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REACHING BEYOND THE ACQUIRER-TARGET DYAD IN M&A -

LINKAGES TO EXTERNAL KNOWLEDGE SOURCES AND TARGET FIRM VALUATION

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ABSTRACT

Access to unique knowledge of a target firm is the strategic rationale for many firm acquisitions with the expectation of improving the acquirer's innovation performance. We argue that the acquisition price reflects opportunities for value creation through innovation and investigate whether acquirers pay not just for the target firm's knowledge but also for the opportunity to access localized knowledge when targets are embedded in the knowledge flows of their region. Accordingly, we integrate embeddedness theory with literature on the expectations for knowledge-based value creation in M&A. We hypothesize that target firms that are highly embedded in local knowledge flows have higher acquisition prices. Using data on 520 technology-oriented firm acquisitions in Europe between 2001 and 2010, we find that the acquisition price increases with the target firm's local embeddedness. The effects are weaker when an acquirer's knowledge base is closely related to the localized knowledge, suggesting that local embeddedness conditions the ability of acquirer and target to absorb localized knowledge.

Keywords: firm acquisitions, local embeddedness, localized knowledge, patents, knowledge relatedness

Jel codes: G34, O3, P48

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INTRODUCTION

In August 2014, the Swiss pharmaceutical giant Roche decided to acquire Santaris Pharma, a Copenhagen-based biotechnology company that commercializes a novel technology developed at the University of Southern Denmark, and to convert the company into one of Roche's now seven global innovation centers. Christoph Franz, chairman of the board of Roche, calls himself a big fan of the Danish life science industry and explains: "Why do we have a Roche Innovation Centre in Copenhagen? The answer is obvious; because that's where the talent is. We go where there are talented people and solid science."¹

Gaining access to technological knowledge through firm acquisitions is a central theme in innovation research (Grimpe, 2007; Makri, Hitt, and Lane, 2010; Chondrakis, 2016; Bhussar *et al.*, 2022; Shafique and Hagedoorn, 2022). When knowledge and technology intensive firms are acquired, the specifics of their R&D activities and patents become salient for determining an acquisition price. Acquiring firms likely pay a higher price for a target firm when their expectations to create value in the merged entity increase, i.e. when combining the acquirer's and target's knowledge bases is particularly promising because it may spur the acquirer's innovation performance (Grimpe and Hussinger, 2014).

While the extant research has thus typically focused on the acquirer-target dyad, evidence on the importance of a target firm's external linkages to sources of knowledge is rather scant. This is surprising, given that the literature on open innovation would lead us to believe that a firm's innovation performance crucially depends on its ability to acquire knowledge from outside the firm's boundaries, for example from universities, suppliers, customers or competitors (e.g., Chesbrough, 2003; Laursen and Salter, 2006; Leiponen and Helfat, 2011). Moreover, knowledge flows are oftentimes geographically localized (Audretsch and Feldman, 1996; Alcácer and

¹ This vignette, developed by the authors, is based on an interview published in MedWatch (https://med-watch.dk/Top_picks_in_english/article9186308.ece) as well as newspaper and database research.

Chung, 2007), highlighting the role of co-located knowledge sources and the linkages that a target firm may have to them. Yet, it is unclear how valuable the target firm's localized linkages are for an acquiring firm, independently from the value that the target's knowledge and resources could create for the acquirer.

This paper intends to address this gap. We ask how the external linkages that a target firm may have to localized sources of knowledge influence the price that acquiring firms are willing to pay because they expect these linkages to create value over and above the value of the target firm's knowledge and resources alone. Our reasoning relies on mechanisms from theory on embeddedness going back to Granovetter (1985) who argues that economic action is embedded in social relations. Firms that develop rich linkages with local science and engineering communities benefit from shared trust which facilitates access to local knowledge flows inaccessible to outsiders (Song, Asakawa, and Chu, 2011). However, achieving embeddedness requires consistent interaction with local communities over time (Spedale, van Den Bosch, and Volberda, 2007; Tallman and Chacar, 2011; Rogan, 2014). These conditions make the local embeddedness of a target firm salient for the value considerations of an acquirer because a highly embedded target firm would provide immediate access to local knowledge flows. When target firms lack local embeddedness, acquirers would need to invest time and resources for establishing it.

Further, we explore boundary conditions which are likely to affect the degree to which the local embeddedness of a target firm affects the acquisition price because its embeddedness becomes more or less valuable to the acquirer. More specifically, we focus on the degree to which the knowledge that localized knowledge sources can provide is related to the acquirer's and target's knowledge bases, respectively. Our theoretical logic for the moderating effects rests on the role that the local embeddedness of a target firm can play for absorbing local knowledge effectively and efficiently (Cohen and Levinthal, 1990; Todorova and Durisin, 2007). In that sense, local embeddedness will likely be most valuable for an acquirer when its existing knowledge base is largely unrelated to the localized knowledge. In this case, the acquirer would find it difficult to absorb the unfamiliar knowledge without the help of the target firm. Moreover, an acquirer will likely value a target's local embeddedness more when the target's knowledge base is highly related to the localized knowledge. Under this condition, the potential of the target firm to exploit localized knowledge based on its embeddedness reaches its maximum.

We test these theoretical predictions using a sample of 520 technology-oriented mergers and acquisitions in Europe in the ten-year period from 2001 to 2010. We complement the transaction data with patent information on the acquirer and target firm from the European Patent Office (EPO) and regional patent data from the OECD to construct measures of firm knowledge bases and localized knowledge in regions. Following prior research (Grimpe and Hussinger, 2014), we utilize the price paid for the target firm as an indicator for the acquiring firm's expected value creation by means of innovation in the future (Barney, 1988; Brandenburger and Stuart, 1996). Our empirical study confirms the hypothesized relationships.

The contribution of our research is two-fold. First, extant acquisition studies in the strategy and innovation literature emphasize the potentials for innovation performance from the acquisition of knowledge and technology intensive firms when the knowledge bases of acquiring and target firms are combined (e.g., Makri *et al.*, 2010; Bauer *et al.*, 2018), i.e. they typically focus on the acquirer-target dyad. However, a recent stream of research focuses on the role of acquisitions for obtaining the wider network of relations of target firms (Hernandez and Menon, 2017; Hernandez and Shaver, 2018). Studies that have looked beyond the dyad and considered a target

firm's external linkages focus on market relationships with a target firm's clients which are at risk of being disrupted by the acquisition, stifling customer knowledge sharing and eventually jeopardizing the success of the entire acquisition (Rogan, 2014; Degbey and Pelto, 2021). We extend this line of research in two ways. On the one hand, we integrate research on open innovation (e.g., Chesbrough, 2003; Laursen and Salter, 2006; Leiponen and Helfat, 2011) into literature on firm acquisitions and focus on the external sources of innovation that target firms have established linkages with and that crucially determine a firm's innovation capabilities after the transaction. On the other hand, while prior research has mostly been interested in the preservation or dissolution of a target's external linkages, we investigate how valuable acquiring firms expect a target's external linkages to be, separate from the expected value of the target's knowledge and resources. In fact, prior acquisition studies seem to be based on the implicit, yet important assumption that a target firm's knowledge base also reflects the opportunities to benefit from localized knowledge. However, the expected value of such external linkages has not been theorized nor documented in the empirical literature on firm acquisitions. Hence, our approach opens up new opportunities to theorize about conditions under which a target's local embeddedness is particularly desirable for acquirers, moving more systematically beyond the acquirer-target dyad.

Second, while the acquisition of knowledge and technology intensive firms is one way in which firms can acquire external knowledge (e.g., Grimpe, 2007; Fernald, Pennings, and Claassen, 2015), research on open innovation has demonstrated that the firms' choice set is typically broader, including many different channels and governance modes of external knowledge acquisition (Laursen, 2012, provides a review). These encompass, for example, licensing (e.g., Leone and Reichstein, 2012), collaborations (e.g., Olsen, Sofka, and Grimpe, 2017) or strategic

alliances (e.g., Kok, Faems, and de Faria, 2020). Our theoretical reasoning focusses on a mechanism that is distinct for the M&A channel of external knowledge search, i.e. firms acquire a target firm which does not just contribute its own knowledge but also embeddedness with a broader network of local knowledge sources. Better understanding the expected value that acquirers can derive from the target's embeddedness can be useful for future theorizing about a more comprehensive model of external knowledge search in which (a) acquirers take advantage of the local embeddedness that they have acquired by starting local collaborations or (b) substitute local embeddedness with other modes of external knowledge acquisition, such as alliances, when acquisition prices for highly embedded target firms are high. In that sense, our research highlights considerations about the costs of different open innovation strategies which have implications for managerial decision making.

