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Alliance-to-acquisition transitions: The technological performance implications of acquiring one's alliance partners

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A B S T R A C T

Drawing on organizational learning theory, we investigate the technological performance implications of acquiring one's alliance partners. We do so using a sample of 252 firms in four high tech industries, who jointly announced 2,398 acquisitions and filed 125,440 new patent applications, in the period of our analysis. We argue a history of collaboration will allow the acquirer to more easily identify and absorb the target's knowledge, and show that the share of 'alliance-to-acquisition transitions', in the total set of the firm's acquisitions, increases the firm's inventive *quantity*. We also argue that a history of collaboration reduces the opportunity to encounter unknown and unexpected knowledge, which will affect both the *type* and *quality* of invention. We find support for the former, and show that the share of alliance-to-acquisition transitions increases the firms exploitative tendencies. In terms of the latter, we find a weak relationship between the share of transitions and overall patent quality, but find that the share of transitions does not affect the number of high quality breakthrough inventions. In so doing, we provide new insights, relevant to the acquisition literature, the literature on transitional governance, and the literature on organisational learning, and position alliance-to-acquisition transitions as a mechanism for altering the firm's technology production function.

1. Introduction

Knowledge is one of a firm's most strategically important resources. Knowledge facilitates the development of new technologies, new products and new services. In industries characterised by constant change and innovation, an ability to create new knowledge is essential to the firm's survival (Conner and Prahalad, 1996; Grant, 1996; Kogut and Zander, 1992).

Firms rarely, however, have a sufficiently large or sufficiently diverse knowledge pool to continuously create new knowledge (Chesbrough, 2006; Cohen and Levinthal, 1990). In fact, to sustain continuous inventive activities, firms must compliment their internal technological processes by searching for new knowledge, beyond their organizational boundaries (Puranam and Srikanth, 2007; Savino et al., 2017). Acquisitions are one commonly used way of doing this (Makri et al., 2010; Uhlenbruck et al., 2006; Vermeulen and Barkema, 2001). Through an acquisition, the acquiring firm gains access to the target firm's knowledge stock, technological capabilities, and innovation streams (Ahuja and Katila, 2001; Ghoshal, 1987; Hitt et al., 1996).

Acquisitions, however, are challenging (Moeller et al., 2005), and acquisitions aimed at knowledge and technology are particularly prone to complication and disappointment (Chaudhuri and Tabrizi, 1999; McCarthy and Aalbers, 2016). Information asymmetries (Arrow, 1974), for example, regarding what knowledge the target firm has and how tacit it is, make it difficult to estimate synergies ex ante (Grant, 1996; Hennart 1988; Hennart and Reddy, 2000; Puranam et al., 2009). Ex post, the delays and disruptions that this creates often reduce the technological performance of both the target (Kapoor and Lim, 2007) and the acquiring (Hitt et al., 1991) firms.

But what if the acquirer buys a firm that it already knows? In this paper, we consider the effect of a prior alliance, between the target and the acquirer, on the technological performance of the acquiring firm. Alliances are interorganisational cooperative arrangements, between firms, to share resources, in order to achieve a particular goal (Colombo et al., 2006). Alliances should be beneficial in an acquisition because they reduce information asymmetries. They provide the firm with the opportunity to identify key knowledge, technology and people in the target firm (Dyer and Singh, 1998; Gulati et al., 2009), and to understand their (in)compatibilities with those of the acquiring firm (Kale et al., 2000). In other words, alliances should improve both acquisition

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performance and, more importantly, the acquiring firm's overall technological performance.

The benefits of prior alliances to acquirers has been recognized. Scholars acknowledge that alliances are often an 'intermediate step' on the path to an acquisition (Zaheer et al., 2010). Surprisingly, however, only a handful of studies have considered the interplay between acquisitions and alliances (e.g., Estrada et al., 2010; Hagedoorn and Sadowski, 1999; Zaheer et al., 2010) and most of this has focused on the financial implications. None of it, to the best of our knowledge, has considered the technological performance implications. To do so is important because, from an organizational learning perspective, technological performance helps us to understand how organizations absorb and use external knowledge (Ahuja and Katila, 2001) and, from a corporate governance perspective, its helps us to understand the returns to acquisitions.

Drawing on insights from organization learning theory (e.g., Amburgey and Miner, 1992; Levitt and March 1988), which suggests that different governance forms support different types of learning (e.g., Osborn and Hagedoorn, 1997; Schildt et al., 2005), we predict that the *share* of alliance-to-acquisitions transitions, in the total set of the firm's acquisitions, will affect the firms technological performance in three ways. First, we argue that an alliance will increase the ease with which the target's knowledge can be integrated, such that a greater share of alliance-to-acquisition transitions will increase the *quantity* of inventions produced by the firm. Second, we argue that an acquisition involving an alliance partner will bring less 'new' or 'unexpected' knowledge, and it will reactivate old knowledge creation routines (Kok et al., 2020; Sørensen and Stuart, 2000), which will affect the *type* of inventions produced, in that it will lead to more exploitation. Finally, we argue that the familiarity that comes from acquiring an alliance partner will positively affect the overall *quality* of the inventions produced, but will negatively affect the number of trajectory-shifting 'breakthroughs' inventions produced (Dong et al., 2017), which require new knowledge and technological space (Schoenmakers and Duysters, 2010).

We test these hypotheses using data on the alliance, acquisition and patent portfolios of 252 firms, in four high tech industries, operating in the period 1990–2015. We collect alliance and acquisition data from the *Thomson Reuters SDC* database, financial data from *Compustat*, and patent data from the *European Patent Office (EPO)*. Our results largely support our hypotheses.

In doing so, we make a number of contributions. For example, we contribute to the *acquisition literature* by providing insight on the value of alliance-to-acquisition transitions and to the *literature on transitional governance* by considering the technological performance implications of these transitions. Our key contribution, however, is to the *literature on organisational learning*. We contribute to this literature by positioning alliance-to-acquisition transitions as a distinct mechanism that allows firms to alter their technology production function. Within this, we add to specific discussions on breakthrough innovation and on the learning effects of repeated governance modes. We add to the former by showing that alliance-to-acquisition transitions are not the right tool for creating breakthroughs and add to the latter by providing empirical evidence which shows that the share of transitions affects the firm's technological performance in terms of inventive type, quantity and quality.

2. Background

2.1. Knowledge and knowledge recombination

Knowledge is one of the firm's most strategically significant resources (Grant, 1996; Kogut and Zander, 1993). Knowledge, and the way in which it is created, combined and recombined, allows the firm to develop new products, services and technologies (Fleming, 2001; Nelson and Winter, 1982). In industries characterised by change, access to sufficient quantities of sufficiently new knowledge components is, therefore, essential to the firm's survival (Ahuja and Katila, 2001; Conner and Prahalad, 1996; Fleming, 2001; Grant, 1996; Kogut and Zander, 1992). Research shows that the larger the set of components available to a firm, the greater the number of combinations and subsequent inventions it can generate (Fleming, 2001). Firms rarely, however, have a sufficiently large or sufficiently diverse internal knowledge pool to sustain continuous inventive activities (Chesbrough, 2006; Cohen and Levinthal, 1990). Instead, they must continuously search for new knowledge inputs, beyond their organizational boundaries (Caloghirou et al., 2021; Puranam and Srikanth, 2007; Savino et al., 2017).

2.2. Acquisitions and knowledge recombination

Research describes a number of governance forms that can be used to access new and different knowledge outside the firms organisational boundaries (Chuaet al., 1999; Miles and Covin, 2002; Schildt et al., 2005). Acquisitions are one commonly used way of doing this (Makri et al., 2010; McCarthy and Aalbers, 2016; Vermeulen and Barkema, 2001).

Acquisitions provide the firm with access to the target's knowledge stock, technological capabilities, and innovation streams (Ahuja and Katila, 2001; Ghoshal, 1987; Hitt et al., 1996). As such, acquisitions increase the size of the acquiring firm's knowledge base (Ahuja and Katila, 2001; Cloodt et al., 2006; Makri et al., 2010). Because, in an acquisition, the firm not only gains access to the resources that motivated the acquisition – in terms of the target's knowledge, technology or human capital – but 'everything else too', technological acquisition also increases the diversity of the firms knowledge (Wei and Clegg, 2020; Yli-Renko et al., 2001).

One would expect, therefore, that acquisitions should have a positive effect on the technological performance of the acquiring firm. Prior studies suggest, however, that performance depends heavily upon the acquiring firm's ability to effectively identify, transfer and absorb the target's key knowledge components (Makri et al., 2010; Sears and Hoetker, 2014).

Information asymmetries, between the target and the acquirer, complicate this process (Arrow, 1974). Pre-acquisition, information asymmetries make it difficult for the acquirer to understand what knowledge resources the target has, how tacit they are (Polanyi, 1963), how embedded they are in an individual, group, organization, or network, and how intertwined and "bundled" they are with other resources (Nonaka, 1994; Nonaka and Von Krogh, 2009; Zaheer et al., 2010). Post-acquisition, the discovery of resource incompatibilities leads to integration difficulties, and hampers the realization of technological synergies. (Hennart and Reddy, 2000; Kale et al., 2000; Puranam et al., 2009). The delays and disruptions that this can cause can be so large that acquisitions often negatively affect the technological performance of both the target and the acquiring firm Kapoor and Lim (2007)., for example, report that an acquisition can reduce the target firm's inventive output by as much as 50%, while Hitt et al. (1991) report that an acquisition can reduce the acquirer's inventive output by almost 20%.

Existing research has highlighted several mechanisms by which knowledge transfer can be improved between the target firm and the acquirer. For example, Ahuja and Katila (2001) and Cloodt et al. (2006) argue that the level of overlap between the knowledge bases of the target and acquirers facilitates communication, and the transfer of knowledge post-acquisition, meaning that related technological acquisitions tend to be more successful. In this study, we propose an alternative mechanism – in the form of an alliance – which, we argue, will affect the ease with which knowledge can be identified and transferred from the target to the acquirer.

2.3. Alliances and alliance-to-acquisition transitions

Strategic alliances are formal arrangements between independent firms. In an alliance, firms pool resources, often in the form of knowledge and technology (Mowery et al., 1996; Rosenkopf and Almeida, 2003), in order to reach a mutually agreed objective (Colombo et al., 2006). There is a rich literature on the use of strategic alliances as a tool for accessing new and different knowledge, which shows that firms that engage in alliances tend to be more innovative (Columbo et al., 2006; Deeds and Hill, 1996; Kotabe and Swan, 1995; Montoya-Weiss and Calantone, 1994; Shan et al., 1994) De Man and Duysters (2005)., for example, report that 73% of alliance studies find that alliances positively affect the firms inventive output.

