The role of diversification profiles and dyadic characteristics in the formation of technological alliances: Differences between exploitation and exploration in a low-tech industry

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Abstract

This paper posits that firms' corporate and technological diversification profiles and their relatedness in terms of products and technologies impact their propensity to form alliances for exploitation and exploration. The empirical investigation employs a dataset of all tire producers worldwide between 1985 and 1996 that combines detailed firm level data on establishment, patenting, and alliance activities. The results support these theoretical predictions and indicate that exploitative alliances are driven primarily by complementarity in terms of corporate diversification strategies, as well as partner characteristics (e.g., size, age, and technological capabilities). Moreover, firms with similar product portfolios but uneven technological performance are more likely to engage in exploitative interactions. In contrast, exploration alliances are driven by strong partner similarity across all firm characteristics and product portfolios. Both market and technological diversification have positive effects on the propensity to engage in explorative alliances while technological distance has a negative one.

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1 Introduction

Most of the world's largest corporations are actively engaged in corporate diversification via products, markets or technologies (Rumelt, 1982; Hitt et al., 1997; Suzuki and Kodama, 2004; Ravichandran et al., 2009) as an avenue to boost performance (Robins and Wiersema, 2002; Tanrivedi and Lee, 2008). Thus, corporate diversification is commonly employed by firms to consolidate competitive positions (Penrose, 1959; Porter, 1987), create positive synergies across different divisions (Teece, 1982), insulate against external threats (Amit and Livnat, 1998), and capitalize on related products and customers (Tallman and Li, 1996; Miller, 2006). Likewise, technological diversification is consistently identified as a key contributor to firm growth (Granstrand, 2000), performance (Leten et al., 2007) and innovation (Huang and Chen, 2010) through significant economies of scale, scope, speed, and space that complement each other (Fai, 1999). As a result, the degree of technological diversification has increased significantly in the last decades (Giuri et al., 2004), and intricate technological portfolios are common today among leading firms in many industries (Cantwell and Piscitello, 2000; Quintana-Garcia and Velasco, 2008).

Besides diversification strategies, which mandate significant resource commitments, firms may also acquire competences and leverage existing assets through external links with other companies (Stuart, 2000; Giuri et al., 2004; Wang and Zajac, 2007). Driven by technological change and global competition, *exploratory* inter-firm agreements that involve bilateral exchanges of technologies like public-private partnerships, outsourced or networked R&D and technological alliances have gained significant momentum in recent years (Gulati, 1995a; Stuart, 1998; Kale et al., 2000; Kim and Inkpen, 2005; Gnyawali et al., 2011).[1] Similarly, *exploitative* agreements that capitalize on existing technological competencies such as subcontracting, original equipment manufacturing (OEM), licensing, or joint venture projects are responsible for significant one-way flows of technologies, which have boosted productivity of many small and medium firms in emerging markets (Lee and Beamish, 1995; Narula and Sadowski, 2002). Broadly encapsulated under the concept of *technological alliances*, these interactions have been extensively employed by firms for both exploitation and exploration [2] (Rothaermel and Deeds, 2004; DeMan and Duysters, 2005; Yamakawa et al., 2011). However, these functional types of alliances are qualitatively different as explorative agreements focus on the search for new knowledge, while exploitative ones emphasize the use of existing

[1] For example, in 2003, contracted-out R&D for US manufacturers grew three times faster than the internal one, public-private R&D partnerships flourished with 2,936 cooperative R&D agreements, and the number technological alliances worldwide was almost 700 (NSF, 2006).

[2] This study adopts a broad definition of alliances that includes a range of interactions from simple contractual agreements (licensing, technology sharing) to establishment of new separate entities (JV) or joint R&D projects.

knowledge (March, 1991).

With respect to the drivers of these alliances, the literature has proposed a variety of explanations spanning different levels of analysis (Hagedoorn, 1993; Oxley, 1999; Garcia-Canal et al., 2008). Accordingly, firms form alliances as a way to access new markets (Glaister, 1996) and technologies (Kale et al., 2000) while deriving certain strategic benefits from these relationships such as lower uncertainty and costs (Narula, 2003) or greater market power (Kogut, 1991). Yet, the question of how firms select alliance partners has received less attention in the literature (Nielsen, 2003). A survey of more than 40 studies suggests that partner complementarity, commitment, and compatibility (fit) are the key drivers of alliances (Shah and Swaminathan, 2008). While all these attributes are vital for forming a successful alliance, their effects are contingent on other factors such as the context of the alliance (Kale and Singh, 2009), firms' experience (Rothaermel and Boeker, 2008), level of mutual trust (Gulati, 1995b), and idiosyncratic characteristics of managers (Einsehardt and Schoonhoven, 1996) and agreements themselves (Shah and Swaminathan, 2008).

While this large body of research provides many insights into the drivers of alliances, it still lacks depth in several areas. First, despite the plethora of studies examining multiple issues surrounding diversification strategies on one hand, and alliances on the other, these streams of literature remain, in essence, autarkic (Mowery et al., 1998; Giuri et al., 2004). Furthermore, with few exceptions (Samharya, 1995; Fai, 1999; Wang and Zajac, 2007), most studies on firm diversification adopt a skewed view of this phenomenon, focusing solely on one aspect (e.g., product, market, international or technology). Second, alliances are often examined at isolated levels of analysis, either the transaction, firm, dyad, or network. Instead, recent advances in the literature advocate the use of more comprehensive frameworks for analysis across multiple levels which are better suited for capturing the heterogeneity behind the motives for forming alliances and provide also richer predictions in the presence of competing explanations (Wang and Zajac, 2007; Duysters et al., 2007; Lin et al., 2009). Finally, most empirical studies on alliances are confined to high-tech sectors (e.g., IT, electronics or biotechnology) and firms from the developed Triad (i.e., North America, Japan and Europe) as a result of data availability across countries and industries (Schilling, 2009). This restricts significantly the generality of their findings and policy implications regarding non-high-tech industries and developing nations (Hirsch-Kreinsen, 2008; Szirmai, 2009), which remain severely underrepresented in this literature (De Man and Duysters, 2005).

This study contributes to the extant literature by focusing on the role of diversification across two dimensions (corporate and technological) on formation of technological alliances for exploration and exploitation. It argues that firms' choices are affected by both external opportunities (to increase, complement, or leverage existing technological capabilities) and perceived risks and costs (to coordinate, maintain relationships, protect from unwanted spillovers) that are common for both formation of alliances and diversification strategies. The proposed contributions target three important aspects. First, this work introduces theoretical mechanisms for the relation between firm diversification profiles (corporate and technological) and the decision to form technological alliances. Notably, I argue that both corporate and technological diversification signal superior capabilities and resources that increase the appeal for an alliance and, moreover, provide additional knowledge to firms on how to utilize their technological assets for exploitation and exploration. Second, this study adopts a multi-level approach to address the heterogeneity of drivers behind alliance formation (Wang and Zajac, 2007) and jointly examines the effects of firm- and dyadic- factors on firms propensity to form alliances. To this end, I focus on the effects of technological and product similarity between prospective partners on alliance formation as greater similarity allows firms to lower coordination costs, facilitates mutual learning and takes advantage of existing synergies to improve efficiency. Finally, the empirical investigation focuses on a mature and low-tech industry (i.e., tires) that is characterized by a global reach, significant R&D efforts at the top, and a great variety of diversification strategies. Together, these factors establish the tire industry as a suitable candidate for testing these hypotheses and provide an opportunity to augment the alliance literature by shifting the focus on intra-firm technology transfers to developing countries and alliance drivers in low-tech sectors that still account for a large share of production and employment in many countries (Hirsch-Kreinsen, 2008).

The rest of the paper is structured as follows. The second section develops testable hypotheses for the relationship between firms' diversification profiles and their choices for technological alliances. Then, next section describes the dataset, variables employed, and the estimation choices made in the empirical part followed by a discussion of results (Section 4) and conclusions (Section 5).

2 Theory and hypotheses

2.1 Alliances as vehicles for technology transfers

Over the past decades, driven by both competitive pressures from globalization and rapid advances in technological pace of industries, alliances have become an increasingly popular avenue to enhance firm competitiveness (Contractor and Lorange, 2002). Conceptualized as long-term agreements between firms seeking to improve the competitive position of partners by pooling of resources and capabilities (Hagedoorn, 1993), alliances have been used extensively by firms to access additional resources, minimize transaction costs, and secure market advantages (Anand and Khanna, 2000). Moreover, many alliances nowadays exhibit technological exchanges and target international partners (Narula and Hagedoorn, 1998; Garcia-Canal et al., 2008). In terms of organizational choices, alliances are extremely flexible, ranging from simple long-term contractual agreements with a narrow focus (e.g., long standing licensing or technology-sharing agreements) to formation of new entities (e.g., joint-ventures), all with the goal of maximizing the sought benefits (e.g., mitigate R&D risks, push new industry standards, access new markets) of such collaborations (Teece, 1986; Veugelers and Cassiman, 2002; Wang and Zajac, 2007).

As a result, technological alliances represent today an attractive way for firms to use their technological knowledge to access complementary assets or secure competitive advantages via exploration and exploitation (Santangelo, 2000; Kim and Inkpen, 2005; Duysters et al., 2007; Sampson, 2007). While exploration alliances require partners to learn from each other or acquire new knowledge with the specific purpose of creating new capabilities and competences, exploitation alliances are clearly focused on leveraging existing resources and capabilities for more immediate gains (March, 1991). Although, firms benefit significantly from both types of alliances (Lavie and Rosenkopf, 2006), the choice between exploration and exploitation is a result of a variety of factors that stem from firms' strategic intentions, potential for learning, and the expected returns from their technological assets (Koza and Lewin 1998). Therefore, it is imperative to analyze them separately in conjecture with partners' diversification profiles and their dyadic similarities, and develop an integrative perspective on the relation between various diversification types and alliance choices (Figure 1).

