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How internal and external factors influence the dynamics of SME technology collaboration networks over time

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ABSTRACT

This paper presents a framework to assess the effects of technology collaboration networks (TCNs) on the innovation performance of small and medium-sized enterprises (SME). It includes three factors that affect firm dynamics and could influence the success of the TCN: the macroeconomic cycle (macro-level), the industry life cycle (industry-level) and the age of the firm (firm-level). Previous papers have focused on factors at one specific level, mainly the firm level, but have not looked at these all together and have also failed to take into account how they evolve gradually over time. This study closes this gap using a panel of 44,885 observations for SMEs for the period 2003–2013. The findings confirm the importance of the inclusion of these factors at the macroeconomic, industry and firm level since they influence the TCN and the innovation performance relationship. The implications for managers and policy makers are discussed.

1. Introduction

To survive and prosper in today's highly competitive environment firms are increasingly engaged in innovation (Ferreira et al., 2015). The skill with which firms acquire their technological knowledge determines their level of innovativeness (Nieto and Santamaria, 2007). However, innovation processes generated in-house may lack the necessary expertise which could be obtained externally (Becker and Dietz, 2004). Hence, current competitive pressures are driving firms not only to develop their internal capabilities, but also to establish technology collaboration networks (Tsai, 2009). In fact, the literature has come to suggest that technology collaboration networks (TCNs) are an important vehicle for the creation of technological capabilities. Moreover, innovations have no clear development path and seem to be moving in several technology domains. Technological battles have intensified and technology has become more complex, which suggests that firms need to collaborate so that they can mitigate risks and leverage resources together (Gnyawali and Park, 2009). In light of this importance, firms are relying more extensively on technology collaboration networks to create new innovations (Wang et al., 2015).

The wider use of technology collaboration networks has especially helped small and medium-sized enterprises (SMEs) to overcome the problems associated with the liability of smallness, i.e., they have a resource disadvantage compared to large firms (Franco and Haase, 2015). In particular, they are characterized by limited financial and human resources, and this may affect the level of innovation. Consequently, one of the most frequently cited reasons for SMEs engaging in technology collaboration networks is to generate synergies by exploiting complementary assets and resources with other firms (Zeng et al., 2010).

Despite the importance of investigating the success of technology collaboration networks in the SME context, this area is under-researched in the literature (Franco and Haase, 2015). Only a few studies have attempted to analyze the effect of collaboration on firm performance and inconsistent results have been reported (Lin et al., 2012). A number of papers have found a positive relationship (e.g., Robson and Bennett, 2000 regarding the relationship between collaboration with suppliers and SME growth) while others have found this to be negative (e.g. Nieto and Santamaria, 2007 regarding collaboration with competitors and the novelty of product innovations) or non-significant (e.g. Bougrain and Haudeville, 2002 regarding combined technological collaboration and the chance of success for innovative projects; Belderbos et al., 2015 for some temporal patterns of collaboration and productivity growth).

This lack of consensus about the effect of technology collaboration networks on innovation performance has recently been explained by way of a number of internal and external factors. Nevertheless, previous research has not taken into account the fact that technology

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collaboration networks are dynamic systems that evolve gradually over time and could be developed at different stages of an industry life cycle (e.g. growth versus maturity) and at different points in the economic cycle (e.g. expansion versus recession) and that these factors could affect the success of the TCN. A firm's capabilities, which are a critical factor for the success of the collaboration, are also dynamic and change with the age of the firm. It is therefore important to better understand under what conditions technology collaboration networks play a greater role in promoting innovation in firms.

This paper tries to close this gap in the research and its aim is to examine how internal (firm-level) and external (industry and macroeconomic level) factors influence the dynamics of SME technology collaboration networks over time. Therefore, this approach captures the different dimensions of the evolution of technology collaboration networks. The research draws on different theoretical frameworks such as the Resource-Based View (RBV), particularly the element that explores social capital, contingency theory and the innovation life cycle of an industry. To test the hypotheses, the analysis is based on a large unbalanced panel of 44,885 observations of 6260 innovative Spanish SMEs operating across a wide range of industries during the period 2003–2013 (11 years).

The main contribution of this research is to theoretically and empirically analyze the importance of capturing the dynamics of the evolution of technology collaboration networks through a new set of moderating variables. Rather than considering collaboration benefits as constant and stable, we posit that they depend on three main aspects which are determining factors in the evolution of knowledge spillovers associated with collaboration: the economic environment, the maturity of the industry in which the firm competes, and the age of the firm. This adds to the collaborative technological network literature. It provides an enhanced understanding of the ambiguity of the collaborative technological network-innovation performance relationship. By linking three different dimensions, represented by macro-level, industry-level and firm-level data, the research presented here sheds light on aspects of collaborative networks that former studies, focused on only one level, have failed to demonstrate.

Moreover, this research focuses on SMEs. As Tomlinson and Fai (2013) stated, there is growing interest in understanding how the development of technology collaboration networks affects firm innovation performance, above all in the SME context. SMEs have been playing an increasingly important role in this broad trend for establishing technology collaboration networks, particularly in Europe where most firms are of a limited size. At the European Union (EU) level, by 2015 SMEs represented 90% of all enterprises and employed more than 67% of employees in the European economy. Likewise, SMEs account for more than half of the total added value created by business in the EU. Their capacity to innovate is essential for their success in a competitive global business environment. Meeting this challenge has led policy makers to seek initiatives to stimulate the innovation activity of SMEs. According to the data in the 2015 OECD STI Scoreboard, approximately 17% and 15% of innovative SMEs collaborate with suppliers and clients, respectively. Likewise, it finds that about 10% of innovative SMEs collaborate with public research institutions, while 16% collaborate with international partners. In light of this importance, the Small Business Act for Europe highlights the need to encourage collaboration in order to counter the economic and financial crisis starting in 2008 and in particular to improve the transfer of knowledge between SMEs (European Commission, 2014). Although collaboration is always an effective way for SMEs to improve their innovation performance, the limited alternatives for firms during a recession make this especially important. In this line, this research contributes theoretically by analyzing the role played by the macroeconomic cycle in the impact of TCNs. Similarly, this paper provides theoretical insights into the notion that TCNs might have different effects on innovation performance depending on the degree of industry maturity and the SME´s age. As a result, this paper has important managerial implications in terms of the effectiveness of technology collaboration networks. In particular, it identifies some conditions under which TCNs may lead to a superior innovation performance for SMEs.

The paper is organized as follows. In the next section we present the key theoretical arguments about the dynamics of technology collaboration networks and formulate our hypotheses for empirical analysis. We then describe the data set, variables used and estimation method. Next, the empirical analysis is presented and discussed. Finally, we set out the conclusions, limitations and managerial implications.

2. Theoretical framework

2.1. Technology collaboration networks in SMEs

The Resource-Based View (Penrose, 1956; Wernerfelt, 1984; Barney, 1991) explains how SMEs face specific restrictions in terms of resources and capabilities that may limit their strategic choices when competing with large multinational enterprises. This initial limited endowment of assets and capabilities, particularly internal R & D capabilities, is frequently called “the liability of smallness” because it hinders SMEs in the development of technological capabilities and their ability to innovate (Freeman et al., 1983; Aldrich and Auster, 1986).