Finally, our study informs M&A practice. It encourages potential target firms to showcase their embeddedness with local knowledge production, e.g. joint research publications with local universities, since these linkages can increase acquisition prices. Further, the management of acquiring firms can predict the acquisition prices of potential targets more accurately when they take the embeddedness in local knowledge networks into account, and our empirical approach based on patent citations is immediately applicable in widely-used techniques such as discounted cash flow analyses.

THEORY AND HYPOTHESES

Our theoretical reasoning is designed to explain when acquiring firms would be willing to pay a higher price for an acquisition target. Prior research posits that the price paid for a target firm corresponds to the expected value of the target to the acquirer (Barney, 1986, 1988). It is important to note that acquisition prices represent the ex-ante expectations of acquirers for future

value creation and we cannot claim that these expectations can be realized ex-post. In fact, there is a rich body of literature focusing on the various challenges in post-merger integration (Bodner and Capron, 2018 provide a recent review). Still, acquisition prices and their individual components are important to understand especially for the owners of potential target firms who want, at least in principle, to achieve the maximum valuation on M&A markets. Moreover, we hypothesize effects on acquisition prices directly and do not predict acquisitions premiums, i.e. acquisition prices minus the stock market valuation, used by prior studies focusing exclusively on publicly traded firms (e.g. Hayward and Hambrick, 1997). On the one hand, this allows us to present a more general theory of acquisition price components that extends to the acquisition of private firms. The latter account for 84% of European technology M&A deals covered by Bureau van Dijk's AMADEUS database between 2001 and 2010. On the other hand, financial markets may have taken forward looking information into account, such as the embeddedness of target firms in local knowledge networks. If this is systematically the case, we should find no additional effects on acquisition prices for publicly traded firms in our empirical study and all estimations are subject to a downward bias in finding significant results for the hypothesized relationships. With these explicit considerations in mind, we will first discuss the importance of localized sources of knowledge with respect to a firm's innovation activities before we elaborate on the role of a target firm's local embeddedness to derive our hypotheses.

The role of localized sources of knowledge

There is extensive evidence that the ability to exploit external knowledge is a cornerstone of firms' innovation performance (e.g., Cohen and Levinthal, 1990; Laursen, 2012; Laursen and Salter, 2006). In recent years, innovation networks, communities and linkages have gained a

prominent role in explaining value creation of innovating firms, highlighting that innovators engage in interactions with universities or research institutes, suppliers, competitors, or customers to acquire knowledge externally (von Hippel, 1988; Laursen, 2012). While open innovation methods such as crowdsourcing help firms search for external knowledge in domains that are both geographically and cognitively distant (Afuah and Tucci, 2012), prior research suggests that knowledge spillovers are in fact, to a large extent, geographically localized (Audretsch and Feldman, 1996; Alcácer and Chung, 2007). Relevant knowledge may be tacit in nature and difficult to transfer without close interaction (Fabrizio and Thomas, 2012). Moreover, knowledge sources in a specific location – such as researchers, other firms' employees or customers – may be unable or unwilling to move.

The notion of localized knowledge follows a broad stream of literature that has highlighted how technology creation and innovation are much more concentrated in some geographical areas than in others (Marshall, 1920; Audretsch and Feldman, 1996). Regions with a particularly high concentration of technological activity in an industry are typically referred to as technological clusters (Alcácer and Zhao, 2012). Saxenian (1996) describes how the firms located in a cluster have access to unique knowledge pools which originate from opportunities to interact with universities and firms. Literature provides three main mechanisms by which these localized pools of knowledge emerge. First, technological clusters provide attractive local labor markets. The latter increase the likelihood that scientists and engineers can move to other firms (Almeida and Kogut, 1999) or start-ups (Glaeser and Kerr, 2009) without large relocation costs. These increased levels of job mobility become conduits for the transfer of knowledge which can be tacit or uncodified in nature (Rosenkopf and Almeida, 2003). Second, the colocation of firms increases the likelihood for direct interaction of firms and their employees which enables common knowledge (Jaffe, Trajtenberg, and Henderson, 1993; Powell, Koput, and Smith-Doerr, 1996). Sofka, de Faria, and Shehu (2018) describe for example how colocation in technological clusters makes the investments of firms in R&D and innovation increasingly visible and credible to other firms. Finally, the collocation of firms implies that they have common suppliers and buyers. These value chain links create a shared pool of knowledge by facilitating indirect interaction between competitors (Alcácer and Chung, 2007; Fabrizio and Thomas, 2012).

As a result, the location of a firm has considerable influence on the degree to which it may be able to benefit from localized sources of knowledge. Kuemmerle (1999) shows that firms often have a network of sites at which innovation activities take place while Leiponen and Helfat (2011) find that multi-location of R&D allows firms to access a broad set of external sources of knowledge. Besides establishing a presence in a new location themselves, firms may choose to engage in the acquisition of another firm located close to other sources of knowledge. Acquiring another firm, in that sense, allows firms not only to gain access to the target's knowledge and resources but also to establish itself in a new location.

The value of local embeddedness in firm acquisitions

While the co-location with external sources of knowledge from which a firm seeks to benefit is important, knowledge does not spill over automatically. Instead, we argue that the extent to which acquiring firms can benefit from external sources of knowledge depends on the linkages that the target has established with such co-located sources. We suggest that the target firm plays a key role in absorbing and integrating the localized knowledge and hence to serve as a conduit for knowledge spillovers. If those linkages were unimportant, an acquirer could simply acquire any firm in a specific location or set up a greenfield subsidiary in order to benefit from localized knowledge.

Our reasoning builds on the notion that firms are embedded in their environment to a varying extent, i.e. they are a part of loosely coupled networks of different actors engaged in the transfer of knowledge (Chesbrough, 2003). According to Granovetter (1985), economic action is embedded in social relations. Firms and their agents form ties with other actors in their environment based on ongoing networks of social relations while they continue to interact with those that they can trust. Prior research argues that firms need to form ties with and be embedded in the local scientific and engineering communities in order to obtain contextual and location-specific knowledge that increases the ability to innovate (Powell *et al.*, 1996; Ahuja, 2000; Song *et al.*, 2011).

Phelps, Heidl, and Wadhwa (2012) define a knowledge network as "a set of nodes – individuals or higher level collectives that serve as heterogeneously distributed repositories of knowledge and agents that search for, transmit, and create knowledge – interconnected by social relationships that enable and constrain nodes' efforts to acquire, transfer, and create knowledge (p. 1117)." Hence, participating in these networks provides access to knowledge and information which can ultimately foster innovation (Singh and Fleming, 2009; Demirkan and Demirkan, 2011; Gonzalez-Brambila, Veloso, and Krackhardt, 2013; Guan and Liu, 2016). A major mechanism by which actors become embedded in knowledge networks is social interaction, while informal cultural systems and formal political institutions for embeddedness also exist (Dacin, Ventresca, and Beal, 1999). Within our logic, acquirers consider the value of the embeddedness of a target firm with local knowledge networks when they determine an appropriate acquisition price.

This is even more important when firms that seek to access localized knowledge are challenged by liabilities of foreignness (Zaheer and Mosakowski, 1997). These liabilities may arise from a firm's inability to access particularly the tacit knowledge embedded in the interpersonal networks in a certain location. Even though knowledge may be transferred in a codified form, establishing ties facilitates the transfer of knowledge because recipients of knowledge also get access to the tacit knowledge and may need several interactions to fully assimilate the knowledge (Szulanski, 1996). In addition, embeddedness is essential to acquiring localized knowledge since it provides legitimacy (Song *et al.*, 2011). Network relationships can be lenses through which actors assess one another (Podolny, 2001). Embeddedness creates social capital that helps to build trust relationships important for accessing the core knowledge from local actors (Inkpen and Tsang, 2005). It also enhances a firm's absorptive capacity because embeddedness helps to develop knowledge-processing routines similar to those in the local environment (Lane and Lubatkin, 1998).

