distinct (mediating) role of acquirer knowledge overlap (i.e. the proportion of the acquirer's knowledge base that is also part of the target's knowledge base) and target knowledge overlap (i.e. the proportion of the target's knowledge base that is also part of the acquirer's knowledge base) on the value created by the acquirer or target capabilities (measured as citations weighted patent count or the acquirer or target). While previous studies have focused on target firm knowledge overlap (e.g. Ahuja & Katila, 2001; Cloodt et al., 2006), the authors argue that target and acquirer overlaps are distinct constructs and that they have a distinct impact on "the acquirer's absorptive capacity, knowledge redundancy and exposure to organizational disruption" (p. 49). Regarding target overlap, the authors argue that there is a tradeoff between absorptive capacity and potential for novelty creation. Regarding acquirer overlap, the authors argue that higher overlap results in disruptions and conflict and thus negatively

[11] Technological similarity is measured by patenting in the same narrow patent class, while technological complementarity is measured by patenting in the same broader subcategory but different class. Likewise, science similarity is measured by publishing in the same narrow research community, while science complementarity is measured by publishing in the same broader discipline but different research community.

mediates the impact of both targets' and acquirers' capabilities on value creation. Their main dependent variable is the cumulative abnormal returns of the acquirer at the time of the acquisition, which they see as a measure for expected synergies. They find that the interaction of target overlap and target capabilities has a negative impact on abnormal stock returns (i.e. the higher the target overlap, the less value creation arises from the target capabilities), indicating that the effect of innovative redundancy outweighs the effect of absorptive capacity. Also, a higher acquirer technology overlap is found to negatively mediate the impact of acquirer's capabilities on abnormal returns, arguably because of the organizational conflict that the overlap causes. As the authors only have data on the acquirers' abnormal returns, it is not possible to determine the overall value creation. It is conceivable that the knowledge overlap and capabilities of the target and acquirer affect the bargaining position of the firms rather than the expected synergies – something which is not discussed in their study.

Based on the analysis of 31 case studies in the medium- to high-technology industries, **Colombo and Garrone (2006a, 2006b)** find that acquisitions support innovation when the technological competencies have some overlap so that the parties can learn from each other, but not too similar so as to provide new opportunities. They find that technologically complementary firms increase their R&D expenditures, whereas technologically substitutive firms significantly decrease their R&D, focus on short-term projects and prefer development over research following a transaction. In the latter case, they also witness organizational destabilization and the departure of key employees as well as a change in the R&D profile, becoming more focused and short-term. Reduction in R&D efforts (inputs, outputs and productivity) is found particularly in cases where the firms are product market rivals and possess similar technologies – something that is of interest to competition authorities. The motivation to engage in M&A is also found to impact innovation performance, with technology motivated transaction leading to increased R&D inputs and outputs. Pre-merger collaboration leads to statistically higher R&D output and performance. Domestic mergers are found to lead to a decline in R&D personnel whereas cross-border transactions leave R&D personnel unchanged.[12]

Phene, Tallman and Almeida (2012) analyze 141 M&A transactions in the semiconductor industry, to investigate the impact of the characteristics of the acquirer and target and their relatedness on the exploration (i.e. a post M&A increase in patenting in fields that are core to the target but not the acquirer) and exploitation (i.e. a post M&A increase in patenting in

[12] It is important to note that the survey and case study methodology incurs the problem of selection bias, as managers involved in badly performing acquisitions are less likely to participate than those involved in success stories (e.g. no hostile takeover and few leveraged deals were part of the analysis).

fields that are core to the acquirer) of the acquirer. Over half of the transactions were of an exploitative nature, while only very few were explorative. They find that exploration occurs when the target is technologically unique, geographically close and under higher control by the acquirer. Exploitation is negatively impacted by target uniqueness and positively impacted by geographic proximity and the target's patent stock. Technological relatedness is not found to have a significant impact on either exploration or exploitation.

3.2.4 The role of product market relatedness and resource complementarity

Covering the largest 110 listed US firms in the ICT industry from 1993 to 2000, **Keil et al. (2008)** investigate the impact of external relationships in the form of corporate venture capital (CVC) investments, alliances, JVs and acquisitions as well as the product market relatedness (based on the match of SIC codes) on innovation performance (measured by the number of patents). They find that JVs have a significant positive effect on post transaction patenting, acquisitions have a significant negative impact on patenting while CVC investments and alliances have no statistically significant impact. Grouping product market relatedness in three groups, namely "intra-industry", "related" and "unrelated", the authors find that CVC investments, alliances and JVs show, as expected, an inverted U-shape relationship with innovation performance, i.e. the coefficient for the medium relatedness ("related") was higher than the other types of relatedness. As for acquisitions, they found that the coefficient for "intra-industry" relatedness was the highest and the difference between the "related" and "unrelated" coefficients was statistically insignificant. In the group of "intra-industry" external relationships, acquisitions have the highest positive impact on innovation performance. The absence of an inverted U-shape relationship for acquisitions is speculated to be a consequence of high integration costs outweighing the learning benefit.

Hoberg and Phillips (2010) investigate the role of product market relatedness on merger pair formation and post-transaction performance. Establishing the product market relatedness using the companies' product description in financial reports, they find that companies acquire targets with a similar product profile. Regarding post transaction performance, they find that product market relatedness has a positive impact on profitability and sales.

King, Slotegraaf and Kesner (2008) study the role of resource complementarity and substitutability on Jensen's alpha (i.e. the abnormal stock return) of the acquirer. In their sample of 133 acquisitions from 1994-1997 in high technology industries, they find that overall, Jensen's alpha is zero, i.e. there are no abnormal returns to the acquirer. The R&D

intensity of acquirers relative to their industry peers is significantly lower, suggesting that firms are using acquisitions as a substitute for internal development. The interaction term of target R&D and acquirer R&D is significant and negative while the interaction between the acquirer marketing resources and the target's technology resources is significant and positive. This indicates that acquirer's R&D and target's R&D are substitutes while complementary resources (marketing and R&D) contribute to firm performance. Relatedness between acquirer and target is found to positively impact abnormal stock returns.

Valentini and DiGuardo (2012) build on the idea that innovation, in contrast to an invention, requires complementary resources and capabilities such as marketing and production (Teece, 1986). An M&A transaction can make these resources available to the other party of the transactions and thereby alter the incentives to invest in R&D, both with regards to quantity and type. In addition, innovation depends on the knowledge of both the acquirer and target and in how far they can be combined. They investigate the impact of M&A (including the technological and product market distance) on the profile of innovative activity, namely the depth and breadth of technological knowledge. Depth refers to the impact of a focal company's innovation on future innovation, measured by the number of forward citations, and breadth refers to the impact on different fields, measured by Herfindahl-Index of concentration of the technological fields of the forward citations. Accounting for the endogeneity of the decision to engage in M&A, they find that the technological distance, which they refer to as the diversity of knowledge bases of the acquirer and target, is found to have no direct impact on either depth or breadth, but has a positive effect in deals involving companies that have a high market relatedness. They authors attribute this to the difficulty of integrating diverse technology bases, which is alleviated if the firm are related in the product market. Product market distance, measured by the identity of SIC codes (and used as a proxy for the diversity of the acquirer and target downstream resources) is found to have a positive impact on innovation performance, which they attribute to the wider applicability of the technology. The authors conclude that technology and product market relatedness appear to be substitutes and that companies should either acquire companies in distant product markets or companies in close product markets but with different technologies. It is important to note that the authors measure the innovation impact only two years after the transaction, which may be too short to pick up the actual impact of the transaction.

3.2.5 Technological relatedness and alliances

As alliances can serve as an alternative to M&A as a means to learn, combine complementary technologies and source external knowledge and technology (Keil et al., 2008; Mowery et al., 1996; Rosenkopf & Almeida, 2003), I discuss here three studies that investigate the role that technological relatedness plays in the formation and outcomes of alliances.

Using data on 151 joint ventures (involving 229 firms) where at least one firm is from the US, **Mowery, Oxley and Silverman (1998)** study the impact of technological overlap on the choice of alliance partner and the impact of an alliance on ex post development of technological overlap. For each alliance between firm i and j, they select a matched pair involving firm i and a firm k that is in the same industry as j, closest in size to j and has not formed an alliance with i. They then conduct a logit regression with the dependent variable being a binary variable equal to one if an alliance has been established and 0 for the non-allied control group, and the independent variable including a linear and squared term for technological overlap (measured as “patent cross-citation rate” and “common patent citation rate”). They find evidence for an inverted U-shape relationship between technological distance and the likelihood or alliance formation.

Nooteboom et al. (2007) discuss the positive and negative effects of cognitive distance (which they equate with technological distance) on innovation performance: “[C]ognitive distance yields opportunities for novel combinations of complementary resources. However, at a certain point cognitive distance becomes so large as to preclude sufficient mutual understanding needed to utilize those opportunities” (p. 1017). They argue that the impact of cognitive distance on innovation depends on whether the aim is to explore (i.e. break with the dominant design) or to exploit (i.e. routinized learning). If the aim is exploitation, they expect a positive effect of cognitive proximity whereas if the aim is exploration, then a higher cognitive distance is beneficial. They test their hypothesis on a sample of 116 large companies in the chemicals, automotive and pharmaceuticals industries, regressing total patents, exploratory patents (count of patents in technology fields in which the focal company has patented in in the five years before the alliance) and exploitative patents (count of patents in technology fields in which the focal company has not patented in in the five years before the alliance) on the cognitive distance (measured as the correlation of revealed technological advantage), including a squared term, and a series of control variables. They find an inverted U-shaped relationship between technological distance and innovation. This relationship is also found for exploratory patents, but neither the linear nor quadratic term of distance was significant for explaining exploitative patents.