Recently, though, the idea that firms are embedded in a social context of networks, linkages or relationships with other social entities has attracted interest among numerous RBV authors studying social capital. The concept of social capital has been identified as a crucial asset when it comes to SMEs being innovative because by establishing networks of partners it provides the firm with opportunities to access various resources that would be beyond its reach if it were to act in isolation (Yli-Renko et al., 2001; Elfring and Hulsink, 2003).

Because of their limited internal resources, SMEs are expected to engage in technology collaboration networks to search for and access external resources required for innovation (Franco and Haase, 2015). A collaborative technological network is an agreement involving two or more partners for the purpose of accessing technological resources without the need to acquire or hold these through traditional routes.

Although this paper does not aim to provide a detailed description of the possible effects of technology collaboration networks on SMEs, we will provide a brief summary of the current debate about their costs and benefits (for a recent and exhaustive survey, see Franco and Haase (2015)).

There is a growing body of research looking at how technology collaboration networks can help SMEs overcome the liability of smallness and enhance their abilities when it comes to launching new products. First, firms can benefit from the complementarity of assets and competencies contributed by their respective partners within the collaboration (Ferreira et al., 2015). Since firms need constant renewal of their technological capabilities, the exploitation of synergies allows them to incorporate the newest technological advances and adopt new technologies. Second, technology collaboration networks allow firms to internalize R & D spillovers, which are inter-firm knowledge flows where there are benefits not only for the innovator but also for the other parties involved (Becker and Dietz, 2004), and whose effect is much larger for smaller firms (Chun and Mun, 2012). By collaborating, firms acquire tacit (*know-how*) and explicit (*know what*) knowledge (Davidsson and Honig, 2003) that helps them to transform this learning into commercially successful products and to commercialize complex technology. This question is particularly relevant in the context of SMEs due to the weaker absorptive capacity of smaller organizations (Ebersberger and Herstad, 2013). According to Cohen and Levinthal (1990), absorptive capacity is a firm´s general ability to value, assimilate, and commercialize new, external knowledge. Furthermore, resource constraints are a key reason for engaging in technology collaboration networks. Collaborations are seen as a means to realize cost-savings and reduce uncertainty among partners in the network (Ferreira et al., 2015).

Nevertheless, coordinating, managing and controlling the activities of the different parties involved in the collaboration are a source of transaction costs (Becker and Dietz, 2004). These costs are particularly important for SMEs given their constraints in resources and capabilities. Previously, searching for partners and building up trust have come at an information cost and the outcome is often uncertain. Furthermore, coordinating distinct organizational practices as well as combining complementary resources often creates a source of coordination costs (Becker and Dietz, 2004). In particular, the more partners involved in the network, the more complex the transfer of information. Knowledge spillovers may also create problems for collaborators. Risks include loss of proprietary information and dependence on a partner, resulting in the possibility that potential collaboration partners could adopt opportunistic behavior resulting in additional agency costs.

Despite the extensive evidence on the importance of technology collaboration networks, many researchers emphasize that our knowledge on the effect of TCNs on the economic success of innovation activities is still limited and ambiguous in the area of SMEs (Lin et al., 2012; Franco and Haase, 2015).

In general, the literature concludes that technology collaboration networks are a useful way for SMEs to improve their innovativeness, but their impact varies depending on internal factors and also some external factors. The internal factors are related to innovation investment (e.g. Ebersberger and Herstad, 2013) or capacities such as the absorptive capacity (e.g. Tsai, 2009; Lin et al., 2012), experience in collaborating (Nieto and Santamaria, 2007), and customer relationship capability (Tzokas et al., 2015), among others. The external factors analyzed are the selection of partners (e.g. Howells et al., 2004), trust (Lai et al., 2011), the type of network (e.g. De Man and Duysters, 2005), market turbulence (e.g. Wang et al., 2015), government R & D support (e.g. Kang and Park, 2012), and the industry life-cycle (Audretsch, 1987; Audretsch and Feldman, 1996; Bos et al., 2013; Wang et al., 2014) among others.

In summary, technology collaboration networks are becoming increasingly important in creating technological knowledge for firms. Since SMEs are more dependent on external resources, they are particularly sensitive to this issue (Ebersberger and Herstad, 2013). However, technology collaboration networks come with a number of advantages and disadvantages. Thus, it is imperative to understand when and under what conditions these collaborations are most beneficial to the firm, above all in the SME context.

This paper is in line with previous papers but instead of individually analyzing one type of factor, it analyzes internal and external factors jointly and also looks at technology collaboration networks as dynamic systems that evolve gradually over time. In particular, those external factors whose effects are widespread and affect all firms from all industries are represented by the economic cycle (e.g. expansion versus recession). The economic cycle can affect both the level of innovation investment and also the success of innovation collaboration. We also include other external factors that directly affect the industry in which the firm operates. These are represented by the industry life cycle (e.g. growth versus maturity) because this reflects both where the innovation activity takes place and its evolution and also the internal rivalry in the industry as competition differs at each stage. The two variables are therefore complementary, allowing us to reflect different dimensions of the external factors and have characteristics that evolve over time. With respect to internal factors, we focus on the age of the firm in order to reflect the evolution of its resources and capabilities, and, in particular, its experience. These are critical success factors for collaboration and are also dynamic.

Thus, as we explain in the next section, the benefits associated with a collaborative technological network change with the dynamics in which the collaboration takes place. That is to say, they are not constant and evolve with changes that are external and/or internal to the firm.

2.2. Hypotheses

In this section we explain how the macro-economic cycle, industry maturity and the age of the firm influence the innovation performance of technology collaboration networks for SMEs.

2.2.1. Effects of macro-economic dynamics on technology collaboration networks

According to contingency theory, a firm's performance depends on the fit between the organization and its environmental contingencies (Donaldson, 2001). As a result, managers have to analyze a firm's environment and the internal characteristics of that firm in order to adjust their strategies accordingly. Some authors refer to this approach as the "*contingent resource based view*" (e.g. Atuahene-Gima et al., 2006) to stress that the contribution of the resources to the competitive advantage depends on internal and external factors.

Drawing on this approach, we examine the economic cycle (economic expansion versus economic recession) as a key environmental condition that moderates the effect of technological collaboration on innovation performance. As Wang et al. (2015, p. 1930) stated, environmental factors "*affect the attractiveness, feasibility, and uncertainty associated with collaborations*". Economic expansion is associated with a rapidly growing economy that accelerates job creation and output expansion and increases business activity, generating new opportunities for firms to invest in innovation. Moreover, the standard of living improves and consumers have larger budgets and can spend more on innovative products. Similarly, governments encourage and fund further innovation in firms and research institutions.

Conversely, an economic crisis or recession is characterized by uncertainty, demand contraction, declining sales and profits as well as greater competition between firms. Firms are more fragile financially and their likelihood of closing down or exiting the industry increases. A recession also affects governments who do not have enough resources to fund innovation projects or campaigns to encourage this innovation. Demand shrinks and consumers' purchasing power declines, leading them to purchase commodities rather than more expensive products such as innovative products. Thus, during recessions firms are forced to control costs and tend to reduce their innovation efforts because of low profit margins and a generally pessimistic outlook. In contrast, there are other research streams that consider innovation as being counter-cyclical and argue that recessions are a fertile environment for firms to innovate because the existing rents decrease in a recession and firms might be encouraged to introduce new products and processes. In particular, Filippetti and Archibugi (2011) observed that most of the firms in their study reported keeping their innovation investment unchanged in spite of the crisis.