Traditionally alliances and acquisitions have been treated as alternative mechanisms for accessing knowledge beyond the boundaries of the firm (Hennart, 1988; Vanhaverbeke et al., 2002; Villalonga and McGahan, 2005). Increasingly, however, it is being recognised that alliances often evolve or, 'transition' into acquisitions, meaning that firms often acquire their alliance partners (e.g., Garette and Dussage, 2000; Hagedoorn and Sadowski, 1999; Porrini, 2004; Stettner and Lavie, 2014; Yang et al., 2011; Zaheer et al., 2010; Zollo and Reuer, 2010). Using an alliance as an intermediate step on the road to an acquisition, of course, makes sense. Alliances provide the acquirer with the opportunity to learn 'from' and to learn 'about' the target (Anand and Khanna, 2000; Inkpen, 1998; Sarkar et al., 2009). They are an opportunity for the acquirer to identify key knowledge, technology and people in the target firm (Dyer and Singh, 1998; Gulati et al., 2009), and to understand their (in)compatibilities with those of the acquiring firm (Kale et al., 2000). In other words, an alliance should reduce information asymmetries between the target and the acquiring firm, enable the acquirer to estimate synergies, ex ante, and to realize them, ex post, leading to better technological performance.

2.4. Governance forms and organisational learning

Organizational learning theory suggests that the *way* firms add and integrate new knowledge elements – that is, the way they learn – effects *what* they learn (Argote and Miron-Spektor, 2011; Levitt and March 1988). Organizational learning theory has been widely applied in research on the effects of both alliances and acquisitions (e.g., Ahuja and Katila, 2001; Dikova et al., 2010; Vermeulen and Barkema, 2001). It suggests that different governance modes support different types of learning (Osborn and Hagedoorn, 1997) Schildt et al. (2005)., for example, use organizational learning theory to argue that less integrated external governance modes, like Corporate Venture Capital (CVC) investment, are more effective for exploration, relative to more integrated governance modes, like acquisition, which are better for exploitation. This is, they suggest, because less integrated external venture governance modes provide greater flexibility and adaptability to change. In the same vein, we argue that, from an organizational learning perspective, the share of alliance-to-acquisition transitions that the firm makes, in its total set of acquisitions, should effect what and how the acquiring firm learns. We expect this to be visible in terms of the quantity, quality and type of inventions that the firm produces.

2.5. The technological performance of alliance-to-acquisition transitions

The existing literature on alliance-to-acquisition transitions tends to focus either on the conditions under which alliances transition to acquisitions (Estrada et al., 2010; Folta, 1998; Kogut, 1991; Vanhaverbeke et al., 2002) or on the implications of a transition in terms of the firm's financial performance (e.g., Porrini, 2004; Zaheer et al., 2010). There is nothing, which we know of, which considers the technological implication of such acquisitions. To do so is important, however, for at least three reasons. First, technological performance is important from the perspective of organizational learning and innovation: it helps us to understand if and how firms absorb and use external knowledge. Second, technological performance is important for understanding the market for corporate control. Finance and accounting based studies generally find that acquisitions have a negative impact on firm performance (e.g., Moeller et al., 2005). Agency problems are often used as an explanation (Jensen, 1986). This conclusion, however, is difficult to understand, given the popularity of acquisitions. Evaluating the technological performance of acquiring firms provides additional insights on the returns to acquisitions. Third, technological performance is important from a resource-based view perspective. The resource based view suggests that acquisitions are an important tool for redeploying resources into more productive uses (Anand and Singh, 1997). Through acquisitions, firm-specific assets housed within one organization are combined with assets in another to improve the productivity of the combined assets (Haspeslagh and Jemison, 1991). Evaluating the post-acquisition technological performance of firms therefore also provides evidence on the efficiency of this process.

3. Hypotheses

3.1. Alliance-to-acquisition transitions and inventive quantity

First, we argue that, from an organisational learning perspective, the acquisition of alliance partners should affect the *quantity* of inventions produced by the acquiring firm.

Alliances allow firms to build mutual trust (Aalbers, 2010; Carson et al., 2003; Gulati, 1995) and relational capital, which improves communication (Larsson et al., 1998; Poppo and Zenger, 2002). This not only facilitates the exchange of information, capabilities and skills (Aggarwal, 2020; Kale et al., 2000), but creates understanding, which helps to mitigate conflict, at the next stage, that may hamper technological performance (Lin and Germain, 1998; Martin et al., 1998). Alliances also lead to the development of 'partner specific absorptive capacity' (Dyer and Singh, 1998), 'partner-specific experience' (Hoang and Rothaermel, 2005), and 'inter-organizational routines' (Zollo et al., 2002), all of which refers to the firm's ability to identify, recognize, and assimilate valuable knowledge in a specific alliance partner. Alliances, in other words, provide firms with the opportunity to learn from and about each other (Anand and Khanna, 2000; Inkpen, 1998; Sarkar et al., 2009), which reduces information asymmetries, and improves the transfer of knowledge from the target to the acquirer (Levitt and March, 1988).

Together, the implication is that acquirers, who had an alliance with their target, will better understand what knowledge elements the target has, will have pre-existing routines for accessing and exchanging knowledge (Kale et al., 2000), will be better able to recognize and to assimilate key knowledge (Dyer and Singh, 1998), and will better understand resource (in)compatibilities (Kale et al., 2000). This should facilitate the integration process (Ariño and De La Torre, 1998) and improve technological performance. Thus, we hypothesize that:

Hypothesis 1: A greater share of alliance-to-acquisition transitions, in the acquirer's total set of acquisitions, will have a positive impact on the firm's inventive quantity

3.2. Alliance-to-acquisition transitions and inventive type

Next, we argue that, from an organisational learning perspective, the acquisition of alliance partners should affect the *type* of inventions produced by the acquiring firm.

The literature on organisational learning identifies two broad patterns of learning behaviours and two knowledge types: exploitation and exploration (Lavie and Rosenkopf, 2006; Phene et al., 2012). Exploration is the "pursuit of new knowledge" (Levinthal and March, 1993, p.105). It involves "search, variation, risk taking, experimentation, play, flexibility, discovery, [and] innovation" (March, 1991, p.71). By contrast, exploitation is "the use and development of things already known" (Levinthal and March, 1993, p.105). Exploration involves "refinement, choice, production, efficiency, selection, implementation, [and] execution" (March, 1991, p.71).

Firms must explore and exploit; neither learning pattern is superior. The two learning patters, however, require different knowledge input and different organisational support (Brown and Eisenhardt, 1997; Lavie and Rosenkopf, 2006; Nickerson and Zenger, 2002; Siggelkow and Levinthal, 2003). Exploration, for example, requires more and more diverse knowledge inputs and freedom for "non-routine problem solving" (Lavie et al., 2010, p.122). According to classic innovation literature (e.g., Gilsing and Nooteboom, 2006; March, 1991) exploration is about combining new knowledge. Exploitation, by contrast, is the recombination of existing knowledge (Gilsing and Nooteboom, 2006; March, 1991). It requires fewer new knowledge inputs but more established refined routines to process it (Jansen et al., 2006; Wang et al., 2017).

The implication, by extension, is that alliance-to-acquisition transitions will differ in the degree to which they support explorative and exploitative learning. We suggest that alliance-to-acquisition transitions will lead to more exploitative inventions for three reasons in particular.

First, and in terms of the novelty of the knowledge inputs, an alliance-to-acquisition transition will bring less 'newness' to the acquiring firm. Alliances, as argued above, provide the acquiring firm the opportunity to learn from and about each other (Anand and Khanna, 2000; Inkpen, 1998; Sarkar et al., 2009). Firms do not explore, however, by accumulating familiar knowledge; they explore when they add new knowledge to their knowledge base (Antonelli, 2011; Gilsing and Nooteboom, 2006; Hidalgo and Hausmann, 2009). Acquisitions often bring unseen, and (initially) unwanted knowledge, and it is this novelty that forces the acquirer to explore previously unknown and unimagined opportunities (Puranam et al., 2006; Wry and Lounsbury, 2013). New knowledge, 'involving technologies the firm has little previous experience with' (Schild et al., 2005, p.495) leads to exploration (Katila, 2002). In other words, acquisitions involving alliance partners will add knowledge that naturally leads to exploitation.

Second, and in terms of routines, alliance-to-acquisition transition will reactivate old knowledge creation routines, prevalent at the time that the alliance collaboration was initiated (Kok et al., 2020; Sørensen and Stuart, 2000). Routines are repositories of organizational knowledge (Levitt and March 1988). They facilitate smooth and stable organizational functioning but they are subject to inertia (Levitt and March 1988; Nelson and Winter, 1982). Experiences with specific routines generates familiarity and increases the likelihood of routines being reused (Finkelstein and Haleblian, 2002; Haleblian et al., 2006). Over time, this leads naturally to refinement, to exploitation and, eventually, to incremental innovation (Levitt and March 1988; Sørensen and Stuart, 2000; Tushman and Anderson, 1986). In other words, acquisitions involving alliance partners will cause the firm to continue doing what it always did, to prefer local search over new discovery, and to favor the further refinement of familiar component combinations over the creation of new ones (Carnabuci and Operti, 2013; Levitt and March 1988; Stuart and Podolny, 1996). The result will be an increase in the exploitative tendencies of the firm.

Finally, and in terms of control, alliances and acquisitions differ in the degree to which they are controlled (e.g., Roberts and Berry, 1985; Stettner and Lavie, 2014). Specifically, alliance are less constrained than acquisitions, in the sense that, in an alliance, two partners cooperate, as equals, while in an acquisition, the acquirer instructs the target. Prior work suggests, however, that looser coordination and control is necessary for exploration and tighter coordination and control is necessary for exploitative learning (Schildt et al., 2005). In other words, the transition from an alliance to an acquisition will change the governance form in such a way that it will favor the production of exploitative knowledge over explorative knowledge.

Thus, we expect that acquisitions of targets with which the focal firm previously collaborated with are more likely to lead to an increase in exploitative invention. Therefore:

Hypothesis 2: A greater share of alliance-to-acquisition transitions, in the acquirer's total set of acquisitions, will increase the firm's exploitative tendencies

3.3. *Alliance-to-acquisition transitions and inventive quality*

Finally, we argue that, from an organisational learning perspective, the acquisition of alliance partners will have a mixed effect on inventive *quality*: positively effecting 'general inventive quality' and negatively effecting the production of high-quality 'breakthroughs'.

In terms of overall invention quality, we suggest that alliances allow firms to build trust (Krishnan et al., 2006; Aalbers, 2010; Carson et al., 2003; Gulati, 1995), to create relational capital, and to develop a common vocabulary (Grant, 1996; Sears, 2018). Post-acquisition, this leads to a better exchange of information, capabilities and skills (Aggarwal, 2020; Kale et al., 2000), which improves absorption (Lane et al., 2001) and increases learning (Lane and Lubatkin, 1998).Therefore, alliance-to-acquisition transitions allow for a higher quality of information exchange, which improves overall inventive quality (Gupta and Govindarajan, 1991).

That said, we expect a different effect when it comes to breakthrough inventions. 'Breakthrough' inventions (Dong et al., 2017) are 'foundational' inventions that spark a shift in the technological trajectory (Ahuja and Lampert, 2001; Dahlin and Behrens, 2005; Tellis et al., 2009). They are the basis of 'future' technologies, products and services (Ahuja and Lampert, 2001). Firms invest in the development of breakthrough innovation because research shows that those that develop breakthrough innovation tend to perform better and to survive longer (Abernathy and Utterback, 1978; Cooper and Schendel, 1976; Henderson and Clark, 1990; Hill and Rothaermel, 2003; Rosenbloom and Christensen, 1998; Tushman and Anderson, 1986).