2.2 Firm diversification profile

Starting with the seminal work of Penrose (1959), many studies have examined the link between diversification and firm performance (Palich et al., 2000). Despite this large body of work, these effects are still debated in the literature (Hitt et al., 1997). Most theoretical studies argue that diversified firms will be more successful, as they possess a wider range of alternative mechanisms (e.g., predatory pricing, cross-subsidization, capital and labor flexibility) to deal with competitive pressures and environmental uncertainty. These mechanisms allow them to be more proficient in exploiting their market power (Amit and Livnat, 1988), capitalize on technological resources (Barney, 1997), and take advantage of economies of scale and scope (Rumelt, 1982). However, at high levels of diversification, firm's operating costs surge as well. Thus, as firms expand further away from their core specialty (i.e., prod-

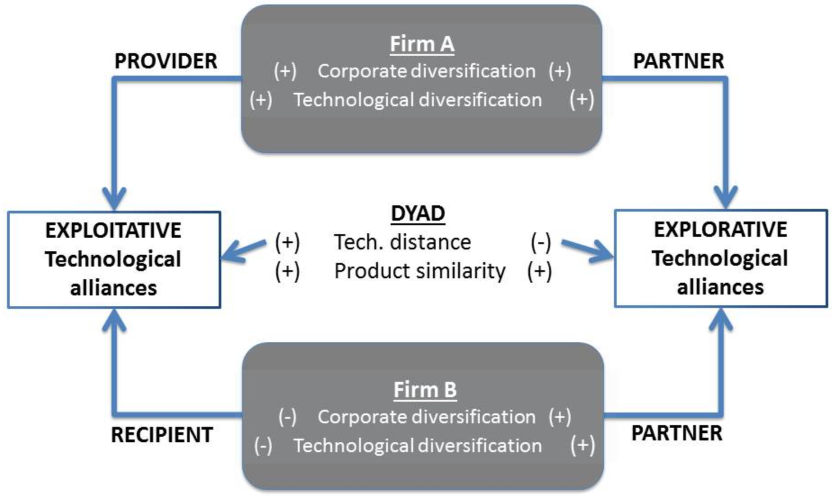

Figure 1: Conceptual framework regarding diversification profiles and alliance decisions

ucts, markets or technologies), these costs rise sharply (Hitt et al., 1994) suggesting that intermediate levels of diversification could yield the biggest benefits (Geringer et al., 1989). This conjecture is confirmed by recent empirical evidence which indicates a curvilinear relationship between the degree of diversification and firm performance (Palich et al., 2000), contingent on industry- and firm-specifics (Hitt et al., 1990).

In relation to alliance formation, the size and composition of firm's technological resources are indicative of its potential for setting up technological alliances (Rothaermel, 2001) and licensing deals (Arora et al., 2001). However, this potential is not automatically realized without additional efforts to manage and nourish such partnering relationships (Chesbrough, 2007; Miotti and Sachwald, 2003). When a firm diversifies, it implicitly acquires greater knowledge (of markets, products, consumers, competitors, technologies, etc.), which in turn allows it to identify better and faster external opportunities (e.g., form an alliance) for the exploitation and exploration of its technological capabilities. Therefore, to integrate these different aspects of firm diversification in relationship with its choices for technological alliances, I consider markets and technologies as the two most common aspects of firm diversification strategies (Hitt et al., 1997; Granstrand, 2000) and argue that they will impact firms' decision to form a technological alliance.

2.2.1 Corporate diversification

Corporate diversification means branching out into new business opportunities, either in the form of new markets or new products, both with important consequences for firm competitiveness (Rumelt, 1982). For this study I will focus mainly on one aspect of corporate diversification strategy, namely new markets or niches (Palich et al., 2000). In today's globalized world, firm activities often sprawl across multiple industries, which makes it difficult to assign them a single (or even a main) industry affiliation. Some extreme examples of this would be industrial conglomerates such as General Electric in the USA, Japanese Keiretsus, or the Korean Chaebols that are actively involved in numerous lines of business. Market diversification across is defined as the business expansion into new market segments that have not been targeted in the past, where firms can realize benefits through economies of scale and superior internal routines[3]. In general, firms diversify across multiple markets to consolidate their competitive position, create synergies between divisions, cope efficiently with competitors, and insulate against external threats (Amit and Livnat 1988).

2.2.2 Technological diversification

Technological diversification is described as the expansion of firms' knowledge base into a wider range of technical fields (Miller, 2006). This increase in the size and depth of firm's technological portfolios has become a surging trend in industrialized countries (Breschi et al., 2003; Leten et al., 2007) supporting arguments regarding the role of technology for competitive advantage and market success (Granstrand 2003). Thus, greater technological endowments bear positive effects on firm economic and innovative performance, leading to a better and sustainable competitive position (Suzuki and Kodama, 2004; Garcia-Vega, 2006; Huang and Chen, 2010). Moreover, as technological diversification is a subject of path-dependencies (Cantwell and Andersen, 1996), it actually represents a good predictor for firms' long-run product diversification strategies (Pavitt, 1998)[4].

2.2.3 The relationship between corporate and technological diversification

The relationship between corporate (in the form of either market or product diversification) and technological diversification is quite complex (Fai, 2004). Patel and Pavitt (1997) were the first to show that the degree of technological diversification for large firms was much greater than the product one. Firms tap into different of business niches, which in turn require a set of technological capabilities and products, and these bases tend to co-evolve

[3] This is an inter-industry indicator for firm's success across multiple domains of activity.
[4] This is an indicator for firm's overall technological performance.

over time. As a result, technological breadth is often a good predictor for introduction of new products, which in turn increases its market share and allows it to penetrate new markets and niches (Pavitt, 1998). Thus, regardless of choices in terms of these diversification strategies (e.g., focus on one or both; concurrently or sequentially), their interaction remains an important source of firm dynamism and growth over time (Granstrand, 2003). As both the needs of consumers and the firm competences evolve in response to changes in demand and competitive position, more resource-business couplings are typically added than scrapped by firms, which results in increased diversification (Fai, 2004).

In terms of theoretical explanations, the resource-based arguments focus on the relatedness between products from economies of scale and scope and the limited range of resources. Alternatively, evolutionary economics emphasizes the evolution of products and markets as a result of their underlying technologies. Employing routines and learning-by-doing firms are able to generate slack to be used for product diversification, where search and selection processes build on existing technological competences, seeking synergies for new corporate avenues for diversification (Mowery et al., 1998; Piscitello, 2004). Hence, the interplay between technological and corporate diversification appears to be strong and mostly positive in theory, but the direction and strength of this relationship are yet to be assessed empirically in the literature (Fai, 2004).

2.3 Diversification profiles and alliance decisions

Combining arguments from the dynamic capabilities theory (Teece et al., 1997; Luo, 2000) and organizational learning (Levitt and March, 1988; March, 1991), I argue that firms that are more diversified across markets and technologies will be more likely to engage in technological alliances for both exploitative and explorative reasons. This will occur through several mechanisms.

First, *corporate diversification* across different markets can be seen both as a substitute and a complement for technological alliances. In support of the former, firms need to commit exta resources for the management of both diversification and alliances, and quite often with similar objectives (Tsang, 1998). Therefore, if a firm is not able to reach certain niches due to limited resources or capabilities, setting up an alliance with a partner in that market represents a viable alternative to internal diversification (Giuri et al., 2004). Subsequently, firms are faced with a "make, buy or ally" decision, which shifts resources between internal development of dynamic capabilities via diversification strategies and outsourcing to external partners via an alliance (Geyskens et al., 2006).

In contrast, market diversification can stimulate alliance formation by providing firms with additional knowledge on potential avenues to capitalize on existing technological assets or develop new technical capabilities that meet better the needs of these markets. Thus, corporate diversification across markets establishes future channels for exploration and exploitation of technological opportunities outside firm's core-industry (Luo, 2000). Consistent with these arguments, studies on market diversification in an international context propose a complementary relationship between resources and capabilities required for alliance formation on one hand, and diversification strategies on the other (Tsang, 1998; Brouthers and Hennart 2007). Moreover, market diversification increases both firms' appeal as an alliance partner (given the extended capabilities required to be successful in multiple markets), and the access to a larger pool of potential partners from all these markets in which it is active. Hence, diversification provides firms with more options for both exploitation and exploration of their technological assets (Makino and Delios, 1996). Ultimately, firm's ability to generate synergies between its technological competences and its diversification strategies determines its economic performance (Piscitello, 2004).

Second, *technological diversity* is directly linked with firm's involvement in technological alliances, as highly diversified firms in terms of technology are not able to rely exclusively on internal R&D efforts (Garcia-Vega, 2006; Cassiman and Veugelers, 2006). Many of them need to acquire and complement their in-house knowledge with external sources such as in-licensing or joint research with third parties, e.g., research institutes, universities, and even competitors (Narula, 2003). In these cases, firms with large technology portfolios rely heavily on external sources of knowledge through either acquisition, outsourcing or collaboration (Granstrand, 2000; Cassiman and Veugelers, 2006). Despite this, sharing technology with other firms in the industry is a double-edge sword. On one end, it implies a negative relationship between technological diversity and alliances, since firms would like to maintain exclusive rights on internal technical expertise, and therefore minimize any possible spillovers to competitors (Rivette and Kline, 1999; Granstrand, 2000; Lin et al., 2009). Oppositely, most firms have a much larger base of technologies than products (Gambardella and Torissi, 1998; Breschi et al., 2003) due to the increasing complexity of product and processes over time (Rycroft and Kash 1999). Thus, most of these technologically-diversified firms go well beyond their core-business in terms of technical competencies, and alliances give them the ability to exploit successfully this pool of technological assets in related industries, or even via collaborations with competitors (Patel and Pavitt, 1997; Gambardella et al., 2007). As a result, technological diversification brings more exploration and exploitation opportunities encouraging alliance formation (Giuri et al., 2004)[5]. Well-diversified firms

[5] Giuri et al. (2004) find a strong correlation (0.83) between firm diversification and involvement in alliances, contingent on industry and temporal characteristics.

will prefer to exploit their technical know-how in alliances where they will act as providers of technologies for other firms, or seek new possibilities for exploration in collaborative partnerships with other well-endowed firms.

Finally, tapping the global technology markets (for exploitation) and the quest for technological partners (for exploration) are both complex processes, marked by continuos trials and frequent failures (Arora et al., 2001; Kale, Dyer and Singh, 2002). Firms face significant difficulties in finding appropriate partners for exploitation and exploration, as this requires balancing different characteristics of prospective partners and their potential impact on the alliance objectives and success (Kale and Singh, 2009). As a result, partner selection in alliances is largely determined by the perception of appropriation and coordination concerns vis a vis prospective partners (Gulati and Singh, 1998). In this context, diversification may also reflect knowledge about markets and technologies which a firm acquires as a byproduct of its activities (Granstrand, 2000). While firms may poses significant technological assets that cater to both partners within and outside their core area of activity, they often have difficulties in identifying these opportunities, especially in distant areas of activity. Firms with broader knowledge of other markets, products, and technologies will take advantage of learning effects and economies of scale and scope (Teece et al., 1997), increasing further their reach to new alliance partners. Thus, diversity across these dimensions has a positive influence on firms' prospects for new alliance objectives and prospective partners (Kogut and Zander, 1992). This reasoning is particularly salient for larger firms that do not face a significant resource constraint in terms of exploitation and exploration of technologies in-house, but are actually actively seeking to optimize the usage of their technological assets (Teece, 2006).