But in general, recessions threaten firm survival (Srinivasan et al., 2011). In this adverse environment, the firm largely depends on its innovation strategies in order to maintain its competitiveness and its subsequent chance of survival.

As the firm does not have enough resources to diversify the innovation programs and this is costly and risky, the firm will be committed to its existing technological collaborations. Due to their success they are seen as offering the firm its best chance for survival. This situation will be similar for all participants in the collaboration. So, as each partner needs the collaboration to be a success to maintain its competitive position, informal obligations are generated between partners, reinforcing existing collaboration, constituting a more stable framework for interaction, decreasing transaction costs, and leading to more effective collaboration.

Each partner is highly motivated to devote the necessary resources, capabilities and knowledge and combine these in productive combinations in order to achieve the goals of the collaboration. Although collaborative efforts do not always work out as planned, the firms' economic restrictions lead partners to avoid the wasteful use of resources (due to these being scarce), including time, thereby increasing the productivity.

Finally, turbulent markets provide a greater incentive for managers to find ways to become more informed so that they can seek profitable ideas and make effective decisions, leading to more effective collaboration (Wang et al., 2015). Moreover, technology collaboration networks help to provide access to information by allowing for the diffusion and use of knowledge spillovers that are complementary to those of the individual firm (Belderbos et al., 2004).

SMEs are more likely to be influenced by the macro-economic environment than large firms because this stage of the cycle requires substantial resources. For resource-scarce small firms and those struggling with funding, the resources required in economic downturns can be too great. Additionally, a recession implies increased uncertainty and risk. While larger firms have the resource slack to absorb the failure of an innovative product, smaller firms find it more difficult to offset this lack of sales and profits for one product with those for other products (Rosenbusch et al., 2011).

Thus, the economic recession places greater pressure on the partners in a technological collaboration network who face the need to obtain insights to improve the effectiveness of the collaboration. That does not mean that during periods of expansion firms are not interested in the success of collaborations, but as external and internal factors are more favorable to innovation there is less pressure on them. Firms have more diverse innovation programs, more resources and opportunity problems can arise. In this line, Lin et al. (2009) argue that firms in stable environments face less pressure to find the right partners and to ensure the smooth functioning of the alliance.

The previous arguments would suggest that the macro-economic cycle should moderate the effects of technology collaboration networks on the innovation performance of SMEs, enhancing this relationship during weaker economic periods. Thus, we propose the following hypothesis:

Hypothesis 1. *The weaker the point in the macro-economic cycle, the stronger the effect of technology collaboration networks on the innovation performance of SMEs*

2.2.2. Effects of industry dynamics on technology collaboration networks

The industry life cycle is considered in our study because the innovation process evolves and changes systematically over the life-cycle (e.g. Bos et al., 2013; Tavassoli, 2015). This evolutionary interpretation of an industry over time also affects the benefits from collaboration.

In the previous literature various approaches have been used to define what actually constitutes an industry life cycle (Vernon, 1966): evolutionary economics (Klepper and Graddy, 1990), technology management (Utterback and Abernathy, 1975), and organizational ecology (Hannan and Freeman, 1977). One important conclusion drawn by all of them is that an industry life cycle can be depicted as three main stages: growth, maturity and decline (Miles et al., 1993). In this paper, we follow the approach of Karniouchina et al. (2013), who include the earliest stage of the life cycle (referred to by many authors as introduction) under the growth stage of the life cycle. Even today, most products follow the growth, maturity and decline stages, although some products may experience some differences in their life-cycles (Tibben-Lembke, 2002).

The first stage of the life cycle is usually characterized by high levels of uncertainty in the market (Tavassoli, 2015) and heterogeneity between firms (Karniouchina et al., 2013), as it is the birth and subsequent growth of a new industry (Wang et al., 2014). There are no widely accepted standards with respect to product specifications, volume of production is typically low, and the new product is marketed through a variety of exploratory techniques. In a period of rapid technological development, as happens when an industry is emerging, producers are particularly concerned with the degree of flexibility they have to modify their product lines and capabilities in order to maintain a competitive advantage as new market preferences, competitors and technologies appear (Vernon, 1966). This competition is based on the quality and variety of products (Bos et al., 2013). However, usually no single firm has all the internal capabilities necessary to undertake every activity and additionally internalization may imply excessive sunk costs. Technological collaboration helps firms to increase their absorptive capacity to understand the new technology and ideas developed in other firms by promoting the rapid transfer of self-contained pieces of information (Hamel, 1991). Thus, TCNs are likely to exert an important influence in the early stages of introducing a new product, when know-how is critical and firms are particularly concerned with their ability to respond rapidly to new knowledge as well as learning from it. Likewise, as technological collaboration tends to be relatively long-term, it offers the potential for creating trust through embedded ties as well as the possibly of creating greater willingness to exchange high-quality information and know-how (Rowley et al., 2000). And in particular, some authors emphasize that not only does the increased trust associated with collaboration promote a firm's willingness to exchange knowledge and other resources, it also enhances its capacity to do so (Eisingerich et al., 2010).

The role of tacit knowledge in generating innovative activity is presumably greatest during the early stages of the industry life cycle (Tavassoli, 2015), before product standards have been established and a dominant design which defines the specifications for the entire product category (Utterback, 1994) has emerged (Audretsch, 1998). The propensity to generate this innovative activity through technological collaboration will also be greatest during this stage, as the theory of knowledge spillovers suggests. Given its tacit, rather than explicit, nature, this knowledge is difficult to codify and thus can only be transmitted informally, which often involves direct and repeated contact. Likewise, since tacit knowledge often involves demonstration rather than enunciation it typically requires time to be explained and learnt (Polanyi, 1966).

Specifically, access to swift and effective communication between the producer and customers, suppliers and even competitors is of great value in the early stages of the life-cycle, when the product and market situations are uncertain (Tavassoli, 2015). Given that collaborations not only facilitate the transfer of information between two organizations but also foster learning by yielding new information, they are expected to be particularly effective for innovation in the early stages of the industry.

As an industry evolves and enters a mature stage, product, management, manufacturing, and marketing techniques become highly refined and standardized (Karniouchina et al., 2013). The quality, variety and characteristics of the product that were priorities characterizing the early stages are replaced by cost (economies of scale) and price requirements in the mature stage (Bos et al., 2013; Karniouchina et al., 2013), leading to a structural change in inter-firm rivalry (Wang et al., 2014) These same forces continue and intensify into the decline stage, where rivalry among existing firms is fierce, sometimes in the form of price wars (Vernon, 1966; Karniouchina et al., 2013). Thus, during the latter stages of the industry life cycle, explicit knowledge (i.e., knowledge that can be codified) plays a relatively more important role in generating innovative activity than tacit knowledge. Although the explicit nature of knowledge facilitates knowledge flows, it decreases the value of the knowledge because it makes imitation easy (Bell and Zaheer, 2007). Thus, the mature stage of the industry life cycle is characterized by a regimen of weak appropriability, that is, an environment where firms cannot adequately protect their intellectual property (Teece, 1986). While this control problem might exist for any innovation in that stage, the problem of requiring strict property rights is more acute when innovation is happening through technological collaboration instead of being internalized. It is precisely the greater risk of unintended knowledge spillovers faced by collaboration partners which enhances this appropriability problem. Likewise, to the degree that products in the later stages of the industry life cycle tend towards homogeneity and there are more similar organizational routines, the knowledge spillover benefits of collaboration become less relevant.