Stuart (1998) investigates the alliance formation of semiconductor firms from 1986 to 1992 based on a network theoretic approach. In particular, he studies the impact of crowding and prestige on the decision to form alliances, both at the firm level ("Which individual firms engage in alliances?") and the dyad level ("Which two firms engage in an alliance?"). Crowdedness refers to a technology field in which many firms are active (measured by the sum of the dyadic citations overlap of semiconductor firms) and a prestige refers to seminal contributions in a technology field (measured as forward citations of a firm). At the firm level, he finds that firms in crowded positions and that have a higher prestige are more likely to form alliances. The positive impact of crowding is attributed to absorptive capacity, the avoidance of duplication and attracting others that want access to the market center. The positive impact of prestige is attributed to the ability to establish contractual terms that are more favorable. At the dyad level, he finds that firms with high technology overlap (i.e. a close structural position in the network) are more likely to form an alliance than those firms with low overlap. Also, alliances were more likely when at least one firm had a high level of prestige.

Finally, in their review the literature of the relationship between alliances (and M&A) on innovation, De Man and Duysters (2005) conclude that alliances in "which the partners have an overlapping or similar knowledge base outperform alliances in which companies have no similar knowledge background" (p. 1380).

3.2.6 Summary of findings

Regarding the selection into M&A, several studies have found that acquirers experience weaknesses in their innovation efforts: Acquirers were found to have lower R&D intensity (Bloningen & Taylor, 2000), receive fewer patent citations (Zhao, 2009), a lower R&D productivity (Gantumur & Stephan, 2010) and low patenting output (AlAzzawi, 2008). In the pharmaceutical industry, Danzon et al. (2007) find that acquirers have a high number of patent expirations and low earnings growth. This finding is corroborated by Higgins and Rodriguez (2006), who show that it is firms with a high "Desperation Index" that acquire other companies, and Ornaghi (2009), who finds that patent expirations and the lack of new products increases the likelihood to engage in M&A. A notable exception to the above studies is that by Bena and Li (in press), who show that more innovative firms are more likely to be acquirers.

In contrast, targets are often found to be successful innovators (e.g. AlAzzawi, 2008). Hall (1988) finds that the R&D conducted by targets was valued highly by acquiring firms. Grandstand and Sjölander (1990) find that large companies acquire successful small innovative firms. Desyllas and Hughes (2009) find that targets have been strong innovators in the past but experienced weak R&D productivity recently. In contrast, Bena and Li (in press) find that target firms are less innovative, have a lower R&D productivity and experience a low growth of innovation output.

Several studies have found that M&A and R&D are substitutive activities for possible acquirers (e.g. Bloningen & Taylor, 2000; Hitt et al., 1991; King et al., 2008). In contrast, Cassiman and Veugelers (2006) find evidence for complementarity between M&A and R&D.

Regarding the role of technological distance, studies have typically found that technological relatedness (e.g. technological proximity, technological complementarity, ex ante knowledge flows) increases the chances of merging (e.g. Bena & Li, in press; Hussinger, 2010). AlAzzawi (2008) find that prior knowledge flows and technological proximity have a positive impact on the merger decision. Marco and Rauser (2011) show that both technological proximity and actual spillovers increase the likelihood of merging and that proximity has more explanatory power than spillovers. Frey and Hussinger (2006) show that technological proximity increases the expected benefit of M&A only in cross-border transactions but not in domestic transactions. Stuart (1998) finds that alliances are more likely among technologically close firms whereas Mowery et al. (1998) find evidence for an inverted U-shape relationship. Grimpe and Hussinger (2013) show that there is an inverted U-shape relationship between technological relatedness and acquisition price. Accounting for the legal title that patents represent (in addition to characterizing the knowledge base), they find a monotonously positive relationship between technological relatedness in fields where the target has preemptive power (measured by XY-type citations) and the acquisition price.

Several studies have found that there is an inverted U-shape relationship between technological distance and innovation performance following M&A (Ahuja & Katila, 2001; Cloodt et al., 2006; Prabhu et al., 2005). Nooteboom et al. (2007) also find an inverted U-shape relationship between technological distance and ex post innovation in alliances.

Ornagi (2009) find that higher technological relatedness (in contrast to product market relatedness) leads to poorer ex post stock market performance and innovation productivity (but not to a decline in R&D investments). Makri et al. (2010) showed that innovation quality is positively impacted by knowledge complementarity but not knowledge similarity, and that knowledge complementarities facilitate strategic renewal while knowledge similarities facilitate incremental renewal. Colombo and Garrone (2006b) find that technological complementarity results in an increase in R&D investments, whereas technological similarity results in a reduction. Phene et al. (2012) find that technological relatedness has no impact on either ex post exploration or exploitation. Several studies have also focused on the interplay between technological and product market relatedness (e.g. Colombo & Garrone, 2006b). Valentini and DiGuardo (2012) find that technological distance has no impact on knowledge depth and breadth ex post, but a positive impact on deals involving high market relatedness (i.e. technological relatedness and product market relatedness are substitutes).

3.2.7 Target choice vs. post M&A innovation performance

In investigating the relationship between M&A and technological relatedness, most studies have focused either on the choice of target or the post acquisition innovation performance of the combined firm. While the latter investigation is very interesting from a (merger) policy perspective, the former investigation is much more amenable for empirical research for several reasons: As has been noted by Hussinger (2010), there are many confounding effects that make it difficult to determine the role that an acquisition plays in the ex post performance. This is particularly pronounced for the acquisition of small firms by large firms. Furthermore, the ex post performance in terms of R&D is difficult to interpret in a normative way as a reduction in R&D due to the avoidance of duplicate projects may be welfare enhancing (Veugelers, 2006). There are also endogeneity concerns, as the innovation outlook of the acquirer may impact the choice of technologically distant vs. close targets and the causal interpretation of technological distance impacting ex post innovation performance may not be warranted. As for the impact of technological relatedness on ex post M&A patenting, studies have difficulties addressing timing and value aspects. It is conceivable that the acquisition of distant targets requires more time to yield patents, as novel recombinations of technologies require time. Also, the combination of distant technologies may yield higher value innovations compared to the combination of close technologies.

In contrast, the choice of M&A target is not subject to these problems. The choice model presented below takes endogeneity explicitly into account. It is possible to determine the role of technological distance when a large company acquires a small company. Timing issues as in the above case do not arise. Hence, the focus of this research is on the ex ante role of technological distance and other innovation metrics, either in terms of the choice of M&A target or the price paid for the target.

3.3 Hypotheses

The technological distance between the acquirer and the target can have both a positive and a negative impact on the expected benefits of an M&A transaction. On the one hand, technological proximity is associated with higher contemporary absorptive capacity as the acquirer is in a better position to assess and assimilate the target's technological competencies (Ahuja & Katila, 2001; Cohen & Levintal, 1990). A similar knowledge base of the acquirer and target is associated with shared methods and skills, which facilitate communication and learning, whereas dissimilar knowledge bases require time consuming and potentially disruptive integration processes (Ahuja & Katila, 2001; Haspeslagh & Jemison, 1991; Kogut & Zander, 1992; Lane & Lubatkin, 1998). For example, Grant (1996) noted that shared languages and meanings facilitate the efficient integration of team members. Overlapping knowledge bases also offer the potential to avoid duplication and leverage economies of scale (Ornaghi, 2009). Furthermore, technological proximity can benefit the acquirer from a strategic perspective, enabling the firm to resolve (potential) patent disputes, to operate more freely in its R&D activities and to build a patent fence that prevents third parties from competing with it (Grimpe & Hussinger, 2013).

On the other hand, technological distance can increase the potential to learn from the target and generate new innovations that build on different technological bases (Sapienza et al., 2004). A substantial gain of new knowledge can be achieved when distinct technology fields are used together: Consider the combination of automotive technology and information technology to build networked cars or the combination of biotechnology, computer science and engineering giving rise to the field of bioinformatics. The sales, profits and potentially higher margins that can be generated from new products incorporating these technologies provide direct benefits to the company. Different technological approaches can be combined to solve new problems or old problems can be solved by the other firm's technological know-how (Barney, 1988; Cohen & Levinthal, 1990; Keil et al., 2008). Heterogeneous experience and information has been found to support learning (Haunschild & Sullivan, 2002). Accepted beliefs about "how to do things" are more likely to be challenged when the knowledge bases of the firms exhibit some distance, engendering a constructive conflict and potentially leading to new insights (Dehne, 2013; March, 1991). Furthermore, the acquisition of distant technologies provides the future absorptive capacity to assess these technologies going forward. Also, it provides a means to diversify technologically and thereby to reduce the reliance on technologies that may become obsolete. Finally, M&A may be seen as a means to enter distant technologies quickly, while close technologies may be developed in-house. Distant technologies may be very difficult to develop internally due to the lack of internal competencies, the long time period required to build these competencies and potential resistance towards change within the corporation. M&A may provide a means to obtain these technologies externally more quickly and less costly.

In order to balance the impact of the benefits and disadvantages of technological distance, acquirers are expected to choose firms with an intermediate level of technological distance. In fact, Cohen and Levinthal (1990) argued that "[while] common knowledge improves communication, commonality should not be carried so far that diversity across individuals is substantially diminished" (p. 134). Likewise, Sapienza et al. (2004) argue that "both too small and too great an overlap will inhibit growth, the first because limited knowledge overlap hampers local search and knowledge assimilation and the second because great knowledge overlap hampers the creation of novel knowledge combinations" (p. 809). In addition to the theoretical arguments, the existing evidence on an inverted U-shape relationship between technological distance and post M&A innovation performance would suggest that rational acquirers choose targets with an intermediate level of technological distance.

Hypothesis 1: Acquirers choose targets with an intermediate level of technological distance.

