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Sticky partnerships or fresh starts? How failed project applications shape organisations' collaborative behaviour in R&D networks

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ABSTRACT

Prior inter-organisational collaboration is a well-established antecedent of tie formation in competitive publicly funded R&D networks. But what happens when organisations come together to develop a project proposal and apply for funding, but their application is unsuccessful? This paper investigates how the joint experience of failure influences future tie formation, and how this effect varies for organisations with different levels of cognitive proximity. The analysis builds on a policy-induced collaborative network of approved and rejected R&D project proposals in Valencia region (Spain), in 2016 – 2022. The findings suggest that unsuccessful funding applications have a positive and stronger influence on partners' future tie formation than successful ones. Moreover, the propensity of actors to re-engage following a rejection is greater if they are cognitively distant. The paper demonstrates that empirical work on R&D network dynamics may be systematically underrating partners' prior funding application failures as a fundamental antecedent of tie formation.

KEYWORDS
Network evolution; R&D partnerships; regional innovation policy; unfunded projects; cognitive proximity

JEL CLASSIFICATION
D85, O32, R58, O38, O31

1. Introduction

Organisations with a history of prior engagement seem to gravitate towards each other, on the basis of previously established mutual trust, shared norms and expectations (Gulati 1995; Gulati and Gargiulo 1999; Sorenson, Rivkin, and Fleming 2006; Zaheer, McEvily, and Perrone 1998). However, what exactly qualifies as prior engagement remains open to debate. For instance, what happens when organisations come together to develop a joint project proposal and apply for funding, but their application is unsuccessful – does this contribute differently to social proximity and future tie formation than when funding is secured? Our study addresses this question in the context of publicly financed programmes to support collaborative R&D networks, by looking at the effects of two types of prior engagement: failed vs successful joint research project applications.

Government funded R&D programmes are closely scrutinised for their potential to foster otherwise unlikely organisational links (Luukkonen 2000) and produce research and innovations with broad societal impact (Wanzenböck and Piribauer 2018). Scholarly interest in R&D collaborations has grown in parallel with investigations into their antecedents, from organisational, to relational (e.g. proximity among partners), to network-based perspectives (Autant-Bernard et al. 2007; Balland, Boschma, and Ravet 2019; Broekel and Hartog 2013; Paier and Scherngell 2011). Understanding the drivers of tie formation is key to unpacking the complexity of the partner selection process and the setup of joint projects, and could provide information on the effectiveness of publicly subsidised programmes.

Most existing studies assessing the evolution of R&D networks, focus exclusively on partnerships that received financial support (Autant-Bernard et al. 2007; Caloffi, Rossi, and Russo 2015; D'Este, Guy, and Iammarino 2013; Heringa, Hessels, and van der Zouwen 2016; Paier and Scherngell 2011). Yet, in competitive publicly funded R&D programmes, many partnerships' applications are rejected at the grant application stage, for reasons ranging from project quality to misalignment with policy priorities or evaluation criteria. For instance, after excluding ineligible and low quality submissions, the average success

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rate for applications to Horizon 2020, the European Union's (EU) flagship research and innovation funding programme, is 24% (McCarthy 2017). Despite the high volume of rejected applications, previous research has largely overlooked the corresponding partnerships (Bornmann, Leydesdorff, and Van den Besselaar 2010; Wanzenböck, Lata, and Ince 2020). Thus, little is known about the influence of failed applications on both organisations' collaborative behaviour and the whole R&D network.

On the one hand, joint experience of rejection could encourage organisations to re-engage as a way of recovering some of the costs associated with the original partner search and proposal development activities (Amoroso 2014; Takalo, Tanayama, and Toivanen 2013; Vlaar, van den Bosch, and Volberda 2006). On the other hand, rejection might also prompt a reassessment of partner suitability. If the application failure highlights a mismatch in partner expertise (incompatibility) or reputational considerations, this might trigger a search for new partners (Wanzenböck, Lata, and Ince 2020). Hence, it is unclear whether failed project applications end up reinforcing existing patterns of collaborative behaviour, similar to prior successful applications, or on the contrary: serve to reverse them. Relying on evidence from funded partnerships alone is likely to provide only a partial explanation for how publicly funded R&D network structures come into being.

Only a small number of empirical studies use samples that include approved and rejected projects, and all of them test for the effect of organisations' characteristics – size, reputation, network position – or overall consortia composition on the probability of grant award (Barajas and Huergo 2010; Enger 2018; Enger and Castellacci 2016; Wanzenböck, Lata, and Ince 2020). None of them explicitly explores how the outcome of the evaluation process (success vs failure) influences the network dynamics and subsequent partner selection. In the present study, we address this gap by investigating: (1) how prior experience of forming a partnership and jointly applying for funding – when the application is ultimately unsuccessful – influences tie formation; and (2) the effect of this experience for partners with different levels of cognitive proximity. The empirical analysis is based on a policy-induced collaborative network of approved and rejected R&D projects, in the Spanish region of Valencia, during the period 2016–2022.