Breakthrough inventions occur in the presence of new knowledge, new knowledge domains and knowledge production routines (Dahlin and Behrens, 2005; Schoenmakers and Duysters, 2010; Sørensen and Stuart, 2000; Phene et al., 2006). Because acquisitions involving prior alliance partners present acquirers with few of these, we suggest that firms with a greater share of alliance-to-acquisition transitions will not produce more breakthrough patents.

In fact, we argue that the share of alliance-to-acquisition transitions will reduce the number of breakthroughs. Alliances enable the acquiring firm to reduce the information asymmetries present in an acquisition. They are an opportunity for the firm to learn about how best to use each other's resources and how to obtain potential value-creating combinations (Agarwal et al., 2012; Puranam et al., 2009). They are in other words, a tool for reducing risk. Acquisitions involving alliance partners increase the size of the acquiring firm's knowledge base, but do not broaden it, through the addition of new and unexpected knowledge (Phene et al., 2006). A tightening of governance regimes will also lead to more exploitation, as will the reactivation of old knowledge creation routines (Kok et al., 2020; Nerkar, 2003; Sørensen and Stuart, 2000). As a result, the firm will increasingly favor specialization over experimentation (Levinthal and March, 1993), which will reduce the probability of producing a 'breakthrough' invention.

Taken together, therefore, we expect that acquisitions involving alliance partners will increase overall inventive quality but will decrease the number of breakthrough inventions. Thus:

Hypothesis 3a: A greater share of alliance-to-acquisition transitions, in the acquirer's total set of acquisitions, will positively affect overall inventive quality

Hypothesis 3b: *A greater share of alliance-to-acquisition transitions, in the acquirer's total set of acquisitions, will negatively affect the number of breakthrough inventions produced*

4. Methods

4.1. *Empirical setting*

We test our hypotheses using a sample of firms in the high-tech industry. We make use of this setting simply because firms in the high tech industries have a high propensity to patent (Fontana et al., 2013), and are known to make use of alliances (Columbo et al., 2006) and acquisitions in the pursuit of innovation (McCarthy and Aalbers, 2016), meaning there is sufficient data to test our hypotheses. Following Cloodt et al., 2006), we define the high-tech industries as the pharmaceuticals (SIC-code 283), computers (SIC-code 357), electronics and communications (SIC-code 36), and aerospace and defense (SIC-codes 372 and 376) industries.

4.2. Data sources

4.2.1. Alliance and acquisitions data

We use the *SDC Platinum Mergers & Acquisitions* and *Joint Venture & Strategic Alliances* Database to build a sample of firms that are actively making alliances and acquisitions. We refine the *SDC Mergers & Acquisitions* Dataset to identify all acquisitions announced and completed by large (net asset ≥ US$1bn), publicly listed, high-tech acquirers, in the period Jan 1990–Dec 2015. We exclude recapitalizations, self-tenders, and repurchases, minority stakes (i.e. acquisitions for less than 50.1%), and acquisitions in which the acquirer increases an existing majority stake (e.g., from 95% to 100%). From this, we identify a unique set of large acquirers in high tech industries. Then, we use the *SDC Joint Venture & Strategic Alliances* dataset to track the firm's alliance-making activities. We do not apply any exclusion criteria and include all strategic alliance announced by the firms in our sample in the period Jan 1985-Dec 2015.

4.2.2. Technological performance data

We use data from the European Patent Office (EPO) to track the inventive activities of the firms in our sample. In doing so, we follow, for example, Bekkers et al. (2020).

The EPO (est 1973) provides patent protection to applicants in 38 countries, which includes the (then) 28 members of the European Union, plus 6 non-member states.[1] It processes approximately 180,000 patent applications per year (2019). Of these, 55% come from applicants outside its membership[2] and 72% come from large multinationals, such as Huawei (China), Samsung (Korea), LG (Korea), United Technologies (US) and Siemens (Germany) .[3]

While smaller than its US counterpart, in a variety of dimensions,[4] "the EPO has gained a level of economic importance similar to that of the USPTO" (Harhoff and Reitzig, 2004, p.488). The EPO's 38 members account for 21% of the world economy and the USPTO's 1 member accounts for 24%. The two databases are similar – Kim and Lee (2015) reports "very strong and significant correlations" in their comparison of specific high tech fields – and both are commonly used in research. For example, *this journal*[5] has published 389 research articles in the period 1996–2021 on firm performance using the USPTO and 313 that used the EPO.

We choose to use the EPO, over the USPTO, primarily, because EPO patents "provide a better indication of valuable technological activities" (Belderbos et al., 2014, p.844). In fact, "EPO patents have become the dominant indicator of innovative activity" (Belenzon and Patacconi, 2013, p.1496). This is because "the cost of patenting at the EPO is 2–5 times greater than at USPTO, the workload of patent examiners is four times smaller, and the EPO has a 20–30% lower patent-granting rate than USPTO" (Belderbos et al., 2014, p.844). USPTO examiners have "strong financial incentives to accept rather than reject applications" (Belenzon and Patacconi, 2013, p. 1497) and because of this USPTO patents are so 'very easy to get' (Jaffe and Lerner, 2004, p. 36) that commentators have suggested that they are 'essentially worthless, both economically and as a signal of technological strength' (Belenzon and Patacconi, 2013, p.1509).

Moreover, the EPO provides highly accurate information regarding, for example, the applicant's address, which allows firms and patents to be matched effectively. We use data from the EEE-PPAT, which is produced by ECOOM (Catholic University of Leuven) and Eurostat, and provides harmonized patent applicant names to improve the matching procedure, when assigning patents to firms (Du Plessis et al., 2009; Magerman et al., 2009; Peeters et al., 2009)

4.2.3. Other data sources

We use the Standard and Poor's Compustat database, which reports financial, statistical, and market information on all active and inactive stock listed companies, since 1962. We use it to collect firm-level financial data necessary for the construction of control variables (see below).

4.3. Dependent variables

We construct a number of dependent variables: *Inventive Quantity,* to describe the effect of the share of transitions on the *quantity* of inventions, *Inventive Exploitation,* to describe the effect on the *type* of invention, and *Inventive Quality,* to describe the effect of *quality*.

4.3.1. Inventive quantity

We define *Inventive Quantity* as the total number of patent applications made by Firm *i* at time $t + 1$. Each patent thus represents a single invention. We follow, for example, Belderbos et al. (2014, 2010), Leten et al. (2016, 2007), Lecocq et al. (2012) and Breschi et al. (2003), and count the number of patent applications, as opposed to the number of patents granted. We do so because "patent application data provide[s] a broader indicator of the variety of technological activities of the firm… [creating] a more complete picture, especially in the case of explorative technological activities' (Belderbos et al., 2010, p,874). Moreover, patent-granting decisions at the EPO take 5–6 years on average, a fact that makes granted patents a poor and incomplete indicator of the firms' recent technological activities (Belderbos et al., 2010; 2014; Harhoff and Wagner, 2009). We follow Belderbos et al. (2014; 2010), Blind et al. (2009), Brouwer and Kleinknecht (1999) and Tappeiner et al. (2008) and make use of the application date when assigning patents to years. Specifically, we use the patent's 'priority date' – that is, the date at which the applicant first sought protection, at any patent office – as opposed to its 'application date' – that is, the date at which the applicant sought protection at the EPO – when describing the date at which the patent was created (De Rassenfosse et al., 2013). For robustness checking purposes we also create *Weighted Inventive Quantity*, which we define as the number of patent application made by Firm i at time $t + 1$, divided by firm revenue at time t.

4.3.2. Inventive exploitation

We make use of the *Cooperative Patent Classification* (CPC) codes, listed on the patent application, to create the *Inventive Exploitation* variable, in order to describe inventive type.

The CPC classification system is an international classification system used by both the EPO and the USPTO. According to it, patents are filed, first, into one of 9 'sections', each of which is denoted with a letter. They are then filed into one of 136 'classes', which are denoted with a

[1] The 38 member states are: Albania, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Monaco, the Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, San Marino, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, and the United Kingdom. The 6 non-member in which the EPO provides protection include Bosnia and Herzegovina, Cambodia, Montenegro, Morocco, Republic of Moldova and Tunisia.

[2] The majority come from US (25%), German (15%), Japanese (12%), Chinese (7%) and (6%) French applicants

[3] See: https://www.epo.org/about-us/annual-reports-statistics.html

[4] The USPTO (est 1975) is larger than EPO in terms of patent applications (392,617 versus 181,406), employees (12,652 versus 6,608) and budgets ($3.69 billion versus €2.5 billion).

[5] Research Policy

Table 1
Patents and CPC codes.

Firm ID	Priority year	Patent ID	Technological codes	Forward Citations		
				Number of citations	5 year period	Percentile
1	2003	1	A01, B01, C,01	10	2004–2008	11th
1	2005	2	A01, B01, E01, F01	8	2006–2010	9th
1	2009	3	A01, B01	16	2010–2014	13th
1	2011	4	B01, E01	20	2012–2016	15th
1	2013	5	A01, B01, C01	21	2014–2019	15th
		6	A01, B01	598	2014–2019	99th
		7	A01, B01	2	2014–2019	2nd
		8	A01, Y01	4	2014–2019	3rd
1	2014	9	B01, E01	8	2015–2020	9th

two digit code. For example, A01 denotes the 'agriculture; forestry; animal husbandry; trapping; fishing' category. CPC codes are used to describe the technological content of the invention. They are commonly used to track the knowledge that is used by a firm to develop new inventions (e.g., Bekkers et al., 2020; Carnabuci and Operti, 2013; Yayavaram and Ahuja, 2008).

We define *Inventive Exploitation* as the share of exploitative patents made by Firm *i* at time $t+1$. We label a patent exploitative when it has the exact same configuration of CPC codes as one of the patents that it produced in the previous ten years ([t-10, $t = 0$]). Following Carnabuci and Operti (2013), we count the number of exploitative patents the firm files, in a given year, and divide this by the total number of applications, to describe the firm's exploitative tendency. For robustness checking purposes we create three additional variables: (1) *Inventive Exploration* is the share of patent produced by Firm i at time $t + 1$ with a new configuration of CPC codes; (2) *Number of Exploit Patents* is the absolute number of exploitative patents made by Firm *i* at time $t + 1$; and (3) *Number of Explore Patents* is the absolute number of explorative patents.

4.3.3. Inventive quality

Finally, we create two measures of *Inventive Quantity*. First, we follow the literature which uses forward citations as a general indicator of patent quality (e.g., Mowery et al., 2002; Sterzi, 2013; Briggs, 2015; Ferrucci and Lissoni, 2019; Harhoff et al., 2003). We define *Forward Citations* as the number of forward citations that the firms patent's receives. Since more recently granted patents had less time to gain forward citations, we counted the forward citations received by each patent in an equal time span of five years. For robustness checking purposes, we also created a weighted version of this, called *Weighted Forward Citations*, in which we divided the number of citations to the patent by the number of patent applications made by the firm.