Incorporating all these arguments, well-diversified firms (across markets and technologies) will be more likely to get involved in technological alliances altogether, and in accordance with the theory of dynamic capabilities (Teece 2007). Firms' degree of diversification reflects their knowledge of markets and products (Granstrand, 2000) as well as their success in acquiring external technological knowledge via inter-firm collaborative and licensing agreements (Contractor and Lorange 2002; Chesbrough, 2007). Hence, as they become more diversified, firms will be more likely to engage in alliances for both exploitation and exploration rationales.

Finally, diversification will trigger different alliance strategies regarding exploration and exploitation. Firms with significant abilities (in terms of market and technical know-how) have the possibility to engage in both exploitative alliances (where they can leverage their technological assets) and exploration alliances (in which to actively exchange and produce new technical knowledge). In contrast, firms with lower capabilities, as proxied by less market and technological diversification will be less likely to form technological alliances for exploration, as their technical and corporate know-how is not sufficiently developed to attract the interest of better-endowed firms in the industry (Koza and Lewin, 2000; Rothaermel and Deeds, 2004). As a result, these firms will be eligible only for exploitative alliance, in which they will likely act as recipients of technologies from more diversified and technologically-endowed partners in exchange for other privileges such as market access, production facilities, distribution channels (Giuri et al., 2004; Yang et al., 2011).

In light of all these considerations, I propose the following hypotheses:

> **H1.** *Corporate and technological diversification of a firm will increase its propensity to engage in exploitation alliances as a provider of technology (a) or in an exploration alliance as a technological partner (b).*

2.4 Dyadic characteristics and alliance decisions

In addition to the diversification profiles of prospective partners, their joint characteristics (similarities or dissimilarities) are also important for alliance formation and its success (Kale and Singh, 2009). Such dyadic similarities between firms in terms of products, markets and technologies are generically referred to as ”business relatedness” (Koh and Venkatraman, 1991) but its definition and operationalization varies significantly in the literature (Wang and Zajac, 2007). Given that firms’ resources and capabilities can be conceptualized across multiple dimensions (e.g., products, markets, technologies) and levels of analysis (e.g., business units, plants, managers), I focus on the two most common dimensions of business and technological relatedness, namely products and technologies.

2.4.1 Product similarity

Product similarity is defined as the overlap in the production space between two prospective alliance partners. Firms seek synergies from collaborations to increase their efficiency levels. Similar firms poses similar types of assets and operations, yielding immediate gains from collaborations. This conjecture is supported by most empirical findings in the literature. For instance, Wang and Zajac (2007) show that business similarity (computed using 4 digit NAICS codes) impacts firms’ decision to ally or acquire. Lee et al. (2008) find a U-shaped relationship between organizational similarity and the subsequent learning in an alliance. Finally, Yang et al. (2010) argue that firms’ similarity in terms of status (i.e., its position among peers) influence their partnering decisions. While the literature suggests that synergetic benefits are greater from complementary resources in the case of acquisitions (Harrison et al., 2001), I extend these rationales and argue that product similarity of firms will have a positive effect on the propensity to form technological alliances.

Alliances present firms with opportunities to enrich their existing technical knowledge (via exploration) and cash-in on their technological assets (via exploitation). Contingent to these functions, they also grant access to partners' pools of resources and capabilities (Stuart, 2000; Doh, 2000) with different implications for exploitation and exploration. For the latter, organizational learning theory suggests that product similarity is necessary for a successful alliance, as it facilitates organizational efficiency (Garette and Dausauge, 2000) and encourages mutual learning (Teece, 2006). The required consensus over controversial decisions in an alliance could trigger costly and time consuming negotiations and delays which will affect the success of the alliance. As a result, similar firms are better positioned to work as alliance partners that tap into benefits arising from their business similarity (Tanriverdi and Venkatraman, 2005), while reducing costs and uncertainty surrounding the alliance.

Furthermore, exploration alliances are set-up with an explicit goal of acquiring new knowledge (Inkpen, 2001). In turn, this objective mandates similarity (in terms of skills, routines, products, competences) to meet successfully the learning objectives of such partnerships (Harrison et al., 2001) and generate economic benefits for firms (Gulati 1995a). Firms with similar products are more likely to share inputs, technologies and markets, which makes them more aware of each other's potential for contribution in the alliance, as well as in terms of ex-post expectations regarding the scope of knowledge transfer and access to privileged information (Bleeke and Ernst, 1995). Moreover, similarity between partners presents opportunities for greater value creation in the alliance in the absence of conflicting economic interests and informational asymmetries (Wang and Zajac, 2007). Thus, explorative endeavors focusing on learning are more likely to be successful if the two partners are more similar (Mowery et al., 1998).

In contrast, exploitative alliances are commonly set-up as contract-based partnerships with a unidirectional transfer of technology, which include licensing, subcontracting, or distribution agreements (Das and Teng, 2000). In these cases, product similarity is important for both the provider and the recipient of technology for similar reasons. The technology-providing firm cannot manage a successful transfer of knowledge to its partner if it is not active in the same niche of production. Likewise, the ability of the recipient firm to receive and implement successfully new technologies is conditioned by the degree of fit with the technology provider (Mowery et al., 1998). When both prospective alliance partners have similar product portfolios they are better able to evaluate each others' assets, and the ability of the alliance to deliver positive outcomes. In such situations, firms can benefit easily from complementary assets (i.e., technology is transferred from one firm to the other in exchange of financial, marketing or production compensation). Furthermore, product similarity generates naturally knowledge about each other, and reduces the existing informational asymmetries surrounding the alliance (Wang and Zajac, 2007). As a result, product similarity increases firms' incentives to form an exploitative alliance by maximizing their joint benefits of resource combinations from similar assets and reducing appropriation and coordination concerns (Tanriverdi and Venkatraman, 2005; Lee et al., 2008).

Following these arguments, I hypothesize that firms which are similar in terms of product portfolios to be more likely to engage in technological alliance for both exploitation and exploration:

> **H2.** *Product similarity between a pair of firms has a positive effect on their propensity to form an exploitation alliance (a) or an exploration one (b).*

2.4.2 Technological distance

Prior studies of alliance performance and partnering decisions using patent statistics reveals a positive relationship between technological similarity of partners and alliance occurrence, especially in high-tech industries where both alliances and large technological portfolios are quite common (Lane and Lubatkin, 1998; Stuart, 1998; Wang and Zajac, 2007). These studies rely on the assumption that the technological similarity or relatedness of partners increases their absorptive capacity, and allows them to tap more successfully into each others' pools of knowledge (Cohen and Levinthal, 1990). That ultimately leads to greater diffusion of knowledge and cross-fertilization of ideas among the alliance partners producing more value. While most existing studies hypothesize a linear relationship between firms' technological similarity (or its inverse concept, technological distance) and the decision to ally or acquire, the evidence about the sign and shape of this relationship remains mixed (Folta, 1998; Colombo, 2003; Sampson, 2007; Mc Gill, 2007).

Similarly to the effects of product similarity on alliance choices, I expect that technological distance (dissimilarity) to have different implications for firms' propensity to engage in exploration and exploitation. Thus, technological distance is a major barrier for the successful transmission of technical knowledge, as greater distance implies lower absorptive capacity (Cohen and Levinthal, 1990). Therefore, technologically-distant partners will be conducive of only exploitative interactions and specialized roles in the alliance: the firm with less expertise will rely more on external sources of knowledge and act as a *recipient* of technology in these exploitative agreements, while its partner will make use of its existing competencies to become a *provider* of technology. Moreover, greater distance between firms with limited absorptive capacity will increase coordination and implementation costs for both partners, as well the the risk of leakage of technical information. These costs and risks will discourage partners from engaging in these types of agreements when they are very different (i.e., distant) in terms of technological portfolios. Therefore, technological distance will have positive effects on firms' propensity to engage in exploitation alliances (technology provider-recipient relationships) but this effect would be greater at intermediate levels of distance.

Likewise, a large distance between prospective partners in terms of internal technological capabilities will deter the formation of exploration alliances (Sampson, 2007). In these cases, highly innovative firms will limit their search to the nearest firms in terms of technological assets (Rothaermel and Boeker, 2007), therefore reducing the coordination and appropriation risks of the alliance (Gulati and Singh, 1998). This conjecture is supported also by the existing empirical evidence, which suggests that firms with less distant technological capabilities are more likely to form an alliance (Mowery et al., 1998), stimulate cross-learning (Lane and Lubatkin, 1998) and innovation in the post-alliance period (Ahuja, 2000; Sampson, 2007). Therefore, greater technological distance is likely to reduce firms' propensity to engage in explorative alliances.

However, if technological distance between two prospective partners is zero (i.e., there is a complete overlap between the technological assets of these firms) the opportunities for learning are greatly reduced (Hagedoorn, 1993; Yang et al., 2010). Pooling together very similar resources and competences does not encourage exploration, and leaves little room for creativity, as partners have little room to learn from each other. Therefore, diversity in terms of partner technological capabilities may actually increase firm learning (Sampson, 2007) and enhance their absorptive capacity (Cohen and Levinthal, 1990). Subsequently, firms face a trade-off between choosing a similar (low distance) partner in technological capabilities but decrease their exploration opportunities, and choose a different (distant) one that creates more possible combinations and learning avenues but with higher coordination and appropriation risks. This effect will be even more salient for firms in low-tech industries, where average technological differences across firms are larger than those in high-tech industries with more even distribution of R&D expenditures across all firms (Hirsch-Kreinsen, 2008). In light of these arguments, technological distance between two prospective partners will exhibit a negative and non-linear effect on their propensity to engage in an exploration alliance.