Acquisitions are unique ways by which acquirers can change their networks because they take control of the target firm's external relationships by "collapsing" the network nodes of acquirer and target firm (Hernandez and Menon, 2017; Hernandez and Shaver, 2018). The empirical results for the performance effects of altering networks through acquisitions are mixed. On the one hand, the network positions of acquirer and target firm can be complimentary and allow the acquirer to achieve more favourable network positions, e.g. increasing network centrality (Hernandez and Shaver, 2018). On the other hand, acquisitions can jeopardize the embedded ties of a target firm, e.g. when the trust in established relationships is doubtful after the acquisition (Spedale *et al.*, 2007). Eventually, the emergence of network synergies from acquisitions depends on specific characteristics. For example, Lavie, Lunnan, and Truong (2022) show how the value capture from alliances after an acquisition depends on the similarity and complementarity of businesses with the acquired firm. For the purpose of our reasoning, the actual realization of network synergies post acquisition is irrelevant for the price setting which occurs ex ante. Instead, we reason that acquisition prices will be higher when an acquiring firm can expect to find itself in a more favourable network position because it has the opportunity to benefit from the local network of the target firm.

In that sense, we argue that the acquisition of a target provides acquiring firms with a shortcut to being embedded in a certain local environment. Depending on the degree of embeddedness, the target may offer valuable opportunities to the acquirer to access the localized knowledge which would otherwise require time and resources to be developed. As a result, the local embeddedness of a target firm constitutes a value component when acquirers determine acquisition prices. In sum, we hypothesize:

Hypothesis 1: There is a positive relationship between the target firm's embeddedness in the local environment and the price paid by the acquirer.

Following our baseline Hypothesis 1, we explore the heterogeneity of the proposed price effects for specific acquirer and target firms. We develop boundary conditions based on the acquirer's existing knowledge base as well as the target firm's knowledge base, respectively. These knowledge bases are likely to determine the degree to which acquirers will be willing to pay higher prices when they expect to benefit from the local embeddedness of the target firm. We start by focusing on the relatedness between an acquirer's knowledge base and localized knowledge in the region of the target firm.

Combining various knowledge bases is likely to provide opportunities for creating novel technologies, products or processes through a process of knowledge recombination (Fleming, 2001; Cassiman and Veugelers, 2006). The knowledge endowment of a given firm constrains its possibilities for knowledge recombination. These possibilities increase significantly once a firm

has access to external knowledge which is different from its existing knowledge base since many more combinations become feasible (Rosenkopf and Almeida, 2003; Sears and Hoetker, 2014). Obtaining opportunities to benefit from localized knowledge in a region by acquiring a target firm therefore provides such a chance for knowledge recombination.

A central antecedent for creating knowledge recombinations in firms is their ability to absorb the external knowledge. For this purpose, firms benefit from absorptive capacities for identifying relevant knowledge, assimilating it with firms' existing knowledge and exploiting the resulting combinations (Cohen and Levinthal, 1990). Especially the assimilation stage can be problematic when internal and external knowledge are substantially different and the requirements for creating compatibility are high. Under these conditions, external knowledge needs to be transformed substantially before it can be usefully combined with existing knowledge (Todorova and Durisin, 2007). In contrast, external knowledge can be more readily absorbed when knowledge sources and recipients are similar (Lane and Lubatkin, 1998). We reason that these considerations for knowledge absorption make the local embeddedness of target firms salient when acquirers determine acquisition prices.

The local embeddedness of a target firm can be particularly valuable to an acquirer when the local knowledge is largely unrelated to the acquirer's existing knowledge stock. The knowledge from such locations would be unfamiliar to an acquirer and therefore costly to absorb. Under these conditions, target firms which are well embedded hold particular value for acquirers because they turn into the interfaces for integrating increasingly unrelated knowledge. By doing so, the embeddedness of a target firm can become the efficient conduit for absorbing local knowledge that is unrelated to an acquirer's existing knowledge stock. What is more, increasingly unrelated knowledge combinations are harder to predict ex-ante (Katila and Ahuja, 2002).

A locally embedded target firm can increase the predictability of promising knowledge combinations from unrelated, local knowledge.

The reverse relationship also holds true. If an acquirer's existing knowledge base is highly related to the knowledge in the target region, efficient absorption can be accomplished without the involvement of a deeply embedded target firm. Based on the knowledge relatedness, acquirers would be able to assess valuable knowledge sources in a location directly and potentially even bypass the target firm for accessing them. We conclude that the degree of relatedness between an acquirer's knowledge base and the localized knowledge in the target's region affects the degree to which local embeddedness of a target firm drives the acquisition price. The local embeddedness of a target firm is particularly valuable for an acquirer when the local knowledge is largely unrelated and therefore hard to assess and absorb for an acquirer directly. Under these conditions, expectations of an acquirer for creating value from the local embeddedness of the target firm are particularly high, resulting in price premiums. We propose:

Hypothesis 2: There is a positive relationship between the target firm's embeddedness in the local environment and the price paid by the acquirer, and this effect is weaker when the relatedness between the acquirer's existing knowledge base and the localized knowledge in the target's region is high.

Next, we focus on the boundary condition for the relationship expressed in our baseline hypothesis that emerges from the relatedness between a target firm's knowledge base and the localized knowledge in the target's region. This consideration is different from the reasoning for Hypothesis 2 because the relatedness between target firm and localized knowledge affects the value for the acquirer only indirectly by making the target's local embeddedness more valuable. More specifically, we reason that the value of a target firm in an acquisition increases when the target firm is highly embedded in its region's knowledge flow and the knowledge bases of target firm and region are highly related.

Within our logic, local embeddedness creates relational opportunities to access localized knowledge but the knowledge that can be accessed might vary in the degree to which it is useful for the target firm. These considerations for usefulness make the assessment of relatedness between target and localized knowledge salient. Cohen and Levinthal (1989) tie a firm's absorption of external knowledge to its own R&D investments. Valuable knowledge spillovers are more likely to occur between organizations with similar R&D activities (Lane and Lubatkin, 1998). Shared skills, languages, and cognitive structures make it easier for one firm to learn from another (Kogut and Zander, 1992; Makri *et al.*, 2010). Hence, target firms are more likely to benefit from knowledge in the region. Besides, firms become more appropriate and desirable collaboration partners when their knowledge is potentially useful to external partners (Alexy, George, and Salter, 2013). Hence, the relatedness between knowledge of a target firm and its region likely makes it a more attractive and legitimate collaboration partner in a region.

Taken together, we conclude that target firms with knowledge that is highly related to the localized knowledge of the region will benefit the most from local embeddedness. Accordingly, an acquirer can expect to benefit not just from the target firms' knowledge but also from its capacity to absorb localized knowledge in its region. Conversely, a target firm that is highly embedded in its region might have limited value to an acquirer when the local knowledge is largely unrelated to the target's knowledge base and potentially irrelevant. Given these expectations, acquirers are likely to pay comparatively higher acquisition prices for target firms that combine

embeddedness and relatedness with the target region's knowledge base. Hence, our last hypothesis reads:

Hypothesis 3: There is a positive relationship between the target firm's embeddedness in the local environment and the price paid by the acquirer, and this effect is stronger when the relatedness between the target firm's existing knowledge base and the localized knowledge in the target's region is high.

METHODS

Data

Our database is retrieved from the M&A database ZEPHYR, which is published by Bureau van Dijk. ZEPYHR covers more than 900,000 transactions worldwide that have been reported since 1996. For the purpose of our study, we select all M&A deals based on the following criteria: First, we only consider majority acquisitions in the ten-year period from 2001 to 2010. Minority acquisitions are excluded as they may be motivated by risk diversification and may not imply taking control of the target's assets and know-how. Second, we only focus on deals among European firms. This restriction follows from our choice to use patent data from the European Patent Office (EPO). A sample that also covers firms in the US and Japan would need to correct for the so-called home bias of patenting, which describes that firms are more likely to file for patents at the patent office in their home country (Dernis and Khan, 2004). Third, we exclude transactions for which either multiple acquirers or targets are listed due to potentially confounding effects for our measurements. Finally, we restrict our sample to acquisitions in which both the acquirer and

target firm are in a knowledge and technology intensive industry, i.e. an industry in which competitive advantage is based on knowledge and technology and constitutes an important motivation for engaging in the acquisition.²

The M&A data are linked to balance sheet data for the acquirer and target firms from Bureau van Dijk's AMADEUS database and with firms' patent records at the EPO using the PATSTAT database and the OECD patent citation database. The match between firms and patents is carried out based on firm names and addresses in both databases. We employ a computer-supported, text-based search algorithm to support the matching and manually check each suggested match. The sample is restricted to those transactions with patents involved, i.e. in which either the acquirer or the target have at least one patent, which results in a final sample of 520 transactions.