The choice model used to test hypothesis 1 is built on the assumption that acquirers choose to engage in a transaction with the firm for which the net gains are highest (see Section 3.4 for more details). As the transaction price also reflects the expected (gross) gains from engaging in a transaction, the conjecture about choice behavior should also be transferable to the transaction price (Grimpe & Hussinger, 2013). Barney (1988) argued that firms can only obtain above normal returns when the acquirer has private information on the target that others do not have or when there is the potential for synergies from a combination that other firms cannot achieve**.** With many potential bidders, a higher price can be paid for a target if the value of the target to one firm is higher than the value to another firm, e.g. because of technological synergies (Adegbesan, 2009). How the value gain due to synergies is distributed between the acquirer and target depends on competition and bargaining, but Adegbesan (2009) showed that acquirers achieve a positive share of the gains (Grimpe & Hussinger, 2013). Building on the arguments provided in support of hypothesis 1, I expect that the transaction price will be highest when the target and acquirer are at an intermediate level of technological distance.

Hypothesis 2: The transaction price is highest when the target and acquirer exhibit an intermediate level of technological distance.

The mediating conditions that affect the relationship between technological characteristics and target choice have received little attention. I focus on characteristics of the acquirer that impact the role of technological distance on target choice. As will be shown below, the acquirer characteristics cannot be used as independent variables in the discrete choice model as they appear in the nominator and denominator. However, interaction effects can be used in this setting (Davies, Greenwood & Li, 2001).

Using M&A transactions to enter new technology fields or new product markets is associated with significant uncertainty for the acquirer. Also, a higher distance in either domain is likely to be associated with higher asymmetric information to the detriment of the acquirer, making it difficult for the acquirer to engage in value enhancing transactions (King et al., 2008; Reuer, 2005). I expect that uncertainty and asymmetric information in both domains will make a transaction less likely. When a company acquires a technologically distant firm, it is likely to prefer it to be at least close in product market so as to limit the uncertainty and amount of asymmetric information of a transaction. In contrast, when a technologically close firm is acquired, it has more capacity to deal with the uncertainty and asymmetric information that distant product markets entail.

Hypothesis 3: The higher the product market (technological) distance between the acquirer and the target, the more will acquirers prefer firms which are close in technological (product market) space.

Regarding the mediating factors that impact the acquirer's reference for technologically close or distant firms, I argue that acquirers use M&A transactions to acquire technologically distant firms when they are performing poorly, either financially or in their innovation efforts, so as to renew strategically and to reposition themselves (e.g. Capron & Mitchell, 2009). Agarwal and Helfat (2009) state that "[s]trategic renewal includes the process, content, and outcome of refreshment or replacement of attributes of an organization that have the potential to substantially affect its long-term prospects" (p. 282). Especially listed acquirers are likely to be put under pressure from their shareholders to induce such strategic renewal when their financial or innovation performance is weak. For example, Agarwal and Helfat (2009) describe how IBM reacted to its weaknesses in software and consulting by acquiring Rational Software and Price-Waterhouse Coopers Consulting, thereby shifting the company's knowledge base.

Hypothesis 4: Acquirers which are underperforming either financially or in their innovation performance acquire technologically distant firms.

3.4 Econometric model, data, measures and descriptive statistics

3.4.1 Choice Model

Hall (1988a) developed a model where the selection of M&A targets from the perspective of the *acquirer* is a matching process in which a firm maximizes the gains from a transaction, taking into account target characteristics, acquirer characteristics and the relationship between the target and acquirer. Each actual acquirer is given the choice among the actual target as well as a control group of non-chosen targets (together the *choice set*), with the decision being based on the characteristics of the firms in the choice set. The model was subsequently used by Hussinger (2010), Frey and Hussinger (2006) and AlAzzawi (2008).

Let X_i denote a vector of firm i's characteristics (e.g. total assets, patents, technological profile, etc.) and $V(X_i) = V(X_1, X_2, X_3 \ldots)$ the value of the assets of firm i, representing the discounted future cash flows that can be generated from these characteristics. The value is not necessarily equal to the stock market value of the firm as M&A transactions typically involve the payment of a premium above the stock market value, owing to the fact that the target firm's assets are of higher value to an acquirer, e.g. because of technological or production synergies, than what they are traded at the market (Jensen & Ruback, 1983). Due to shocks that can make assets less productive in their current use, disequilibrium arises, leading to M&A activity that reallocates resources to their most productive use.

Denoting j the acquiring firm, S the choice set of target firms and $V_j(X_i)$ the value increment to the acquirer j attributable to the acquisition of firm $i \in S$, firm j will acquire firm $i \in S$ under the following two conditions:

$$V_j(X_i) - P_i > V_j(X_k) - P_k \quad \forall\ (k \neq i) \in S$$

$$V_j(X_i) - P_i \geq 0$$

where P_i denotes the price that j has to pay for acquiring firm i. The two conditions say that firm j acquires firm i if the net gain is larger than the net gain of acquiring another firm in the choice set and that the net gain is positive. Prices are endogenous in the model as different potential acquirers value the potential target differently. The acquisition price is unobservable and assumed to be a function of the target's characteristics and the relationship between the target and acquirer. Concretely, the net profit of the acquisition to the acquirer is split into an observable and an unobservable part:

$$V_j(X_i) - P_i = f(X_i, X_j) + \varepsilon_{ij}$$

ε_{ij} is assumed to follow an extreme value distribution. The probability that firm j acquires firm i is then modeled using a conditional logit function:

$$P(j\ acquires\ i|S) = \frac{\exp\left(f(X_i, X_j)\right)}{\sum_{k \in S} \exp\left(f(X_k, X_j)\right)}$$

Denoting the measurable components of the value of the target with lower case v, The function $f(X_i, X_j)$ is specified as the value that the acquiring firm attributes to firm i's assets $v_j(X_i)$ and the equilibrium price (e.g. stock market value) $v(X_i)$:

$$f(X_i, X_j) = v_j(X_i) - v(X_i) = \beta_1 X_i + \beta_2 X_j + \beta_3 (X_j X_i).$$

In sum, the net gain from an acquisition is modeled as a function of the target characteristics, acquirer characteristics and the relationship between the target and the acquirer. As the acquirer characteristics occur both in the nominator and denominator, the effect of acquirer characteristics (β_2) cannot be estimated. However, below I estimate the interaction effects of acquirer characteristics with the technological distance and the target's innovation characteristics.

Model implementation

Regarding the choice set that acquirers are facing, two strategies are implemented. First, in most studies, each acquirer is given a choice set that includes all firms it could acquire (AlAzzawi, 2008; Hall, 1988a; McFadden, 1978). This leads to a very large choice set which can cause estimation problems, including imprecisely measured coefficients. As a result, authors often use a random subset of all firms in the choice set. In this study, each firm is given the choice among a random sample of a maximum of 500 firms. The disadvantage of this approach is that the choice set will include firms that are highly unlikely to be chosen by the acquirer (e.g. General Electric could be part of the choice set of Pfizer or a small engineering company).

Second, I put more structure on the choice set, such that each acquirer can choose among all firms which (a) have the same 2-digit primary SIC code as the target, (b) have assets not in excess of twice the acquirer's assets (for the sample consisting of transactions where both the acquirer and target are listed firms and where financial information is available) and (c) have applied for at least one patent in the five years prior to the transaction (see Bena & Li, in press, for a similar approach). This is arguably a setting which is more realistic to investigate the relationship between technological distance and acquisition choice and the conditioning factors that impact this relationship.

The implementation of the modeling in STATA allows for the choice sets to vary between acquirers both in terms of size and composition. Also, it is possible to estimate multiple acquisitions by an acquirer in a given year.

In a subsequent paper, Hall (1988b) estimates two variants of the above model. First, she estimates the choice model from the perspective of the target rather than the acquirer. Second, she applies a nested logit model where firms are grouped by industry. The results of both variants were found to be consistent with the findings from the main model presented above where the choice is modeled from the acquirer's perspective.

In addition to the discrete choice model, I will test hypothesis 2 using a hedonic price model, regressing the transaction value on a series of target characteristics (Grimpe & Hussinger, 2013; Hall, Jaffe & Trajtenberg, 2005). Estimation is done using an OLS estimator.

3.4.2 Data

The dataset comprises 538 M&A transactions in the time period 1985-2006. The transactions were obtained from Thomson Reuters' SDC M&A database which covers public as well as private transactions. The transactions are filtered according to the following criteria: The transaction has to be completed, involve an acquisition of at least a 10% stake in the target, before the transaction the acquirer had to own less than 50% of the target and following the transaction the acquirer had to own at least 50% of the target.[13,14] I restrict the sample to

[13] This is in line with the definition given by Desyllas and Hughes (2009). In addition, I add the requirement that at least 10% have to be acquired in the transaction in order for the transaction to be of substantial economic significance.
[14] In 96% of the transactions covered, a 100% share of the target was acquired.

domestic transaction in the US, i.e. both the target and the acquirer have to be US based firms.[15] Finally, both the target and the acquirer had to have applied for at least one US patent (which was subsequently granted) in the five calendar years prior to the transaction.