This yields the final hypothesis:

> **H3.** *Technological distance between a pair of firms has a positive effect on their propensity to form an exploitation alliance (a) and a negative non-linear effect on their propensity to form an exploration one (b).*

3 Method

3.1 Sample and data collection

The dyadic dataset employed in this study includes data on tire producers worldwide between 1985 and 1996, collected from various issues of two industrial journals, namely the *European Rubber Journal* and *Rubber and Plastic News*[6]. The tire industry exhibits a wide range of international collaborations thus providing a propitious environment for testing my hypotheses. Its geographic representation remained constant over the time interval considered (around 80 countries) and it exhibited possitive growth rates for the number of firms (4%), production plants (2.5%), and active technological alliances (6%) (for details see Table 3). Regarding the latter, most exploitative alliances (i.e, production/marketing agreements, ongoing licensing, etc.) occur between a firm from a developed country and one from a developing one, while explorative alliances (i.e., R&D projects, cross-licensing, etc.) form between firms from developed countries (Table 6). In terms of size, large firms (i.e, top 50 firms in the industry) are those that engage exclusively in exploitative alliances as providers of technology and as technological partners in explorative ones, given the concentration of R&D efforts towards the top of the industry [7]. Furthermore, most of these agreements are international, given the overall concentration of the industry at a global level (e.g., the "Big Three" -Michelin, Goodyear and Bridgestone- hold around 45% of the global market).

The dataset includes details on all tire producers worldwide: location and opening year of each of their plants; type of ownership, number of employees; tire types produced, available technology, and production capacity. However, there is some variance in terms of availability of data across years and countries, resulting in an unbalanced panel. Since I am interested in the occurrence of agreements between two firms in the industry, both when serving as a provider or as a recipient of technology, the dataset is organized as *directed dyads* in the case of exploitative alliances and *non-directed dyads* for explorative ones[8]. In the directed dyads ij, corresponding to an exploitation alliance, firm i is considered the source (i.e., provider) of technology, while j is the target (recipient) of it, resulting in an unidirectional transfer of technology from i to j. In contrast, in the undirected dyadic data corresponding

[6] The resulting agreements have been cross-checked with alliance and joint-venture data from Thomson's *SDC Platinum* restricting our search to horizontal agreements involving tire producers

[7] For example, the "Big Three" (Michelin, Goodyear and Bridgestone) contribute roughly to almost 40% of the R&D investments, and are responsible directly or indirectly (i.e, through majority-owned subsidiaries) for a third of the technological alliances in the industry.

[8] Thus, in each year we have observations on all the potential alliances between two firms A and B (on average there are 400 firms active firms), resulting in a total of more than 160,000 possible observations for each year. After matching these dyads with the specifics, the working sample is approximately 400,000 paired observations for the 12 years covered, pending on the models' specification.

to an explorative alliance, it is not possible to make this distinction as both partnering firms contribute with technical knowledge to the alliance, and these exchanges are bilateral in nature.

3.2 Dependent variables and model

The dependent variable captures the probability of an alliance between firm A and firm B in year t. The purpose of the alliance can be either *exploitation* or *exploration.* Thus:

$$P_{ABtn} = F[X_{At}, X_{Bt}, D_{ABt}]$$

where P_{ABt} is the probability that A and B will engage in a technological alliance of either exploitative or explorative nature (n), F is the cumulative probability function, X_{At} is a set of A's characteristics, X_{Bt} is a set of B's characteristics and D_{ABt} describe dyad's characteristics. Data on the type and details of these technological alliances comes from the European Rubber Journal. Following Lavie and Rosenkopf (2006), I code this qualitative information from alliance announcements, and distinguish between *exploration* (i.e., joint R&D projects , R&D based joint-ventures) and *exploitation* alliances (i.e., those with a technological component but mainly concerned with joint marketing, service, OEM, licensing, supply or production) between all possible firm dyads (pairs). Different from Lavie and Rosenkopf (2006), this study focuses solely on the horizontal dimension of technological alliances and therefore it does not have a "hybrid alliance" category, which would combine knowledge-generating R&D with vertical integration of other activities. This focus on horizontal alliances is driven both by arguments for theoretical clarity (Phelps, 2010), and the empirical particularities of the industry, which indicate a very high incidence of technological partnerships exclusively among tire producers, as the top 20 tire producers are responsible for 80 to 90% of R&D and innovation in this industry (ERJ, various issues). Hence, I construct two binary dependent variables which equal 1 if there is an exploitative alliance (*exploit_alliance*) or an exploratory one (*explore_alliance*) and 0 otherwise.

3.3 Independent variables

I measure *corporate diversification* as the percentage of total sales from other products/services than tires. This data is available for the 75 largest tire manufacturers in the world from various issues of the *European Rubber Journal.* For the rest I assume that their corporate diversification is zero, which is reasonable given their small assets against the significant resource requirements to penetrate other markets. However, to control for potential biases from these missing observations regarding firms' sales, I include also a "no-data" dummy for all firms that are missing this information. Consistent with my assumption, these coefficients suggest that, on average, smaller firms are less likely to form an alliance, especially an exploitative one. Furthermore, over time, some tire producers have been acquired by larger conglomerates or divested their efforts to other non-tire areas of business resulting in extreme values for market diversification[9]. However, considering their historical and relative importance for the industry I do not eliminate any of these potential outliers from my final sample but instead, I perform some additional checks to make sure that they are not biasing my results[10].

Technological diversification is computed using international patent data from Derwent Innovation Index (ISI Thomson) across different IPC (International Patent Classification) classes. All patents contain one or more technology field (IPC) given by a patent examiner that signals a certain application or technical function. A search in Derwent using keywords ("tyre" or "tire") combined with a manual filtering of recipients based on name matching, led to the collection of a pool of patents specific to tire technology between 1963 and 2010. An excerpt of the main (i.e., top 25) classes and subclasses associated with tire technologies is given in Table 8 and includes different technological processes that range from production of pneumatic or solid tires (B60C; B29D 30/00) to component manufacturing such as cords (D02G 03/48) or bands (B60C 11/00), and post-production tasks such as pressure measurements (G01L 17/00), testing (G01M 17/02) or repairing processes (B29C 73/00). This collection of tire related patent data reveals that the knowledge base of this industry extends beyond tire producers. An example of this broad knowledge base is the growing body of patents held by different car manufacturers (Honda, Ford, BMW, etc.) in key contingent areas like automotive, electronics and engineering, which exhibit significant growth potential for the future. Moreover, this pool of patents suggests that the complexity of tire technologies has increased over time, as reflected by the growing number of IPC classes, contradicting the conventional wisdom on innovation in a "low-tech" industry such as this one. Using this patent data, I compute a diversification measure using a technological concentration index for each firm in the tire industry. Previous studies document that 4-digit level measures are very robust already (Van Zeebroeck et al., 2006)[11]. Since I focus only on

[9]Dunlop is one of these cases in which after its acquisition by BTR Plc. many of its operations have been sold to third parties, resulting in a very small contribution of 1-2% tire sales to BTR's total sales. Other outliers are companies such as Nokia Corporation (Finland), Fulda (Germany); Inoue Rubber (Thailand); Trelleborg AB (Sweden) that have aggressively diverted their focus to contingent areas such as industrial elastomer parts, electronics and automotives, advanced polymers, etc., which have also resulted in lower contribution of tire to their total sales

[10]In an additional analysis I eliminate all firms with percent of sales from tires of less than 10% and obtain similar results. These estimations are available upon request

[11]Overall, the IPC-4 scheme contains about 70,000 entries (classification symbols) arranged in a tree-

one industry (thus one core-technology, i.e., tires) I use an even finer (8 digit) granulation of IPC codes to capture more accurately differences in technological specialization and the overlap between various tire producers.

Thus, the technological diversification index is computed as the inverse of a modified Herfindhal index for the top 25 IPC classes ($k = 1, 25$) in which a firm A is patenting:

$$TECHDIV_A^{25} = 1/\sum_{k=1}^{25}(p_A^k)^2$$

where

$$p_A^k = \frac{N_A^k}{\sum_{k=1}^{n} N_A^k}$$

and p_A^k is the percentage of firm A's patents in IPC-8 subclass k of the total number of classes (n) . If k is not among the top 25 patent classes in which A patents, I assume $(p_A^k)^2 \to 0$, an assumption that holds in most cases, given the great level of detail of patent data employed. Hence, a higher value for TECHDIV implies greater diversification, thus more IPC classes covered by a firms 'patents and a more even spread across these classes. For an example, see Table 8 in Appendix A. As a robustness test, I also explore other measures of diversity employed in the literature (*technological breadth* as the count of IPC-8 classes in which a firm patents tire technology, an entropy measure, and the sum of the logs of one over the variable in each class), all with similar results.

Production similarity is captured using production sets of two partnering firms (A and B). Since these are discrete variables (e.g. categories of tires they produce), I compute a Jaccard index following the formula:

$$PRODSIM_{A,B} = \frac{T_A \cap T_B}{T_A \cup T_B}$$

where $PRODSIM_{A,B}$ is the computed production similarity score between firm A and firm B and T_A and T_B represent their production sets in terms of tire types from A and respectively, B. Following the ERJ statistics I consider 9 types of tires: passenger, light truck, heavy truck or bus, agricultural, motorcycle, earthmover/all terrain, pneumatic industrial, aircraft, and racing tires. Most producers tend to specialize, designating specific production tasks to certain facilities, so that plants that produce more than 3-4 types of tires are quite rare[12] $T_m \in 1..9, m = A, B$ and $PRODSIM_{A,B} \in (0, 1)$ and bigger values for $PRODSIM_{A,B}$

like structure. About 10 percent of these groups are main groups (further details are available at: http://www.wipo.int/classifications/ipc/en/).

[12] 53 percent of the firms produce maximum three tire types, and only 9 firms worldwide produce 7 or more types.

indicate greater similarity between A and B.

I compute the *technological distance* between two tire producers as an Euclidian distance in terms of IPC classes in which partners patent most frequently (have a higher propensity to patent). Thus, the distance between two firms A and B in year t is:

$$TECHDIST(A,B) = \sqrt{\sum_{k=1}^{25}(p_k^A - p_k^B)^2}$$

where p_k^A is the percentage of firm A's patents in IPC subclass k (IPC 8-digit classification), respectively B's patents in class k (p_k^B). I survey the 25 largest patent classes for each tire manufacturer, thus if k is outside these top values then p_k^A and p_k^B equal zero. Since these percentages do not sum up to one (e.g. a patent might fall into multiple IPC classes) the resulting distance measure ranges from 0 (totally similar) to 5 (totally different).