The relevance of government funding for collaborative R&D is significant; it accounts for roughly one-third of total annual R&D expenditure in the EU (Eurostat 2023). It is also one of the primary mechanisms exploited by regional, national and supranational governments to steer innovation in a particular direction and foster unlikely partnerships (Larrue 2021). For instance, the EU uses its Framework Programme (FP) funding calls to encourage critical mass in areas that strengthen Europe's global competitiveness (Marques Santos, Molica, and Conte 2024). At the local level, tools, such as smart specialisation funding, allow regional governments to strategically re-wire innovation networks towards priorities that match local strengths and development goals (Foray, David, and Hall 2009). Given the emphasis on directionality, understanding how the allocation of competitive government funding shapes innovation networks requires closer scrutiny.

The paper makes three contributions. First, conceptually, it challenges existing assumptions about the types of prior interaction that promote continued engagement. While the literature emphasises the reinforcing role of past successful joint applications, we show that rejections can be potentially more influential in driving network evolution. Drawing on the proximity framework, this paper adds to prior work by demonstrating that social proximity may be rooted in past failure and that, although cognitive distance has been shown to deter initial tie formation, it can enhance the likelihood of continued collaboration following a rejection. Second, empirically, this study reveals the limitations of using data exclusively from funded partnerships to explain R&D network formation. Omitting information on failed project applications risks some proportion of newly formed ties being attributed to chance, when they could in fact be driven by unobserved past failures. Third, from a policy perspective, the paper offers original evidence on the broad effects of public instruments targeting R&D collaboration, including the emergence of informal links between partners in an unsuccessful application. It could also be useful for policymakers to know how actors decide to readjust their partner selection process in response to funding rejection in competitive R&D calls.

The paper is structured as follows. Section 2 examines the possible mechanisms underlying the relationship between partnerships' prior experience of failure and future tie formation by drawing on transaction cost theory and the literature on interorganisational alliance formation. Section 3 describes the data and the methodology, highlighting some context-specific features of the Valencian region and its publicly funded

R&D system. It also provides details of the variables and estimation methods used in the analysis. Results are presented in Section 4, while Section 5 offers a summary of the main findings along with potential directions for future research.

2. Theoretical framework

2.1. The impact of failed project applications on partners' future re-engagement

In organisational networks, prior collaboration between a pair of actors can be a strong driver of tie formation (Gulati and Gargiulo 1999; Walker, Kogut, and Shan 1997). This is especially relevant in a regional context, where the actors are likely to know each other and to have had previous interactions. Scholars attribute this phenomenon to social proximity. According to Boschma's original definition (Boschma 2005, 66), 'relations between actors are socially embedded when they involve trust based on friendship, kinship, and experience'. In other words, if two organisations have had a shared experience in the past, they are more likely to engage in a future collaboration as opposed to two organisations that have never interacted with each other before. Repeated engagements, in the form of past partnership or R&D collaboration, result in stronger network ties (Granovetter 1973) and promote knowledge-based trust and resource sharing between the participating entities (Bstieler, Hemmert, and Barczak 2017; Gulati 1995; Santoro and Saparito 2003; Zaheer, McEvily, and Perrone 1998). Repeated interactions can also provide a certain level of predictability that reduces the perceived risk of conflict (Usai, Marrocu, and Paci 2017; Uzzi 1996). Evidence on the impact of social embeddedness for tie formation has been detected in EU's FP networks (Autant-Bernard et al. 2007; Paier and Scherngell 2011), as well as national and regional R&D networks (Caloffi, Rossi, and Russo 2015; D'Este, Guy, and Iammarino 2013; Heringa, Hessels, and van der Zouwen 2016).

While the effect of prior funded partnerships on the evolution of government sponsored R&D networks has been studied extensively, much less is known about partnerships whose funding application is unsuccessful. Yet, it is reasonable to assume that such cases – where partners are unable to enter formal project execution due to funding rejection – are relatively common in competitive R&D programmes. Understanding their experience can significantly advance our knowledge of network construction and evolution. Based on the nature and depth of interactions involved, partners' experience of jointly developing a proposal that is ultimately rejected differs in important ways from that of a successful funding application. In the case of success, organisations will generally transition into project execution, where the extended engagement involved allows each of the partners to better assess the other's credibility, reliability and knowledge base. By contrast, when a proposal is rejected, actors are left with a more limited set of interactions, although those are far from insignificant. The preparation of a joint competitive proposal is both demanding and time-consuming (Hünermund, Lopes Bento, and Pellens 2022), and involves its own set of costs. Distinguishing between the two types of experiences is important, because it underscores that our knowledge on the impact of funded partnerships on tie formation cannot automatically be applied to unsuccessful ones. The latter merit closer examination precisely because the dynamics of interaction and their potential influence on future collaborative behaviour are distinct.

In this section, we examine the potential influence of rejection on partners' future collaborative behaviour. We draw on two streams of literature – transaction cost theory and the formation of interorganisational alliances – to distinguish how joint experience of failure is associated with the formation of partner ties in R&D networks and whether it reinforces or weakens existing patterns of interorganisational coupling.