The evolution of the innovation process over the life-cycle of the product must also be taken into account because the underlying knowledge conditions vary (Bos et al., 2013; Tavassoli, 2015), and hence so do the benefits from collaboration. For the introduction of radical innovations, seen in the early stages of the life-cycle, the importance of technological collaboration for acquiring specific knowledge is significantly greater than it is for incremental innovations. This is because firms are less able to independently develop and implement radical innovations which imply more complex development processes than incremental innovations (Brockhoff et al., 1999).

Based on the above arguments, we propose the following hypothesis:

Hypothesis 2a. *The less mature the industry, the stronger the effect of technology collaboration networks on a SME´s innovation performance.*

However, evidence shows that in most mature industries (e.g. automotive industry) firms join technology collaboration networks. The underlying reasoning is that during this stage firms have to deal with the contraction of demand and strong competition (Wang et al., 2014) but also need to develop new varieties with different specifications despite the expected return on investment being lower than in the early-stages (Tavassoli, 2015).

Additionally, since in this stage firms mainly compete on price, attention is devoted to reducing production costs (Bos et al., 2013) and collaboration is a way to share costs and risks. Partners will be more committed to the remaining partners. As a result, we would expect the positive effects of reducing costs through collaboration to increase as the industry evolves towards the maturity and decline stages.

Finally, as we have said before, firms are more heterogeneous in the earlier stage (Karniouchina et al., 2013) and this also affects their knowledge stocks. As Gilsing et al. (2008) state, a firm's potential for learning from external knowledge depends on the similarity of the partners' knowledge bases, in such a way that learning potential declines as the dissimilarity of knowledge stocks increases.

Based on previous arguments, we also propose the alternative hypothesis:

Hypothesis 2b. *The more mature the industry, the stronger the effect of technology collaboration networks on a SME´s innovation performance.*

2.2.3. Effects of firm dynamics on technology collaboration networks

New entrants or younger firms face disadvantages when competing with established firms due to their lack of experience, or "liability of newness" (Stinchcome, 1965). Under the resource-based-view and dynamic capabilities perspective, young firms tend to lack substantial financial and human resources, plant, equipment, and other physical resources; and they also have less well developed internal routines, structures and skills. These firms will tend to accumulate new resources and develop new capabilities over time (Teece et al., 1997). Thus, they lack the appropriate assets and capabilities and have less time to implement the best practices necessary to develop new products. In particular, when developing their internal technological capabilities young firms suffer from a shortage of personnel with sufficient "expertise", typically gained through training or "learning by doing" processes. Thus, young SME firms may find it particularly difficult to deploy, develop and combine their innovative capabilities (Rosenbusch et al., 2011). An exception could be some global firms, which could take advantage of international markets and resources extraordinarily early in their development (Engel and del-Palacio, 2009).

However, a firm's innovation success depends not only on existing internal resources, but also on the knowledge that can be derived from external sources (Hotternrott and Lopes-Bento, 2016) such as networks (Becker and Dietz, 2004). Technology collaborations networks provide young firms and SMEs access to a broader and more diversified knowledge base (Hotternrott and Lopes-Bento, 2016), reducing the problem of technical competences in young firms by providing access to their partners' technological know-how (Zahra and Filatotchev, 2004).

In this context, technology collaboration networks empower younger firms to develop their internal capabilities and exploit external technological skills, but also to overcome the impediments to R & D research and lead to them investing, to produce significant returns for all investors or partners.

Another major problem for young firms that could be overcome by participation in a TCN is that they often have less information on market conditions than older and more established firms. The new product development literature emphasizes the importance of knowing specific customer preferences, needs and habits to the success of new products (Marion et al., 2012). Since technology collaboration networks are relationships where participants generally share information and work together to improve their joint innovation performance, they should reduce the higher rates of uncertainty typical in young firms and provide advice and information on market conditions. Consequently, one would expect young firms to benefit more from collaboration than established firms because the market information available to established firms is not as limited.

Moreover, one would expect technology collaboration networks to significantly shorten the development time for innovations and, therefore, the time to market for new products. This time reduction is particularly critical for young SMEs who need to stay up-to-date with the latest technological developments.

However, the previous literature also finds that older firms' past internal knowledge development strategies can be a source of experience and other capabilities and these can increase their capacity to absorb external knowledge (Wuyts and Dutta, 2014) and provide greater opportunities to handle and benefit from more alliance partner types (de Leeuw et al., 2014). In contrast to these advantages for older firms, they also develop routines, organizational principles and procedures that provoke a tendency to inertia (Sørensen and Stuart, 2000) and organizational rigidities which will constrain the firm's ability to take advantage of external knowledge spillovers (McCann and Folta, 2011). This may be an impediment to effective innovation (Lin et al., 2012). In other words, they may be more reluctant to integrate technological advances from other firms into their own activities or routines (Bruderl and Schussler, 1990).

Conversely, younger SMEs are characterized by having less established routines and skills, and therefore they are more flexible in adopting new routines (Hannan and Freeman, 1984). This may be key to enhancing their learning capacity in new areas (McCann and Folta, 2011) in order to generate knowledge to adapt to new or dynamic environments (Lavie et al., 2010; Hotternrott and Lopes-Bento, 2016). This flexibility also provides young firms with a high learning potential that can be used in their relationship with partners (Hotternrott and Lopes-Bento, 2016). As a consequence, flexibility could be more beneficial for the joint development of successful innovations than the specialization of assets found in older SMEs (Rosenbusch et al., 2011).

Based on previous arguments, our third hypothesis is the following:

Hypothesis 3. *The greater the firm´s age, the weaker the effect of technology collaboration networks on a SME´s innovation performance*

The theoretical framework is summarized in Fig. 1.

3. Research method

3.1. Sample

The data to test our hypotheses were obtained from the Spanish Technology Innovation Panel (PITEC), which is compiled by the Spanish National Institute of Statistics (INE) with the support of several official institutions: the Spanish Foundation for Science and Technology (FECYT) and the COTEC Foundation, based on the Community Innovation Survey (CIS) type questionnaire. Since 2003 this database

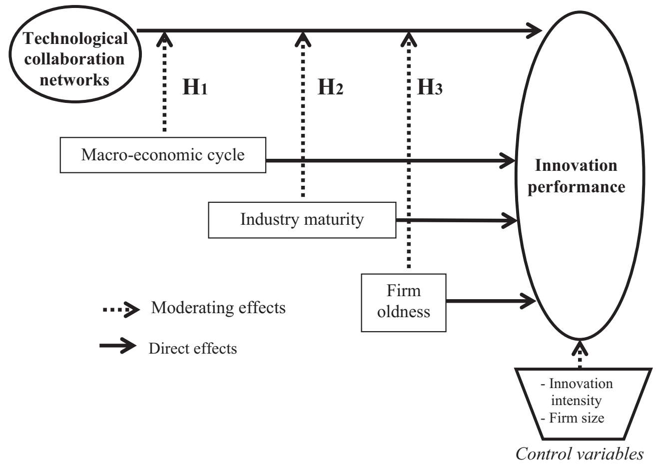

Fig. 1. Research Model.
Source: Own elaboration

has been collecting extensive information of great quality and reliability about the innovation and collaborative technological activities of Spanish firms over time. It allows us to create time series to study the evolution and impact of innovation in different business sector as well as to identify the different innovation strategies adopted by companies. This database provides some anonymized data in order to provide individual level information and to maintain the confidentiality required by data protection laws. López (2011) describes the procedure applied at the PITEC and demonstrates that the use of anonymized data from PITEC instead of original data produces reliable results.