Finally, we add data on the characteristics of the target's region, which we define at the NUTS-3 level.³ This involves both statistical data from Eurostat, the statistical office of the European Union, as well as regional patent information from the OECD's REGPAT database. The choice of the NUTS-3 level follows a number of considerations about the appropriate delimitation of regions for the purpose of our study, including the availability of data. In that sense, the notion of spatial proximity facilitating knowledge spillovers seems to be best reflected in the rather small-scale NUTS-3 regions which is in line with prior literature (e.g., Grimpe and Patuelli, 2009). However, we acknowledge that such a regional delimitation may underestimate the importance of clusters that span multiple NUTS-3 regions. Our choice of the NUTS-3 level then

² We follow the industry classification of Eurostat (https://ec.europa.eu/eurostat/cache/metadata/en/htec_esms.htm). ³ The Nomenclature of Territorial Units for Statistics (NUTS) is a geocode standard for referencing the subdivisions of countries for statistical purposes. There are 1342 NUTS-3 regions in Europe, which typically refer to the county or district level.

constitutes a useful, conservative delineation of regions for our empirical tests since clusters that span NUTS-3 regions reduce the odds of significant results in our estimation models.

Measures

Dependent variable.

Our dependent variable is the price paid by the acquirer for the target firm. The price approximates the value that the acquiring firm expects to create when combining the target with the acquirer (Barney, 1988; Grimpe and Hussinger, 2014). Due to the skewness of the price distribution, we take its natural logarithm. The vast majority of acquisition activity involves firms that are not listed at the stock market, particularly in a European context. This holds true for the acquisitions in our sample (i.e. 84% of the deals). For this reason, we cannot readily rely on stock market based measures of acquisition premia as an alternative dependent variable (e.g., Hayward and Hambrick, 1997). Nevertheless, in a robustness check we take the acquisition price minus a target firm's total assets normalized by the target firm's total assets so that we get a percentage value as the dependent variable which serves as a simple approximation of the premium that the acquirer is willing to pay over and above the value of the target's assets.

Explanatory variables.

Our main explanatory variable to test Hypothesis 1 is the target firm's embeddedness in the region it is located in. To measure embeddedness, we use the backward citation stock of the target firm's patents to those patents produced in the target region. Using citation links allows to trace the extent to which a target firm builds on localized knowledge which we normalize by the target firm's patent stock to account for differences in target firms' patent productivity. Citation links serve as indicators of knowledge flows that oftentimes reflect more formal but also informal forms of interaction or innovation networks. Prior literature has frequently used citation links between patents as evidence for knowledge spillovers (e.g., Jaffe *et al.*, 1993). The actors in a region form ties with each other in order to obtain location-specific knowledge, for example from local scientific and engineering communities (Szulanski, 1996; Song *et al.*, 2011).

We acknowledge that patent citations are unlikely to represent the full extent of local embeddedness of a target firm. However, the benefits of the approach emerge from the rules and regulations of patent offices. That makes citations a proxy for knowledge networks that are meaningful and credible because they determine the extent of legal patent rights. Further, given the official rules, patent citations are comparable across multiple countries. Nevertheless, measuring embeddedness through patent citations is likely to be a conservative approach because the interactions of engineers and scientists in a region are likely to be much more frequent and varied in nature. Alternative network measures such as alliance data (e.g. Lavie *et al.*, 2022) can make it difficult to establish the degree to which knowledge-specific linkages were created and network surveys are best suited for capturing individual networks (e.g. Brennecke *et al.*, 2021). An additional advantage of using patent citations for capturing regional embeddedness emerges from the fact that patent statistics are publicly available and widely used in M&A analysis. Hence, such embeddedness measures can inform managerial practice quickly.

To test Hypotheses 2 and 3, we calculate two relatedness measures which are based on the firms' and the region's patent portfolios. For Hypothesis 2, we calculate the technological relatedness of the acquirer's patent portfolio with the target region's patents; for Hypothesis 3, we calculate the relatedness of the target's patent portfolio with the target region's patents. For both measures, we use the proximity measure proposed by Jaffe (1986). It captures the extent to which the acquiring or target firm and all actors in the target firm's region (including firms, universities and other entities, but excluding the focal target firm) develop technology in the same technology classes as defined by the International Patent Classification (IPC).⁴ Following prior literature, we use the three-digit IPC level (Makri *et al.*, 2010). We then calculate separate patent stock measures per three-digit IPC class for the acquiring and target firm and for the target's region in year *t* on the basis of equation (1).

$$PATSTOCK_t = (1 - \delta)PATSTOCK_{t-1} + PAT_t$$
(1),

where PAT_t describes the number of patents in year *t* and δ a depreciation rate which we set to 15% as is common practice in the literature (Griliches and Mairesse, 1984; Hall, Jaffe, and Trajtenberg, 2005).

Equation (2) below provides the definition of the technology relatedness measure which is defined as the angular separation of the patent class distribution vectors F of the acquiring or target firm i and the target's region r. The technology vectors F for each acquiring or target firm i and region r can be interpreted as their respective technology portfolio. We use these vectors as a percentage of the total patent stock in order to eliminate patent portfolio size differences between the acquiring or target firm and the target region's patent portfolios. In technical terms, the relatedness measure T equals the scalar product of these vectors normalized by their scalar products with themselves:

$$T_{ir} = \frac{F_i F_r}{\sqrt{(F_i F_i)(F_r F_r)}}.100$$
 (2)

The measure takes the value of one for any two identical technology vectors and zero if there is no overlap of the acquiring or target firms' patent portfolios and the patent portfolio of the other

⁴ See the classification published by the World Intellectual Property Organization (WIPO), http://www.wipo.int/classifications/ipc/en/

entities in the target's region. A value higher than zero consequently indicates some overlap. To test Hypothesis 2, we employ the relatedness measure between the acquiring firm's patent portfolio and the target region's patent portfolio (excluding the target firm's own patents) in an interaction with the target firm's embeddedness. For testing Hypothesis 3, we use the relatedness measure between the target firm's and the target region's patent portfolio (excluding the target firm's own patents) in an interaction with the target firm's embeddedness.

Control variables.

We control for a number of factors on the firm and regional level that may affect the price paid for the target firm. Following Grimpe and Hussinger (2014), we use the patent stock of the target firm, calculated on the basis of equation (1), normalized by the target firm's total assets (in millions of Euros) to control for the knowledge base of the acquisition target. We further control for the value of the target firm's patents by including the stock of forward citations that the target firm's patents received in a five-year window after the grant. Patent citations are commonly used as an indicator of patent value (e.g., Trajtenberg, 1990). Since there is a high correlation between the number of citations a firm receives and the patent stock, we divide the citation stock by the target's patent stock. To control for the relatedness between the acquirer and target firms' knowledge bases, we include the relatedness measure as defined above based on the acquirer and target firm patent portfolios, both in linear and squared terms.

We also control for other target characteristics. Total assets of the target firm (in millions of Euros) are used to control for firm size. The target firm's return on assets as defined as the sum

of profits earned by the firm and the capital gains of assets over total assets controls for its profitability. Financial leverage of the target firm is controlled for by liabilities over total assets.⁵ Further, we include the target firm's age measured in years and a dummy variable indicating whether the target firm is listed on the stock market. To control for the position of the target firm in its region, we include the target's turnover as a share of the region's GDP. This measure indicates to what extent the target firm occupies a more or less dominant position that offers opportunities for market growth.

The acquisition price may also be influenced by the acquiring firm itself, more specifically the expectations of the acquirer to create value by acquiring the target firm. Here, we include the acquiring firm's total assets (in millions of Euros) to control for the acquirer's size and the acquirer's patent stock divided by total assets.

Moreover, we include variables that control for characteristics of the transaction. Here, we include a dummy variable that takes the value of one if both the acquirer and the target firms are in the same two-digit NACE industry class to capture horizontal acquisitions. To control for differences between domestic and international transactions we include a dummy variable that takes a value of one in the case of a cross-border deal. We also control for whether the acquirer and target firms are located in the same NUTS-3 region. In a robustness check, we run our analyses excluding those transactions where acquirer and target firm are located in the same region to control for the different importance that a target's embeddedness in the region could have when the acquirer is located in the same region. Further, we control for the relative size between the acquirer and target firm defined as the ratio of acquirer total assets to target total assets.

⁵ As the variable for liabilities is missing in some cases, we include a dummy variable that takes a value of one in the case of missing liabilities and zero otherwise. The coefficient is not reported in the results table. Liabilities are set to zero if missing.

Next, we include control variables for the target firm's region. We include the size of the region as measured by regional employment and the share of highly skilled workers in the region. We also control for the regional patent stock normalized by the number of highly-skilled workers in a region, i.e. the potential inventors of patented technology. We use a Hirschman-Herfindahl Index (HHI) to control for the concentration in regional technology portfolios. The HHI is defined as the sum of the squared shares of patents of all entities in the region. A value of the HHI closer to its maximum indicates that the patent ownership in the region is highly concentrated. A value closer to zero indicates rather distributed regional patent ownership. Moreover, we include the average deal value of all transactions in same NACE two-digit industry and country as the target based on the ZEPHYR database to control for systematic differences in the acquisition price across industries and countries.