From a transaction cost theory perspective, the organisational structures needed to set up an R&D alliance are costly (Amoroso 2014). During the application stage, organisations face costs related to partner search and selection. They include identification of potential collaborators and assessment of their qualities and intentions, to avoid the occurrence of subsequent conflicts stemming from cultural, organisational or strategic resources misfits (Vlaar, van den Bosch, and Volberda 2006). This selection process is influenced by multiple factors, including trust, commitment, complementarity and potential value or financial payoff (Shah and Swaminathan 2008). Effective evaluation of these aspects requires administrative coordination and consumes both time and effort. At the same time, the decisions could be highly consequential. Cummings and Holmberg (2012) note that partner selection is a critical aspect of successful alliance development and that even superior alliance management may not be sufficient to overcome poor initial partner screening and selection. If a project application is rejected, the organisations involved may try to recover some of these search and selection costs by re-submitting their proposal to a later open call. In this case, the joint experience of failure will serve as a driver of subsequent tie formation. Evidence on the capacity to capitalise on the initial investment is provided in studies that find a positive correlation between past partnership experience and lower application costs (Takalo, Tanayama, and Toivanen 2013). Also, in research on the participation of Spanish firms in FP R&D consortia, Barajas and Huergo (2010) found that prior experience in preparing a project proposal increased the probability of applying to the next call and, more importantly, that this effect was greater if the previous proposal had been rejected, providing evidence of cost-optimisation strategies among applicants.

The second mechanism that might push 'unsuccessful' partners to re-engage is the level of social proximity developed in the project application stage. To highlight the types of interaction that occur prior to project execution, we rely on the literature on R&D alliance formation, which most closely mirrors the process of crafting a joint project proposal. By its nature, the project application stage implies the construction of what Todeva, Knoke, and Chaharbaghi (2005, 133) call 'a well-documented consensus'. Far from a mere administrative task, this process requires negotiation between the partners to reach agreement on shared goals, task distribution and resource commitments (human, financial and other). These are neither trivial nor straightforward aspects. For instance, agreeing on a specific project idea involves both ideation (generation and elaboration of a project idea) and prioritisation (assessment of its merits against possible alternatives), which are crucial for the formulation of a novel proposal (Perry-Smith and Mannucci 2015). Reaching a consensus might be complicated by the heterogeneity of organisations involved. Different partners will inevitably bring their own perspective and expectations which could be challenging to reconcile (Barnes, Pashby, and Gibbons 2002; Inkpen and Tsang 2005). This is an especially relevant factor if the actors operate in distinct sectoral and institutional settings. Some level of alignment between norms, policies and strategies is required to overcome divergent orientations (public vs. private entities) and knowledge appropriation (Al-Tabbaa and Ankrah 2016; Ankrah et al. 2013; Bruneel, D'Este, and Salter 2010; Muscio and Vallanti 2014). It is because of those interactions, conducted within the tight constraints of a competitive public call, that we anticipate the emergence of social proximity between the partners, which is rooted in the shared effort of building a collective vision and formulating a project proposal. This joint effort might also lead project members to remain committed to a shared idea that they find original, relevant and feasible. Abandoning the relationship following funding rejection, implies forfeiting both the time and effort invested in developing the partnership and the resources devoted to drafting the proposal itself, especially if the latter is challenging or even impractical to pursue with a different set of partners.

At the same time, there is evidence to suggest that organisations do learn from their experience and use the feedback from the funding agency to refine their application strategy in order to increase the likelihood of application success in future rounds (European Commission Directorate-General for Research and Innovation 2017). Hence, we cannot assume that they will automatically approach prior partners, especially if the rejection underscores perceived misalignment of partners' expertise (incompatibility) or reputational considerations. Effective partnerships typically involve a balance among complementary resources and expertise. If the rejection feedback highlights weaknesses in the proposal's value and/or quality, organisations might conclude that their current partner does not offer the required complementarities. This is likely to trigger a search for new partners that can increase the chances of a future winning proposal (Nielsen 2003; Wu and Cavusgil 2009). Reputation has also been shown to matter; one of the few studies that directly examines competitive R&D project applications is by Wanzenböck, Lata, and Ince (2020, 1137), who argue that 'consortium-specific factors have a significant influence on the chances of success of collaborative project applications.' They show empirically that, in the context of EU FPs, reputation is positively associated with funding allocation. This means that organisations involved in an unsuccessful application will search for partners with a proven track record of securing funding, in order to increase their chances of success in future calls.

Yet, despite the potential for partner readjustment following rejection, we posit that the desire to recover the cost of searching for suitable partners, establishing a collaborative relationship and drafting a joint proposal is more likely to influence the organisations' collaborative choices. We therefore hypothesise that:

H1: Prior joint participation in an unsuccessful project application is positively associated with partners' future re-engagement.

2.2. The moderating effect of cognitive proximity

The literature on R&D networks emphasises the influence of cognitive proximity for the frictionless formation of interorganisational alliances. From a network perspective, cognitive proximity has been shown to positively impact tie formation (Broekel and Boschma 2012; Cantner and Meder 2007; Simensen and Abbasiharofteh 2022; Werker, Korzinov, and Cunningham 2019), supported by management and innovation research, which proposes a conceptual rationale for this relationship. Organisations need sufficient absorptive capacity to benefit from their interactions (i.e. to identify, interpret and exploit the partner's knowledge) (Cohen and Levinthal 1990; Nooteboom 2000). Some level of cognitive proximity is therefore required for organisations to develop mutual understanding and tap into the value of their partner's knowledge.