From this database we have selected those observations relating to small and medium sized enterprises (SMEs are those firms with fewer than 250 employees) as they are the focus of this study. After excluding some outliers (e.g. firms with no sales or employees), the final sample consists of an unbalanced panel of 44,885 observations for 6260 SMEs for the period 2003–2013.

3.2. Measures

3.2.1. Dependent variable

The dependent variable in all the models is *innovation performance*. According to Engel (2014, p. 6), an innovation must be a novel idea which concludes with being introduced into the market. This is operationalized as sales from new products as a percentage of total sales because this reflects the success of new products. A product is considered new when in the period t-2 to t the firm has introduced a new or significantly improved good or service (new to the firm) into its market before its competitors (new to the market).

Several authors have previously and recently used this measure (e.g., Cassiman and Veugelers, 2006; Díez-Vial and Fernández-Olmos, 2015; Kafouros et al., 2015; Hotternrott and Lopes-Bento, 2016) instead of patents since not all innovations are patented (Fukugawa, 2016), it is difficult to identify the influence of patents on final revenue (Guadix et al., 2016) and patenting does not necessarily measure new products or the commercial success of new products (Hotternrott and Lopes-Bento, 2016).

3.2.2. Independent variables

The key independent variable is the *collaborative technological network (TCN)* which is operationalized using a dummy that equals 1 if the company participates in technology collaboration networks with other agents during t-2 to t and 0 otherwise.

The macro-economic cycle, industry maturity and firm age are three moderator variables that may influence innovation performance but also, as we have stated in the previous section, moderate the effects of technology collaboration networks. So they are included in the model as independent variables and also through their interaction with the TCN.

As the *macro-economic cycle* is a multi-dimensional factor, it is measured by way of a factorial analysis on the basis of 8 items extracted from the statistics published by the National Statistics Institute (i_1 to i_6) and the Ministry of Justice (i_7 and i_8) in Spain: (i_1) Gross Domestic Product (GDP), (i_2) Gross Domestic Product per capita, (i_3) the trade balance, (i_4) the economic confidence index, (i_5) the number of unemployed workers, (i_6) the public debt to GDP ratio, (i_7) the number of new foreclosures and (i_8) the number of bankruptcy procedures. The four first items point in the same direction, that is, they are key indicators of economic activity and future economic prospects for investors. The other four items point in the opposite direction, that is, they predict how fast the economy is contracting. All these items are directly related to the economic cycle, since they improve or deteriorate depending on whether it is in a period of expansion or recession. For example, in recession years GDP decreases, unemployment increases and the number of bankruptcy procedures also rises, among other effects. However, the opposite happens in a period of expansion. Thus, the macro-economic environment factor was composed of the sum of the scores for each item, and the greater the value of this factor the worse the point in the macroeconomic cycle and vice versa, a lower value is interpreted as a better macroeconomic situation. The sign of the factor loadings was negative for the four first items and positive for the other four, as was expected, to indicate contraction (see Table 1).

The reliability analysis (Cronbach's alpha = 0.979) confirms that the macro-economic environment items are highly reliable (i.e., the total alpha value is higher than 0.6). Moreover, the exploratory and confirmatory factor analyses have confirmed the construct validity. The analyses were carried out using Stata software version 13 and the results of the test are shown in Table 1.

In previous studies the industry life cycle has been measured by the categorization of industries into the growth, mature or declining phases based on the trend of real industry sales (e.g., Audretsch, 1987; Bos et al., 2013). In particular, Bos et al. (2013) provide a continuous measure of maturity for each industry (i.e. industry specific) based on the sales of those industries. When using this measure in our study we followed their methodology.

We first estimated the following equation for all of the 20 industries identified in the sample (see Table 1):

$$\ln(S_{jt}) = \propto_0 + \propto_{1j}\, t + \propto_{2j}\, t^2 + \varepsilon_{jt} j{:}1..20 t{:}1.11 \tag{1}$$

where $ln\ (S_{jt})$ is the natural logarithm of real sales in industry j (j = 1, …, 20) at time t, and t and t^2 is time and time squared (t = 2003, …, 2013). The real sales of each industry are obtained from the Spanish National Statistics Institute.

Based on Eq. (1) and following Bos et al. (2013) we calculate the *industry maturity* (M_{jt}):

$$M_{jt} = -\frac{\partial ln(S_{jt})}{\partial t} = -[\propto_{1j} + 2\ \propto_{2j}\ {*}t] \tag{2}$$

M_{jt} is decreasing in sales growth as it is derived from the negative sign of the Eq. (2). As a result, the highest values of M_{jt} represent economic activities with the lowest sales growth, i.e., in the late stages of the industry life cycle (Bos et al., 2013).

Finally, *firm age* is measured by the natural logarithm of the number of years (plus one to avoid having ages of zero) elapsed since the year of establishment (Fukugawa, 2006). This value captures the effect of accumulated experience in the firm. This operationalization in logarithmic form is required to remedy the significant positive skew which is evident in the pre-transformed count measure. One year might be insignificant for a middle aged firm but could have a great importance for a newly-established firm.

3.2.3. Control variables

In line with previous literature, we also control for two firm-specific

Table 1
Definitions of variables.
Source: Own elaboration

	Definition	
Dependent variable		
Innovation performance	Ratio of new products sales to total sales x 100	
Independent variable		
Technological collaboration	Dummy, equals to 1 if the firm participates in technological collaboration networks during t to t − 2	
Moderators		
Macro-economic cycle	A factor extracted from 8 items with the following loadings: − 0.949 *(Z_GDP) + − 0.965 * (Z_GDP_ per_capita) + − 0.939*(Z_the_trade_balance) + − 0.836*(Z_the_economic_confidence_index) + 0.987 *(Z_the_number_of unemployed_workers) + 0.835 * (Z_the_public_debt_to_GDP) + 0.977* (Z_the_number_of_new_foreclosures) + 0.982 *(Z_the_number_of_bankruptcy_procedures). A greater value of this variable indicates a worse macro-economic cycle.	
	Reliability and validity in macro-economic cycle assessment	
	Reliability analysis	
	Cronbach´s alpha value	0.979
	Exploratory Factor Analysis	
	Kaiser-Meyer-Olkin test (KMO)	0.741
	Bartlett´s test of sphericity	0.000
	Principal Component Analysis	Component 1 = 7.010
	Varimax (orthogonal) Rotation	Component 2 = 0.501
	Components of Eigen Values	Component 3 = 0.387
	Confirmatory Factor Analysis	
	Likelihood Ratio test	0.000
	Population Error	
	Root Mean Square error of approximation	0.000
	Size of Residuals	
	Standardized root mean squared residual	0.057
	Coefficient of determination	0.996
Industry Maturity	A continuous variable based on Bos et al. (2013) measure of maturity industry. Industries used → 1: Mining, energy, water and waste activities; 2: Food, beverage and tobacco processing; 3: Textile, clothing, leather and footwear; 4: Wood and cork, paper and graphic arts; 5: Chemicals and pharmaceuticals; 6: Rubber /plastics; 7: Miscellaneous non-metallic mineral products; 8: Manufacture of fabricated metal products, except machinery and equipment; 9: Electronic, electrical and optical equipment; 10: Machinery and equipment; 11: Transport equipment; 12: Miscellaneous manufacturing industries, repair and installation of machinery and equipment; 13: Transportation and storage; 14: Hospitality; 15: Information and communication; 16: Real estate services; 17: Professional, scientific and technical activities; 18: Administrative and support service activities; 19: Arts, entertainment and recreation activities; 20: Other services	
Firm oldness	Ln (number of years since establishment + 1)	
Control variables		
Innovation intensity	Ratio of total innovation expenditures to turnover x 100	
Firm size	Ln (number of employees)	

idiosyncrasies that are traditionally found to affect a firm's innovation performance. We control for the firm's innovation effort intensity using an input indicator, namely innovation expenditure as a percentage of turnover (*innovation intensity*). This indicator includes not only spending on internal and external R & D, but also non-R & D expenditures such as training, introducing innovation into the market and advertising (Díez-Vial and Fernández-Olmos, 2015). Finally, we include *firm size* (e.g. Belderbos et al., 2004) as the natural logarithm of the number of employees. Since large firms are more likely to exploit economies of scale and have broader pools of qualified human resources, it would be reasonable to assume that this variable has a positive effect on innovation performance.