Second, we count the total number of 'breakthrough' patents made by Firm i at time $t+1$. We term this measure *Breakthrough Inventions*. We follow the literature (e.g., Ahuja and Morris Lampert, 2001; Kerr, 2010, Popp et al., 2012; Srivastava and Gnyawali, 2011; Zheng and Yang, 2015), and identify breakthrough patents as those that receive forward citations in or above the 99th percentile of all patents within a particular patent class. In other words, we define a breakthrough patent as a patent that is in the top 1% most cited patents in each patent class. We counted the number of such patents, granted to each firm, each year, as reported by the EPO. Again, we compare all patents in an equal five year period. For robustness checking purposes, we also created a version, termed *Weighted Breakthrough Inventions,* in which we divided the number of breakthroughs inventions made by the firm, in a given year, by its total number of patent applications.

4.3.4. Illustration

As an illustration, Table 1 provides a fictitious overview of 9 patent applications made by *Firm 1* in the period 2003–2014. It reports that, in 2012, for example, *Firm 1* did not file a patent but filed for 4 in 2013. Thus, *Firm 1* had an *Inventive Quantity* of 0 in 2012 and 4 in 2013. Turning to the technological codes Table 1 reports that *Patent 5* shares the same combination of CPC codes as *Patent 1*. Similarly, *Patent 6* and *7* have the same combination of codes as *Patent 3*. As *Patent 5, 6* and *7* are in technological fields in which *Firm 1* was already active, we label these as 'exploitative'. Thus, 3 out of the 4 patents that *Firm 1* filed in 2013 are exploitative, leading to an *Inventive Exploitation* value of 0.75 in 2013. Finally, Table 1 reports number of forward citations that each patent receives in the five years after it was filed. *Patent 4* for example received 20 citations in the five year period 2012–2016. This places it in the 15th percentile of most cited patents within its particular CPC classes. *Patent 6*, by contrast, receives 598 citations, which places it in the 99th percentile. We label *Patent 6*, therefore, as a high quality, breakthrough invention. Thus, in terms of the *Inventive Quality* measures, *Firm 1* has 20 forward citations in 2011 and of 616 in 2013, 0 breakthroughs in 2011 and 1 in 2013.

4.4. Independent variable

All the firms in our sample make acquisitions. We create a variable to compare the performance of firms based on the share of alliance-to-acquisition transitions that they engage in. We term this variable the *Share of Transitions*. We program this as follows. First, we used the firm's CUSIP codes to identify alliance-to-acquisition transitions. We matched the CUSIP codes of each acquirer-target dyad in the acquisitions dataset to the CUSIP codes of all firm-partner dyads in the alliance dataset. When the same dyad appeared in both sets, we defined it as an alliance-to-acquisition transition. We imposed no additional restriction beyond the fact that the acquisition should be announced after the alliance was announced. Next, we count the total number of alliance-to-acquisition transitions executed by the firm in a given year. We then compute the *Share Transitional Acquisitions* by dividing the number of alliance-to-acquisition transitions, in a given year, by the total number of acquisitions announced by the firm in the same year. The result is the creation of a continuous variable that describes the *Share of Transition* as being between 0 – when none of the firm's acquisitions, in a given year, involve alliance partners – and 1 – when all of the firm's acquisitions, in a given year, involve alliance partners.

4.5. Control variables

We control for a number of factors – in terms of the firm, its behavior, and its knowledge base – which may influence its technological performance.

In terms of firm characteristics, we control for *(Log) Firm's Revenues*, which we use as an indicator of size, because bigger firms are better able to leverage the benefits of technological acquisitions (Ahuja and Katila, 2001). We also control for *R&D Intensity*, which we calculate by dividing the firm's R&D expenditures by its revenues, because R&D intensive firms are better able to extract the benefits from technological acquisitions (Cohen and Levinthal, 1990).

In terms of the firm's behavior, we control for the *Number of Acquisitions* initiated by the firm in a given year, because acquisitions affect innovation performance (Hitt et al., 1990; Makri et al., 2010). We control for the share of *Inter-Industry Acquisitions*, which we estimate based on overlap in four-digit SIC codes, because acquisitions in the same industry are more easily integrated, and therefore, tend to perform better (Datta and Jessup, 2013; Schildt et al., 2005). We also control for the share of *International Acquisitions*, because cultural differences complicate knowledge transfer, and therefore yield fewer benefits (McCarthy and Aalbers, 2016).

In terms of the knowledge base, we control for the *Acquirer's knowledge base size*, which we measure as the total number of patents filed by the acquirer, since firms with larger knowledge bases will be better able to realize synergies with the target (Ahuja and Katila, 2001). In the same way, we control for the *Target's knowledge base size*. In both cases we assume that knowledge decays over time (Garud and Nayyar, 1994), and therefore only use patent filed in the previous 10 years. We control for the age of the acquiring firm's knowledge base (*Acquirer's knowledge base age)*, which we estimate as the average age of the patents owned by the acquiring firm, because firms with outdated knowledge are more prone to suffer from technological inertia (Narula, 2002). We control for *Acquirer's knowledge base diversity* and *Target's knowledge base diversity* by looking at the distribution of patents across different four-digit CPC codes, because more diverse knowledge bases have been linked to improved technological performance (Dell'Era and Verganti, 2010). We used the Herfindahl index to compute diversity, with higher values indicating a greater spread of patents across CPC codes (Srivastava and Gnyawali, 2011). Finally, we controlled for the distance between the firm's knowledge base and the targets' (*Target's knowledge base distance*), because overlapping knowledge bases can be more easily combined (Cloodt et al., 2006). To capture this, we used the measure develop by Jaffe (1986), and measure the degree of overlap in the distribution of CPC codes between the acquiring firm and its targets. We estimate all knowledge based controls on the targets side in the aggregate when the acquirer makes multiple acquisitions in the same year.

4.6. Method of analysis

We consider the effect of the share of alliance-to-acquisition transitions (*Share Transitions*) on *Inventive Quantity, Inventive Quality* and *Inventive Exploitation*.

Both *Inventive Quantity* and *Inventive Quality* (which we measure using both *Forward Citations* and *Breakthrough Inventions*) are over-dispersed count variables, which only takes non-negative integer values, and have a skewed distribution. For such a dependent, a linear regression model would result in inconsistent, biased, and inefficient estimates (Greene, 2003; Hausman et al., 1984). A Poisson or negative binominal regression model could be used for such variables. Because Poisson modeling makes a strong assumption regarding equal mean and variance – which is not true in our case – we use a negative binomial model instead to estimate the effect of the *Share Transitions* on *Inventive Quantity* and *Inventive Quality*.

The *Inventive Exploitation* variable is a fractional variable that varies between zero and one, and sometimes takes the value of zero and one. For such a dependent variable, using a linear regression model would be inappropriate, as it would predict nonsensical value below zero and above one (Ramalho et al., 2011). Using a Tobit model would also result in inconsistent estimates due to, for example, violations of the assumptions of constant variance and normal errors or misspecifications caused by lack of observations at both bounds (Cook et al., 2008). A fractional logistic regression model is the appropriate tool for modeling fractional outcomes (Papke and Wooldridge, 1996, 2008; Villadsen and Wulff, 2018). We therefore use a fractional logistic regression model to estimate the effect of the *Share Transitions* on *Inventive Exploitation.*

We include firm and year dummies and robust standard errors in all analyses to correct for the correlation of observations arising from including the same firm over multiple years.

Table 2
Correlations and descriptive statistics.

	Variables	Summary Statistics				Correlation Table															
		Mean	S.D	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Share Transitions	0.05	0.19	0	1	1															
2	Inventive Quantity	150.95	293.68	1	2499	0.02	1														
3	Inventive Exploitation	0.76	0.24	0	1	0.13	0.21	1													
4	Inventive Quality – Forward Citations	118.04	232.72	0	1568	0.05	0.77	0.23	1												
5	Inventive Quality – Breakthrough Inventions	0.53	1.69	0	19	0.00	0.50	0.13	0.68	1											
6	Firm revenues	23,287	31,848	246.22	233,715	0.03	0.39	0.10	0.26	0.19	1										
7	R&D intensity	0.12	0.11	0	1.63	0.00	−0.07	0.22	−0.06	−0.05	−0.23	1									
8	Number of acquisitions	2.89	2.51	1	25	−0.08	0.14	0.02	0.07	0.06	0.33	−0.11	1								
9	Share Inter-Industry Acquisitions	0.73	0.38	0	1	0.01	0.13	−0.09	0.10	0.07	0.21	−0.25	0.22	1							
10	Share International Acquisitions	0.48	0.43	0	1	−0.03	0.10	0.01	0.10	0.08	0.08	−0.08	−0.05	−0.01	1						
11	Firm's Knowledge Base Size	1622	2773	2	19,282	0.04	0.58	0.20	0.53	0.34	0.54	−0.10	0.18	0.17	0.15	1					
12	Firm's Knowledge Base Age	4.4	1.36	0.5	8.34	0.05	−0.08	0.03	−0.12	−0.08	0.16	−0.07	0.01	0.01	0.04	0.12	1				
13	Firm's Knowledge Base Diversity	0.86	0.1	0	0.99	−0.03	0.24	−0.08	0.23	0.14	0.27	−0.20	0.04	0.17	0.10	0.29	0.09	1			
14	Target Firm's Knowledge Base Diversity	0.65	0.27	0	0.98	0.05	0.09	−0.02	0.09	0.07	0.09	−0.01	0.10	−0.01	−0.02	0.08	0.11	0.18	1		
15	Target Firm's Knowledge Base Distance	0.55	0.31	0	1	−0.15	0.06	−0.26	0.05	0.03	0.05	−0.28	−0.03	0.22	0.11	0.08	−0.01	0.33	−0.10	1	
16	Target Firm's Knowledge Base Size	70.68	110.65	1	639	0.10	0.28	0.19	0.17	0.12	0.57	−0.08	0.31	0.16	−0.11	0.38	0.18	0.18	0.07	−0.07	1

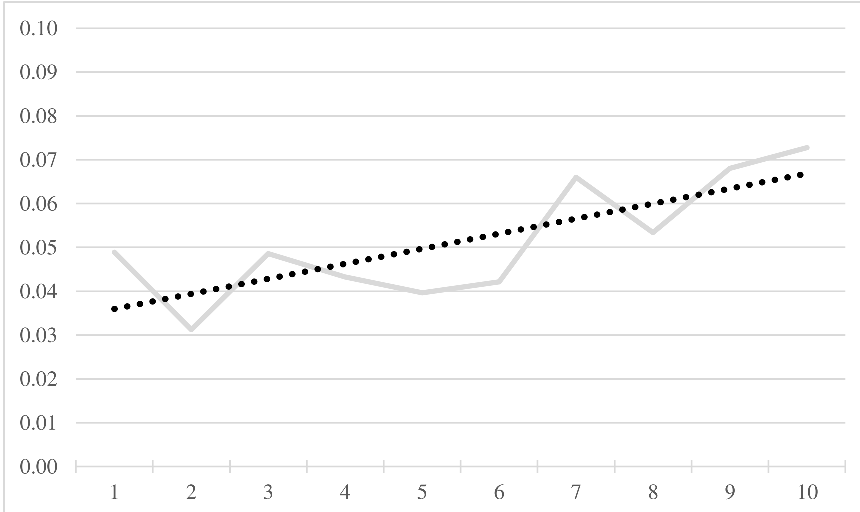

Fig. 1. Graph of share transition and inventive quantity deciles.