Finally, we control for time effects by including a set of year dummies for the years from 2001 to 2009, with 2010 being the reference category. Five industry dummies indicate the target firm's industry affiliation. They are defined based on the Eurostat industry aggregation that distinguishes high-tech, medium high-tech, medium low-tech, and low-tech manufacturing, as well as knowledge-intensive and low knowledge-intensive services. High-tech manufacturing is the reference category in our estimations.

Model

Our empirical model estimates draw from the market value function that allows to analyze the separate components of the total firm value (Griliches, 1981; Hall *et al.*, 2005; Czarnitzki, Hussinger, and Leten, 2020). In that sense, the value of a target firm is a function of its technological and non-technological assets as well as the characteristics of the region in which it is located, the acquirer itself, and the transaction. Hence, our multivariate ordinary least squares

(OLS) regression can be understood as a way to estimate the contribution of each individual component or regressor to the target price, keeping all other regressors constant. The patent citations underlying our local embeddedness measure are already determined when the patents are granted which implies that they are unlikely to pose concerns of endogeneity biases for our particular outcome variable.

RESULTS

Descriptive statistics

Table 1 presents summary statistics. The average acquisition price equals 42 million Euros while the average total assets of the target firms are 110 million Euros. Target firms have an average patent stock of 0.83 patents (or 0.01 if divided by total assets). On average, the targets' patent stock receives 0.31 citations within a five-year window after grant. With regard to the relatedness variables, we find that the relatedness of the acquirer firm's patents with the target region's patents is lower than the relatedness between the target firm's patents and the patents in its region.

Moreover, it turns out that 31% of the transactions are cross-border transactions and 33% of the transactions occur in the same industry. In 9% of the transactions, acquirer and target firm are located in the same region. Target firms are on average 29 years old, indicating that our sample is not dominated by young companies that are acquired soon after inception. Target firms exhibit on average a low return on assets. The liabilities over assets equal on average 0.43.

The regions in which the target firms are located have an average workforce of 257.000 individuals, which suggests that most M&A transactions take place in larger regions. Almost every second individual in these regions is a highly skilled worker and regions have a patent stock per highly skilled worker of 2.75, indicating that the regions are knowledge intensive.

[Insert Table 1 about here]

Table 2 shows pairwise correlations. The generally low correlations among the explanatory and control variables indicate that we do not face multicollinearity issues.

[Insert Table 2 about here]

Multivariate analysis

Table 3 shows the results of OLS estimations to test our hypotheses. The first specification serves as a benchmark model (Model 1) to show the effects of the control variables on the acquisition price. The estimated coefficients largely show the expected signs. Target size and patent stock are positively associated with the acquisition price. We also find an inverse U-shaped relationship between the acquirer-target technological relatedness and the acquisition price which is in line with prior literature (Ahuja and Katila, 2001). Acquisition prices are lower for those with high leverage and those that are listed. Larger acquirers turn out to pay higher acquisition prices while they also pay more when the target firm is small compared to the acquirer. Acquisition prices are also higher for horizontal acquisitions and when acquirer and target are located in the same region. With respect to the region, we find that acquisition prices are higher in smaller and more knowledge-intensive regions in terms of patents. Moreover, the coefficient of the Herfindahl index is positive, indicating that acquiring firms pay a higher price for a target firm if patent ownership in the region is more concentrated. Finally, acquisition prices are higher in regions where generally higher acquisition prices can be observed. The remaining control variables turn out to be not significantly related to the acquisition price.

[Insert Table 3 about here]

Model 2 includes the main explanatory variable, i.e. the target's local embeddedness, which we find to be positively and significantly related to the acquisition price. In that sense, Hypothesis 1 cannot be rejected. The economic effects are sizable. A change of one unit of the embeddedness

variable, which is for instance equivalent to each of the target firm's patents citing an additional patent from the region, increases the deal value by 4% at the mean (42 million EUR), i.e. by 1.68 million EUR.

Models 3 and 4 alternately introduce the interaction terms between the target's embeddedness and the acquirer-region (Model 3) and target-region (Model 4) relatedness. We find a negative interaction effect for acquirer-region relatedness, suggesting that the expected value of the target's embeddedness decreases when the acquirer's knowledge base is more closely related to the region's knowledge base. Conversely, we find a positive interaction effect when we consider the relatedness between the target's and the region's knowledge bases, indicating that the value of the target's embeddedness to the acquirer increases when relatedness is high. As a result, we also find support for Hypotheses 2 and 3. Finally, Model 5 contains all moderations simultaneously and shows fully consistent results.

Robustness checks

We perform several checks to demonstrate the robustness of our results. First, we check whether the acquirer has already been present in the target firm's region prior to the focal acquisition. For that purpose, we identify all inventors of the acquirer firm's patents who were located in the target firm's region prior to the acquisition since such presence would indicate that the acquirer had already conducted innovation activities in the target firm's region. It turns out that only 19 acquirers had prior activities in the target's region so that we create a dummy variable that takes the value of 1 if that is the case. Model 1 in Table 4 shows that our results hold if the acquirer's prior innovative activities in the target's region are accounted for. The newly added variable is not significant, indicating that an acquiring firm will not pay a different price for a target if it has prior innovation activities in the target's region. This confirms the notion that co-location alone is not enough to benefit from localized knowledge.

Second, Model 2 in Table 4 shows the results of a robustness check that excludes all acquisitions in which both acquirer and target firm are located in the same region. While all regressions control for this fact, Model 2 shows that our results hold in the subsample of acquirers and targets located in different regions.

Third, Model 3 in Table 4 shows the results when the dependent variable is the acquisition premium, defined as the acquisition price minus the target's total assets and normalized by the target's total assets. Again, we find our results to be fully consistent with the main model results.

Finally, we run additional tests to isolate the effect of target firm embeddedness. More specifically, we test whether the effect of the latter is moderated by cross-border M&A or whether the acquirer's local embeddedness affects the results. We find insignificant results for both. When we create a relative local embeddedness measure between target and acquiring firm, effects increase significantly with target firm embeddedness, in line with our hypotheses. The results are available from the authors upon request.

[Insert Table 4 about here]

DISCUSSION

In this research, we investigate the role of local embeddedness for target firm acquisition prices, a source of expected value creation for acquirers which has not been accounted for in the extant research. For this purpose, we integrate mechanisms from the literature on embeddedness and geographically confined knowledge flows into models explaining knowledge-based value in firm acquisitions. Within our reasoning, local embeddedness of a target firm constitutes an independent price component in an acquisition because highly embedded firms provide superior access to

localized knowledge. Acquirers are aware of these advantages but rarely describe them in isolation. For example, the founder of robotics producer Kiva in Massachusetts, which was acquired by Amazon in 2012, stated in 2022 the following about the location advantages: "With this kind of ecosystem, you've got access to new ideas, new talent, and venture funding".⁶ In other instances, the value of access to local knowledge through acquisitions becomes visible when they resonate with regulators. For example, the British government had prevented the acquisition of the largest UK chip producer Nexperia by a Chinese company in 2022 by arguing, among other issues, that the acquisition would provide access to the larger cluster of technologically advanced semiconductor firms in Wales and thereby jeopardize national security.⁷

These examples also hint at the importance of context for the effects of local embeddedness on acquisition prices. Hence, we establish boundary conditions for the baseline hypothesis by considering the relatedness of localized knowledge with the acquirer and the target firm's existing knowledge bases. We hypothesize that local embeddedness has a lower effect on acquisition prices when acquirers have knowledge related to the target region and are not dependent on a locally embedded target firm for absorbing it. In contrast, we theorize that local embeddedness of a target firm will be most valuable for an acquirer when the knowledge is also highly related to the target firm's knowledge base. We test and support these hypotheses based on a comprehensive dataset of 520 technology-oriented mergers and acquisitions in Europe from 2001 to 2010 combined with data on regional patent stocks.

⁶ <u>https://www.bostonglobe.com/2022/08/15/business/amazon-irobot-how-massachusetts-became-leader-robotics-industry/</u>, accessed: January 10, 2023.

⁷ <u>https://www.theguardian.com/technology/2022/nov/16/british-government-blocks-takeover-of-welsh-semiconduc-tor-producer</u>, accessed: January 10, 2023.