More than facilitating knowledge absorption, the cognitive proximity between firms from the same industry, helps in the identification and assessment of potential alliance partners, which reduces the partner search and selection costs. Strategy and management research argues that the ability of the firm to evaluate a partner's resources and capabilities depends precisely on its experience in the partner's domain (Reuer and Lahiri 2014; Vanhaverbeke, Duysters, and Noorderhaven 2002). Therefore, belonging to the same sector could be advantageous in terms of reducing information asymmetries and the risks of adverse selection. At the same time, cognitive distance can be viewed as an asset in terms of combining distinct knowledge bases. Empirical studies show that collaboration between dissimilar partners who contribute diverse competencies, is also associated with higher output, both in terms of publications (Werker, Korzinov, and Cunningham 2019) and number of explorative patents (Gilsing et al. 2008).

The key argument here is that as cognitive distance increases, then, up to a certain threshold, so do the opportunities for learning and novel recombinations. Beyond that threshold, cognitive distance will preclude mutual understanding and the ability to exploit these opportunities (Nooteboom et al. 2007; Wuyts et al. 2005). In sum, organisations might struggle to forge partnerships with cognitively distant partners and will generally avoid it; however, once a link has been established, the potential benefit of the relationship, in terms of innovative output, is likely to be significant (Werker, Korzinov, and Cunningham 2019).

Given the difficulties associated with setting up a formal R&D collaboration involving cognitively distant partners, it is reasonable to assume that organisations that have already 'paid' the hidden operational costs of establishing a (cognitively) diverse consortium, will be *particularly* motivated to capitalise on their initial investment following rejection of the original project application. In addition, the high reward associated with the presence of cognitively heterogeneous team members is likely to act as a further incentive to maintain the relationship and jointly re-apply to a subsequent open call. Based on the above discussion, it follows that the cognitive distance between partners will strengthen the positive relationship between joint experience in project application failure and future tie formation. We therefore hypothesise that:

H2: The cognitive distance between partners strengthens the positive relationship between prior joint participation in a failed R&D project application and future re-engagement.

3. Data and methodology

3.1. Regional context

Our empirical analysis is based on a series of policy initiatives aimed at stimulating R&D cooperation in the Spanish region of Valencia. The policies were framed as part of the regional smart specialisation strategy (RIS3-CV),[1] and were financed by a mix of local and European Regional Development funding. Their main objective is to support interaction between different actors in the Valencian innovation ecosystem, as a way

[1]Smart specialisation is one of the pillars of European Cohesion Policy. It encourages regions to undertake bottom-up exploration of their local technological and scientific assets and translate them into future competitive advantage (Foray, David, and Hall 2009). Following this framework, the RIS3-CV strategy defines several priority areas, which provide a roadmap for the design of public R&D policies and actions in the region. The total budget allocated in the strategy for the 2014–2023 period exceeded €1.6 bn, making it one of the most important public policy instruments for stimulating regional research and innovation (Generalitat-Valenciana 2019).

of developing joint solutions to common problems. The 2022 EU Regional Innovation Scoreboard classifies Valencia as a moderate innovator. It is characterised by a highly fragmented business fabric, with a predominance of micro and small enterprises, which are only weakly connected to the regional network of universities and research centres. These features make the Valencian case comparable to many regions in south and east Europe (Caloffi, Rossi, and Russo 2015; Silva, Silva, and Carneiro 2017).

The set of policy measures was managed by two independent entities: the Valencian Institute for Business Competitiveness (IVACE[2]) and the Valencian Innovation Agency (AVI[3]). IVACE was established in 1984 to increase the competitiveness and overall innovation capacity of regional Small and Medium Sized Enterprises (SMEs). AVI was created in 2018, specifically to manage Valencia's innovation strategy and enhance the regional production model. Within the smart specialisation framework, these two organisations operate in parallel to promote the generation, exchange and exploitation of new knowledge in the Valencian region. Together, they manage approximately 75% of all public funding designated for the implementation of the RIS3-CV strategy (Generalitat-Valenciana 2019).

Our sample consists of collaborative R&D projects (i.e. those with more than one partner or beneficiary), which applied for funding from one of the following three competitive programmes in the period 2016–2022: *R&D in cooperation* (managed by IVACE), *Strategic projects in cooperation* and *Consolidation of the business value chain* (both managed by AVI). While the programmes handled by each organisation have some differences in terms of eligibility criteria, both aim to enhance cooperation among regional actors and support the creation of new products, processes or services. The main features of these policy programmes are described below:

- *project typology*: all three programmes aim to support downstream R&D projects which deal with (1) industrial research and design or (2) experimental development;
- *participants*: all three programmes target local innovation actors registered in the region of Valencia;
- *eligibility criteria*: *R&D in cooperation* is open only to private companies with mandatory involvement of at least one SME; the two programmes managed by AVI are open to all types of organisations (firms, universities, research centres, hospitals, non-profits, etc.), with mandatory involvement of a public research organisation, but no requirement for it to be listed as a consortium partner (subcontracting is also permitted);
- *co-financing requirements*: all three programmes require a minimum 15% co-financing from all consortium partners;
- *funding*: the eligible project budget for *R&D in cooperation* is between €80,000 and €500,000, while for AVI programmes the eligible project budget is minimum €500,000;
- *project duration*: 1-2 years for IVACE, and 1-3 years for AVI;
- *evaluation criteria*: all three programmes have overlapping evaluation criteria based on: (i) proposal quality; (ii) consortium technical and financial capacity to implement the project; (iii) team complementarity; (iv) expected project impact and alignment with the regional RIS3-CV, social and environmental goals.