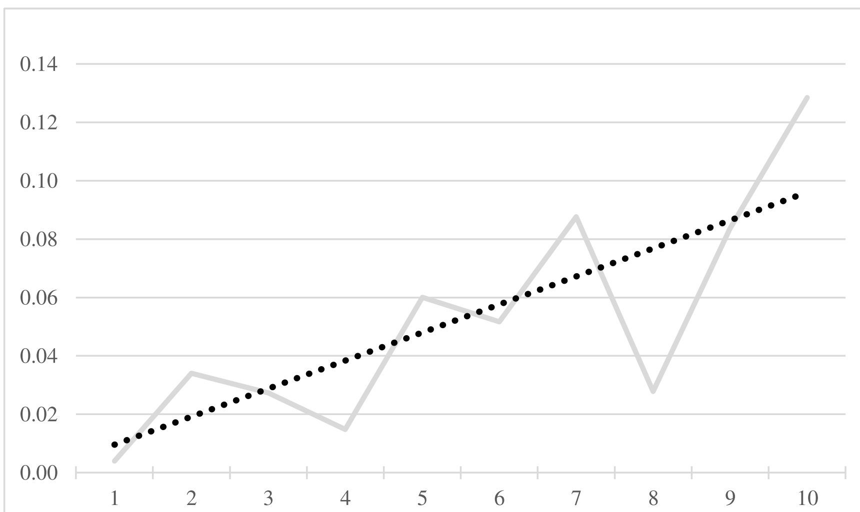

Fig. 2. Graph of share transitions and inventive type deciles.

5. Results

5.1. Descriptives

Our sample is a pooled cross section of 831 acquisition-years. It includes 252 unique firms who announced 2398 acquisitions, included in our analysis, and filed 125,440 patent applications in the years that they are studied. At the time of the analysis, they had 1348,664 patents in their collective knowledge bases Table 2. provides an overview of the sample; it reports descriptive statistics and the correlations between our variables. A number of points on Table 2 are noteworthy.

First, Table 2 describes the *Share Transitions*. This is a continuous measure which describes the share of alliance-to-acquisition transitions in the acquirers total set of acquisitions. It varies between 0 – when none of the acquirer's acquisitions in a particular year involved alliance partners – and 1 – when all of the acquirer's acquisitions in a given year involved alliance partners Table 2. reports that the mean in our sample is 0.052. This means that, in a given year, 5.2% of acquisitions involved targets with which the acquirer had a prior alliance.[6] This is lower but in line with the 6% reported by Zaheer et al. (2010) and the 7% reported by Porrini (2004). It remains an economically significant amount, however, given that, for example, US$ 3.5 trillion was spent on acquisitions in 2019, in the completion of 48,776 deals.

Second, and in terms of the dependent variables, the *Inventive Quantity* variable suggests that the firms in our sample produce between 1 and 2499 patents per year, with the average firm producing 150 patents per year. The variable *Targets Knowledge Base Distance* measures the degree of overlap in CPC codes between the target and the acquirer.

[6] Because only 5% of acquisitions involve prior alliance partners, the *Share of Transitions* variable is zero in the majority (742) of the (831) acquisition-years in our sample. A zero for the *Share of Transitions* implies that the firm did not announce any acquisitions in a particular year that were transitions. Econometrically the large number of zeros is not problematic because the *Share of Transitions* is an independent variable in our model.

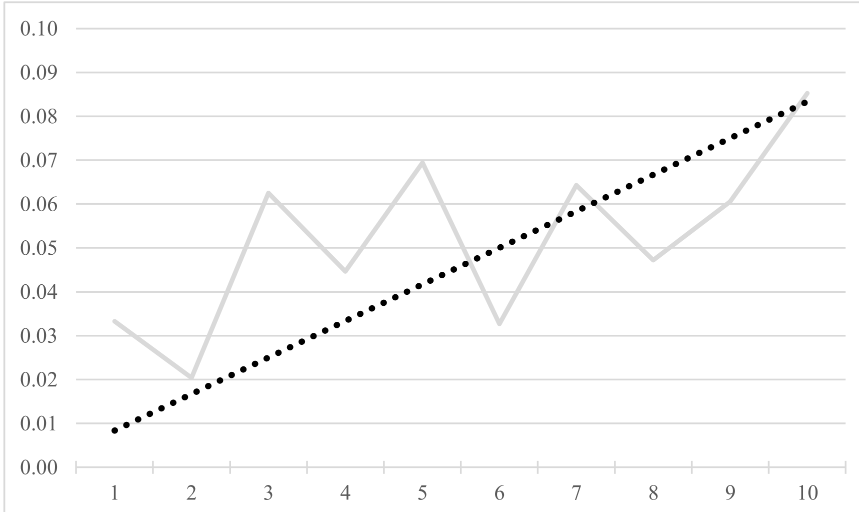

Fig. 3. Graph of share transitions and general inventive quality deciles.

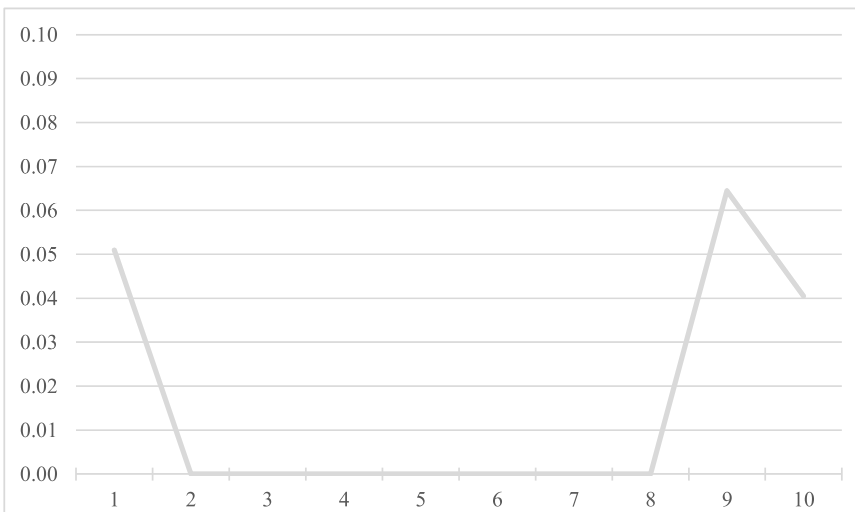

Fig. 4. Graph of share transitions and breakthrough inventive quality deciles.

A mean of 0.55 implies that the target and the acquirers are roughly active in 50% of the same field as the target. This would seem to suggest that there is as much of a chance to explore, post-acquisition, as there is to exploit. In terms of outcomes, however, the *Inventive Exploitation* variable suggests that 76.3% of patents filed are, on average, exploitative – meaning they use familiar combinations of CPC codes – and 23.7% are explorative – meaning they use unfamiliar combinations of codes. Turning to *Inventive Quality,* the *Forward Citations* variable suggests that the patents in our sample received between 0 and 1568 citations in the five years after the application date, with the average patent receiving 118 citations, and the *Breakthrough Inventions* variable suggests that the firms in our sample produce, on average, 0.5 high-quality breakthrough patents per year.

Third, the *Firm Revenues* variable on Table 2 reports that the average focal firm in our sample has revenues of $23,387 million and the *Firm's Knowledge Base Size* variable suggests that while the average firm had 1622 patents in its knowledge base, the largest had 19,282. The average target by contrast had a knowledge base with 70 patents and the largest had 639.

Fourth, Table 2 reports that all pair-wise correlations are below 0.7, which suggests that multicollinearity is not an issue in our models. We computed VIF values to validate this, and obtained a maximum value of 1.64, and a mean of 1.25, both of which are well below the cut-offs used to indicate multicollinearity (Hair et al., 1992; Studenmund and Cassidy, 1992).

Finally, we divided each of the four dependent variables into deciles, and inspected the way in which the *Share of Transitions* was distributed across these Fig. 1. plots the mean *Share of Transitions*, on the Y-axis, per *Inventive Quantity* decile, on the X-axis Fig. 2. repeats this for *Inventive Type*, and Figs. 3 and 4 repeat it for each of the *Inventive Quality* measures. In line with our expectations, the rising trendline in Figs. 1–3 imply that the *Share of Transitions* is positively associated with a higher level of patenting, a higher share of exploitative patents, and a higher level of general patent quality Fig. 4. suggests, however, that there is not a clear association between breakthrough patents and the *Share of Transitions*.

5.2. Main results

Table 3 reports our results Table 3a. reports the effect of the *Share of Transitions* on *Inventive Quantity*, Table 3b reports the effect on *Inventive Exploitation*, and Table 3c reports the effect on *Inventive Quality*. On each table we report the main results, and a number of additional analyses and/or robustness checks. Twelve of the 14 models reported are

Table 3a
On the relationship between the share of transitions and inventive quantity.

	Main Model		Robustness Checks	
	Dependent: Number of Patent Applications		Dependent: Weighted Number of Patent Applications	
	Neg Binomial		Neg Binomial	
	(1)	(2)	(3)	(4)
Share Transitions		0.332***		0.317**
		[0.126]		[0.136]
(Log) Firm Revenues	0.354***	0.350***	−0.532***	−0.539***
	[0.115]	[0.115]	[0.096]	[0.096]
R&D Intensity	0.312	0.274	0.513	0.524
	[0.336]	[0.337]	[0.387]	[0.379]
Number of Acquisitions	−0.027*	−0.023	−0.013	−0.013
	[0.015]	[0.015]	[0.016]	[0.016]
Share Inter-Industry Acquisitions	−0.062	−0.069	−0.011	−0.018
	[0.078]	[0.079]	[0.087]	[0.087]
Share International Acquisitions	−0.123	−0.124	−0.197***	−0.207***
	[0.078]	[0.077]	[0.074]	[0.075]
Firm's Knowledge Base Size	0.152***	0.151***	0.036	0.035
	[0.033]	[0.033]	[0.022]	[0.022]
Firm's Knowledge Base Age	−0.344***	−0.345***	−0.374***	−0.374***
	[0.035]	[0.034]	[0.038]	[0.038]
Firm's Knowledge Base Diversity	3.518***	3.584***	1.245	1.532
	[1.207]	[1.186]	[1.449]	[1.406]
Target Firm's Knowledge Base Diversity	0.230**	0.222**	0.180*	0.170*
	[0.103]	[0.102]	[0.100]	[0.098]
Target Firm's Knowledge Base Distance	0.139	0.182*	0.012	0.041
	[0.107]	[0.108]	[0.098]	[0.100]
Target Firm's Knowledge Base Size	−0.089	−0.095	−0.007	−0.019
	[0.129]	[0.128]	[0.134]	[0.129]
Firm Dummies Included	Yes	Yes	Yes	Yes
Year Dummies Included	Yes	Yes	Yes	Yes
Constant	0.019	−0.051	−5.320***	−5.546***
	[0.954]	[0.939]	[1.171]	[1.130]
Observations	831	831	831	831
Pseudo R^2	0.213	0.214	0.161	0.161
AIC	7873.80	7870.21	440.77	442.76
BIC	8747.49	8748.62	1309.74	1316.45
Log Likelihood	−3751.90	−3749.10	−36.389	−36.383

Robust standard errors in brackets.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

negative binominal regressions. *Models 5* and *6* are fractional logistic regressions. All models demonstrate a high goodness of fit, with a Pseudo R2 of between 0.161 (*Model 3*) and 0.408 (*Model 14*).