These findings have two implications for research on knowledge and technology-oriented firm acquisitions. First, existing strategy research on the acquisition of high-tech firms rests on the mechanism that the combination of acquirer and target firm knowledge has the potential to improve innovation performance (e.g., Makri *et al.*, 2010; Bauer *et al.*, 2018), i.e. focuses on the acquirer-target dyad as a source of value creation. However, this perspective neglects that acquirers will also obtain the network of relationships of their target firms (Hernandez and Menon, 2017; Hernandez and Shaver, 2018). Within this general logic, we integrate the specific notion that an acquirer would not just pay for obtaining the knowledge base of the target firm but also for access to localized knowledge flows from which the target firm benefits.

In that sense, we advance recent research that has looked beyond the dyad and considered a target firm's external linkages with respect to market relationships (Rogan, 2014; Degbey and Pelto, 2021). While these studies focus on the preservation or dissolution of external ties, our research is complementary in that it seeks to better understand to which extent acquiring firms factor in external linkages when they decide on the price that they are willing to pay for a target. Emphasizing the linkages to external sources of knowledge, such as universities or research institutes, suppliers, competitors or customers, our research takes an open innovation perspective to theorize why these linkages are important to an acquirer's expected value creation (e.g., Chesbrough, 2003; Laursen and Salter, 2006; Leiponen and Helfat, 2011). While our setup allows to isolate the role of external linkages vis-à-vis the target firm's knowledge base, more research is needed to study an acquiring firm's subsequent innovation performance.

In this regard, the acquisition of high-tech firms is a distinct mode by which firms can acquire external knowledge (Grimpe, 2007; Fernald *et al.*, 2015) within a broader stream of research on external knowledge search (Laursen, 2012). We advance the M&A angle of external knowledge search by exploring one of its distinct aspects, i.e. acquirers obtain not just new knowledge from a target firm but also its position in the knowledge flows of its region. Other prominent forms of knowledge search, such as licensing (e.g., Leone and Reichstein, 2012), collaborations (e.g., Olsen *et al.*, 2017) or strategic alliances (e.g., Kok *et al.*, 2020), can hardly convey the benefits of local embeddedness. However, understanding the specific price component that acquirers are willing to pay to obtain local embeddedness has wider implications for future research on external knowledge search. Most immediately, acquirers are comparatively more likely to start local collaborations when they have paid a higher acquisition price for obtaining the local embeddedness of their target firm.

Implications for management

These academic insights are also important for management practice along at least three dimensions. First, our findings inform a broader group of stakeholders who have to judge the appropriateness of acquisition prices. Mergers and acquisitions are consequential decisions for firms, challenging managers to explain acquisition goals and prices to a variety of stakeholders such as investors, analysts, employees, regulators or the general public. Hence, a convincing logic has practical value for the communication of mergers and acquisitions as well as its analysis. We show that access to localized knowledge is a separate price component and can justify higher acquisition prices. This is the case when firms select targets that exhibit high local embeddedness. In other words, acquiring firms as well as their advisors should observe the local embeddedness of a target firm. If they fail to do so and systematically ignore the opportunities for benefitting from localized knowledge beyond a potential target firm's knowledge base, they are likely to be outbid in price negotiations and to forgo opportunities for value creation. Conversely, our reasoning can result in realistic expectations for acquisition prices when target firms lack the embeddedness with their region.

Second, our findings have also consequences for target firms. We establish local embeddedness of target firms as an asset that firms should strive for not just with a narrow focus on immediate effects for their innovation performance but also with an eye for the broader signaling value to potential acquirers. Hence, our findings provide guidance to target firms and their investors for increasing acquisition prices from potential acquirers. Accordingly, a potential target firm should showcase the attractiveness of its local environment as well as its embeddedness with the region as a mechanism to maximize acquisition prices. The latter can easily go unnoticed unless target firms publicize successful collaborations with leading local knowledge sources such as universities or suppliers. This can be accomplished through joint research publications or targeted press releases showcasing the strength of a firm's ties with local knowledge production.

Finally, assessing appropriate acquisition prices for knowledge based assets is inherently a challenging task. Our study offers not just a rationale for the value of local embeddedness of targets firms but also an applicable proxy for measuring it based on patent citations. Patent data is publicly available and widely used. Hence, acquirers or their advisors can utilize the value of patent statistics more fully by using patent citation linkages with the target region. With this empirical tool at hand, acquirer and target firms can make more accurate predictions about acquisition prices when they rely on tools such as discounted cash flow analysis. This enables them to adjust their own price expectations and anticipate the offers of other potential bidders.

CONCLUSION

Our findings and limitations raise some new questions which could be fruitful pathways for future research. First, patent-based measures are subject to industry differences in the likelihood of patenting. While the importance of patenting has been growing rapidly in many industries over the recent years, including industries outside the manufacturing sector (Makri *et al.*, 2010), our empirical findings are potentially not readily transferable to industries with low patent propensities and thus require comparative studies for confirmation. At the same time, we see significant potential in these low-patent propensity industry studies since the absence of patent rights would make licensing agreements unlikely which should make relational advantages and embeddedness increasingly salient as a price component in acquisitions.

Second, the measures to identify local embeddedness may considerably underestimate the availability of location resources. In that regard, it would be particularly interesting to take the access to other resources such as university research into account. In principle, scientific publications should be widely available even outside of regional clusters but certain types of interactions, e.g. in development, are likely to benefit from access to university scientists through embedded relationships. It would be useful to understand for which types of knowledge and activities the embeddedness effects are most salient.

Third, our data do not allow to actually observe a target's legitimacy in a region which we assume to play an important role for benefitting from knowledge spillovers. Qualitative studies for specific acquisitions or experimental studies might be able to isolate such value components. Also, while we control for the regional concentration of patent ownership, we have not in detail looked into competition aspects that may gain relevance if various actors compete for access to localized knowledge. Similarly, while we can assume that the number of firms bidding for a particular target firm is associated with a higher acquisition price (e.g., Barney, 1988; Chondrakis, 2016), these bidding contests are notoriously hard to observe, making it difficult to control for such potential influence. Future research may, for example, use a strategic factor market lens to disentangle the heterogeneous value that various bidders put on different value components of acquiring a target firm.

Lastly, future research could provide more granular evidence on the processes by which acquiring firms leverage targets to access localized knowledge. It would be particularly interesting to map a target firm's collaborative ties with actors in a local innovation system (e.g. alliances) and how the nature of various ties influences an acquirer's expectations for value creation. This also calls for longitudinal research that observes an acquirer's actual value creation over time, as well as the processes by which acquirers do achieve and not only expect value creation. An intriguing aspect within the realization of value creation post M&A may come from a hiring after the acquisition is completed. Extant research discusses these "acquihires" as a mechanism by which acquirers can benefit from the target's employees (Boyacioğlu and Özdemir, 2016; Bakir, Ozdemir, and Karim, 2021) but a deeply embedded target firm might also provide new opportunities to hire from regional labor markets.

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TABLES

Table 1: Summary statistics

	Mean	Std. dev.
Deal value (mEUR)	42.43	134.25
Deal value (log.)	2.11	2.05
Target total assets (mEUR)	109.94	258.62
Target total assets (log.)	3.44	1.68
Target patent stock	0.84	3.83
Target patents/assets	0.01	0.05
Target citations/patents	0.31	0.80
Acquirer-target relatedness	0.48	10.88
Target return on assets	0.02	0.29
Target liabilities over assets	0.43	0.37
Target age (years)	29.41	28.23
Target is listed (d)	0.16	0.36
Target turnover as a share of regional GDP	47.81	408.25
Acquirer total assets (log.)	13.60	2.64
Acquirer patents/assets	0.00	0.02
Relative size	443471.80	6078009.00
Crossborder acquisition (d)	0.31	0.46
Horizontal acquisition (d)	0.33	0.47
Different regions (d)	0.91	0.29
Regional employment	256.96	197.03
Regional employment (log.)	5.27	0.78
Regional scientists/employment	0.48	0.36
Regional patents/scientists	2.75	1.63
Regional HHI	0.55	0.98
Average deal value per industry/country	60.80	177.96
Target regional embeddedness	2.50	6.26
Acquirer-region relatedness	0.06	0.31
Target-region relatedness	0.16	0.46