The patent portfolio of each company was determined based on the NBER patent file, which contains patents assigned at the USPTO up to 2006. This file indicates the name of the assignee as of the issue date, and extensive efforts have been made to standardize assignee names (Bessen, 2009; Hall, Jaffe & Tratjenberg, 2001).[16] A dynamic matching of patents accounting for reorganization and M&A transactions is conducted for North American Compustat firms (Bessen, 2009). Overall, there are 1.44 million patent filings by 115 thousand US based firms between 1973 and 2005. The approx.7,000 Compustat firms that are covered in this analysis account for .90 million of the patent filings. For listed firms, the patent data was matched to the transactions using the 6-digit CUSIP code.[17]

In addition to listed firms, I included firms that have received VC financing at one point in their life. Companies which received VC financing but later went public are already covered in the above sample. The data on VC financing was obtained from the Thomson Reuters Venture Capital database. The VC financed firms were matched to the NBER standard firm name based on an algorithm from the Apache Lucene library (Schnitzer & Watzinger, 2014).[18] This dataset was subsequently matched to the M&A transactions based on the permanent company ID for private companies provided by Thomson Reuters. I checked manually that the acquired company coincides with the standard firm name in the NBER file. If the names did not constitute a very close match, the transaction was dropped from the dataset.[19]

Both public and private companies are included in the choice set of the conditional logit model. Companies that engage as acquirers in a particular year are excluded from the choice set of other firms in that year, owing to the imprecision of the financials and technology profile around the time of a merger. For part of the analysis, I restrict the sample to 380 transactions for which financial information is available from Compustat, thereby covering

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[15] As I use US patent data, this restriction prevents any concern regarding different patenting behaviors of non-US firms vis-à-vis US firms.
[16] For example, there are in excess of 100 assignee names (primarily different abbreviations and misspellings) that refer to the company IBM (Bessen, 2009).
[17] CUSIP codes are in the first instance about securities. The first 6 digits denote the issuer, while the subsequent three digits refer to specific securities of an issuer.
[18] I would like to thank Martin Watzinger for making this matching available to me.
[19] Overall, most companies in the sample transactions are matched to the patent data with the CUSIP rather than the permanent company ID.

only public acquirers and firms in the choice set. The financials in the last full financial year prior to the acquisition are used in the analysis.

I do not account for the motivation to engage in M&A in the selection of transactions for two reasons. First, whether or not a transaction occurs for technology related reasons is almost always a matter of degree rather than a binary variable. The threshold above which a transaction is to be considered as being motivated by technology is necessarily arbitrary. Second, the criteria to determine the importance of technology in the motivation are subject to criticism and / or difficult to quantify.[20] In light of merger reviews, one may expect a tendency to stress technology related motivations at the expense of market power related motivations.

3.4.3 Measures

Dependent variable 1: In the choice model, the dependent variable is an indicator function equal to one if a firm in the choice set is acquired and 0 if it is not acquired.

Dependent variable 2: For the hedonic market value equation (Hall, Jaffe & Trajtenberg, 2005), the dependent variable is the natural logarithm of the transaction price. If less than 100% is acquired in the transaction (accounting for approximately 4% of the transactions), I have imputed the implied value of a 100% stake by dividing the transaction price by the percentage share acquired. The natural logarithm was taken as the transaction values are skewed (see also Grimpe & Hussinger, 2013).

Technological distance: Two distinct distance measures have been included in the analysis. Introduced to the literature by Jaffe (1986), the angular separation is the most widely used measure of technological distance. It is also called the cosine distance or uncentered correlation index. It measures technological distance of two firms by the degree to which they take out patents in the same technological areas. More formally, it measures to what degree the vectors f, which describe the technological profiles of firms based on the classification of patents, point in the same direction, controlling for the length of the vector. The angular separation between firm i and firm j is calculated as follows:

[20] For example, Ahuja and Katila (2001) suggested using patenting activity of the target in the prior five years as an indication that the transaction is technology motivated. Also, those transactions for which technology was mentioned in company statements as an important element of the transaction were considered to be technologically motivated. While the first criterion does not take into consideration of whether the patents are of importance to the acquirer, the second method is exposed to subjective judgment. Makri et al. (2010) exclude transactions valued at above $500 million arguing that such transactions are likely to be motivated by increasing market power and economies of scale rather than knowledge transfer. The role that technology and innovation has played in the larger mergers in the pharmaceuticals and ICT industries questions this assumption. Finally, Sears and Hoetker (2014) define technological acquisitions as acquisitions where both the target and acquirer are high technology firms.

$$Angular\ separation_{ij} = \frac{f_i f_j'}{\sqrt{(f_i f_i')^*(f_j f_j')}}$$

where f_i represents firm i's technology profile. The measure ranges between 0 and 1, where 1 denotes no distance between firms.

The second technological distance measure is the Jaffe covariance. This measure is similar to the angular separation with the exception that no adjustment is made to the length of the vectors (Bloom et al., 2013).

$$Jaffe\ covariance_{ij} = f_i f_j'$$

For both distance measures, all patents filed in the five years prior to the transaction, and subsequently granted, will constitute the patent portfolio of the respective company (e.g. Podolny & Stuart, 1995).[21] The distance measures listed above will be calculated at the 37 technology subcategories determined by Hall, Jaffe and Trajtenberg (2001) as is standard in the literature.[22] Unlike most other research, I take into account multiple classifications per patent to increase the precision of the measurement of the technological profile (Benner & Waldfogel, 2008). It is important to note that both measures can range between 0 and 1 and that they are decreasing functions of distance: a value of 0 indicates a high distance whereas a value of 1 indicates no distance.

Technological distance is an auxiliary concept in the context analyzed here. The concepts that are expected to drive the relationship between (a) technological distance and target choice and (b) technological distance and transaction value are, inter alia, learning, gain of new knowledge, absorptive capacity and strategic value. The angular separation is the most widely used measure for technological distance, but, as argued in related research by the author, is likely less well suited in many research settings than alternative distance measures. The Jaffe covariance (Bloom, Schankerman & van Reenen, 2013) has been shown by this author to outperform the angular separation in three important respects (Stellner, 2014). First, the Jaffe

[21] For example, if a transaction is announced on 17 July 2004, the patents applied for between 1 January 1999 and 31 December 2003 will constitute the firms' patent portfolios. As the decision to acquire another company is made many months ahead of the announcement of a deal, it is reasonable to allow for this time lag in determining the patent portfolio. Ahuja & Katila (2001) found that changing time period over which patents are considered to be part of the technology portfolio leads to highly correlated measures.

[22] I have shown in related research, that the choice of the level of aggregation is not as important as the choice of distance measure. For example, calculating the angular separation at different levels of the classification hierarchy results in highly correlated measures.

covariance has been shown theoretically to have strong microeconomic foundations, while the angular separation has not (Bloom et al., 2013).[23] Second, the Jaffe covariance satisfies the independence of irrelevant patent classes, a criterion proposed by Bar and Leiponen (2012). In contrast, the angular separation does not satisfy this criterion. This criterion is important in that it more accurately accounts for the technological diversification of the firms which are compared. Third, I have shown that the Jaffe covariance has an attractive statistical property in that it does not exhibit a bias when the propensity to patent changes. Standard distance measures such as the angular separation were found to have a bias and be imprecisely measured in small samples (Benner & Waldfogel, 2008). As such, the Jaffe covariance is arguably more suitable when establishing the distance between firms with small patent portfolios.[24] I expect the choice of distance measure to have a significant impact on the results of the analysis.

Product market distance: Product market distance is set to 0 if the 2-digit SIC codes do not overlap, 1 if the acquirer and (potential) target have the same 2-digit SIC code but different 3-digit SIC codes, equal to 2 if the acquirer and (potential) target have the same 3-digit SIC code but different 4-digit SIC codes, and equal to 3 if the acquirer and (potential) target have the same 4-digit SIC code.[25]

Log(Patent stock): The size of the patent portfolio is determined by the number of patents applied for in the five calendar years prior to the transaction. As is standard in the literature, patents are assumed to depreciate by 15%, i.e. a patent applied for 4 years prior to the transaction counts as 0.52 towards this measure (Hall, 1990; Grimpe & Hussinger, 2013). Due to the skewed nature of the variable, I use the natural logarithm of the variable.

Patenting growth: The growth in patenting activity is calculated as the number of patents applied for in years 1, 2 and 3 prior to the transaction relative to patents applied for in years 4, 5 and 6 prior to the transaction.[26]

Log(R&D expenditures): This measure equals the natural logarithm of the R&D expenditures in the last financial year prior to the transaction.

[23] The theoretical model used by the authors is with respect to spillovers. It is based on a communication model in which knowledge exchange occurs between the constituent parts (i.e. the scientists) of a company. I have shown theoretically by slightly adjusting their model and also empirically, that the Jaffe covariance is effectively the average pairwise distance between the constituent technological elements of two companies as represented by their patents.

[24] In related research, I have shown that neither measure is very sensitive to the level of the classification hierarchy (e.g. class or subclass) when comparing many firms.

[25] See McGahan and Villalonga (2005) and Valentini and DiGuardo (2012) for a similar approach.

[26] To avoid the division by 0 if no patent was applied for in years 4, 5 and 6 prior to the transaction, I have added one patent to the patent portfolios for years 4,5 and 6 as well as the portfolio for years 1, 2 and 3 prior to the transaction (in analogy to Yang, Wei & Chiang (2014)).

Technological diversification: This is measured as the number equivalent entropy of target firms in the following way: Let f_{ik} denote the share of technology field k (out of K fields) in the technology portfolio of firm i. Then the number equivalent entropy (NEE) is defined as:

$$NEE_i = e^{\sum_{k=1}^{K} f_{ik} * \ln\left(\frac{1}{f_{ik}}\right)}$$

The number equivalent entropy ranges between 0 and the number of technology fields (Schmidt-Ehmcke & Zloczysti, 2008). The number equivalent entropy is only equal to the actual number of fields a firm is active in if the share of each field is the same. For example, a firm active in 12 fields and with a number equivalent entropy of 10 is as diversified as a firm having its technology spread equally between 10 fields.

Log(Total assets): This is measured as the natural logarithm of the total assets in USD at the end of the last financial year prior to the transaction. This is a measure of the size of the company (Desyllas & Hughes, 2009; Powell, 1999). As this variable is skewed, the natural logarithm is used.