3.4 Controls

Most findings in the literature agree on the significance of firm specifics on alliance formation. Hence, firm size impacts the degree of technology production and sharing (Bayona et al., 2001; Veugelers and Cassiman, 2002; Miotti and Sachwald, 2003; Gambardella et al., 2007), although controlling for its technological endowments may dissipate this effect (Veugelers, 1997). I employ firms' production capacity as a direct measure of their size in the regressions (*size*) and subsequently use also other variables (e.g. number of plants, employees) as proxies for size, with similar results to the ones reported here. Firm's *age* is computed using the opening year of its first plant. Within our sample the median age is around 50 years, consistent with a mature industry.

Technological portfolios facilitate the creation and diffusion of new technologies, cross-fertilization of ideas between alliances partners, and improvements in the absorptive capacity of firms (Cohen and Levinthal, 1990). To quantify firms' technological capabilities, I use international patent statistics. Patent stocks for all firms in the industry are computed using USPTO patent grants (*patents*) and the perpetual inventory method with an annual discount rate of 15 percent, common in the contingent literature. Similar results are obtained using Derwent domestic patent data, which has a global coverage but is less suitable for international comparisons due to existing differences across national patenting regulations and fees.

Moreover, the success of such inter-firm partnerships is conditioned by participants' capacity to learn and adapt to each other's way of doing business, while taking advantage of their counterparts' abilities. In such situations, prior or existent ties between firms increase the efficiency of a link through relational routines (Dyer and Singh, 1998) and greater trust base (Gulati, 1995b), leading to faster technological cross-learning (Kale et al., 2000). Thus, the existence of formal ties and higher degrees of integration (e.g. majority holdings or joint-venture projects, as opposed to minority ones) are expected to impact the amount and quality of technologies exchanged between two firms. These formal ties between firms are coded using a set of dummies that equal one if one of the firms is a *minority* holding, *majority* holding, or a *joint venture*[13].

3.5 Estimation technique

Considering all possible firm dyads increases significantly the number of observations for our variable of interest, but introduces an additional problem: since the observed number of *1*s for P_{ABt} is extremely low (only 0.15 percent for exploitation alliances and 0.03 for exploration ones), running a regular probit or logit estimation will underestimate P_{ABt}. To cope with this, I employ a rare event logit model that generates approximately unbiased and lower-variance estimates of logit coefficients and their variance-covariance matrix by correcting for small samples and rare events (King and Zeng, 2001). A technical overview of this estimator is presented in the Appendix A.1[14]. All estimations report robust standard errors clustered on dyad.

A second concern regarding the propensity of a dyad to form an alliance refers to the endogeneity of this decision. Commonly in the literature alliance formation is conceptualized as a two-stage process (Stuart, 2000): first, firms decide whether they want to partner up based on their internal characteristics (i.e., technological assets, experience, strategic intent, competitive pressures, etc.) and second, they seek a suitable alliance partner for their specific needs. To cope with these endogeneity concerns, I use a two-stage correction model (Heckman, 1979). In the first stage, using a probit model I estimate the focal firm's probability of entering an agreement as a function of its size, age, patent stocks, home market size and dynamics. The focal firm is defined as the firm in the dyad with the largest number of patents (if both firms in the dyad have the same number of patents, the focal firm is arbitrarily considered the first firm of the dyad), and corresponds to the technology provider is the case of exploitation alliances, respectively firm1 for exploration ones[15]. The results of the first stage probit are used to compute an Inverse Mills Ratio which is used to correct for self-selection in the second stage (rare-event logit) which estimates the probability of two

[13]The omitted category here is *no relationship*

[14]It should be noted that the differences between standard logit and rare-event logit estimates (ran using the relogit package in Stata) turn out to be negligible in this analysis. The former are available upon request.

[15]In the first stage the unit of analysis is the (focal) firm

firms to form an exploitation or an exploration technological alliance [16].

4 Results

Table 4 provides descriptive statistics, while Table 5 presents the matrix of paired correlations for the main variables, all of which are within acceptable limits. The base results for exploitation alliances are displayed in Table 1 while those for explorative interactions are presented in Table 2. All estimations use a rare event logit estimator and include heteroscedasticity and autocorrelation consistent standard errors clustered on the dyad.

I start with a basic specification for *exploitative* alliances (**Model 1**) that incorporates only firm controls (size, age, technological capabilities of both provider and recipient, and existing relationship, if any, between them), two dummies for no availability of sales data, the Inverse Mills Ratio correction from the Heckman procedure, and a trend variable for capturing existing heterogeneity across time. This will serve throughout the paper as a benchmark for testing the proposed hypotheses. The results confirm that, on average, bigger and older firms with technological endowments tend to engage more in alliances as providers of technology, whereas technology recipients are smaller, less endowed, and much younger. Formal ties between tire producers increase significantly their chances of exchanging technology and this effect is amplified by the degree of integration, so that the likelihood of a technology transfer is higher for a joint venture project than for a majority or a minority holding. Firms for which no sales data is available (i.e., outside the top 75 largest tire manufacturers worldwide) are less likely to form an exploitation alliance, either as a provider or as a recipient. Finally, the Inverse Mills Ratio is significant suggesting that there are indeed selection issue regarding the choice of forming an alliance.

Models 2 and 3 explore the effects of diversification profile on the propensity to form an exploitative technological alliance. Corporate diversification of firms has a positive effect for firms' engagement in these alliances as technology providers and a negative one as technology recipients, supporting hypothesis H1a. This suggests that firms who are better diversified outside the tire domain, are more likely to set-up technological alliances for exploitation (Model 2). In contrast, the effects of technological diversification appear not to be related to alliance decisions (Model 3). This suggests that the degree of technological diversification is not indicative of firms' decision to enter exploitation alliances, neither as providers nor as recipients of technologies. In terms of dyadic properties, the analysis suggests that product similarity (as measured by the Jaccard index) is a strong predictor of exploitative technological partnerships (**Model 4**) confirming hypothesis H2a. Likewise, technological

[16] In the second stage the unit of analysis is the dyad (pair of firms)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	only controls	H1a		H2a	H3a		all
Controls							
Log size provider	6.475***	6.143***	6.524***	6.340***	6.209***	5.965***	5.674***
	[0.831]	[0.834]	[0.836]	[0.865]	[0.871]	[0.877]	[0.868]
Log size recipient	-0.208**	-0.210**	-0.206**	-0.249**	-0.205**	-0.251**	-0.256**
	[0.096]	[0.095]	[0.096]	[0.104]	[0.096]	[0.108]	[0.105]
Age provider	0.447***	0.427***	0.449***	0.433***	0.430***	0.406***	0.390***
	[0.059]	[0.059]	[0.059]	[0.061]	[0.062]	[0.062]	[0.061]
Age recipient	-0.009+	-0.008	-0.009+	-0.011+	-0.011**	-0.013**	-0.012**
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Log patents provider	22.814***	21.651***	22.937***	22.115***	21.920***	20.789***	19.752***
	[3.027]	[3.027]	[3.035]	[3.117]	[3.211]	[3.197]	[3.147]
Log patents recipient	-0.156	-0.101	-0.201	-0.108	-0.149	-0.105	-0.106
	[0.145]	[0.148]	[0.161]	[0.147]	[0.149]	[0.156]	[0.181]
Time trend	0.075+	0.088**	0.076**	0.090**	0.080**	0.081+	0.117**
	[0.038]	[0.043]	[0.038]	[0.040]	[0.040]	[0.044]	[0.049]
Minority holding	3.966***	4.243***	3.974***	3.872***	3.969***	3.815***	4.075***
	[0.428]	[0.477]	[0.427]	[0.433]	[0.447]	[0.432]	[0.487]
Majority holding	5.584***	5.522***	5.750***	5.468***	6.008***	5.807***	6.030***
	[0.865]	[0.747]	[0.935]	[0.732]	[0.933]	[0.780]	[0.782]
Joint-venture	5.776***	5.851***	5.795***	5.956***	5.848***	5.951***	6.059***
	[0.668]	[0.690]	[0.679]	[0.659]	[0.683]	[0.643]	[0.650]
No data provider	-0.947***	-0.916***	-0.972***	-0.993***	-95.382***	-90.687***	-1.032***
	[0.204]	[0.213]	[0.204]	[0.196]	[13.550]	[13.505]	[0.207]
No data recipient	-0.934***	-0.701***	-0.932***	-0.894***	-0.962***	-1.017***	-0.645**
	[0.254]	[0.261]	[0.255]	[0.257]	[0.201]	[0.194]	[0.308]
IMR	-99.234***	-94.346***	-99.808***	-96.378***	-93.322***	-91.253***	-86.376***
	[12.783]	[12.790]	[12.826]	[13.172]	[13.256]	[13.256]	[13.299]
Firm-level variables							
Corporate diversif provider		0.014**					0.023***
		[0.006]					[0.006]
Corporate diversif recipient		-0.015**					-0.013+
		[0.007]					[0.008]
Tech diversif provider			0.004				0.000
			[0.006]				[0.006]
Tech diversif recipient			0.018				0.026
			[0.030]				[0.029]
Dyadic-level variables							
Product similarity				1.792***			2.066***
				[0.474]			[0.494]
Tech distance					0.155**	0.125**	0.153**
					[0.069]	[0.054]	[0.066]
Tech distance^2						-0.300	
						[0.210]	
N	426,922	426,922	426,922	426,914	356,802	356,802	356,802
Mean VIF	3.49	3.18	3.24	3.33	3.44	5.06	2.38

Table 1: Firm and dyadic determinants of *exploitative* technological alliances. Rare-event logistic regression

Notes: The dependent variable equals 1 for exploitative technological alliances, and 0 otherwise; all models include a constant, not reported due to space constraints; the "no data" dummies to control for missing sales data for providers and recipients; †, ** and *** indicate variables that are significant at the 10%, 5% and respectively 1%; Robust standard errors clustered on dyad in parentheses; Mean VIF (Variance inflated factor) computed across all dependent variables) distance between firms in terms of patent portfolios appears to stimulate exploitative interactions between firms (**Model 5**). When testing for non-linear effects the coefficient of these squared variable is negative but not statistically significant (**Model 6**), indicating that both product similarity and technological distance between two firms relate positively and linearly to the formation of exploitation alliances. Finally, all variables are incorporated in the full model (**Model 7**). Despite minor collinearity issues, the results are fairly robust: bigger, more experienced and diversified firms have a higher propensity to provide technology while younger, smaller and less diversified ones usually receive it. Market diversification is indicative of firm's role in exploitative interactions (i.e., provider or recipient). Similarity in terms of production is a strong driver of these agreements while technological similarity or diversity is not necessary for these interactions. The computed variance inflation factors for all models and variables are most times within the appropriate range. The only exception is when the squared terms of technological distance is included (VIF=8.56). Thus, dropping this squared term in our final full model improves dramatically the overall the standard errors of our estimates, resulting in an acceptable VIF value of 2.38.