(d) dummy variable; (log.) in logarithm

Table 2: Pairwise correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1 Deal value (log.)	1.00)																					
2 Target total assets (log.)	0.58	3 1.00)																				
3 Target patents/assets	0.10	0 -0.07	1.00																				
4 Target citations/patents	0.10	5 0.18	0.15	1.00																			
5 Acquirer-target relatedness	0.0	5 0.12	0.00	0.06	1.00																		
6 Target return on assets	-0.0	0.09	0.02	-0.03	0.00	1.00																	
7 Target liabilities over assets	0.0	0.16	0.00	0.12	0.02	0.17	1.00																
8 Target age (years)	0.13	3 0.36	-0.09	-0.04	0.18	0.06	0.07	1.00															
9 Target is listed (d)	0.14	4 0.41	-0.03	0.07	-0.02	0.03	-0.23	0.29	1.00														
10 Target turnover/reg. GDP	0.08	8 0.38	0.00	0.07	0.07	0.01	0.00	0.25	0.16	1.00													
11 Acquirer total assets (log.)	0.34	1 0.46	-0.02	0.12	0.02	0.15	0.23	0.22	0.18	0.09	1.00												
12 Acquirer patents/assets	0.1	0.08	-0.04	-0.07	-0.01	-0.13	-0.05	0.23	0.16	-0.02	0.18	1.00											
13 Relative size	-0.03	3 -0.19	0.00	-0.03	0.00	0.00	-0.06	-0.02	-0.03	0.01	0.06	-0.01	1.00										
14 Horizontal acquisition (d)	0.0	9 -0.13	-0.09	-0.12	0.06	-0.10	-0.28	-0.04	-0.06	-0.02	-0.11	-0.11	-0.03	1.00									
15 Crossborder acquisition (d)	-0.20	0 -0.15	-0.01	-0.16	0.06	0.09	0.14	-0.14	-0.18	0.01	-0.11	-0.10	-0.04	0.07	1.00								
16 Different regions (d)	0.13	5 0.00	-0.03	0.06	0.01	0.10	0.20	-0.16	-0.21	-0.02	0.08	0.06	0.02	0.03	0.21	1.00							
17 Regional employment (log.)	-0.12	2 -0.05	0.03	-0.13	-0.01	0.06	0.02	-0.04	-0.07	-0.01	-0.05	-0.05	0.00	0.07	0.04	0.03	1.00						
18 Regional scientists/empl.	0.02	2 0.14	-0.02	0.15	0.02	0.03	0.21	0.14	0.05	0.21	0.17	-0.04	-0.07	-0.15	0.12	-0.02	-0.08	1.00					
19 Regional patents/scientists	0.13	3 0.11	0.07	-0.10	0.11	-0.06	-0.15	0.20	0.19	0.24	-0.04	0.04	0.01	0.04	0.00	-0.17	0.21	0.22	1.00				
20 Regional HHI	0.23	5 0.15	-0.01	-0.10	0.03	0.04	-0.04	0.21	0.22	0.02	0.11	0.40	-0.02	0.07	-0.11	0.04	0.06	-0.11	0.20	1.00			
21 Average deal value ind/cou.	0.20	0.17	0.01	0.07	0.00	0.02	-0.06	0.05	0.15	0.08	0.08	0.04	-0.02	0.05	-0.05	-0.11	-0.04	0.13	0.19	0.06	1.00		
22 Acquirer-region relatedness	0.23	3 0.14	-0.04	-0.07	0.02	-0.02	0.02	0.25	0.18	0.00	0.17	0.63	-0.01	-0.07	-0.02	0.06	-0.13	-0.05	0.01	0.44	0.08	1.00)
23 Target-region relatedness	0.1	7 0.14	0.12	0.85	0.02	0.01	0.08	-0.11	0.06	0.00	0.13	-0.06	-0.02	-0.07	-0.15	0.10	-0.15	0.18	-0.12	-0.08	0.00	-0.07	1.00
24 Target regional embeddedness	0.20	0.31	0.00	0.01	0.01	0.05	0.36	0.12	-0.07	0.00	0.24	-0.07	-0.02	-0.24	-0.18	0.12	0.18	0.19	0.01	-0.06	-0.05	-0.06	-0.03

(d) dummy variable; (log.) in logarithm

Model 1	Model 2	Model 3	Model 4	Model 5
0.67***	0.64***	0.65***	0.66***	0.67***
(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
4.43**	4.37**	4.30**	5.00***	4.92***
(0.01)	(0.02)	(0.02)	(0.00)	(0.00)
-0.26	-0.30	-0.32	-0.86***	-0.87***
(0.32)	(0.25)	(0.22)	(0.00)	(0.00)
1.54***	1.65***	1.65***	1.53***	1.54***
(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
-0.24	-0.24	-0.25	-0.30	-0.31
(0.34)	(0.34)	(0.32)	(0.13)	(0.11)
-0.89**	-1.08***	-1.01***	-1.05***	-0.98***
(0.02)	(0.00)	(0.01)	(0.00)	(0.01)
-0.00	-0.00	-0.01*	-0.00	-0.00
(0.26)	(0.17)	(0.10)	(0.28)	(0.17)
-0.90***	-0.83***	-0.86***	-0.50*	-0.53*
(0.00)	(0.00)	(0.00)	(0.09)	(0.07)
-0.00	-0.00	-0.00	-0.00	-0.00
(0.50)	(0.51)	(0.45)	(0.47)	(0.41)
0.11**	0.11**	0.10**	0.09**	0.09**
(0.01)	(0.02)	(0.03)	(0.04)	(0.05)
1.10	1.86	-1.03	2.84	0.08
(0.78)	(0.64)	(0.76)	(0.45)	(0.98)
0.00***	0.00***	0.00***	0.00***	0.00***
(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
0.35**	0.39**	0.44***	0.53***	0.57***
(0.04)	(0.03)	(0.01)	(0.00)	(0.00)
-0.14	-0.08	-0.13	-0.01	-0.05
(0.53)	(0.72)	(0.57)	(0.97)	(0.80)
1.20***	1.12***	1.15***	1.09***	1.11***
(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
-0.25**	-0.30**	-0.29**	-0.31***	-0.30***
(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
0.27	0.19	0.23	0.09	0.13
(0.28)	(0.48)	(0.38)	(0.72)	(0.60)
0.18***	0.19***	0.18***	0.17***	0.17***
(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
0.19**	0.21**	0.18**	0.20***	0.17**
(0.02)	(0.01)	(0.03)	(0.01)	(0.02)
0.00*	0.00*	0.00*	0.00**	0.00**
(0.10)	(0.10)	(0.08)	(0.05)	(0.04)
	Model 1 0.67*** (0.00) 4.43** (0.01) -0.26 (0.32) 1.54*** (0.00) -0.01*** (0.00) -0.24 (0.34) -0.89** (0.02) -0.00 (0.26) -0.90*** (0.00) 0.11** (0.00) 0.11** (0.01) 1.10 (0.78) 0.00*** (0.00) 0.35** (0.00) 0.35** (0.00) 0.35** (0.00) 0.35** (0.00) 0.35** (0.00) 0.35** (0.00) 0.35** (0.00) 0.35** (0.00) 0.35** (0.00) 0.35** (0.00) 0.35** (0.00) 0.35** (0.00) 0.35** (0.00) 0.35** (0.00) 0.25** (0.00) 0.25** (0.00) 0.25** (0.00) 0.25** (0.00) 0.25** (0.00) 0.19** (0.02) 0.00* (0.21) 0.19** (0.02) 0.00* (0.21) 0.00* (0.25) 0.11** (0.00) 0.35** (0.00) 0.25** (0.00) 0.19** (0.02) 0.00* (0.21) 0.19** (0.02) 0.00* (0.21) 0.19** (0.02) 0.19** (0.02) 0.10* (0.21) 0.19** (0.00) 0.19** (0.02) 0.10* (0.21) 0.19** (0.00) 0.19** (0.02) 0.00* (0.21) (0.22) 0.11* (0.02) 0.11* (0.02) 0.11* (0.02) 0.11* (0.02) 0.11* (0.02) 0.11* (0.02) 0.11* (0.02) 0.11* (0.02) 0.11* (0.02) 0.11* (0.02) 0.11* (0.02) 0.11* (0.02) 0.11* (0.02) 0.11* (0.02) 0.11* (0.02) 0.11* (0.01) 0.12* (0.02) 0.11* (0.02) 0.11* (0.02) 0.11* (0.02) 0.11* (0.02) 0.11* (0.02) 0.00* (0.10) 0.11* (0.02) 0.00* (0.10) (0.	Model 1Model 2 0.67^{***} 0.64^{***} (0.00) (0.00) 4.43^{**} 4.37^{**} (0.01) (0.02) -0.26 -0.30 (0.32) (0.25) 1.54^{***} 1.65^{***} (0.00) (0.00) -0.1^{***} 1.65^{***} (0.00) (0.00) -0.1^{***} -0.01^{***} (0.00) (0.00) -0.1^{***} -0.1^{***} (0.00) (0.00) -0.1^{***} -0.1^{***} (0.00) (0.00) -0.1^{***} (0.00) -0.24 (0.34) (0.34) (0.34) -0.89^{**} -1.08^{***} (0.02) (0.17) -0.90^{***} -0.83^{***} (0.00) (0.00) -0.00 (0.00) -0.00 (0.00) -0.00 (0.00) -0.00 (0.01) (0.01) (0.02) 1.10 1.86 (0.78) (0.64) (0.00) (0.03) -0.14 -0.08 (0.53) (0.72) 1.20^{***} (0.03) (0.03) (0.01) 0.27 0.19 (0.28) (0.48) 0.18^{***} 0.19^{***} (0.00) (0.01) 0.00^{*} (0.01) 0.00^{*} (0.01)	Model 1Model 2Model 3 0.67^{***} 0.64^{***} 0.65^{***} (0.00) (0.00) (0.00) 4.43^{**} 4.37^{**} 4.30^{**} (0.01) (0.02) (0.02) -0.26 -0.30 -0.32 (0.32) (0.25) (0.22) 1.54^{***} 1.65^{***} 1.65^{***} (0.00) (0.00) (0.00) -0.01^{***} -0.01^{***} (0.00) (0.00) (0.00) -0.1^{***} -0.01^{***} (0.00) (0.00) (0.00) -0.24 -0.25 (0.34) (0.34) (0.32) -0.89^{**} -1.08^{***} -1.01^{***} (0.02) (0.00) (0.01) -0.90^{***} -0.83^{***} -0.86^{***} (0.02) (0.17) (0.10) -0.90^{***} -0.83^{***} -0.86^{***} (0.00) (0.00) (0.00) -0.00 -0.00 -0.00 -0.00 -0.00 -0.00 (0.50) (0.51) (0.45) 0.11^{**} 0.10^{**} (0.01) (0.02) (0.03) 1.10 1.86 -1.03 (0.78) (0.64) (0.76) 0.00^{***} 0.00^{***} (0.00) 0.35^{**} 0.39^{**} 0.44^{***} (0.01) (0.03) (0.01) $0.53)$ (0.72) (0.57) 1.20^{***} 1.12^{***} 1.15^{***} $(0.0$	Model 1Model 2Model 3Model 4 0.67^{***} 0.64^{***} 0.65^{***} 0.66^{***} (0.00) (0.00) (0.00) (0.00) 4.43^{**} 4.37^{**} 4.30^{**} 5.00^{***} (0.01) (0.02) (0.02) (0.00) -0.26 -0.30 -0.32 -0.86^{***} (0.32) (0.25) (0.22) (0.00) 1.54^{***} 1.65^{***} 1.65^{***} 1.53^{***} (0.00) (0.00) (0.00) (0.00) -0.1^{***} -0.01^{***} -0.01^{***} (0.00) (0.00) (0.00) (0.00) -0.1^{***} -0.01^{***} -0.01^{***} (0.00) (0.00) (0.00) (0.00) -0.1^{***} -0.01^{***} -0.01^{***} (0.00) (0.00) (0.00) (0.00) -0.1^{***} -0.24 -0.25 -0.30 (0.34) (0.34) (0.32) (0.13) -0.89^{***} -1.08^{***} -1.05^{***} (0.02) (0.00) (0.01) (0.00) -0.00 -0.00 -0.00 (0.26) (0.17) (0.10) (0.28) -0.90^{***} -0.83^{***} -0.50^{**} (0.00) (0.00) (0.00) (0.00) (0.00) (0.00) (0.00) (0.00) (0.00) (0.00) (0.00) (0.00) (0.00) (0.00) (0.00) (0.00) (0.00)