Table 1 provides a summary of the variables and their definitions.

3.3. Econometric model and estimation method

The standard regression approach is not appropriate when the distribution of the dependent variable exhibits censoring at zero, as happens for our dependent variable *innovation performance*. Therefore, a dynamic Tobit analysis is applied (Wooldridge, 2006), which can be written as:

$$y_{it} = 0 \, if \, y_{it}^{*} \leq 0$$

$$y_{it} = y_{it}^{*} \, if \, 0 < y_{it}^{*} < 0$$

$$y_{it} = 100 \, if \, y_{it}^{*} \geq 100$$

$$\text{where} \, y_{it}^{*} = x_{it}^{'} \beta + \varepsilon_{\text{it}}$$

In our empirical model the explanatory variables were lagged by one period to account for the fact that innovation takes time to materialize (Kafouros et al., 2015). Lagging the regressors one period also corrects for potential simultaneity between technology collaboration networks and innovation performance

Either fixed effect or random effect specifications can be used to control for unobserved heterogeneity, a typical problem in panel data analysis. In this paper, random-effect estimates are realized in the panel Tobit models for several reasons. First, random effect models show a greater efficiency compared to fixed effect models, leading to smaller standard errors and higher statistical power when detecting effects (Hsiao, 2014). Second, as Tobit is a non-linear function, the likelihood estimator for fixed effects is biased and inconsistent, and thus, fixed-effect estimates cannot be made (Kafouros et al., 2015). Third, the Breusch-Pagan Lagrangian Multiplier (LM) test for random effects indicates that under all definitions of models the random effect model performs better than the pooled Tobit model.

4. Results

Table 2 shows the main descriptive statistics and the correlations for the variables included in this study. Most of the correlations are fairly low except those with industry maturity and macro-economic cycle. To assess potential problems of multicollinearity, variance inflation factors (VIFs), conditioning indices, and variance decomposition proportions were calculated. The maximum VIF obtained was 1.54, which is substantially lower than the conservative cut-off of 10 for multiple regression models. Likewise, the maximum conditioning index for our variables was 15.74, which is well below the cut-off value of 100 used to identify substantial variance inflation. These results reveal that the regression estimates presented are not biased by the presence of severe multicollinearity

The results of our regressions are presented in Table 3. We have run four regressions for our dependent variable (innovation performance) to test the stability of our results. The first regression is the baseline model that only includes the control variables (Model 1). The second regression displays the independent variable technological collaboration without moderator variables (Model 2). The third regression is estimated with all the independent variables but without interaction variables (Model 3) and finally the fourth regression is estimated with the independent, moderator and interaction variables (Model 4). Although we obtain stable results through each model, we also confirm the robustness of our results by way of the bootstrap method (Wooldridge, 2006).

We obtain that all independent variables significantly affect the performance measure. While technological collaboration has a positive and significant effect (1% level), the analysis shows that the macro-economic cycle, the industry maturity and the firm oldness has a negative impact (1% level, 5% level and 1% level, respectively) on

Table 2
Descriptive statistics and Spearman correlations.

Variable	Mean	Std Dev	Min	Max	1	2	3	4	5	6	7	VIF
1. Innovation performance	22.314	34.575	0	100	1	2						
2. Technological collaboration	0.353	0.478	0	1	0.120	1						1.02
3. Macro-economic cycle	8.640	6.652	1.171	18.443	−0.044	−0.000	1					1.49
4. Industry maturity	−0.490	4.152	−11.672	18.081	−0.040	−0.069	0.604	1				1.54
5. Firm oldness	3.003	0.642	0.693	4.997	−0.057	−0.064	0.183	0.273	1			1.29
6. Innovation intensity	0.211	1.966	0	97.854	0.268	0.262	−0.069	−0.178	−0.271	1		1.02
7. Firm size	3.501	1.197	0	5.517	0.006	0.050	0.016	0.082	0.382	−0.250	1	1.19

Note: Correlations above 0.04 are significant at p-value < 0.01.

innovation performance. Moreover, as we expected, each control variable (innovation performance and firm size) has a highly significant positive effect on innovation performance.

With respect to the interaction variables, which are the main focus of this research, Model 4 shows that the interaction effect between technological collaboration and the point in the macro-economic cycle has a positive and significant coefficient (β = 0.315; p-value < 0.01), which does not lead us to reject Hypothesis 1.

The estimation for the interaction effect between technological collaboration and industry maturity is slightly significant (β = 0.351; p-value = 0.076). This result allows us to conclude that the relationship between technological collaboration and innovation performance is dependent on the phase in the life-cycle of each industry, being stronger in the later stages. This leads us to reject Hypothesis 2a but not Hypothesis 2b.

Finally, model 4 shows that the coefficient of the interaction term between technological collaboration and firm age is negative and statistically significant (β = −2.574; p-value < 0.01), providing support for Hypothesis 3.

To facilitate the interpretation of the moderation effects, the interaction effects are further illustrated in Fig. 2. Since technological collaboration is a binary variable, we do not employ standardized variables following Aiken and West (1991). In particular, we show the effects of the macro-economic cycle, industry maturity and firm oldness as moderators in Fig. 2a, b y c, respectively. The plots reveal that, as expected, the relationship between technological collaboration and innovation performance is higher when the macro-economic cycle is recessive, the industry maturity is high and the firm oldness is high.

Low Collaboration: mean- 1 standard deviation High Collaboration: mean + 1 standard deviation.

5. Discussion

As a first result we have obtained that the participation of SMEs in technology collaboration networks provides them with more benefits in terms of their new products launched in the market. This may happen because technological collaboration entails the direct transfer of knowledge for the purpose of new product development.

Likewise, as we expected, a weak point in the macro-economic cycle has a direct negative effect on innovation performance. An economic recession provokes instability, uncertainty, and economic and financial problems for governments, firms, and consumers. Government budgets shrink and there is less money for innovation. Firms find that they lack available resources and/or have greater difficulties in accessing funding to be allocated to innovation projects. In addition, consumers have less money to spend. As a consequence they experience changes in their preferences and needs and their spending on non-basic products falls. This results in lower demand for innovative (usually more expensive) products and innovation performance decreases.

Industry maturity has a direct negative effect on innovation performance. In this stage of the life cycle, established industry norms and organizational activities are highly routinized and standardized (Karniouchina et al., 2013), and as a consequence SMEs have a lower propensity to develop new products and industries become less

Table 3
Tobit Regression results. Random effects.