Models 8 through **14** (Table 2) perform similar estimations in the case of exploration alliances that occur only in 0.04 percent of possible dyads in the dataset. The firm-level controls imply that in such partnerships both firms are rather large, young and with significant technological capabilities (i.e., large patent stocks). The results of **Models 9** and **10** strongly support the second part of my first hypothesis (H1b), suggesting that both corporate and technological diversity of prospective partners have positive effects on their propensity to engage in exploration via a technological alliance. Regarding the impact of dyadic characteristics, the results provide partial support for my hypotheses. Thus, product similarity between firms is positively associated with formation of exploration technological alliances (**Model 11**), while greater differences in terms of technological endowments of firms has a negative effect (**Model 12**). However, despite some evidence (**Model 13**), due to multicollinearity issues it is impossible to provide a strong support for non-linear effects. Despite centering these terms the VIF values remain high (4.45), although below critical threshold of 10 discussed in the literature. As a result of these statistical issues in estimating the joint impact of all these variables (VIF 9.32), in **Model 14** I exclude this quadratic term.

4.1 Robustness checks

To further validate these findings, I perform additional checks that target several key aspects. Specifically, I include country fixed-effects (to address the unobserved effects of cross-

Variables	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
	only controls	H1b		H2b	H3b		all
Controls							
Log size firm1	7.031***	7.099***	7.408***	7.055***	6.749***	6.855***	6.195***
	[0.825]	[0.797]	[0.895]	[0.805]	[0.823]	[0.836]	[0.841]
Log size firm2	-0.198**	-0.166+	-0.169+	-0.155+	-0.156+	-0.153+	-0.190+
	[0.098]	[0.091]	[0.095]	[0.092]	[0.091]	[0.091]	[0.100]
Age firm1	-0.486***	-0.495***	-0.514***	-0.492***	-0.471***	-0.479***	-0.433***
	[0.058]	[0.057]	[0.063]	[0.057]	[0.059]	[0.060]	[0.060]
Age firm2	-0.012**	-0.011**	-0.012**	-0.012**	-0.013**	-0.013**	-0.016***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.006]
Log patents firm1	24.700***	25.151***	26.081***	24.989***	23.932***	24.348***	21.798***
	[2.999]	[2.923]	[3.235]	[2.947]	[3.048]	[3.101]	[3.075]
Log patents firm2	0.191**	0.152+	0.140+	0.029	0.150+	0.158+	0.069
	[0.091]	[0.086]	[0.083]	[0.098]	[0.086]	[0.087]	[0.098]
Time trend	0.093**	0.080**	0.084**	0.081**	0.065+	0.079**	0.123***
	[0.037]	[0.036]	[0.035]	[0.036]	[0.038]	[0.037]	[0.044]
Minority holding	3.832***	3.912***	3.822***	3.924***	3.827***	3.860***	3.929***
	[0.413]	[0.414]	[0.405]	[0.417]	[0.424]	[0.434]	[0.428]
Majority holding	5.580***	5.525***	5.563***	5.677***	5.779***	5.790***	6.122***
	[0.544]	[0.532]	[0.529]	[0.540]	[0.635]	[0.642]	[0.639]
Joint-venture	5.929***	5.758***	5.707***	5.724***	5.712***	5.778***	6.009***
	[0.622]	[0.631]	[0.578]	[0.618]	[0.620]	[0.641]	[0.598]
No data firm1	-0.892***	-0.868***	-0.863***	-0.870***	-0.883***	-0.871***	-0.859***
	[0.195]	[0.198]	[0.194]	[0.202]	[0.196]	[0.196]	[0.212]
No data firm2	-0.913***	-0.955***	-0.911***	-0.906***	-0.937***	-0.911***	-0.755***
	[0.245]	[0.242]	[0.243]	[0.245]	[0.248]	[0.254]	[0.250]
IMR	-107.403***	-109.203***	-113.052***	-108.502***	-103.963***	-105.735***	-95.056***
	[12.653]	[12.324]	[13.627]	[12.431]	[12.846]	[13.068]	[12.982]
Firm-level variables							
Corporate diversif firm1		0.016***					0.024***
		[0.006]					[0.006]
Corporate diversif firm2		0.036***					0.033***
		[0.007]					[0.010]
Tech diversif firm1			0.018***				0.016***
			[0.005]				[0.006]
Tech diversif firm2			0.027***				0.032***
			[0.009]				[0.009]
Dyadic-level variables							
Product similarity				1.659***			2.045***
				[0.450]			[0.478]
Tech distance					-0.160**	-0.175	-0.151**
					[0.066]	[0.198]	[0.064]
Tech distance^2						0.092+	
						[0.051]	
N		427,032	427,032	427,032	356,899	356,899	356,899
Mean VIF		3.19	3.25	3.33	3.45	5.07	2.78

Table 2: Firm and dyadic determinants of *explorative* technological alliances. Rare event logistic regression

Notes: The dependent variable equals 1 for explorative technological alliances, and 0 otherwise; all models include a constant, not reported due to space constraints; the "no data" dummies to control for missing sales data for providers and recipients; †, ** and *** indicate variables that are significant at the 10%, 5% and respectively 1%; Robust standard errors clustered on dyad in parentheses; Mean VIF (Variance inflated factor) computed across all dependent variables) country heterogeneity), run the analysis in various sub-samples of the dataset (e.g., exclude sequentially the biggest firms in the industry), use a more conservative measure of alliance formation (i.e., "new" alliances, defined as longstanding technological agreements between partners that have not been engaged in the past), and employ other estimation methods and control variables. These robustness checks are carried out for both exploitative and explorative alliances, and overall, their results support my previous conjectures. These results are not reported here due to space constraints, but are available upon request.

The inclusion of country *fixed-effects* wipes out the impact of firm size and weakens the significance of the recipients corporate diversification, while gradual exclusion of the big tire producers (top 3, and then top 5) indicates that within such sub-samples both providers and recipients are less technological diversified. The analysis of *different samples* (before and after 1992, as the median year in my dataset) reveals that smaller firms and minority holdings were more inclined to share technologies between 1986 and 1991 than the following period. Moreover, employing a *more conservative measure* for alliance formation by analyzing only "new" agreements (defined as technology exchanges between two firms that have not interacted in the past in our sample) draws similar conclusions to the main analyses. Finally, while my measure of corporate diversification (percent of sales from non-tire products) is drawing closely to a measure of unrelated diversification, I have also employed a different measure (i.e., the number of tire types produced) as a proxy for related diversification, which is positive but not statistically significant in most of the estimations. This suggests that only firms with superior capabilities that allows them to successfully diversify in unrelated areas are able to form technological alliances for both exploitation and exploration.

Furthermore, I check the results against other *estimation methods* (i.e., multinomial logit, which allows three choices for each dyad, i.e., 1-exploitation alliance; 2-exploration alliance and 3- no alliance, under the assumption that these are independent, which is confirmed by the data), *data samples* (using a smaller sample that contains all the *1*s and a random draw of 5 percent of zero observations to minimize the possible bias arising from the large number of zeros) and *control variables* [17]. All these results are in line with my main findings.

Finally, I check for *potential interdependencies* in formation of exploration and exploitation alliances using a bivariate probit. This estimator determines jointly parameter estimates for exploitation and exploration alliances allowing contemporaneous correlation between the error terms of these two equations. The estimated coefficients are in line with those of the relogit estimations, reinforcing my previous conjectures. Moreover, the rho parameter of the

[17] I test several alternative measures for firm size (*log number of plants* and *log number of workers*), technological similarity (*tech_common*) using a dummy variable if the firm employs radial tire technology, cross-ply or both; technological diversity using *tech_breadth* as the number of IPC-8 classes in which a firm patents).

model suggests indeed that the choice for these two types of alliance choices are not strongly correlated (Chi-square=0.412, p=0.516), supporting my initial choice to run separate regressions for each outcome.

5 Discussion and conclusions

There is a growing consensus among scholars that in order to remain competitive, firms must balance exploration and exploitation across different markets and technologies (March, 1991). In the past, most firms have focused on the internal dimension of technology exploration and exploitation preferring to undertake R&D and utilize its results in-house (Chesbrough, 2007). However, with increasing global competition and technological change, firms opt more and more for alliances as a mean to optimize their exploration-exploitation opportunities (Lavie and Rosenkopf, 2006).

This study argues that diversification profile of a firm affects its possibilities and choices for technological alliances. In doing so, it proposes several contributions to the extant literature. First, it links theoretically firms' diversification strategies with their alliance choices. Specifically, it looks at two main measures of diversification, namely corporate and technological, which give a broad picture of firms' strategies across industries and technologies. Firms can be extremely successful in one of these dimensions or a combination of them, which results in different needs and strategies for forming alliances. Second, following previous work in this area, this study combines both firm-level and dyadic-level explanations to address the important heterogeneity behind the drivers of alliance formation (Wang and Zajac, 2007). Third, different from most previous studies on alliance formation, which focus solely on one dyadic characteristic, this paper distinguishes between product and technological similarities between prospective partners and their implication for exploitation and exploration. Finally, this study is set in the context of a mature and low-tech industry (tires) that usually gets bypassed by the alliance and innovation literature. While the aggregate R&D intensity of the industry justifies its "medium low-tech" label, technology has always played a significant role in the tire domain and it is actively pursued by the industry's leaders, which makes it a prime background for testing these effects.

My results emphasize different effects of the hypothesized variables on the propensity to engage in alliances based on the type of technological exchanges observed. I find that corporate diversifiers (across industries) tend to engage more in technological alliances either as partners (exploration) or as providers (exploitation). This finding is in line with both Teece's (2007) dynamic capability theory and the diversification strategy literature (Granstrand, 2000), suggesting that through corporate diversification firms acquire new knowledge regarding potential avenues to capitalize on existing technological assets. Moreover, the recent surge in inter-firm agreements worldwide suggests that such advantages in terms of exploitation of technological capabilities have become increasingly important in today's competitive and global environment of firms (Makino and Delios, 1996). Furthermore, the support for the role of technological diversification on exploration alliances is strong and robust, supporting prior conjectures in the literature (Giuri et al, 2004; Gambardella et al., 2007). Thus, exploration in technological alliances relies heavily on partners with large and diversified portfolios as it increases the avenues for learning and collaboration.