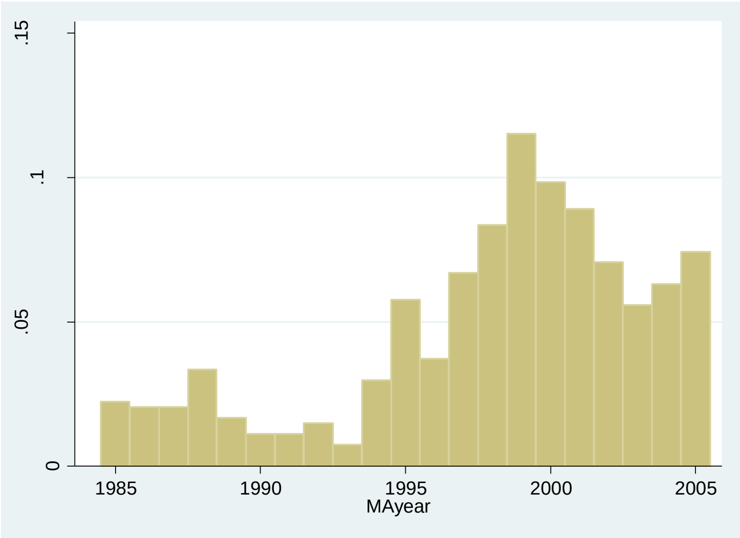
Return on assets (RoA): This is measured as the ratio of earnings before interest and tax over total assets (EBIT) in the year prior to the transaction.

Sales growth: This is measured as the ratio of sales in year one prior to the transaction and sales in year two prior to the transaction.

Due to the outliers in the data, the measures for return on assets and sales growth are winsorized at 1% in each tail.

3.4.4 Descriptive statistics

The dataset comprises 340 acquirers engaging in 538 transactions over the period 1985 to 2005. As can be seen in Graph [1], the vast majority of transactions (81%) occurred in the period 1995 to 2005. A sharp rise of M&A activity over the 1990s and a subsequent dip following the dot-com bubble are clearly visible. The targets in these transactions successfully applied for 32k patents in the 10 years prior to the acquisition, constituting an average of 60 patents per target.



Graph [1]:Share of M&A transactions per year (total 538)

As shown in Table [1], with regards to the acquirer industry affiliation, over 80% of the transactions occurred in one of the top five industries, namely Business Services (19.5% of targets), Electronic & other Electric Equipment (19.3%), Instruments (17.8%), Industrial Machinery & Equipment (13.9%) and Chemical & Allied Products (13.2%).[27,28] 87% of the transactions in the sample involve acquirers in a high technology sector based on the definition of Hall and Vopel (1996).[29]

		Target Sector						
		Business Services	Instruments & Related Products	Electronic & Other Electric Equipment	Industrial Machinery & Equipment	Chemical & Allied Products	Other	SUM
Acquiror Sector	Business Services	11.9%	0.6%	1.1%	1.3%	0.0%	0.2%	15.1%
	Instruments & Related Products	1.5%	10.8%	2.0%	1.9%	0.7%	0.6%	17.5%
	Electronic & Other Electric Equipment	1.3%	1.1%	11.0%	1.3%	0.0%	0.7%	15.4%
	Industrial Machinery & Equipment	4.3%	0.9%	3.5%	7.2%	0.0%	0.7%	16.7%
	Chemical & Allied Products	0.0%	3.5%	0.0%	0.2%	12.1%	3.2%	19.0%
	Other	0.6%	0.9%	1.7%	2.0%	0.4%	10.8%	16.4%
	SUM	19.5%	17.8%	19.3%	13.9%	13.2%	16.2%	100.0%

Table [1]:M&A transaction by 2-digit SIC code

27 Note that “Drugs” have SIC code 283 and form part “Chemicals and Allied Products” (SIC code 28).
28 The studies by Ahuja and Katila (2001) and Cloodt et al. (2006), which have found a curvilinear relationship between technological distance and ex post innovation performance, have focused on the same or similar industries. Ahuja and Katila (2001) focus on the chemicals industry, while Cloodt et al. (2006) have 72% of their acquirers in the pharmaceuticals or electronics & communications industries.
29 The characterization of high technology industries is based on the R&D-intensity and on investment horizons. High technologies are constituted of 2-digit SIC codes 28, 35, 36, 37, 38, 48, 73 and 87 (Desyllas & Hughes, 2009; Hall & Vopel, 1996).

Transactions where the acquirer and target share the same 2-digit, 3-digit and 4-digit SIC code account for 61%, 50% and 32%, respectively, of the sample. In 96% of the transactions, a 100% stake was acquired.

The size of the choice set for each acquirer depends on whether private companies are included and whether the choice set is constituted of a random sample of firms or a matched sample (Table [2]). Strata are defined by acquirer and year of M&A transactions (e.g. transactions by firm Cisco in year 2000).

				Choice set statistics				
#	Sample *	Transactions	Strata	Size	Average	Median	Min.	Max.
1	Public & private, matched (SIC)	538	507	172,259	341	363	9	776
2	Public & private, random	538	507	244,841	484	484	473	495
3	Public, matched (SIC, size)	380	362	48,199	134	146	3	245
4	Public, random	380	362	65,336	182	190	35	256

* Matched refers the case where the choice set is constituted of firms in with the same 2-digit SIC code as the target and, in the case of public firms for which financials are available, where assets are not in excess of twice the acquirer's assets. Random refers to the case where the choice set is allocated randomly the acquirers.

Table [2]: Sample size and choice set characteristics

As financial data is only available for public firms, the following table illustrates the mean and standard deviation as well as correlation coefficients only for public firms, both for actual targets and the entire choice set (Table [3]). The sample moments and correlation coefficients for the sample including private firms can be found in the appendix. The angular separation and Jaffe covariance are included sequentially, so the expectedly high correlation between the two measures does not pose estimation problems. As for the other variables, the correlations are mostly quite low. Technological diversification and the size of the patent portfolio have a higher correlation. However, the correlation coefficient is below the recommended 0.8 threshold, above which multicollinearity may cause problems (Gujarati, 1995; King et al., 2008).

Descriptive statistics and correlation matrix (Public firms excluding choice set)

#	Variable	Sample	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12
1	Angular separation	379	0.56	0.34	1.00											
2	(Angular separtion)^2	379	0.42	0.35	0.97	1.00										
3	Jaffe covariance	379	0.27	0.25	0.81	0.85	1.00									
4	(Jaffe covariance)^2	379	0.14	0.22	0.64	0.72	0.95	1.00								
5	Product market overlap	379	1.40	1.29	0.28	0.30	0.27	0.25	1.00							
6	Size of patent portfolio (ln)	379	1.78	1.58	0.22	0.17	-0.09	-0.13	0.06	1.00						
7	Patenting growth	379	1.62	1.72	0.01	0.00	0.02	0.01	0.08	0.07	1.00					
8	Technological diversification	379	2.56	1.95	0.05	-0.02	-0.31	-0.32	0.03	0.72	-0.06	1.00				
9	R&D expenditures (ln)	379	2.59	1.57	0.17	0.14	-0.06	-0.11	0.17	0.55	-0.07	0.44	1.00			
10	Total assets (ln)	379	5.02	1.70	0.06	0.01	-0.22	-0.26	0.06	0.59	-0.07	0.56	0.76	1.00		
11	Return on assets	379	- 0.08	0.38	-0.18	-0.22	-0.30	-0.29	-0.05	0.19	0.00	0.22	0.14	0.50	1.00	
12	Sales growth	379	1.24	0.83	0.05	0.06	0.11	0.12	0.01	-0.02	0.26	-0.12	0.01	-0.08	-0.14	1.00

Descriptive statistics and correlation matrix (Public firms with choice set matchtched according to SIC and assets)

#	Variable	Sample	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12
1	Angular separation	48567	0.29	0.33	1.00											
2	(Angular separtion)^2	48567	0.19	0.30	0.96	1.00										
3	Jaffe covariance	48567	0.14	0.21	0.89	0.92	1.00									
4	(Jaffe covariance)^2	48567	0.06	0.16	0.70	0.80	0.93	1.00								
5	Product market overlap	48567	1.10	1.07	0.27	0.29	0.32	0.29	1.00							
6	Size of patent portfolio (ln)	48567	1.79	1.51	0.07	0.03	-0.07	-0.10	-0.04	1.00						
7	Patenting growth	48567	2.10	2.46	0.02	0.01	0.00	-0.01	0.04	0.16	1.00					
8	Technological diversification	48567	2.57	1.92	-0.01	-0.08	-0.19	-0.20	-0.10	0.68	0.00	1.00				
9	R&D expenditures (ln)	48567	2.18	1.68	0.14	0.09	0.03	-0.02	0.06	0.54	0.13	0.40	1.00			
10	Total assets (ln)	48567	4.62	1.74	0.04	-0.01	-0.08	-0.11	-0.04	0.53	0.08	0.48	0.78	1.00		
11	Return on assets	48567	-0.11	0.41	-0.10	-0.12	-0.14	-0.13	-0.10	0.13	0.00	0.18	0.15	0.47	1.00	
12	Sales growth	48567	1.40	1.32	0.04	0.05	0.07	0.07	0.04	-0.04	0.15	-0.10	0.00	-0.04	-0.12	1.00

Table [3]: Sample moments and correlation (Public firms)

3.5 Empirical results

The following table reports the results for the conditional logit model with four samples. Samples 1 comprises both private and public transactions, and the choice set is matched based on the 2 digit SIC code of the target. Sample 2 also comprises both private and public transactions, but the choice set is matched randomly. Samples 3 comprises only public transactions for which financial data is available, and the choice set is matched based on the 2 digit SIC code of the target and the acquirer's assets. Sample 4 comprises only public transactions for which financial data is available, and the choice set is matched randomly.[30]

[30] In line with the prior literature that has used the conditional logit model for the choice of M&A targets, the results are reported with their coefficients (AlAzzawi, 2008; Bena & Li, in press; Hussinger, 2010).