Table 3: OLS regression results for the acquisition price

	Model 1	Model 2	Model 3	Model 4	Model 5
Acquirer-region relatedness	0.28	0.30	0.64***	0.25	0.58***
	(0.31)	(0.32)	(0.00)	(0.37)	(0.00)
Target-region relatedness	0.28	0.41	0.39	-0.43	-0.43
	(0.47)	(0.31)	(0.34)	(0.20)	(0.20)
Target regional embeddedness		0.04***	0.04***	0.05***	0.05***
		(0.00)	(0.00)	(0.00)	(0.00)
Target regional embeddedness*acqreg. relatedness			-0.36***		-0.34***
			(0.00)		(0.00)
Target regional embeddedness*tarreg. relatedness				0.95***	0.93***
				(0.00)	(0.00)
Constant	-1.92**	-1.32	-1.43	-1.27	-1.38
	(0.04)	(0.17)	(0.14)	(0.17)	(0.14)
N	520	520	520	520	520

 $\frac{1}{p < 0.1, ** p < 0.05, *** p < 0.01}$ The table shows regression coefficients with standard errors in parentheses below. All specifications also include industry dummies, year dummies, a dummy for missing liabilities and a dummy for missing regional information. The latter two variables were not significant in any specification.

	Model 1 Additional control for intra-region M& A	Model 2 Subsample of cross-region M&A	Model 3 Dependent variable: acquisition premium
Target total assets (log.)	0.67***	0.64***	-0.22***
	(0.00)	(0.00)	(0.00)
Target patents/assets	4.91***	3.05***	3.90***
	(0.00)	(0.00)	(0.00)
Target citations/patents	-0.86***	-0.88**	-0.11
	(0.00)	(0.02)	(0.21)
Acquirer-target relatedness	1.55***	1.60**	0.92***
	(0.00)	(0.02)	(0.00)
Acquirer-target relatedness (sq.)	-0.01***	-0.01**	-0.00***
	(0.00)	(0.02)	(0.00)
Target return on assets	-0.30	0.80	-0.35
	(0.12)	(0.26)	(0.18)
Target liabilities over assets	-0.96***	-1.00***	-1.19***
	(0.01)	(0.01)	(0.00)
Target age (years)	-0.00	-0.01	-0.01***
	(0.16)	(0.25)	(0.00)
Target is listed (d)	-0.53*	-0.19	0.01
	(0.07)	(0.58)	(0.96)
Target turnover as a share of regional GDP	-0.00	-0.00	-0.00
	(0.41)	(0.23)	(0.49)
Acquirer total assets (log.)	0.09**	0.09*	0.12***
	(0.04)	(0.05)	(0.00)
Acquirer patents/assets	6.44	-1.02	-5.94***
	(0.18)	(0.78)	(0.00)
Relative size	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)
Horizontal acquisition (d)	0.55***	0.49***	0.25***
	(0.00)	(0.01)	(0.01)
Crossborder acquisition (d)	-0.07	0.02	0.01
	(0.75)	(0.93)	(0.95)
Different regions (d)	1.13***	-	0.19
	(0.00)	-	(0.20)
Regional employment (log.)	-0.30***	-0.26*	-0.03
	(0.01)	(0.05)	(0.60)
Regional scientists/employment	0.15	0.32	0.33**
	(0.56)	(0.27)	(0.02)
Regional patents/scientists	0.17***	0.11*	0.07**
	(0.00)	(0.07)	(0.02)
Regional HHI	0.17**	0.20***	0.17***

Table 4: OLS regression results for the acquisition price – consistency checks

	Model 1	Model 2	Model 3
	Additional control for intra-region M&A	Subsample of cross-region M&A	Dependent variable: acquisition premium
	(0.02)	(0.01)	(0.00)
Average deal value per industry/country	0.00**	0.00**	-0.00
	(0.04)	(0.03)	(0.88)
Acquirer-region relatedness	0.89***	0.63***	0.17
	(0.00)	(0.00)	(0.16)
Target-region relatedness	-0.42	-0.25	-0.33**
	(0.21)	(0.47)	(0.02)
Acquirer has inventors in target region (d)	-1.02		
	(0.16)		
Target regional embeddedness	0.05***	0.05***	0.03***
	(0.00)	(0.00)	(0.01)
Target regional embeddedness*acquirer-region relatedness	-0.38***	-0.34***	-0.07*
	(0.00)	(0.00)	(0.05)
Target regional embeddedness*target-region relatedness	0.91***	0.87***	0.20**
	(0.00)	(0.00)	(0.01)
Constant	-1.47	-0.26	-0.63
	(0.13)	(0.80)	(0.28)
Ν	520	472	520

* p<0.1, ** p<0.05, *** p<0.01The table shows regression coefficients with standard errors in parentheses below. All specifications also include industry dummies, year dummies, a dummy for missing liabilities and a dummy for missing regional information. The latter two variables were not significant in any specification.