Dependent variable	**Innovation performance**							
	Model 1		Model 2		Model 3		Model 4	
Control variables								
Innovation intensity	0.697***	(0.158)	0.668***	(0.158)	0.568***	(0.158)	0.560***	(0.157)
Firm size	2.042***	(0.490)	1.774***	(0.487)	3.684***	(0.520)	3.563***	(0.520)
Independent variables								
Technological collaboration			8.676***	(0.718)	8.096***	(0.717)	13.378***	(3.137)
Macro-economic cycle					−0.313***	(0.059)	−0.424***	(0.071)
Industry maturity					−0.275*	(0.119)	−0.445**	(0.142)
Firm oldness					−10.282***	(0.995)	−9.196***	(1.082)
Interactions								
Technological collaboration *x* macro-economic cycle							0.315**	(0.112)
Technological collaboration *x* industry maturity							0.351†	(0.198)
Technological collaboration *x* firm oldness							−2.574**	(1.005)
Observations	44885		44885		44885		44885	
Wald chi2 test	35.56***		181.55***		554.72***		580.93***	
Log likelihood function	−143336.98		−143263.99		−143075.38		−143061.8	
Random effects vs pooled Tobit	LM = 18042.43***		LM = 17726.94***		LM = 17563.32***		LM = 17443.39***	
Rho	0.465		0.460		0.466		0.466	

Notes: Standard errors in parentheses.
*** p < 0.001.
** p < 0.01.
* p < 0.05.
† p = 0.076.

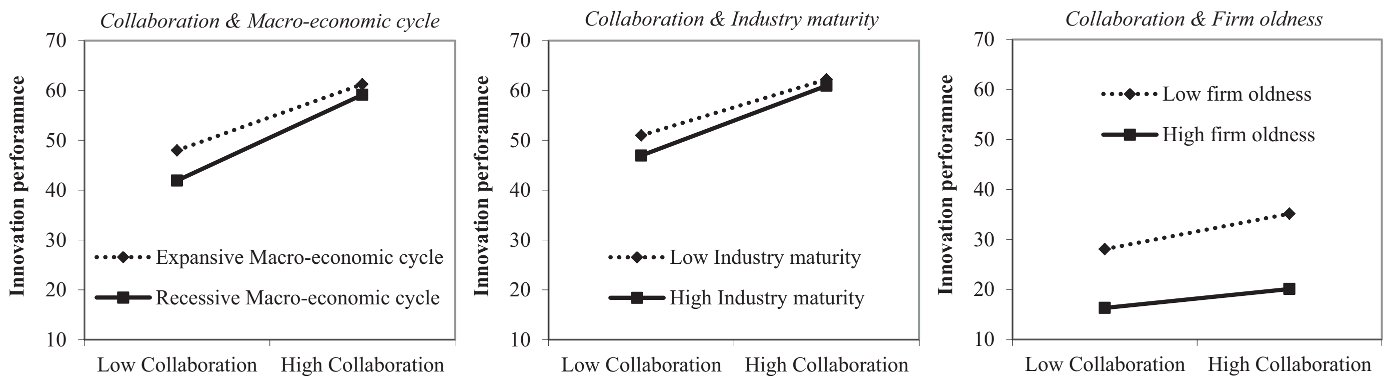

Fig. 2. Interaction effect for collaboration and moderator variables.

innovative (Audretsch and Feldman, 1996).

Similarly, firm age also presents the expected sign. Although young firms are characterized by a limited endowment of resources and capabilities, and in particular those required to develop new products, they may be highly motivated to innovate in order to compete and survive in an unfavorable environment. In addition, although aging is associated with higher rates of innovation expenditure in firms, older firms are likely to develop innovations that have a lower impact on their communities than those developed by younger firms (Sørensen and Stuart, 2000).

During more favorable economic periods (expansion), demand and also the profit earned by firms increases. As a consequence, the level of competition between firms falls and their chance of survival is higher. In this environment, the benefits of participating in a TCN might not compensate for the loss of innovation independence or the coordination costs inherent in a network. In contrast, during weaker economic periods the market conditions change and the pressure on SMEs increases. Demand contracts and firms compete strongly in order to survive. Thus, SME participation in a TCN turns into a great opportunity to share costs, resources and knowledge about the innovation, and to reduce the time required to implement technological advances and their risk, which leads to greater innovation success. Therefore, we confirm that the weaker the point in the macro-economic cycle, the stronger the effect of technology collaboration networks on a SME's innovation performance.

In general, the growth stage of an industry is characterized by high levels of heterogeneity between firms (Karniouchina et al., 2013), including their knowledge stocks. The distance between firms in terms of knowledge is important because previous papers have demonstrated that dissimilarity of partners is detrimental to innovation (Gilsing et al., 2008). This could explain why, due to the greater dissimilarity in the partners' knowledge bases, the learning potential and consequent innovation performance from collaboration is lower in the earlier stages of industries than in the later stages. In contrast, collaboration could be more attractive as the industry approaches maturity. In this stage, intense competition makes it difficult for firms to protect their market share, leading to slower sales growth. The associated low demand becomes a deterrent to potential innovators who want to recoup the costs of their innovative activities. So, collaboration should enable firms to overcome their reduced access to funds and share the fixed costs associated with such investments with others. Thus, when innovations are being developed in more mature industries, there will be more motivation to create these through technological collaboration.

Older firms benefit less from participating in TCNs, since they obtain a lower innovation performance. This result seems to confirm the arguments set out in the hypotheses section. Although older firms often have more availability of resources and capabilities, they also have more organizational rigidities that create problems when coordinating innovation activities with their partners and this would limit their ability to exploit the TCNs innovation activities, and thus, the innovation success. For young firms the opposite is true. Their short lives limit the organizational inertia of the firm, allowing for greater adaptability when they join a TCN. Moreover, young SMEs are prone to integrate the technological advances of other firms into their own activities or routines. Thus, they obtain a greater innovation performance.

Finally, as the literature predicted, the innovation performance effect of technological collaboration will be stronger in firms with greater levels of innovation intensity and size. Thus, R & D engagement increases a firm's innovation performance due to more resources being devoted to science and technology. This often implies the acquisition of more advanced know-how which in turn yields a better result in innovation. Empirically, this impact of innovation intensity on innovation performance was validated by Díez-Vial and Fernández-Olmos (2015).

Moreover, firm size plays an important role in promoting innovative capacity, and as a result innovation performance, due to it offering several advantages in relation to financial capacity, production capacity and exporting, among others (McCann and Oxley, 2013). First, financial resources are particularly necessary when undertaking innovative activities, so smaller firms tend to face greater resource constraints than larger firms. Likewise, reduced production capacity may reduce the possibility of product innovation. Finally, larger firms tend to export more than smaller firms, and firms have more incentives to innovate to gain competitive advantages when competing in international markets.

5.1. Implications to theory

This approach is relevant because the literature on collaboration often highlights a difference in the dimensions of the evolution of TCNs. Some researchers argue that TCNs provide financial resources to SMEs who are finding it increasingly difficult to access funding for new projects as a result of the recent economic recession. Others argue that TCNs play a significant role in the development of new economic sectors. Moreover, collaboration is often a key focus for any strategic management aimed at strengthening the creation and growth of new companies facing the liability of newness. However, there has been no examination of the effectiveness of all these dimensions in explaining the innovation performance of TCNs and, as a consequence, little is known about how effective these dimensions are in this regard.