Figure 1 depicts the distribution of project applications by year. It shows that, during 2016 and 2017, public funding for collaborative R&D projects under the RIS3-CV strategy was managed mostly by IVACE, but the creation of AVI in 2018 opened new lines of financial support for cooperation among regional actors. Approval rates do not fluctuate significantly between years.

3.2. Data collection and sample overview

Information on approved and rejected R&D applications was obtained from public records published on the AVI and IVACE websites, with any missing data points requested directly from the respective agencies. The final sample includes 444 collaborative R&D project applications. Roughly half (50.7%) were awarded public

[2]IVACE webpage: https://www.ivace.es/index.php/es/.
[3]AVI webpage: https://innoavi.es/en/.

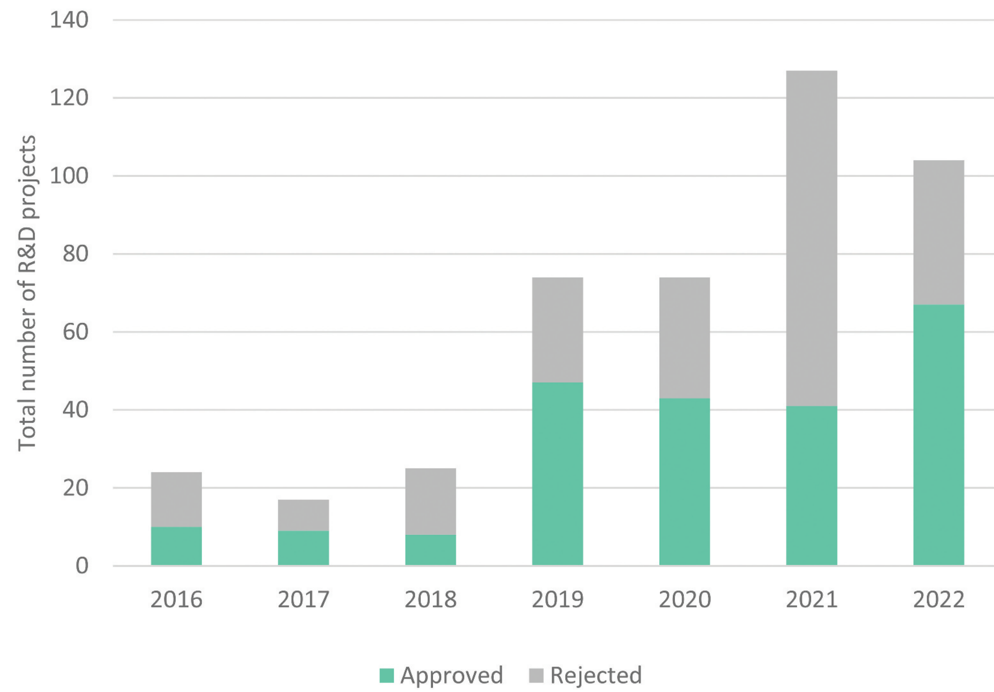

Figure 1. Distribution of approved and rejected R&D project applications per year.

funding, while the rest were rejected. Project team size varies between 2 and 9 partners, with an average of 3 organisations per team (see Table 1).

During the seven years of observation, a total of 554 regional organisations applied to one of the three programmes as part of a team. As in many innovation-focused collaborative networks, 90% of those applicants were private for-profits. Using the SABI database[4], we matched companies using their unique identifiers and retrieved information on their age, size and economic activity. We analysed the characteristics of these companies in more detail to better understand their profiles.

Among programme participants, 36% are microenterprises with a turnover below €2 m and 67% have 50 or fewer employees, which tends to be representative of the Valencian context. It implies, also, that smaller regional players, which generally lack the resources required to compete in international excellence programmes (i.e. Horizon 2020), are quite active in the local R&D network. The average age of the 498 enterprises is 24 years, with a median of 19. The youngest firm had been established for only 1 year when it applied for funding, while others had been in business for more than 100 years. Hence, overall, the sample contains an even mix of young start-up-like enterprises and older well-established firms.

3.3. Variables and models

Given the nature of our hypotheses, we model selection of R&D partners as a function of prior application experience and control for other common drivers of tie formation. Since the number of project applications is uneven across the seven years of observation (see Figure 1) and AVI was established only in 2018, we grouped the data into two time periods: 2016–2020 (t) and 2021–2022 (t + 1). This allows us to examine the structural properties of the regional knowledge network during the second period in light of prior engagement in the first period and ensures, also, that we have a balanced mix of R&D partnerships from both public funding agencies. Furthermore, the event we study is highly infrequent, which means that observing every potential dyad on an annual basis would significantly increase the share of zeros, making it harder to discriminate between the tie vs no tie formation scenario (Diestre and Rajagopalan 2012).

[4]SABI (Iberian Balance Sheet Analysis System) is a database that contains financial information for more than 2.6 m companies in Spain and Portugal.

Table 1. Project descriptive statistics and participants' profile.

Total number of project applications	444
Share of approved applications	50.7 %
Min number of partners per project application	2
Average number of partners per project application	3
Max number of partners per project application	9
Total number of organisations	**554**
Private for-profits[a]	498
Micro enterprise	*178*
Small enterprise	*151*
Medium-sized enterprise	*98*
Large enterprise	*71*
Associations	12
Technology institutes[b]	11
Cooperatives	9
Universities	7
Research institutes	7
Health research institutes	7
Others	3

[a]Based on EU recommendation 2003/361: Micro enterprises: ≤ €2 m turnover; Small enterprises: €2 m - €10 m turnover; Medium-sized enterprises: €10 m - €50 m turnover; Large enterprises: ≥ €50 m turnover.