5.2.1. The share of transitions and inventive quantity

Table 3a reports results for four negative binomial regressions, in which we consider the effect of the *Share of Transitions* on the *quantity* of patents produced.

Models 1 and *2* report the main results. In these *Inventive Quantity* is defined as the number of patents applications made by firm i at time $t+1$. *Model 1* is the baseline model: it reports the effect of the set of control variables on the dependent and it returns a number of significant results. In line with prior literature, the positive coefficient for *Firm Revenues* and *Firm's Knowledge Base Size* suggest, for example, that bigger, richer firms produce more patents, and the negative and significant coefficient for *Firm's Knowledge Base Size* suggests older firms are less productive. *Model 2* adds the *Share of Transitions* to this. In support of Hypothesis 1, the positive and significant coefficient for the *Share of Transitions* (β = 0.332, $p < 0.01$) suggests that the share of transitions positively affects the number of patent applications.

Models 3 and *4* consider the effect of the *Share of Transitions* on the *Weighed Inventive Quantity,* which we defined as the number of patents applications made by firm i at time $t+1$ divided by its revenue at time t. *Model 3* provides a base line and *Model 4* adds our independent to this. The positive and significant coefficient for the *Share of Transitions* (*Model 4*: β = 0.317, $p < 0.05$) suggests that the share of transitions positively *Weighted Inventive Quality* too.

Taken together, Table 3a suggests, in support of Hypothesis 1, that the *Share of Transitions* positively affects the firm's *Inventive Quantity*, whether we use the absolute number of applications or a size-adjusted weighted number of applications as the dependent variable.

5.2.2. The share of transitions and inventive exploitation

Table 3b reports results for six models, to consider the effect of the *Share of Transitions* on the *type* of patents produced, in terms of exploration and exploitation.

Models 5 and *6* report the main results. These are fractional logistic models, in which *Inventive Exploitation* is defined as the share of exploitative patent application made by Firm i at time $t+1$. *Model 5* is the baseline model: it reports the effect of the set of control variables on *Share of Exploitative Patents* as the dependent variable. The model returns a number of interesting results. For example, the positive coefficient for *Firm Revenues* and *Firm's Knowledge Base Size* suggest that larger, richer firms produce a greater share of exploitative patents. Additionally, the negative and significant coefficient for *Target Firm's Knowledge Base Distance* suggests that firms that acquire targets with a knowledge base at larger distance produce a lower share of patents. *Model 6* adds the *Share of Transitions* to this. In support of Hypothesis 2, the positive and significant coefficient for the *Share of Transitions* (β = 0.699, $p < 0.01$) suggests that the share of transitions positively affects the share of exploitative patents.

Defining *Inventive Exploitation* as the share of exploitative patents risks disguising absolute growth in terms of exploration; that is, exploration might grow after acquisition, but at a slower pace than exploitation. *Models 7–10* therefore consider the *Share of Transitions* on the *Number of Exploitative* (*Models 7 and 8*) and the *Number of Explorative* (*Models 9 and 10*) patents produced, as a robustness check. All four model are negative binomial regressions. *Models 7* and *9* again consider the effect of the controls on the respective dependents. *Model 8* and *10* add the *Share of Transitions* to these. A positive and significant coefficient for the *Share Transitions* in *Model 8* (β = 0.354, $p < 0.01$) suggests that firms with a greater share of transitions produce more exploitative patents, in absolute terms. By contrast, *Model 10* reports that the *Share Transitions* does not explain the absolute number of explorative patents.

Taken together, the results reported on Table 3b support Hypothesis 2, which suggests that firms that the *Share of Transitions* leads to an increase in exploitative invention. This findings holds when using the absolute number of exploitative patents and/or the share of exploitative patents in the firms total set of patents, as the dependent variable.

5.2.3. The share of transitions and inventive quality

Table 3c reports results for four negative binominal models, to consider the effect of the *Share of Transitions* on *Inventive Quality. Models 11* and *12* use overall inventive quality, which we define in terms of the number of *Forward Citations* received. *Models 13* and *14* use *Breakthrough Inventions,* which counts the number of breakthrough patents.

Model 11 reports the effect of the set of control variables on *Forward Citations*. It returns a number of interesting results. For example, the *Number of Acquisitions* is seen to be negatively related to the number of forward citations received (β = −0.047, $p < 0.01$), as is the *Target Firm's Knowledge Base Size* (β = −0.245, $p < 0.10$). *Model 12* adds the *Share of Transitions* to this. The positive and significant coefficient (β = 0.323, $p < 0.05$) suggests that the share of transitions positively affects overall patent quality, in terms of the number of forward citations.

Table 3b
On the relationship between the share of transitions and inventive type.

	Main Model		Additional Analysis			
	Dependent: Share of Exploitative Patents		Dependent: Number Exploitative Patents		Dependent: Number Explorative Patents	
	Fractional Logistic		Neg Binomial		Neg Binomial	
	(5)	(6)	(7)	(8)	(9)	(10)
Share Transitions		0.699***		0.354***		0.057
		[0.245]		[0.142]		[0.225]
(Log) Firm Revenues	0.634***	0.620***	0.348***	0.345***	0.439***	0.438***
	[0.127]	[0.125]	[0.085]	[0.085]	[0.128]	[0.128]
R&D Intensity	0.052	−0.023	0.390	0.347	0.364	0.366
	[0.693]	[0.691]	[0.463]	[0.458]	[0.847]	[0.846]
Number of Acquisitions	0.008	0.013	−0.025**	−0.021*	−0.034**	−0.033*
	[0.019]	[0.019]	[0.013]	[0.013]	[0.017]	[0.017]
Share Inter-Industry Acquisitions	−0.061	−0.076	−0.043	−0.050	−0.154	−0.153
	[0.122]	[0.120]	[0.083]	[0.083]	[0.136]	[0.136]
Share International Acquisitions	−0.103	−0.101	−0.131*	−0.132*	−0.037	−0.038
	[0.119]	[0.118]	[0.079]	[0.079]	[0.110]	[0.110]
Firm's Knowledge Base Size	0.065**	0.065**	0.150***	0.149***	0.142***	0.142***
	[0.027]	[0.027]	[0.022]	[0.022]	[0.025]	[0.025]
Firm's Knowledge Base Age	−0.014	−0.020	−0.343***	−0.343***	−0.324***	−0.324***
	[0.042]	[0.042]	[0.028]	[0.028]	[0.042]	[0.042]
Firm's Knowledge Base Diversity	−0.405	−0.597	3.727***	3.806***	9.216***	9.230***
	[1.925]	[1.903]	[1.175]	[1.168]	[2.132]	[2.132]
Target Firm's Knowledge Base Diversity	−0.107	−0.117	0.209**	0.200**	0.122	0.122
	[0.162]	[0.161]	[0.101]	[0.100]	[0.141]	[0.141]
Target Firm's Knowledge Base Distance	−0.343**	−0.255	0.130	0.176*	0.054	0.061
	[0.166]	[0.164]	[0.105]	[0.106]	[0.154]	[0.156]
Target Firm's Knowledge Base Size	0.129	0.116	−0.100	−0.106	−0.097	−0.098
	[0.134]	[0.135]	[0.092]	[0.091]	[0.118]	[0.118]
Firm Dummies Included	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies Included	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.240*	3.359*	−0.151	−0.232	−36.241	−36.339
	[1.896]	[1.891]	[1.059]	[1.055]	[32.013]	[11.190]
Observations	831	831	831	831	831	831
Pseudo R^2	0.201	0.202	0.215	0.216	0.321	0.321
AIC	1281.15	1284.34	7987.17	7982.79	3250.72	3252.66
BIC	2589.32	2601.95	9352.01	9352.35	3878.83	3885.49
Log Likelihood	−363.57	−363.17	−3704.58	−3701.39	−1492.36	−1492.33

Robust standard errors in brackets.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Model 13 reports the effect of the set of control variables on the number of *Breakthrough Inventions*. Interestingly, and, in contrast to *Model 11* and *12, Model 13* reports that the *Number of Acquisitions* and the *Target Firm's Knowledge Base Size* does not explain the number of breakthrough patents produced. *Model 14* adds the *Share of Transitions* to this. A statistically insignificant coefficient for the *Share Transitions* variable suggests that there is no relationship between the share of transitions and the number of breakthrough patents produced.

Taken together, the results reported on Table 3c, provide partial support for the suggestion that the *Share of Transitions* affects *Inventive Quality*. Specifically, we find that the *Share of Transitions* positively affects general inventive quality, measured in terms of forward citations, but it does not explain the number of breakthrough patents produced by the focal firm. Thus, our analysis returns evidence in support of Hypothesis 3a but none to support Hypothesis 3b.

5.3. Additional robustness checks

We conducted a number of additional robustness tests. Specifically, we re-tested our hypotheses using alternative specifications of the dependent, the independent, the controls, the model, and the methods of estimation Table 4. provides an overview of the various tests.

First, we create two alternative independent variables. Specifically, we created: (1) a count of the total number of alliance-to-acquisition transitions; (2) a dummy (*Transition Dummy*) that equals 1 if the acquirer had an acquisition with an alliance partner, and 0 otherwise. We re-estimate our models using each of these independents. Our results, although weaker – likely due to the fact that both measures are cruder than the *Share of Transitions* used in the main analysis – largely support our hypotheses Table 5a. provides an example. *Model R1* shows that the *Transition Dummy* has a positive and significant effect on *Inventive Quantity*, in support of Hypothesis 1 and *Model R2* shows that it has a positive and significant effect on *Inventive Exploitation* in support of Hypothesis 2. *Models R3* shows, however, that there is no relationship between the *Transitions Dummy* and overall *Inventive Quality* and *Model R4* confirms this is also true of *Breakthrough Inventive Quality*. Therefore we can not support Hypothesis 3a or b. Nevertheless, this is a remarkable finding: it suggests that - despite the fact that only 5% of acquisitions are transitions, 'any' transition, in the previous year, irrespective of how many acquisitions the firm does, has a significant effect on inventive type and quantity.