This paper thus looks at which dimensions of the evolution of TCNs are better at fostering new product innovations in SMEs. In seeking to answer this question, this paper makes two theoretical contributions. First, we provide new theoretical insights into the notion that the various dimensions of the evolution of TCNs might have different effects on SMEs. Our current understanding of the dissimilarities in the evolution of the dimensions of TCNs is weak. An important contribution of this paper is its focus on identifying the differences among the most common evolution dimensions of TCNs and how these dimensions affect product innovation in SMEs. Second, this research links the Resource based View with the contingency theory and also takes into account the innovation life cycle literature to suggest that these differences affect the ability of TCNs to foster the development of new products for SMEs.

This study enriches the traditional view of firm collaboration by theoretically explaining and empirically demonstrating the moderating effect of the macroeconomic cycle on the relationship between TCNs and SME innovation performance. In particular, we find that during weaker economic periods, participation in a TCN is particularly important for SMEs because it allows them to achieve a better innovation performance. This paper therefore presents some evidence to support contingency theory since the effectiveness of collaboration depends not only on the characteristics of the partner, but also on contextual factors such as the macroeconomic environment.

Likewise, it extends the innovation life cycle perspective by analyzing the impact of the product life cycle on the effectiveness of TCNs. Our results support the idea that TCNs might have different effects on innovation performance depending on the stage of innovation in the industry in which the firm operates. In particular, these effects are stronger in the later stages of the industry life cycle. These results are consistent with the logic that collaboration improves the innovative ability of SMEs to compete in mature industries.

We also look at how a firm's age influences the effectiveness of TCNs in enhancing SME innovation performance. Our results show that young SMEs benefit more from collaboration than older SMEs. The findings provide support for the resource based view by suggesting that technological collaboration allows young SMEs to preserve their creativity and flexibility while mitigating the inherent liabilities of newness and smallness (Ketchen et al., 2007).

Therefore, the consideration of the evolution of the firm, industry and macro-economic environment, as they gradually change over time, is important if we are to better understand under what conditions technology collaboration networks play a strong role in promoting innovation. Firm age, industry stage of development and macro-economic environment are found to be key moderators of the TCN-innovation performance relationship.

5.2. Implications to practice and policy

This study offers important implications for academics, managerial practice and policy making. For academics, our findings show that technology collaboration networks are dynamic systems that evolve gradually over time and their effects on innovation performance could be enhanced depending on the economic cycle, the stage of the industry life-cycle and the age of the firm. In particular, the study highlights that collaborations under adverse conditions, such as a recession, the maturity life-cycle stage and the liability of newness, could be an opportunity for SMEs because their effectiveness is greater. These findings complete and complement those from previous papers that mainly focus on more favorable contexts.

Managers of SMEs need to decide if and when to engage with technology collaboration networks to exploit innovative ideas and develop new products. In this study we have argued that the same factors that make it difficult for SMEs to compete, namely the economic recession, maturity of the industry and liability of newness, also make technological collaboration more effective. In this sense, our research improves their understanding of TCNs for managers. It shows that collaboration between SMEs and other partners is a valid method for improving their innovation performance, but that not all TCNs will be conducive to innovation performance in the same way. Innovation managers need to suitably design the specific configurations of the firm's collaboration to foster innovation performance in SMEs.

Finally, the study reported here offers implications for policymakers. In general, knowledge of the conditions under which TCNs operate will allow policy makers to better prepare and support domestic SMEs and public institutions involved in TCNs.

Over the last two decades, governments in many countries have instituted policies to promote collaboration but have ignored some influential factors, such the macro-economic context, industry maturity and firm age. The findings of this study suggest that governments need to pay more attention to how collaboration can contribute to the success of their SMEs' innovation performance. In an unfavorable macroeconomic context, such as the one during the last global crisis, policy makers should place greater emphasis on creating policies to facilitate TCNs for SMEs. Moreover, they should more actively engage in collaboration support programs in the more mature industries. It also follows that policy initiatives are more effective when they focus on the need to promote collaboration between younger SMEs.

6. Conclusions

In recent years technology collaboration networks have been recognized as an important factor driving innovation and the success of firms. Indeed, for an increasing number of SMEs, characterized by possessing a limited bundle of resources and capabilities, TCNs are the best way to innovate.

Given the strategic importance of cooperation and the opportunity it offers to access complementary assets and skills, the role of TCNs as a vehicle for effective innovation is of concern to both managers and scholars (Franco and Haase, 2015). A review of the extensive existing literature on the role of TCNs and their impact on firm performance shows that as yet there is still no comprehensive understanding of this effect.

This paper combines several theoretical approaches to collaboration to analyze the effect of TCNs on the innovation performance of SMEs. We have analyzed a comprehensive dataset to extend the current literature by addressing this debate from a dynamic perspective. We posit the notion that TCNs have different effects on SMEs depending on several internal and external factors, such as the macro-economic cycle, industry maturity and firm age. Moreover, we suggest an evolution-based logic that explains these varied effects. Consequently, this paper draws on previous studies to take the first step toward gaining a better understanding of which dimensions of the evolution of TCNs are better at fostering innovation performance for a large sample of Spanish innovating SMEs in 2003–2013.

This study has certain limitations caused in part by the research questions posed by the paper and by the characteristics of the secondary database used. One limitation of the present work is the assumption of causation running from collaboration to innovation performance. In reality, TCNs may not only cause SME innovation performance but also be the result of it. As Kim and Lui (2015) stated, SMEs with new innovative products may be actively sought after as an attractive partner for collaboration. Nevertheless, we have a strong degree of confidence in our results because we partially address this potential endogeneity. Likewise, previous studies have uncovered similar patterns of causality (e.g., Tomlinson and Fai, 2013).

Our study investigates only a limited number of dimensions of the evolution of TCNs. As proposed in the network research literature, there are other variables that may affect the innovation performance of collaboration, such as being located in a Science Park or an SME's absorptive capacity. Further research should be conducted to test the impact of these variables on explaining innovation performance.

In addition, membership of a collaborative technological network has been measured using a dummy variable to measure any technological collaboration (regardless of the type of partner). However, the identification of each type of technological partner (suppliers, customers, competitors, consultants, universities, public firms and/or technology centers) should be carried out to look at this topic in more depth. Moreover, there is a wide range of dimensions to the collaborations (e.g., depth, namely how deep or close the collaboration with partners is, or timing, namely the stage in the product-project development when the collaboration begins) that could be used when studying the collaboration phenomenon and which may result in different performance (Katila and Mang, 2003; Franco and Haase, 2015). Hence, this taxonomy of collaborations could be studied in future research with other databases that provide more detailed information about the characteristics of this collaboration.

Our results provide evidence on the innovation performance of TCNs, but the boundary of our empirical research is limited to only one country, Spain. While the findings might be country-specific, it was argued by Nieto and Santamaria (2007) that the patterns of collaboration in this developed economy are similar to those seen in the majority of European countries. Nevertheless, future research effort could focus on replicating the work in other contexts, examining the institutional contexts under which TCNs may result in superior performance.

In summary, our results could provide useful insights into the relationship between TCNs and the sales of new products for SMEs. This is done by highlighting the differences between the dimensions of the evolution of TCNs, i.e., macro-level, industry-level and firm-level characteristics. These differences should be considered in studies analyzing whether and how technological collaboration has long-term effects on SMEs.

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