[b]The 11 technology institutes in Valencia were established with support from regional business associations and the government between the 1970s and the 1990s as focal points of innovation. They are private research non-profit entities, whose objective is to support regional SMEs in advancing their capacities and innovative activity.

Our unit of analysis is the dyad. We constructed a list of all possible partnership constellations involving the 554 organisations in our 7-year time window, which amounted to $N = n*(n\text{-}1)/2 = 153{,}181$ dyads. In line with other studies, we assume dyads to be at equal risk (*a priori*) of submitting a joint application (Diestre and Rajagopalan 2012; Rothaermel and Boeker 2008), and assume that all organisations were active over the whole period and, therefore, susceptible to forming a partnership. We treat the links between nodes as bilateral (i.e. A-B is identical to B-A). In this empirical set-up, partnership, whether successful or unsuccessful, is a rare event.

Our primary dependent variable *Partner* is a binary one that takes the value 1 if the two organisations in the dyad applied for collaborative R&D funding together, as part of the same team in period t + 1 (regardless of the application's status – success vs failure) and 0 otherwise. Considering both funded and unfunded projects allows us to capture the organisations' partner selection behaviour rather than the selection behaviour of the funding body.

Our primary independent variable *FailedExp*, is dichotomous and is equal to 1 if the two entities in the dyad had joint experience only of failed project applications during period t. We added a second dichotomous variable *SuccessExp* which is equal to 1 if the two entities had joint experience only of successful project applications during period t. Since some of the dyads in the sample have experience of both success and failure, we included the variable *MixedExp* which is equal to 1 if the two organisations have had both successful and unsuccessful applications at time t. For comparison, we calculated a fourth variable *CollabExp,* which reflects the current standard in empirical studies for operationalising past experience. *CollabExp* takes the value 1 if the two organisations in the dyad had *at least* 1 funded project in period t, that is, at least 1 prior collaboration, and 0 otherwise. This means that *CollabExp* is 'blind' to the presence of mixed or failed application experience.

We constructed several control variables to ensure the robustness of the empirical analysis. First, we account for the geographical distance between organisations in the dyad using the variable *GeoDist*. There is now substantial empirical evidence showing that, on average, organisations located closer to one another are more likely to collaborate (Howells 2002; Katz 1994; Ponds, van Oort, and Frenken 2007). *GeoDist* is a continuous variable and measures the straight-line distance (in km) between the registered addresses of the entities in the pair.

Second, we control for differences in project-related experience between the two organisations. In the context of competitive publicly subsidised R&D programmes, the knowledge and management capabilities accumulated from participating in open calls and preparing grant applications – whether successful or not –

are widely regarded as an important non-transferrable organisation-specific asset (Cantner and Meder 2007; Paier and Scherngell 2011). To measure the difference in project-related experience (*ExpDiff*), we calculated the cumulative sum of past applications (successful and unsuccessful) for each of the two nodes in period t. Using the sum for each node, we computed the arithmetic difference between the two values. Hence, *ExpDiff* is a continuous variable that captures the difference in the number of past applications between the two organisations. Higher *ExpDiff* values indicate greater disparities in the partners' experience levels, which suggests a more disassortative tie.

Third, we control for transitivity (or triadic closure), which denotes a particular phenomenon in social networks, whereby two unconnected nodes with a mutual acquaintance tend to establish a link with one another (Ter Wal 2014). Having a third-party reference seems to reduce uncertainty and asymmetric information, while also deterring future partners from exhibiting opportunistic behaviour (Balland, Belso-Martínez, and Morrison 2016; Uzzi 1996). Since triadic closure seems particularly relevant in a regional context, where the reputational consequences of violating established norms are greater (Gulati 1995), we added the variable *TC,* which is equal to 1 if the two nodes in the dyad are connected by a third party in period t through a partnership in a successful or unsuccessful project application and is 0 otherwise.

Fourth, we control for the size of the firms in the dyad. Large companies generally have more resources to invest in and maintain multiple R&D collaborations simultaneously and they have an incentive to enter alliances to maximise spillovers and indirectly monitor the innovative activity in their field (Hernán, Marín, and Siotis 2003). The dummy variable *LargeFirm* is equal to 1 if at least one of the organisations in the dyad is considered a large enterprise, based on annual turnover.

Fifth, since our focus is on public open calls, we control for specific programme requirements that might result in a disproportionately higher number of particular pairs, such as firm-firm, research centre-firm, or others. Our dichotomised control variable *PRO* is equal to 1 if at least one of the two entities is a university, (health) research institute or technology institute.

Our first model takes the following form:

$$Partner_{t+1} = FailedExp_t + SuccessExp_t + MixedExp_t + ExpDiff_t + TC_t + GeoDist + LargeFirm + PRO$$

As a second step, we examine the moderating effect of cognitive proximity on the relationship between joint experience of failed project application and tie formation. This requires the sample to be limited to dyads that include only private for-profits (approximately 81% of the original sample or n = 498), since the EU NACE classification system provides information on their economic activity[5] This reduces the sample of dyads to N = n*(*n*-1)/2 = 123,753. We added a dummy variable for *CogDist*, which reflects the sectoral heterogeneity between pairs of firms, based on their NACE codes. A value of 1 indicates belonging to two different two-digit NACE Rev. 2 sectors. Using degree of sectoral overlap to proxy for cognitive proximity is common in the literature (Balland, Belso-Martínez, and Morrison 2016) and is consistent with the literature on related variety (Frenken, Van Oort, and Verburg 2007) and the assumption that firms operating in similar sectors likely have similar knowledge bases.