Besides these firm characteristics that affect their propensity to form technological collaborations, dyadic characteristics also motivate alliance partnering decisions (Wang and Zajac, 2007). Product similarity is consistently associated with higher probability of setting up both exploitation and exploration alliances. Moreover, this relationship is linear, implying that firms seek partners from similar product areas in both scenarios. Similarly, the results show a strong positive relationship between technological distance and involvement in exploitative alliances, suggesting that partners need to be complementary in this respect (Rothaermel and Boeker, 2007). Oppositely, large technological distances discourage exploration alliances, as both partners require a certain level of overlap to start a mutually convenient collaboration (Sampson, 2007; Yang et al., 2010). The econometric results provide insufficient support for the hypothesized non-linear effect of technological distance on alliance formation. Partly, this is the result of the multicollinearity problem, which prevents an efficient estimation of the coefficient of the squared term of this dyadic measure.

Overall, these findings point out towards a more general trend of *complementarity* (in terms of partner size, age, knowledge, production base and diversification levels) in exploitation alliances. The only exception, and a robust one, is given by the strong positive impact of product similarity of two firms on their propensity to engage in exploitative agreements. Moreover, these results are consistent with the application of "exploration-exploitation" paradigm to alliance formation (Lavie and Roesenkopf, 2006). Organizational inertia, either as market position or technological commitments, results in strong preferences for incumbents towards exploitation of existing assets (Rothaermel, 2001). Oppositely, partner *similarity* along all dimensions (age, size, technological portfolio, production portfolio, diversification strategies), except technological assets, is a strong driver of exploration alliances that involve bilateral technology exchanges and mutual learning (Sampson, 2007). Given the significant dispersion in terms of innovation and R&D efforts between large and small firms in the industry (Bayona et al., 2001), seeking strong technological performance is not surprising[18].

[18]The rate of innovation in large tire producers exceeds that of small-firms by more than 8, or about 8 innovations per thousand of employees (Acs and Audretsch, 1987)

Firms that engage partners in R&D activities will pursue knowledge sharing and development of new technologies and products (Rothaermel, 2001), while those who seek to exploit their technological assets will opt for more hierarchical agreements with unidirectional flows of technologies to their partners in exchange for access to production facilities, marketing or supply agreements, and other non-technological benefits (Rothaermel and Deeds, 2004).

In terms of managerial implications, the results suggest that the organization of technology exploration and exploitation via technological alliances presents both opportunities and additional challenges. Well-diversified firms across different markets are able to harness new knowledge, which in turn increases their appeal and opportunities for more alliances. Likewise, diverse technological portfolios present also greater opportunities for exploration and trigger subsequently superior economic performance (Sampson, 2007). Therefore, firms should invest more in achieving greater diversification across markets and technologies, as these actions will subsequently present firms with more external opportunities for exploration and exploitation. Moreover, the characteristics of prospective partners are indicative of the type of alliance preferred. Dyadic similarities in terms of products and technologies provide the necessary absorptive capability and channels for communication of technological content, and thus favoring exploitative interactions. In turn, firms seeking to learn and develop new technologies via exploration alliances should focus on partners with similar products but very different technological portfolios from their own.

The present study has, of course, several shortcomings that may serve as premises for subsequent work in this area. First, despite its global reach and longitudinal dimension, this analysis is constrained to a single industry which is characterized by a lower number of technological actors, as compared to a younger, more tech-intensive industry (e.g., semiconductors) that is populated by many atomistic, R&D intensive firms. Inherently, this affects the richness and structure of alliance data, so that it is likely to have more exploration in high-tech industries than otherwise. Second, this work focuses exclusively on the within-industry dimension of technological alliances, dictated by the link between our diversification measures, which are all relative to the tire industry. Future extensions of this work could adopt different measures of diversification (e.g., international) and also examine the intra-industry alliances of tire producers to shed light on the links between vertical integration strategies and firm diversification profiles. Such additions may provide a complete and perhaps different picture of alliance activities for tire producers, as they vary or balance their exploration-exploitation strategies across contingent industries and countries. Finally, the issues pertaining to data availability and accuracy are important, especially in the case of firms from developing nations in the 1980s. These problems were addressed where possible through backward revisions of data as new and more reliable statistics were published in the reference industrial journals[19].

In conclusion, this study provides some interesting insights on the interplay between firm diversification and alliance formation in the context of a mature, low-tech sector. Further inquiries are needed to gain better understanding of the motivation and outcomes of such inter-firm connections, and how they possibly differ from the "mainstream" conclusions based on high-tech industries. Such extensions could include comparative studies on other low or medium-tech industries, careful documentation of the alliance terms, and a complete tracks of cooperative relations between partners. Some of these mature industries still exhibit a high technological turnover among the leading companies, but most importantly, compose the backbone of all economies in the world. Thus, understanding the motivation and benefits of such interactions may yield important policy lessons for both developed and developing nations in which mature industries are still responsible for a large share of GDP and employment.

[19] For example many Chinese firms are not reported in the 1980s and early 1990s, although they show up in later statistics with plants dating back to the 1970s

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A Appendix. Additional tables and figures

A.1 The rare-event logit estimator

For a binary outcome variable Y_i (i=1,...,n) denoting $y_t = 1$ (occurence) or $y_t = 0$ (non-occurence) let x_0 be a 1 x k vector of chosen values of the explanatory variables. The method of computing the probability of occurence is a function of the maximum likelihood estimate ($\hat{\beta}$):

$$\Pr(Y_0 = 1/\ \hat{\beta} = \hat{\pi_0} = 1/(1 + e^{-x_0\hat{\beta}})$$

where $\hat{\beta}$ is obtained using the common log-likelihood estimator $\ln L(\beta|Y) = -\sum \ln(1 + e^{(1-2Y_i)x_i\beta)})$

In finite sample of rare events data, the computation of these probabilities is affected by two distinct problems (King and Zeng, 2001). First, $\hat{\beta}$ is a biased estimate of β and this bias can be computed using this formula:

$$b(\hat{\beta}) = (X'WX)^{-1}X'W\xi$$

where $X = [x_1, x_2, ..., x_T]$ is a vector of exogenous explanatory variables, W is the diagonal matrix constructed from $\hat{\pi_T}(1-\hat{\pi_T})w_T$, $\xi = 0.5tr(Q)[(1+w_1)\hat{\pi_T} - w_1]$, tr is the trace operator and w_T equals $w_1 = \varepsilon(y_T)/\bar{y}$ for cases, and w_T equals $w_0 = (1 - \varepsilon(y_t))/(1 - \bar{y}$ for non-cases. Applying this correction reduces also the variance for the bias corrected estimator so that $\tilde{\beta} = \hat{\beta} - b(\hat{\beta})$.

Second, when probabilities are estimated from $\tilde{\beta}$, the changes in this parameter do not affect $\tilde{\pi_f}$ symmetrically and therefore do not cancel out. Hence, the probability calculation can be corrected for this issue by considering the distribution of $f_{\tilde{\beta}}$ of $\tilde{\beta}$ which can be approximated by

$$\Pr(Y_f = 1|x_f) \approx \tilde{\pi_f} + C_f$$
$$C_f = (0.5 - \tilde{\pi_f})\tilde{\pi_f}(1 - \tilde{\pi_f})x_0\nu(\tilde{\beta})x_0'$$

where x_0 are the exogenous values for some arbitrarily chosen comparison group and $\nu()$ is the covariance matrix (King and Zheng, 2001).

Year	Countries	Firms	Plants	Avg. Plants per Firm	Tech_agreem	Patent percent
1985	77	208	368	1.77	75	9.14
1986	77	216	383	1.77	82	9.80
1987	77	218	391	1.79	96	9.13
1988	79	233	401	1.72	101	10.36
1989	80	235	410	1.74	104	9.01
1990	77	238	412	1.73	115	8.81
1991	83	261	417	1.60	122	8.30
1992	84	266	424	1.59	138	8.17
1993	82	288	426	1.48	132	7.19
1994	84	306	449	1.47	144	7.07
1995	84	306	452	1.48	143	6.73
1996	81	310	467	1.51	130	5.96

Table 3: Global tire industry and active technological alliances (1985–1996)

Notes: Tech_agreem refers to the total number of active technological alliances in a certain year; Patent percent refers to the percentage of firms of the total having patents as of that year

Variable	Description	Obs.	Mean	Std. Dev.	Min	Max
Exploit alliance	*dummy for exploitation technological alliance*	764,540	1.00	0.05	0.00	1.00
Explore alliance	*dummy for exploration technological alliance*	762,676	0.00	0.02	0.00	1.00
Log size	*log production capacity (tonnes/year)*	673,929	9.63	1.49	4.40	17.55
Age	*firm age (years)*	714,749	50.94	22.75	10.00	145.00
Log patent stock	*log USPTO patent stock*	762,676	0.22	0.88	0.00	6.00
Minority holding	*dummy for minority holdings*	560,097	0.00	0.02	0.00	1.00
Majority holding	*dummy for majority holdings*	560,097	0.00	0.02	0.00	1.00
Joint-venture	*dummy for joint ventures*	560,097	0.00	0.02	0.00	1.00
Corporate diversif	*percentage of sales from non-tire products*	762,676	25.90	13.80	0.00	99.00
Tech diversif	*inverse Herfindhal top 25 IPC-8 patent classes*	764,540	1.67	4.71	1.00	76.92
Product similarity	*Jaccard index of tire types produced*	760,988	0.37	0.29	0.00	1.00
Tech distance	*Euclidian distance top 25 IPC-8 patent classes*	764,480	0.09	0.25	0.00	2.70

Table 4: Descriptive statistics

Notes: Product similarity and Tech distance are dyadic constructs using values for both firms in a dyad, while the rest of the variables refer to all the firms in the dataset; given that I consider all possible pairs of firms they are virtually symmetric for providers/recipient or firm 1/firm 2 listed in a dyad)