	Public & Private, matched (SIC)		Public & Private, random		Public, matched (SIC, size)		Public, random	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Angular separation	5.659***		6.868***		5.390***		7.134***	
	(0.610)		(0.580)		(0.754)		(0.706)	
(Angular separation)^2	-3.204***		-3.961***		-2.670***		-3.904***	
	(0.632)		(0.608)		(0.764)		(0.740)	
Jaffe covariance		8.993***		10.63***		9.112***		11.46***
		(0.614)		(0.614)		(0.778)		(0.781)
(Jaffe covariance)^2		-7.590***		-8.798***		-7.049***		-9.031***
		(0.747)		(0.775)		(0.892)		(0.974)
Product market overlap	1.065***	1.109***	1.005***	1.051***	1.020***	1.064***	0.868***	0.914***
	(0.107)	(0.107)	(0.0526)	(0.0528)	(0.126)	(0.125)	(0.0596)	(0.0605)
Size of patent portfolio (ln)	0.0840*	0.0718*	0.0891*	0.0749*	-0.157**	-0.155**	-0.146**	-0.152**
	(0.0369)	(0.0360)	(0.0358)	(0.0350)	(0.0519)	(0.0508)	(0.0519)	(0.0514)
Patenting growth	-0.105***	-0.103***	-0.115***	-0.113***	-0.137***	-0.135***	-0.139***	-0.137***
	(0.0247)	(0.0247)	(0.0256)	(0.0258)	(0.0379)	(0.0382)	(0.0376)	(0.0384)
Technological diversification	-0.112***	-0.0175	-0.115***	-0.00124	-0.121**	-0.0167	-0.123**	0.0142
	(0.0314)	(0.0274)	(0.0311)	(0.0263)	(0.0402)	(0.0360)	(0.0400)	(0.0345)
R&D expenditures (ln)					0.244***	0.238***	0.214***	0.207***
					(0.0627)	(0.0628)	(0.0563)	(0.0560)
Total assets (ln)					0.0897	0.0906	0.0791	0.0801
					(0.0601)	(0.0603)	(0.0533)	(0.0532)
Return on assets					-0.0835	-0.0692	0.0111	0.0250
					(0.181)	(0.181)	(0.176)	(0.178)
Sales growth					-0.0859	-0.0866	-0.0931	-0.0926
					(0.0496)	(0.0502)	(0.0554)	(0.0552)
N	172797	172797	245379	245379	48567	48567	65480	65480
Pseudo R^2	0.106	0.099	0.244	0.234	0.145	0.137	0.294	0.282

* p<0.05, ** p<0.01, *** p<0.001; numbers in parentheses are standard errors

Table [4]: Results of conditional logit regression with different choice sets

3.5.1 The role of innovation and financial metrics

Several observations can be made from table [4]. The effect of the size of the patent portfolio differs between the specifications: When private firms are included in the analysis and thus no control is made for the financial characteristics of the firms, a larger patent portfolio is found to increase the likelihood of being acquired. However, this finding suffers from omitted variable bias, as when including other size measures (such as R&D and assets), a larger patent portfolio is found to significantly decrease the likelihood of being acquired. This finding is in line with Frey and Hussinger (2006). A higher growth rate of patenting over the prior six years is found to significantly reduce the likelihood of being acquired. Technological diversification is found to reduce the likelihood of being acquired when the angular separation is used to measure technological distance, but has no significant impact when the Jaffe covariance is used. R&D expenditures have a significant positive impact on being chosen. The other financial characteristics of the target such as assets, return on assets and sales growth were not found to significantly impact the target choice. Overall, the results suggest that targets with weaknesses in their innovation performance as measured by the size of their patent portfolio and the growth of patenting are more likely to be taken over, a finding which is in line with Bena and Li (in press).

3.5.2 The role of product market and technological distance

In all specifications, acquirers prefer targets which are close to them in product market space. This can be due to information advantages, market power motivations, economies of scale or the easier organizational integration (Capron & Shen, 2007; Hussinger 2010; Keil et al., 2008; Seth, 1990; Singh & Montgomery, 1987). This is consistent with the findings by Keil et al. (2008), who show that acquisitions improve post M&A innovation performance most when the target and acquirer are in the same industry. Regarding technological distance, for all specifications, the linear term for technological distance is positive and significant and the squared term is negative and significant, suggesting an inverted U-shape relationship. Independent of whether the angular separation or the Jaffe covariance is used to measure technological distance, the peak of the inverted-U is typically within the data range for the distance measure. Only in the case of specification (6) is the peak above one, the upper bound of the angular separation.

3.5.3 Robustness test to non-linear relationship between technological distance and target choice

As there are only few observations at the declining part of the curve, I have conducted several robustness checks to investigate whether the inverted U-shape holds.[31] First, I check whether the results are robust to sub-sampling on the part of the choice set (i.e. the acquirer choice set is restricted to 100, 50, 20 or 10 firms as well as the actual target). As can be seen in Table [5], the coefficients of the Jaffe covariance remain of the right sign and significant. A similar analysis conducted for the angular separation not reported here provides the same results.

[31] For example, in around 11% of transactions is the Jaffe covariance higher than the peak of the fitted inverted U-curve.

	Public, matched (SIC, size)				
	(1): Full samle	(2): 100 firms	(3): 50 firms	(4): 20 firms	(5): 10 firms
Jaffe covariance	9.112***	8.827***	8.794***	8.628***	9.136***
	(0.778)	(0.773)	(0.764)	(0.831)	(0.887)
(Jaffe covariance)^2	-7.049***	-6.776***	-6.811***	-6.552***	-7.020***
	(0.892)	(0.898)	(0.879)	(0.969)	(1.077)
Product market overlap	1.064***	1.052***	0.982***	0.884***	0.780***
	(0.125)	(0.125)	(0.121)	(0.123)	(0.123)
Size of patent portfolio (ln)	-0.155**	-0.162**	-0.148**	-0.151**	-0.180**
	(0.0508)	(0.0512)	(0.0515)	(0.0553)	(0.0599)
Patenting growth	-0.135***	-0.130***	-0.130***	-0.136***	-0.133***
	(0.0382)	(0.0381)	(0.0384)	(0.0385)	(0.0384)
Technological diversification	-0.0167	-0.0187	-0.0223	-0.0176	-0.00713
	(0.0360)	(0.0351)	(0.0357)	(0.0379)	(0.0407)
R&D expenditures (ln)	0.238***	0.244***	0.227***	0.235***	0.245***
	(0.0628)	(0.0641)	(0.0639)	(0.0661)	(0.0734)
Total assets (ln)	0.0906	0.0892	0.0897	0.0710	0.0552
	(0.0603)	(0.0612)	(0.0618)	(0.0663)	(0.0738)
Return on assets	-0.0692	-0.0959	-0.0795	0.0361	0.155
	(0.181)	(0.181)	(0.184)	(0.211)	(0.230)
Sales growth	-0.0866	-0.0841	-0.0780	-0.0541	-0.0497
	(0.0502)	(0.0517)	(0.0543)	(0.0594)	(0.0692)
N	48567	27162	14516	6289	3367
Pseudo R^2	0.137	0.149	0.163	0.189	0.223

* p<0.05, ** p<0.01, *** p<0.001; numbers in parentheses are standard errors

Table [5]: Subsamples of alternatives in the choice set

Second, I include dummy variables for each decile and run a conditional logit estimation (Table [6]). The decile in which the peak of the inverted-U occurs is excluded from the estimation and serves as the reference point. For the angular separation, I use the 9th decile as the reference point and for the Jaffe covariance, I use the 7th decile as the reference point. In the case of the angular separation, the 10th decile dummy is positive, indicating that the likelihood of being chosen as a target increases relative to the 9th decile. As the increments from one decile to the next decrease, there is evidence that a flattening curve rather than an inverted U-shape better fits the relationship between the angular separation and the likelihood of being chosen as a target. Regarding the Jaffe covariance, the dummy for the 8th decile is higher, while the 9th and 10th decile are lower. This would suggest an inverted U-shape, but the dummy variables are not statistically significant.[32] Hence, there is no robust evidence for an inverted U-shape from this analysis.

[32] For the Jaffe covariance measure, I also included dummies for each quintiles (rather than deciles), so that more observations are included in the highest bucket, potentially leading to significant differences between the 4th and 5th quintile. While the dummy for the 5th quintile is negative, it is not significantly different from the 4th dummy, which serves as the reference point.