Second, we create a number of alternative dependent variables, using slightly different definitions. A number of these were already described in connection to the main results. For example, we used and reported results for *Weight Inventive Quantity,* as a size-adjusted measure of *Inventive Quantity*. Similarly, we used the *Number of Exploitative* patents and the *Number of Explorative* patents as alternatives measures to describe *Inventive Exploitation*. For robustness checking purposes, however, we created a number of additional variables. For example, we created an *Inventive Exploration* variable, as an alternative to *Inventive Exploitation*, which we estimated as the number of patent applications filed with a new combination of CPC codes, divided by the total number

Table 3c
On the relationship between the share of transitions and inventive quality.

	Main Models			
	Dependent: Forward Citations		Dependent: Breakthrough Inventions	
	Neg Binomial		Neg Binomial	
	(11)	(12)	(13)	(14)
Share Transitions		0.323**		0.656
		[0.151]		[0.556]
(Log) Firm Revenues	0.339**	0.327**	−0.093	−0.088
	[0.136]	[0.135]	[0.315]	[0.313]
R&D Intensity	0.419	0.376	−2.535	−2.419
	[0.513]	[0.511]	[3.036]	[3.022]
Number of Acquisitions	−0.047***	−0.044**	0.002	0.007
	[0.018]	[0.018]	[0.045]	[0.045]
Share Inter-Industry Acquisitions	0.051	0.045	0.369	0.445
	[0.104]	[0.104]	[0.361]	[0.357]
Share International Acquisitions	0.001	0.005	0.474*	0.437
	[0.106]	[0.105]	[0.282]	[0.283]
Firm's Knowledge Base Size	0.133***	0.131***	−0.017	−0.025
	[0.033]	[0.033]	[0.054]	[0.054]
Firm's Knowledge Base Age	−0.375***	−0.376***	−0.388***	−0.387***
	[0.044]	[0.043]	[0.107]	[0.107]
Firm's Knowledge Base Diversity	7.405***	7.591***	18.215***	19.578***
	[1.677]	[1.672]	[6.769]	[6.795]
Target Firm's Knowledge Base Diversity	0.463***	0.451***	0.254	0.243
	[0.127]	[0.125]	[0.320]	[0.326]
Target Firm's Knowledge Base Distance	0.331**	0.369**	−0.388	−0.330
	[0.144]	[0.145]	[0.372]	[0.379]
Target Firm's Knowledge Base Size	−0.242*	−0.247*	−0.218	−0.219
	[0.141]	[0.140]	[0.299]	[0.303]
Firm Dummies Included	Yes	Yes	Yes	Yes
Year Dummies Included	Yes	Yes	Yes	Yes
Constant	−4.666***	−4.820***	−24.805***	−24.703***
	[1.301]	[1.297]	[5.229]	[5.254]
Observations	831	831	831	831
Pseudo R^2	0.226	0.227	0.406	0.408
AIC	6992.97	6989.55	1049.73	1334.21
BIC	8017.78	8014.36	1644.78	2604.60
Log Likelihood	−3279.48	−3277.77	−398.86	−398.10

Robust standard errors in brackets.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

of patent applications. We find that our results does not change when we use this variable: we find that the *Share of Transitions* has a negative and significant effect (β = −0.699, $p < 0.01$), on the share of exploratory patent applications. We also create a number of alternative *Inventive Quality* variables. Specifically, we created a *Weighted Forward Citations* measure, in which we divided the number of forward citation by the number of patents, and a *Weighted Breakthrough Inventions* measure, in which we divided the number of breakthrough inventions by the number of patent applications. All of our results provide clear support for *Hypotheses 1* and Hypothesis 2. For *Inventive Quality*, however, we find that the share of alliance-to-acquisition transitions positively affects *Weighted Forward Citations* (β = 0.275, $p < 0.05$), but it does not affect the number of breakthrough inventions produced.

Third, and in terms of our control variables, we use an alternative definition for the *Firm's Knowledge Base Size*. Most of the literature assumes that knowledge decays and used a 10-year period to define relevant knowledge. We create a more conservative measure, which assumes that the relevant period is in fact 5 years. Our results remain the same when we use this measure.

Fourth, and in terms of model specification, we re-estimate the models, dropping the *Number of Acquisitions*, the *Share of Inter-Industry Acquisitions*, and the *Share of International Acquisitions*. These variables could depend on the independent variable and could, therefore, be intermediate outcomes. This would potentially confuse inference Table 5b. presents the result. *Model R5* is a negative binomial regression that considers the effect of the *Share of Transitions* on *Inventive Quantity, Model R6* is a fractional logistic regression that illustrates the effect on *Inventive Exploitation*, while *Model R7* and *R8* are negative binomial regession that zoom in on *Forward Citations* and *Breakthrough Inventive Quality,* respectively. It shows that our results remain stable with/without the acquisition controls. This suggests that out results are not intermediate outcomes and illustrates, therefore, that our interpretation of the results is reliable.

Fifth, and in terms of estimation methods, we use a negative binomial regression to test Hypothesis 1 and *3*. We do this because *Inventive Quantity* and *Inventive Quality* are over-dispersed variables, which only takes non-negative, integer values. He and Tian (2013) solve this problem by using the logarithm of 'one plus' the count variable. Doing so allows OLS to be used to test Hypothesis 1 and *Hypothesis 3*. We follow He and Tian (2013) and re-estimated our models in this way. Our results remain the same, using this estimation method.

Finally, we tested if there is a tendency to acquire alliance partners with a more similar knowledge base, as an alternative explanation for, for example, Hypothesis 2. We test this by constructing a probit model to predict transition likelihoods. Our results indicate that factors such as target size and national borders reduce the likelihood of a transition, but suggest that knowledge base difference/similarity does not predict a transition per se.

6. Discussion

6.1. Academic contributions

In this study, and drawing on insights from organizational learning theory, we develop novel theoretical arguments to connect a firm's use of alliance-to-acquisition transitions to its technological performance. Our results make a number of important contributions.

First, we contribute to the *acquisition literature* by providing insight on the value of alliance-to-acquisition transitions in terms of technological performance. We show that alliance-to-acquisition transitions increase the quantity of inventions produced by the acquirer and change the type of invention produced, leading to a greater share of exploitative inventions. We also find some evidence to suggest that alliance-to-acquisition transitions increase overall quality, but do not affect the number of breakthroughs created. This is a helpful insight given the mixed evidence that exists regarding the performance of acquisitions (e.g., Capron and Mitchell, 2012). Evaluating the post-acquisition innovation output of acquiring firms provides important insights on the returns to corporate investments in acquisition activities (Ahuja and Katila, 2001).

Second, we contribute *to the literature on transitional governance* by considering the technological performance implications of alliance-to-acquisition transitions. This is a contribution because the existing literature (e.g., Hagedoorn and Sadowski, 1999) has tended to focus either on the conditions under which alliances transition to acquisitions (e.g., Estrada et al., 2010; Folta, 1998; Kogut, 1991; Vanhaverbeke et al., 2002), or on the financial implications for the acquiring firm of transitions (e.g., Porrini, 2004; Zaheer et al., 2010). Moreover, the performance studies that have been done present mixed results. Our results show that alliance-to-acquisition transitions impact the quantity, quality

Table 4
Summary of the main and additional analyses/robustness checks concluded.

		Dependent	Independents			Controls	Model Specification	Method of Analysis
			Inventive Quantity	Inventive Exploitation	Inventive Quality	Acquirers Rate Knowledge decay		
Definition for the main Analysis		Count of the number of transitions divided by the total number of acquisitions	Total number of patents produced	Share of patents with a familiar configuration of CPC codes	Number of Forward citations Number of patents in the 99th percentile of most cited patents	10 years	With *Number of Acquisitions*, the *Share of Inter-Industry Acquisitions*, and the *Share of International Acquisitions*	Hypo 1 and 3 are tested with a negative binomial regression method
Alternative definition for Robustness Checking	1	Count of the number of transitions	Total number of patents produced divided by revenue	Share of patents with a new configuration of CPC codes	Number of forward citations divided by number of patents	5 years	Without *Number of Acquisitions*, the *Share of Inter-Industry Acquisitions*, and the *Share of International Acquisitions*	The logarithm of one plus the count is used as the dependent variable. Hypo 1 and 3 are tested with OLS
	2	Dummy indicating a transition		Absolute number of exploration patents	Number of patents in the 99th percentile of most cited patents/ number of patent applications			
	3			Absolute number of exploitation patents				

and type of inventions produced. In so doing, we not only provide insight on the technological performance of such transitions, but we provide nuance too. We support the suggestion, for example, that the *way* firms add and integrate new knowledge elements effects *what* they learn (Argote and Miron-Spektor, 2011).

Our main contribution, however, is to the *literature on organisational learning (*Amburgey and Miner, 1992; Levitt and March 1988*)*. We position alliance-to-acquisition transitions as a distinct mechanism that allows firms to alter their technology production function. And we provide additional insights on how organizations absorb and use external knowledge (Ahuja and Katila, 2001). We show that alliance-to-acquisition transitions increase overall inventive quality and we add to work on breakthrough innovation (e.g Dong et al., 2017.) by showing that alliance-to-acquisition transitions are not the right tool for creating breakthroughs. We argued that because breakthroughs are created by doing something different, not by doing more of the same, more alliance-to-acquisition transitions should have a negative effect on the number of breakthroughs produced. Acquiring more familiar knowledge, we suggested, means less space for new knowledge acquisitions. We find, however, that the share of alliance-to-acquisition transitions has no effect on the number of breakthrough patents produced; neither positively nor negatively. From this, we can conclude, at the very least, that alliance-to-acquisition transitions are not the right route for developing breakthrough inventions.

Finally, we contribute to the discussion on governance forms and learning (e.g Buffart et al., 2020.; Kale et al., 2002; Trichterborn et al., 2016; Schild et al., 2005) and, in particular, on the learning effects implied by the repeated use of specific governance forms. We show that alliance-to-acquisition transitions increase the quantity of inventions produced, weakly affect overall quality, and significantly shift the exploitative tendencies of the firm. By showing the distinct effect of alliance-to-acquisition transitions in this way, we add to our understanding of how and what the acquiring firm learns by means of these changes in governance mode.

6.2. Managerial implications

In the paper we study the technological performance consequence of acquiring ones alliance partners. We show that acquirers with a greater share of alliance-to-acquisition transitions produce more patents than acquirers with a lower share of transitions. We show that they produce more exploitive patents too and we find some evidence to suggest that acquirers with a greater share of alliance-to-acquisition transitions produce higher quality patents. We find, however, that alliance-to-acquisition transitions are not costless. An increase in the share of exploitative patents produced implies, by definition, a reduction in the share of explorative patents produced. To survive, however, a firm needs to both explore and to exploit. The firm also needs to be able to produce high quality, breakthrough inventions if it is to survive in the long term. Our findings suggest that alliance-to-acquisition transitions are not the tool for doing this. By spending time on alliance-to-acquisition transitions managers are potentially incurring the opportunity costs of not developing breakthrough inventions, using other governance forms, such as alliances. We conclude therefore that, practically speaking alliance-to-acquisition transitions are the right strategic choice when the manager wants to entrench their firms in specific knowledge domains, or when the goal is to build or to reinforce the firms existing resources and capabilities. If, however, the manager wants to reposition the firm technologically, or to develop breakthrough innovations, it should look for acquisition targets beyond its alliance partners.