Since we have information on firm age, we can introduce an additional control variable. By virtue of their accumulated industrial experience, mature companies may enjoy a certain status in their surroundings (Balland, Belso-Martínez, and Morrison 2016), prompting other companies to gravitate towards them for the formation of R&D partnerships. Also, in line with the resource-based view, mature companies are likely to favour partnerships with young start-up-like enterprises that provide complementary capabilities and missing or deficient internal knowledge (Ahuja 2000). We capture this effect by including the continuous variable *AgeDiff,* which measures the difference in the two firms' industrial experience, proxied by their years in operation. We generally expect higher values of *AgeDiff* to signal an asymmetric partnership involving a startup and a mature company.

In this second stage, we omit the *PRO* variable since it no longer applies. All observations in the second model are firm-firm dyads.

$$\begin{aligned} Partner_{t+1} = {} & FailedExp_t + (FailedExp_t)*(CogDist) + CogDist + SuccessExp_t + MixedExp_t + ExpDiff_t \\ & + TC_t + AgeDiff + GeoDist + LargeFirm \end{aligned}$$

[5]NACE, Nomenclature of Economic Activities, designates the integrated classification system for products and economic activities in the EU..

Table 2. Descriptive statistics for the full set of variables.

Variable	Description	Obs.	Min	Max	Mean	Share of 0s
Dependent variable						
Partner	Dummy variable that takes the value 1 if the two organisations applied for funding together in period t + 1.	153,181	0	1	0.006	99.0%
Explanatory variables						
FailedExp	Dummy variable that takes the value 1 if the two organisations have *only* unsuccessful joint project applications in period t.	153,181	0	1	0.002	99.4%
SuccessExp	Dummy variable that takes the value 1 if the two organisations have *only* successful joint project applications in period t.	153,181	0	1	0.001	99.5%
MixedExp	Dummy variable that takes the value 1 if the two organisations have both successful and unsuccessful joint project applications in period t.	153,181	0	1	0.0001	99.98%
CollabExp	Dummy variable that takes the value 1 if the two organisations have *at least* one joint successful application in period t.	153,181	0	1	0.001	99.9%
Moderator						
CogDist	Dummy variable that takes the value 1 if the two organisations operate in different two-digit NACE sectors.	123,753	0	1	0.953	4.71%
Controls						
GeoDist	Continuous variable reflecting the straight-line geographical distance (in km) between the two organisations.	153,181	0	272	64.601	0.001%
ExpDiff	Continuous variable reflecting the difference in experience between the two organisations in period t. It is equal to the difference in the total numbers of applications (successful and unsuccessful) filed by each of the two entities.	153,181	0	28	1.391	34.5%
AgeDiff	Continuous variable that reflects the difference in 'industrial status' between the two firms proxied by their years in operation.	123,753	0	141	18.64	2.1%
TC (Triadic Closure)	Dummy variable that takes the value 1 if the two organisations have a partner in common in period t.	153,181	0	1	0.020	98.0%
LargeFirm	Dummy variable that is equal to 1 if at least one of the organisations in the dyad is classified as a 'Large enterprise'.	153,181	0	1	0.240	75.7%
PRO	Dummy variable that takes the value 1 if at least one of the two entities is a university, (health) research institute or technology institute.	153,181	0	1	0.074	92.2%

Table 2 presents an overview of all the variables included in the two stages of the analysis. As expected, the share of zero values among the dependent and independent variables is relatively high. Note also that roughly 95% of firm-firm dyads are cognitively distant. The maximum geographical distance between a pair of entities is 272 km, while the biggest difference in terms of number of applications between two organisations is 28.

Since the dependent variable (*Partner*) is a binary variable and has a high proportion (99%) of zero values, we adopt a rare-event logit estimation model. Specifically, we use a penalised likelihood method called Firth or FL-type logistic regression, which can be implemented in R using the logistf package.

4. Results and discussion

In this section we present the results of the logistic regression model using Firth's bias reduction method, which was used to assess the influence of different types of prior engagement on the probability of tie formation, based on the full sample of observations (Model 1). In a stepwise approach, we first introduce the baseline Model 1.0, which includes only the controls and excludes any information on prior experience. Model 1.1 adds prior collaborative experience (*CollabExp)* – a variable that ignores any information on rejected applications and reflects what most empirical studies that rely exclusively on funded projects would encompass. Model 1.2 incorporates our primary variable of interest, *FailedExp,* and Model 1.3 includes all three possible prior engagement scenarios - *FailedExp, SuccessExp* and *MixedExp*.

Table 3 presents the correlation matrix. As expected, *CollabExp* and *SuccessExp* are strongly correlated, since *CollabExp* is composed of both *SuccessExp* and *MixedExp. Partner* shows a positive correlation with all measures of prior engagement, and, as anticipated, a negative correlation with geographical distance (*GeoDist*).