	Public & Private, matched (SIC)		Public & Private, random		Public, matched (SIC, size)		Public, random	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Angular separation 1st decile Dummy	-2.464***		-3.012***		-2.673***		-3.310***	
	(0.189)		(0.191)		(0.239)		(0.248)	
Angular separation 2nd decile Dummy	-1.700***		-1.935***		-1.827***		-2.045***	
	(0.243)		(0.237)		(0.282)		(0.280)	
Angular separation 3rd decile Dummy	-1.154***		-1.396***		-1.351***		-1.589***	
	(0.221)		(0.225)		(0.262)		(0.274)	
Angular separation 4th decile Dummy	-0.731**		-0.990***		-0.816**		-1.037***	
	(0.228)		(0.231)		(0.269)		(0.267)	
Angular separation 5th decile Dummy	-0.907***		-0.987***		-1.101***		-1.152***	
	(0.242)		(0.242)		(0.283)		(0.295)	
Angular separation 6th decile Dummy	-0.781***		-0.882***		-0.842**		-0.902**	
	(0.236)		(0.237)		(0.269)		(0.275)	
Angular separation 7th decile Dummy	-0.167		-0.337		-0.320		-0.406	
	(0.237)		(0.238)		(0.274)		(0.283)	
Angular separation 8th decile Dummy	-0.257		-0.311		-0.299		-0.292	
	(0.204)		(0.202)		(0.235)		(0.248)	
Angular separation 10th decile Dummy	0.0722		0.00117		0.0907		0.0622	
	(0.188)		(0.191)		(0.212)		(0.228)	
Jaffe covariance 1st decile Dummy		-2.108***		-2.640***		-2.737***		-3.370***
		(0.253)		(0.258)		(0.324)		(0.350)
Jaffe covariance 2nd decile Dummy		-0.910***		-1.138***		-1.489***		-1.722***
		(0.265)		(0.268)		(0.321)		(0.354)
Jaffe covariance 3rd decile Dummy		-0.293		-0.480		-0.866**		-0.957**
		(0.262)		(0.263)		(0.316)		(0.347)
Jaffe covariance 4th decile Dummy		0.0411		-0.0775		-0.541		-0.575
		(0.257)		(0.254)		(0.318)		(0.341)
Jaffe covariance 5th decile Dummy		0.105		0.0228		-0.495		-0.587
		(0.256)		(0.259)		(0.324)		(0.368)
Jaffe covariance 6th decile Dummy		0.00792		-0.0535		-0.269		-0.476
		(0.312)		(0.315)		(0.344)		(0.381)
Jaffe covariance 7th decile Dummy		-0.366		-0.448		-0.612		-0.687
		(0.359)		(0.345)		(0.406)		(0.415)
Jaffe covariance 9th decile Dummy		0.0573		0.193		-0.323		-0.160
		(0.388)		(0.374)		(0.497)		(0.491)
Jaffe covariance 10th decile Dummy		-0.121		-0.0817		-0.570		-0.612
		(0.574)		(0.588)		(0.790)		(0.861)
Product market distance	1.066***	1.109***	1.006***	1.055***	1.019***	1.059***	0.864***	0.911***
	(0.106)	(0.106)	(0.0526)	(0.0537)	(0.125)	(0.126)	(0.0598)	(0.0614)
Controls (Patent measures)		Yes		Yes		Yes		Yes
Controls (R&D metrics; financials)		No		No		Yes		Yes
N	172797	172797	245379	245379	48579	48579	65716	65716
Pseudo R^2	0.106	0.099	0.243	0.232	0.146	0.137	0.295	0.282

* p<0.05, ** p<0.01, *** p<0.001; numbers in parentheses are standard errors

Table [6]: Dummy variables for deciles

Third, I use fractional polynomials to investigate if alternative functional specifications fit the data better than the linear and squared term (Table [7]). As the calculation is computationally intensive, the choice set is limited to the target and 10 non-chosen alternatives. I have restricted the analysis to the samples comprising of public firms, covering both cases of matched and random choice set. For all samples, alternative functional specifications than the linear and squared terms fit the data better. All indicate that a flattening curve fits the data better than an inverted U.

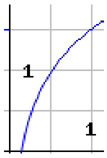
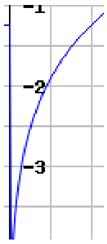
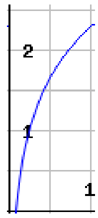
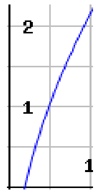
Sample / Measure	*Best specification*	*Graphical*
Sample: Public, matched (SIC, size) *Measure: Jaffe covariance (JC)*	β_1 *(X^(-0.5)-2.64)+ β_2*(ln(X)+1.94) *where X=JC+2.328*e^(-10)* β_1=0.0002161 (t-stat: 8.47) β_2=0.7773188 (t-stat: 9.60)	
Sample: Public, matched (SIC, size) *Measure: Angular separation (AS)*	β_1 *(ln(X)-1.16)+ β_2*(ln(X)*ln(X) - 1.34) *where X=AS+3.818*e^(-10)* β_1=1.003695 (t-stat: 9.79) β_2=0.0494789 (t-stat: 8.58)	
Sample: Public, random *Measure: Jaffe covariance (JC)*	β_1 *(X^(-0.5)-3.49)+ β_2*(ln(X)+2.50) *where X=JC+1.164*e^(-10)* β_1=0.0001852 (t-stat: 9.07) β_2=0.9177666 (t-stat: 10.30)	
Sample: Public, random *Measure: Angular separation (AS)*	β_1 *(X^(0.5)-.436) *where X=AS+7.451*e^(-9)* β_1=3.817814 (t-stat: 14.27)	

Table [7]: Fractional polynomials

In sum, the existence of an inverted U-shape as suggested by Hypothesis 1 is not robustly supported by the data.

3.5.4 Interaction of technological and product market distance

The expected tradeoff between product market distance and technological distance in affecting the likelihood of being chosen as a target is strongly supported as shown by the highly significant negative interaction effects in Table [8]. Hypothesis 3 is thus confirmed.

	Private & Public, matched (SIC)		Private & Public, random		Public, matched (SIC, size)		Public, random	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Angular separation	3.048***		3.956***		3.029***		4.130***	
	(0.218)		(0.169)		(0.274)		(0.215)	
Jaffe covariance		4.218***		5.021***		4.750***		5.738***
		(0.354)		(0.245)		(0.527)		(0.377)
Product market overlap	1.234***	1.349***	1.370***	1.350***	1.108***	1.312***	1.226***	1.222***
	(0.125)	(0.113)	(0.0681)	(0.0544)	(0.152)	(0.135)	(0.0858)	(0.0668)
Product market overlap * Angular separation	-0.301**		-0.667***		-0.151		-0.626***	
	(0.114)		(0.0944)		(0.155)		(0.128)	
Product market overlap * Jaffe covariance		-0.725***		-0.893***		-0.706**		-0.912***
		(0.152)		(0.101)		(0.235)		(0.149)
Controls (Patents)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls (Innovation & Financials)	No	No	No	No	Yes	Yes	Yes	Yes
N	172797	172797	245379	245379	48567	48567	65480	65480
Pseudo R^2	0.103	0.083	0.244	0.217	0.142	0.122	0.293	0.263

* p<0.05, ** p<0.01, *** p<0.001; numbers in parentheses are standard errors

Table [8]: Interactions effects technological distance and product market distance

3.5.5 Interaction with acquirer characteristics

Interacting acquirer characteristics with technological distance and target innovation metrics provides the following results. When the angular separation is used to measure technological distance, no significant interaction effects are found (Table [9]).

	Public, matched (SIC, size)		Public, random	
	(1)	(2)	(3)	(4)
Angular separation	2.783***	2.646***	3.378***	3.249***
	(0.228)	(0.262)	(0.197)	(0.236)
Product market overlap	1.017***	1.020***	0.885***	0.884***
	(0.127)	(0.127)	(0.0592)	(0.0598)
Acq. Return on Assets * Angular separation	0.618		1.278	
	(1.053)		(0.779)	
Acq. Patenting growth * Angular separation		0.0694		0.0810
		(0.0709)		(0.0520)
Controls (Patent, R&D and Financial measures)	Yes	Yes	Yes	Yes
N	48567	48567	65480	65480
Pseudo R^2	0.142	0.143	0.288	0.288

* p<0.05, ** p<0.01, *** p<0.001; numbers in parentheses are standard errors

Table [9]: Interaction of acquirer characteristics with angular separation

When the Jaffe covariance measure is used (Table [10]), I find evidence that the lower the return on assets and patenting growth of the acquirer, the more technologically distant firms are chosen. This would indicate that firms with weak financial and innovation performance do indeed seek firms which are distant to them, supporting hypothesis 4.

	Public, matched (SIC, size)		Public, random	
	(1)	(2)	(3)	(4)
Jaffe covariance	3.566***	3.282***	4.605***	4.107***
	(0.379)	(0.452)	(0.382)	(0.458)
Product market overlap	1.130***	1.141***	1.005***	1.014***
	(0.126)	(0.126)	(0.0602)	(0.0610)
Acq. Return on Assets * Jaffe covariance	2.727**		3.879**	
	(1.000)		(1.212)	
Acq. Patenting growth * Jaffe covariance		0.130		0.203**
		(0.0898)		(0.0777)
Controls (Patent, R&D and Financial measures)	Yes	Yes	Yes	Yes
N	48567	48567	65480	65480
Pseudo R^2	0.120	0.120	0.259	0.258

* p<0.05, ** p<0.01, *** p<0.001; numbers in parentheses are standard errors

Table [10]: Interaction of acquirer characteristics with Jaffe covariance

3.5.6 Technological distance and transaction price

Investigating the impact of technological distance on transaction price, the coefficients do have the right signs for an inverted U-shape relationship between technological distance and transaction price, but they are not significant. As expected, the more assets a company has and the higher the return on assets and the sales growth, the higher the transaction value.