6.3. Limitations and future research

As with all research, ours has a number of important limitations. In this section, we discuss the main limitation of our study and the future research routes that these imply.

First, we only study large firms (>US$1 bn). We do this because large firms produce enough patents and engage in enough alliances and acquisitions to test our hypotheses. We focus on the largest primarily to facilitate data processing; the 252 firms in our sample have 1.3 million patents in their knowledge base. Research suggests, however that acquisitions by smaller and larger firms perform differently (Moeller et al.,

Table 5a
Additional robustness checks.

	Inventive Quantity	Inventive Exploration	Inventive Quality	
	Dependent: Number of Patent Applications Neg Bin (R1)	Dependent: Share of Exploitative Patents Frac Log (R2)	Dependent: Forward Citations Neg Bin (R3)	Dependent: Breakthrough Inventions Neg Bin (R4)
Transition Dummy	0.034**	0.241*	0.061	0.109
	[0.017]	[0.123]	[0.087]	[0.208]
(Log) Firm Revenues	0.106***	0.624***	0.335**	−0.145
	[0.032]	[0.127]	[0.136]	[0.220]
R&D intensity	0.129	0.018	0.412	−1.418
	[0.119]	[0.691]	[0.513]	[0.912]
Number of acquisitions	−0.007*	0.007	−0.047***	0.040
	[0.003]	[0.019]	[0.018]	[0.034]
Share Inter-Industry Acquisitions	−0.012	−0.064	0.049	0.091
	[0.020]	[0.122]	[0.104]	[0.199]
Share International Acquisitions	−0.031	−0.105	0.002	0.142
	[0.020]	[0.119]	[0.106]	[0.211]
Firm's Knowledge Base Size	0.025***	0.062**	0.132***	−0.203*
	[0.008]	[0.027]	[0.033]	[0.111]
Firm's Knowledge Base Age	−0.076***	−0.015	−0.375***	−0.092
	[0.009]	[0.042]	[0.043]	[0.072]
Firm's Knowledge Base Diversity	0.706**	−0.532	7.451***	2.204
	[0.357]	[1.915]	[1.675]	[2.864]
Target Firm's Knowledge Base Diversity	0.082***	−0.116	0.457***	0.076
	[0.030]	[0.161]	[0.127]	[0.281]
Target Firm's Knowledge Base Distance	0.038	−0.308*	0.341**	−0.291
	[0.031]	[0.167]	[0.144]	[0.351]
Target Firm's Knowledge Base Size	0.015	0.136	−0.241*	−0.509
	[0.033]	[0.136]	[0.141]	[0.431]
Firm Dummies Included	Yes	Yes	Yes	Yes
Year Dummies Included	Yes	Yes	Yes	Yes
Constant	0.387	3.321*	−4.706***	−0.517
	[0.340]	[1.890]	[1.299]	[2.263]
Observations	831	831	831	831
Pseudo R^2	0.173	0.201	0.227	0.401
AIC	3415.606	1284.831	6992.530	3103.324
BIC	4766.278	2602.445	8017.340	3977.010
ll	−1421.803	−363.416	−3279.265	−1366.662

2005; Weitzel and McCarthy, 2011). We hope that future research will test our hypotheses in the context of smaller firms and their acquisitions.

Second, we assume that all alliances are the same. We do this because it is standard practice in the alliance-to-acquisition literature (e.g Zaheer et al., 2010.) Yang et al. (2011)., however, argues that different types of alliances have different likelihoods of transitioning into acquisitions. It may be interesting to consider if different types of alliances, with different probabilities of transitioning, result in different technological performance.

Third, we assume that all alliances offer the acquiring firm the same insights on the target firm. Learning, however, is not an 'event' but it an 'innate, ongoing process' (Di Bella et al., 1996). It could be argued that the longer two firms participate in an alliance, the greater the benefit from the alliance (Schildt et al., 2012). It may be interesting, therefore, to consider if the length of collaboration with a partner affects the technological performance of the acquisition.

Fourth, and building upon this, we assume that all alliance-to-acquisition transitions are the same. We do not impose any restrictions on, for example, the size of the alliance, the time spent in the alliance, or the times between the alliance and the acquisition, when identifying alliance-to-acquisition transitions. Nor do we consider if the acquisition was proceeded by one or more alliances. We do this to preserve data as transitions are rare events. Clearly, however, these are factors that will affect the quantity and quality of the exchange (McCarthy and Aalbers, 2016; Schildt et al., 2012). It would be interesting, therefore, to consider how the characteristics of the transition itself affects the technological performance of the acquiring firm.

Fifth, we assume that all acquisitions are the same. We do this following best practice in the alliance-to-acquisition literature (e.g Zaheer et al., 2010.) and because it is the convention to assume that all acquisitions in the high tech industries (e.g Valentini, 2012., 2016), and all acquisitions involving targets that patent (Cloodt et al., 2006), are technology based. There is emerging evidence, however, to suggest that this is not the case (e.g., Aalbers et al., 2021). We hope that future research will look more closely at acquisition motives in high tech industries, and will bring motives into the discussion in the alliance-to-acquisition literature.

Sixth, we focus on three types of technological outcomes – inventive quantity, type and quality – and we describe all of these in terms of patents. We recognize, however, that patents only measure a certain type of invention (Acs and Audretsch, 1989; McCarthy and Aalbers, 2016), and suggest that it may be interesting to explore other innovation-related outcome measures. For example, it would be interesting to see if, post-transition, alliance-to-acquisition transitions are better able to retain more of the targets' key knowledge employees.

Finally, we use forward patent citations to describe patent overall quality, and then identify patents in the 99th percentile of most cited patents, in order to create a count of the number of high quality trajectory-altering breakthrough patents that the firm produces. We do this to align with prior work on breakthrough innovation (e.g., Dong et al., 2017). We recognize, however, that impact, novelty and quality are not the same thing. We hope that future research will look more closely at breakthroughs using other measures. For example, it would be interesting to see if, in the pharmaceutical industry, the share of alliance

Table 5b
Additional robustness checks.

	Inventive Quantity Dependent: Number of Patent Applications	Inventive Exploitation Dependent: Share of Exploitation	Inventive Quality	
			Dependent: Forward Citations	Dependent: Breakthrough Inventions
	Neg Reg (R5)	Frac Log (R6)	Neg Reg (R7)	Neg Reg (R8)
Share Transitions	0.356***	0.685***	0.061	0.579
	[0.127]	[0.245]	[0.087]	[0.516]
(Log) Firm Revenues	0.336***	0.627***	0.335**	−0.091
	[0.115]	[0.124]	[0.136]	[0.310]
R&D intensity	0.200	−0.058	0.412	−3.496
	[0.329]	[0.678]	[0.513]	[2.897]
Firm's Knowledge Base Size	0.152***	0.067**	−0.047***	−0.030
	[0.034]	[0.027]	[0.018]	[0.050]
Firm's Knowledge Base Age	−0.348***	−0.022	0.049	−0.356***
	[0.034]	[0.041]	[0.104]	[0.105]
Firm's Knowledge Base Diversity	3.465***	−0.589	0.002	20.893***
	[1.199]	[1.896]	[0.106]	[6.756]
Target Firm's Knowledge Base Diversity	0.208**	−0.093	0.132***	0.229
	[0.102]	[0.152]	[0.033]	[0.320]
Target Firm's Knowledge Base Distance	0.167	−0.284*	−0.375***	−0.236
	[0.105]	[0.162]	[0.043]	[0.379]
Target Firm's Knowledge Base Size	−0.109	0.119	7.451***	−0.256
	[0.130]	[0.136]	[1.675]	[0.309]
Firm Dummies Included	Yes	Yes	Yes	Yes
Year Dummies Included	Yes	Yes	Yes	Yes
Constant	−0.075	3.197*	−4.706***	−24.963***
	[0.955]	[1.849]	[1.299]	[5.198]
Observations	831	831	831	831
Pseudo R^2	0.213	0.202	0.227	0.404
AIC	7871.212	1282.480	6992.530	1322.592
BIC	8735.454	2595.371	8017.340	2555.199
Log Likelihood	−3752.606	−363.240	−3279.265	−400.296

Robust standard errors in brackets.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

to acquisition transitions affected the number of first-in-class drugs created (e.g., Dong and McCarthy, 2019).

7. Conclusion

In this paper, we consider the effects of acquiring alliance partners on the firm's technological performance, using a sample of 252 firms, 2398 acquisitions, and 125,440 patents.

We find that a greater share of alliance-to-acquisition transitions, in the total set of the acquirer's acquisitions, affects the acquiring firms technological performance. We find that the share of transitions positively affects the total number of inventions produced by the acquirer, supporting the suggestion that an alliance, before the acquisition, provides acquiring firms with the opportunity to learn from and about each other (Sarkar et al., 2009), and facilitate the transfer of knowledge. Zooming in on the type of patents that are produced, however, we find that acquirers with more alliance-to-acquisition transitions produce more exploitative patents and, by definition, less explorative patents. We find some evidence to suggest that share of alliance-to-acquisition transitions affects inventive quality, but find that it does not lead to more breakthrough patents. This is because, we argued, the acquirer already knows the target, it is less likely to get the sort of unexpected knowledge that leads to 'unknown and unimagined opportunities' (Puranam et al., 2006), and is more likely to do what it has always done (Kok et al., 2020). We conclude, therefore, that alliance-to-acquisition transitions are not an innovation panacea: they are useful only for converting existing knowledge into more, possibly higher quality patents, but they lead to more exploitative patents, and are not useful as a tool for exploring new knowledge domains, or for creating breakthrough inventions.

As such, our results offer clear managerial insights on the consequences of acquiring alliance partners; we introduce alliance-to-acquisition transitions as the 'way to go' for more, higher quality, exploitative patents. We also contribute to a number of academic discussions. Specifically, we contribute to the discussion on technological acquisitions (e.g McCarthy and Aalbers, 2016.), which often presents mixed results on performance. We also contribute to the discussion on alliance-to-acquisition transitions, which has, until now, focused either on the antecedents (e.g., Yang et al., 2011) or the financial performance (e.g., Porrini, 2004; Zaheer et al., 2010) of alliance-to-acquisition transitions, without considering the technological impact. Finally, and perhaps most importantly, we contribute to the literature on organisational learning (e.g., Amburgey and Miner, 1992; Levitt and March, 1988), by introducing alliance-to-acquisition transitions as a separate and distinct learning mechanism, and by then exploring how organizations use these mechanisms to absorb and use external knowledge.

CRediT authorship contribution statement

Killian J McCarthy: Conceptualization, Methodology, Investigation, Writing – review & editing. **Hendrik Leendert Aalbers:** Conceptualization, Resources, Writing – review & editing.

Declaration of Competing Interest

The author has no conflict of interest.

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