No	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	Exploit alliance	1.000																
2	Explore alliance	-0.001	1.000															
3	Log size provider	0.053	0.027	1.000														
4	Log size recipient	-0.003	0.020	-0.003	1.000													
5	Age provider	0.045	0.022	0.484	0.001	1.000												
6	Age recipient	-0.005	0.012	0.001	0.484	0.011	1.000											
7	Log patents provider	0.121	0.069	0.397	-0.002	0.310	0.000	1.000										
8	Log patents recipient	-0.003	0.035	-0.002	0.397	0.000	0.310	-0.004	1.000									
9	Minority holding	0.188	0.068	0.025	0.003	0.021	0.003	0.066	0.006	1.000								
10	Majority holding	0.083	0.335	0.022	0.013	0.022	0.008	0.062	0.012	0.000	1.000							
11	Joint-venture	0.228	0.033	0.027	-0.004	0.025	-0.006	0.066	-0.003	0.000	0.000	1.000						
12	Corporate diversif provider	0.022	0.014	0.036	0.002	0.165	0.013	0.137	0.001	0.004	0.000	0.001	1.000					
13	Corporate diversif recipient	-0.011	0.019	0.002	0.025	0.013	0.157	0.001	0.126	0.000	0.013	-0.004	0.009	1.000				
14	Tech diversif provider	0.074	0.061	0.200	0.000	0.201	0.003	0.506	-0.002	0.073	0.051	0.058	0.068	0.003	1.000			
15	Tech diversif recipient	-0.004	0.044	0.000	0.200	0.003	0.201	-0.002	0.506	0.008	-0.002	-0.002	0.003	0.061	-0.004	1.000		
16	Product similarity	0.014	0.003	0.119	0.119	0.088	0.088	0.021	0.021	0.008	0.004	-0.002	-0.072	-0.074	0.025	0.025	1.000	
17	Tech distance	0.016	-0.014	0.119	0.119	0.082	0.082	0.060	0.060	0.007	0.011	0.007	-0.021	-0.024	0.043	0.043	0.199	1.000

Table 5: Paired correlations

	Technology agreements			*Technology agreements*	
Country	**Providers**	**Recipients**	**Country**	**Providers**	**Recipients**
Angola	-	2	Netherlands	2	2
Argentina	-	1	New Zeeland	-	1
Australia	-	3	Nigeria	-	2
Austria	-	2	Norway	-	1
Canada	2	0	Pakistan	-	4
Chile	-	2	Peru	-	3
China	-	32	Philippines	-	6
Colombia	-	3	Poland	-	4
Costa Rica	-	2	Portugal	2	4
Czech Republic	2	1	Russia	-	4
Czechoslovakia	2	8	Slovak Republic	-	2
Ecuador	-	1	Slovenia	1	2
Egypt	-	3	South Africa	12	7
Ethiopia	-	1	Sri Lanka	-	4
Finland	-	1	Sweden	2	4
France	20	5	Taiwan	-	9
Germany	32	13	Tanzania	-	1
Ghana	-	2	Thailand	-	7
Hungary	-	4	Trinidad and Tobago	-	1
India	-	22	Tunisia	-	1
Indonesia	-	12	Turkey	-	8
Iran	-	4	USSR	-	1
Iraq	-	1	United Kingdom	35	5
Italy	26	1	United States	91	24
Ivory Coast	-	1	Uruguay	-	3
Japan	60	10	Venezuela	-	1
Kenya	-	3	West Germany	3	5
Korea, Republic	5	6	Yugoslavia	2	7
Malaysia	3	18	Zaire	-	1
Mexico	-	10	Zambia	-	2
Morocco	-	2	Zimbabwe	-	2
Mozambique	-	2			

Table 6: Tire producers involved in technological alliances worldwide (1985-1996)

Note: These figures include inflows and outflows of technology from a country, which occur via new (exploitation and exploration) alliances between two firms that have not been engaged previously in any collaborations. Thus, renewals or extensions of existing alliances are counted only once in this table; "Providers" counts the number of firms involved in exploitation alliances as providers of technological content, while "Recipients" refers to firms that receive technology in exploitative alliances, or share it with their partners in explorative ones

Year	Type of agreement	Participants	Coding	Additional Information	Source
1990	Minority cross-ownership	Continental AG of Germany and Toyo Tire and Rubber of Japan	EXP	Continental acquired a 30% stake in Ryoto, a subsidiary of Toyo Tire and Rubber. In return, Toyo agreed to take minority holdings in two plants owned by Continental's subsidiaries. The companies hope to share production capacity thus enlarge their markets.	SDC Platinum, Accesed May 2010
1993	JV establishment	Continental AG of Germany, its subsidiary General Tire (USA) and Grupo Carso SAB de CV (Mexico)	EXP	Grupo Carso and General Tire each contributed two plants to the new company, in which Grupo Carso was to hold a majority controlling interest. The venture wants to be the largest Mexican tire manufacturer and service network.	SDC Platinum, Accesed May 2010
1994	Strategic alliance	Grupe Michelin of France and Continental AG of Germany	EXP	The name of the 50-50% JV is Michelin-Continential Projects and it aims to produce tires in Europe and enforce the competitiveness of the two, which will continue to remain competitors. The venture is expected to save each of them around $57 million US.	SDC Platinum, Accesed May 2010
1995	Collaborative agreement	Cooper Tire & Rubber of USA and the ContiTech Group of Germany	EXR	For technical assistance, licensing agreements, and design plus development cooperation; it covers projects in areas such as automotive vibration control, hose products and weather sealing.	Rubber World, Apr 1995, Vol. 212, Issue 1, p14.
1998	Supply agreement	Goodyear (USA) and Sumitomo (Japan)	EXP	Products covered in this agreement: replacement tires	Freedonia Group (1998)
1999	Strategic alliance	Pirelli SpA of Italy and Cooper Tire & Rubber Co. of USA	EXP	Cooper will handle sales and distribution of Pirelli tires in North America, where Cooper is better positioned, while Pirelli will handle Cooper's sale in South America, where it has a strong presence. Cooper will also send personel to Pirelli's Hanford, CA, tire plant, to help straighten out its failing operation. Also technological exchanges are involved.	Rubber & Plastics News; Apr. 2002, Vol. 31 Issue 19, p8.
2000	Collaborative agreement	Goodyear Tire & Rubber Co. of USA and Group Michelin SA of France	EXR	This agreement aims at setting an industry standard and broadening the appeal and availability for run-flat tires; it consists of jointly operated R&D operations based in the Netherlands and license each other's respective run-flat technologies.Goodyear has developed run-flat technology that mounts on a conventional rim, while Michelin has an integrated wheel-and-tire system.	Wall Street Journal. (Eastern edition). New York, N.Y.: Jun 23, 2000. pg. 1.
2002	Outsourcing	Continetal AG of Germany and Metro Tyres Ltd. Of India	EXP	Continental will outsource many of its motorcycle and scooter tires to Metro Tyres' dedicated new plant in Ludhiana, India. Also, the partners have signed long-term agreements covering both off-take production and technological support (US $10m).	Rubber & Plastics News, November 4, 2002
2002	JV establishement	Yokohama Rubber (50%) of Japan and Continental AG (50%) of Germany	EXP	To promote Continental tires to Japanese and Korean automakers. They also signed a contract for exchanging tire technology. (US$ 100m)	Rubber World, Mar2002, Vol. 225 Issue 6, p12.
2003	Strategic alliance	Michelin Group of France and Hankook Tire Co. Ltd of South Korea	EXP	Michelin will purchase a 10% stake in the company, which controls 46% of the Korean tire market. In addition, from 2004 the two companies will join to manufacture Michelin tires in Hankook's existing facilities. In a separate deal, Michelin has agreed to provide its Run-flat technology to Hankook.	China & North East Asia Monitor, Aug. 2003, Vol. 10 Issue 8, p7.
2004	Licesing agreement	Groupe Michelin of France and Toyo Tire & Rubber Co. Ltd of Japan	EXP	The agreements provides Toyo with the most advanced runflat technology (PAX) despite having developed its own runflat tire in the past.Toyo becomes the fourth PAX licensee after Pirelli, Goodyear and Sumitomo Rubber.	European Rubber Journal, Jun 2004, Vol. 186, Issue 6, p8.
2006	Licesing agreement	Qingdao Qizhou Rubber Co. Ltd of China and Amerityre Corp. of USA	EXP	Qingdao Qizhou has signed a license agreement with Amerityre Corp. to make polyurethane elastomer retreads for three large-size OTR mining tyres. (US$ 0.4m)	Urethanes Technology; Oct/Nov2006, Vol. 23, Issue 5, p19.
2008	JV establishement	Pirelli SpA of Italy and the Russian Technologies State Corporation	EXP	The agreement includes construction of a new industrial complex for production of car and truck tyres by 2010 in the Russian region of Samara with governmental support (US$ 300m).	European Rubber Journal, Nov/Dec 2008, Vol. 190, Issue 6, p10.

Table 7: Examples of alliances between firms in the tire industry

Note: These agreements were collected from various sources listed in the last column and may, or may not, involve technology exchanges. Only those that incorporate technology exchanges and have been signed between 1985 and 1996 are the object of this study; Coding EXP is form exploitation alliances, while EXR is for exploration alliances.

	Tire Industry		Michelin		Bridgestone		Goodyear	
Rank	IPC Class	% Patents	IPC Class	% Patents	IPC Class	% Patents	IPC Class	% Patents
1	B60C-001/00	8.49%	B60C-019/00	12.66%	B60C-001/00	7.66%	B60C-001/00	27.76%
2	C08K-003/00	6.95%	B60C-001/00	12.43%	C08K-003/00	6.61%	C08L-009/00	18.93%
3	B60C-023/02	5.97%	B60C-023/02	11.71%	G02F-001/01	6.01%	C08K-003/00	16.40%
4	B60C-023/00	5.36%	B60C-023/04	10.51%	B60C-011/04	5.25%	C08K-005/00	13.09%
5	C08L-009/00	5.18%	B60C-023/00	9.68%	G02F-001/167	5.20%	B60C-011/00	12.78%
6	B60C-005/00	4.53%	B60C-009/18	8.36%	B60C-011/00	4.79%	B29D-030/06	12.46%
7	B60C-019/00	4.52%	C08K-003/00	8.12%	B60C-009/18	4.74%	B29D-030/00	10.73%
8	B60C-023/04	4.48%	G01M-017/02	8.12%	B60C-009/00	4.44%	B60C-009/00	10.73%
9	C08K-005/00	4.48%	C08L-009/00	7.77%	B60C-009/20	4.39%	C08K-003/36	10.25%
10	B60C-011/00	4.42%	B60C-009/20	7.05%	C08K-005/00	4.32%	B29D-030/08	9.78%
Herfindhal	*0.05*		*0.14*		*0.05*		*0.31*	

Table 8: Levels of technological diversification and specialization patterns for the tire industry as a whole and the "Big Three" tire producers (Top ten IPC-8 subclasses): An example