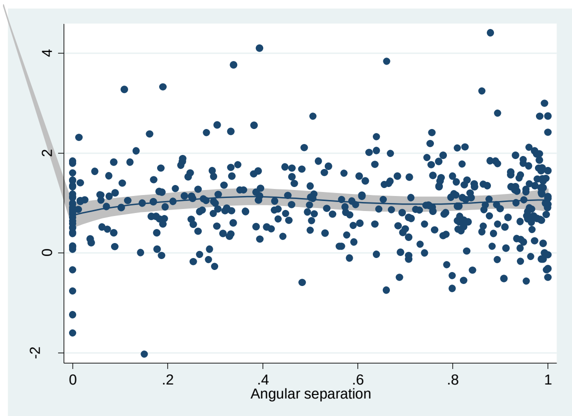
	(1) lImpTV	(2) lImpTV
Angular separation	0.817	
	(0.550)	
(Angular separation)^2	-0.705	
	(0.530)	
Jaffe covariance		0.349
		(0.560)
(Jaffe covariance)^2		-0.296
		(0.626)
Product market overlap	0.0418	0.0378
	(0.0379)	(0.0379)
Size of patent portfolio (ln)	0.0653	0.0635
	(0.0498)	(0.0498)
Patenting growth	-0.0299	-0.0273
	(0.0276)	(0.0276)
Technological diversification	-0.0488	-0.0358
	(0.0366)	(0.0376)
R&D expenditures (ln)	0.179***	0.174**
	(0.0531)	(0.0532)
Total assets (ln)	0.725***	0.731***
	(0.0576)	(0.0577)
Return on assets	0.919***	0.920***
	(0.159)	(0.160)
Sales growth	0.210***	0.208***
	(0.0565)	(0.0567)
Industry dummies	Yes	Yes
Year dummies	Yes	Yes
Constant	-4.187***	-4.138***
	(0.303)	(0.307)
N	377	377
Adj. R-sq	0.795	0.794

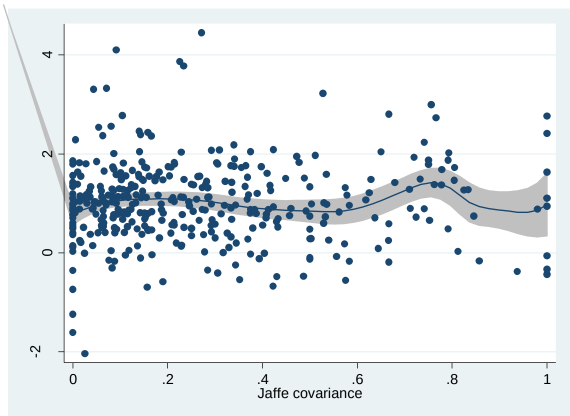
* p<0.05, ** p<0.01, *** p<0.001; numbers in parentheses are standard errors

Table [11]: OLS regression of transaction values

3.5.7 Semi-parametric estimation

Similar to the OLS regression results above, the semi-parametric analysis shown in Graphs [2] and [3] also provides little support for a robust inverted U-shape relationship between technological distance and transaction price (Hypothesis 2).





Graph [2]: Semiparametric regression with angular separation

Graph [3]: Semiparametric regression with Jaffe covariance

3.6 Discussion, limitations and suggestions for future research

In this study I find that the existence of an inverted U-shape relationship between technological distance and the likelihood of being chosen as a target is not very robust. The relationship between technological distance and the transaction price is also investigated parametrically and semi-parametrically, but no statistically robust inverted U-shape relationship is found. Technological distance and product market distance were found to have a significant interaction term, indicating that acquirers trade off the uncertainty and asymmetric information in one domain for the uncertainty and asymmetric information in the other domain. Acquirers which are experiencing weaknesses in their financial and innovation performance have a preference for technologically distant firms, suggesting that they seek to renew themselves strategically, possibly under the pressure of shareholders. Finally, I have shown that the results sometimes differ depending on the distance measure used. As has been argued in related research, the Jaffe covariance is more suitable in most research contexts and I advise other researcher to at least test for the robustness of their findings to the use of the Jaffe covariance.

The study was motivated by the distinct findings on the role of technological distance on target choice and post M&A innovation performance. As the empirical results provided in this study do not close this gap, I provide possible explanations for the results below.

First, decision makers at the acquirer or target firm may act irrationally. The above model is built on the assumption that acquirers and targets are acting in the best interest of their shareholders by maximizing the benefits to be obtained from a transaction. Acquirers may prefer to acquire technologically close firms as they may not want to incur the personal risk, e.g. in the form of job losses, that the acquisition of technologically distant firms entails.

Second, technological motivation of M&A transactions does not mean that M&A is used for technology sourcing or increasing patenting output ex post. Creating economies of scale and scope in the R&D activities constitutes a technological motivation, but it has little to do with technology sourcing. This point has implications on the role of technological distance in the ex ante choice of target and ex post innovation performance: A profit maximizing firm deciding which firm to buy may opt for a technologically close firm with similar R&D

activities which can be combined, thereby generating economies of scale in the R&D activities. The choice of acquiring a technologically close firm may thus be optimal, even if it does not result to increased innovation performance that the acquisition of a more distant firm would entail under the condition that the cost saving outweigh the impact on innovation output. As such, the findings of Ahuja and Katila (2001) and Cloodt et al. (2006) do not necessarily mean that firms should rationally also choose firms with an intermediary level of technological distance.

Third, the puzzle between the ex ante and ex post evidence may arise from the lack of robust testing of the post M&A performance relationship. Existing studies by Ahuja and Katila (2001) and Cloodt et al. (2006) have tested for a non-linear effect by including linear and squared terms, which, as in this study, were found to be significant and of the right signs. No semi-parametric or dummy variable robustness tests were conducted. The findings by Ahuja and Katila (2001) are sensitive to the inclusion of cited patents as part of a company's knowledge base – if these are included, no robust inverted U-shape relationship is found by Ahuja and Katila (2001). From the descriptive statistics provided in these studies, the peak of the inverted U-shape is several standard deviations above the mean value of the distance measure, suggesting that only very few observations exist to strongly support the declining part of the curve.[33] It may thus be, like in this study, that what better describes the data is a flattening curve. A further re-examination of the post M&A performance impact is worth pursuing.

As for the possible explanation why acquirers have a preference for technologically close targets, it is conceivable that the choice of governance mode may be a function of the relatedness of the technologies which a company wants to obtain. Strategic alliances, licensing arrangements, contract R&D and M&A are alternative means to obtain new technologies. As distance technologies are more difficult to assess and value and thus constitute a higher risk, a company may be reluctant to engage in an M&A transaction to obtain these technologies, but prefer to enter a less binding contractual arrangement to benefit from such technologies. As such, the theoretical arguments in support of hypothesis 1 may still be valid, but when having the opportunity to venture into technologically distant fields, there may be a preference for strategic alliances.

Limitations

[33] Unfortunately, the authors do not report the median and deciles of the distribution, thereby leaving it open what exact proportion of the mass is in the declining part of the U-shape.

Several limitations of this study are worth noting. First, the bargaining situation between target and acquirer and the managers' incentives are not taken into account. It may be the case that the target's managers behave differently depending on whether the acquirer is technologically close or distant, e.g. by preferring one suitor over another independent of the price being offered. However, it can be argued that the opposition from the target's managers is likely to be higher when the two firms are technologically close, as this can result in organizational reshuffling and job losses, while in the case of technologically distant acquirers, the target firm has a higher likelihood of operating as it was in the past. Hence, controlling for the self-interest of managers (who arguably prefer distant acquirers) so as to be left with the synergetic effects of M&A transactions is likely to strengthen the result that acquirers choose targets which are technologically close.

In this study I have not controlled for two relationships between the acquirer and the (potential) target that may impact the choice decision and which is correlated with technological distance. First, the existence of pre-M&A alliances between the two firms may impact the likelihood of being chosen as a target either positively (alliances as a means to get to know a firms before acquiring it) or negatively (alliances and M&A as alternative governance modes). Also, firms can build expertise in one mode of external knowledge sourcing (i.e. either alliances or M&A) and continue to pursue this same mode going forward (Carayannopoulos & Auster, 2010; Vermeulen & Barkema, 2001). Second, I have not controlled for the strategic value of patents (e.g. via patent litigations) between the parties. In case the strategic rationale is important in transactions, the inverted U-shape relationship between *knowledge base* relatedness and target choice may be hidden.

Suggestions for further research

An extension of this analysis would be to investigate the role technological distance has on the abnormal stock market returns at the time of the transaction. If synergies are expected, this should lead to a positive cumulative abnormal return to the two firms in aggregate. If the expected synergies are highest at an intermediate level of technological distance and under the assumption that the acquirer can appropriate a part of these synergies in the bargaining process, the cumulative abnormal return to the *acquirer* should be highest at an intermediate level of technological distance.

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APPENDIX

Descriptive statistics and correlation matrix (Private & public firms with choice set matchtched according to SIC code)

#	Variable	Sample	Mean	S.D.	1	2	3	4	5	6	7	8
1	Angular separation	172,797	0.28	0.33	1.00							
2	(Angular separtion)^2	172,797	0.19	0.31	0.96	1.00						
3	Jaffe covariance	172,797	0.15	0.23	0.91	0.94	1.00					
4	(Jaffe covariance)^2	172,797	0.07	0.18	0.73	0.82	0.94	1.00				
5	Product market overlap	172,797	1.20	1.11	0.21	0.24	0.27	0.26	1.00			
6	Size of patent portfolio (ln)	172,797	1.42	1.62	0.08	0.03	-0.05	-0.09	-0.05	1.00		
7	Patenting growth	172,797	2.20	2.34	0.02	0.02	0.01	0.00	0.02	0.21	1.00	
8	Technological diversification	172,797	2.26	1.98	0.01	-0.06	-0.14	-0.16	-0.09	0.73	0.02	1.00

Descriptive statistics and correlation matrix (Private & public transactions excluding choice set)

#	Variable	Sample	Mean	S.D.	1	2	3	4	5	6	7	8
1	Angular separation	538	0.53	0.35	1.00							
2	(Angular separtion)^2	538	0.40	0.36	0.97	1.00						
3	Jaffe covariance	538	0.26	0.25	0.83	0.87	1.00					
4	(Jaffe covariance)^2	538	0.13	0.22	0.65	0.73	0.94	1.00				
5	Product market overlap	538	1.43	1.29	0.21	0.24	0.22	0.20	1.00			
6	Size of patent portfolio (ln)	538	1.63	1.51	0.22	0.18	-0.07	-0.12	0.03	1.00		
7	Patenting growth	538	1.75	1.81	0.01	0.00	0.00	-0.01	0.01	0.08	1.00	
8	Technological diversification	538	2.45	1.91	0.06	0.00	-0.28	-0.29	0.03	0.70	-0.06	1.00

Appendix [I]: Sample moments and correlation (Private & Public firms)