First, we comment on the results of our baseline model (Model 1.0) (see Table 4), which indicate that, with the exception of triadic closure *TC*, which is significant at the 10% level, all control variables are statistically significant at 0.1%. *GeoDist* has an expected negative coefficient, which means that actors located at a greater distance from one another, are less likely to enter into an alliance together, whereas

Table 3. Variables correlation matrix (full sample).

Parameter	CollabExp	SuccessExp	FailedExp	MixedExp	GeoDist	ExpDiff	TC	PRO	LargeFirm
Partner	**0.055**	**0.040**	**0.179**	**0.056**	**−0.038**	**0.207**	**0.035**	**0.119**	0.002
CollabExp		**0.953**	−0.002	**0.304**	**−0.021**	**0.065**	−0.005	**0.024**	**0.012**
SuccessExp			−0.002	0.000	**-0.019**	**0.058**	−0.005	**0.017**	**0.011**
FailedExp				−0.001	**−0.027**	**0.089**	−0.006	**0.060**	**−0.016**
MixedExp					**−0.009**	**0.032**	−0.002	**0.024**	0.003
GeoDist						**−0.060**	**−0.057**	**−0.049**	**−0.012**
ExpDiff							**0.127**	**0.361**	−0.004
TC								**0.125**	−0.001
PRO									**−0.073**

Values in bold are statistically significant ($p < 0.01$).

Table 4. Firth's bias reduction logit regression results for assessing the probability of R&D alliance formation in the full sample.

	Dependent variable: *Partner*			
	(Model 1.0)	(Model 1.1)	(Model 1.2)	(Model 1.3)
CollabExp		1.689***		
		(0.256)		
FailedExp			3.411***	3.446***
			(0.160)	(0.160)
SuccessExp				1.619***
				(0.288)
MixedExp				3.037***
				(0.562)
GeoDist	−0.008***	−0.008***	−0.008***	−0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
ExpDiff	0.127***	0.125***	0.123***	0.121***
	(0.004)	(0.004)	(0.004)	(0.004)
TC	0.244	0.286*	0.422**	0.473***
	(0.131)	(0.131)	(0.131)	(0.131)
PRO	1.475***	1.468***	1.398***	1.381***
	(0.084)	(0.084)	(0.085)	(0.086)
LargeFirm	0.342***	0.330***	0.414***	0.401***
	(0.079)	(0.079)	(0.080)	(0.080)
Constant	−5.472***	−5.480***	−5.579***	−5.590***
	(0.064)	(0.064)	(0.066)	(0.066)
Observations	153,181	153,181	153,181	153,181
Log likelihood	−4747.294	−4728.886	−4578.512	−4553.700
Pseudo R^2	0.181	0.184	0.210	0.214

Robust standard errors are in brackets. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

actors with asymmetric experience of project application, measured by the control variable *ExpDiff,* are more likely to do so. Triadic closure *TC* emerged as a weak predictor of future tie formation, whereas the presence of a public research organisation or a large company in the dyad strongly predicts future tie formation. Table 4 Model 1.1 demonstrates that, consistent with prior studies, the existence of at least one collaboration between two organisations in the past, increases the probability of their entering into an alliance at time t + 1. Exponentiating the estimated log-odds coefficient of *CollabExp*, we can calculate that the presence of at least one prior collaboration between two partners results in a roughly five-fold increase in the odds of their re-engaging at t + 1. As already mentioned, this ignores the potential presence of a rejected application from the partners.

In Model 1.2, the coefficient of our primary variable of interest *FailedExp* is positive and significant. This suggests that prior rejection in a joint application, much like prior success, increases the probability of future tie formation. However, the magnitude of the latter effect is considerably larger with an odds-ratio increase of 30 times. Finally, in Model 1.3, if we control for all possible prior engagement scenarios, the experience of an unsuccessful project application seems to exert a positive influence on future tie formation, and a stronger one than that of a prior successful project application. Using the odds ratio, we can say that if two organisations have experienced only success, the odds of their re-engaging at time t + 1 increase approximately five-fold. If they have only experienced rejection, their odds of re-engaging increase roughly 31 times. The difference between the estimated coefficients of *SuccessExp* and *FailedExp* is statistically significant (based on a Wald test, p-value = 1.8e-8). This provides strong support for our first hypothesis (H1).

Model 3.1 further shows that if we split the variable *CollabExp* into its primary components of *SuccessExp* and *MixedExp,* the estimated coefficient of *MixedExp* is larger than the coefficient of *SuccessExp* and the difference is statistically significant (based on a Wald test, p-value = 0.028). This implies that the effect detected in many empirical studies, which rely exclusively on funded projects, may have been boosted by unobserved failures accompanying successful applications.

Our findings have several implications. First, they provide strong evidence of the presence of cost optimisation strategies among cooperating organisations. As argued earlier, the identification of suitable R&D partners and the establishment of a working relationship carries considerable transaction costs, which would be lost or 'sunk' if the relationship were abandoned due to lack of funding. Naturally, partners will try to benefit from their initial investment by re-applying in subsequent open calls. In an earlier study comparing approved and rejected single-beneficiary projects, Barajas and Huergo (2010) provided evidence of this behaviour. They found that prior experience in FP proposals increased the probability of applying to the next programme and that the effect was stronger if the previous proposal had been rejected. Our results, however, build on and expand this argument: not only do organisations reapply when rejected, but they appear to do so with the same partners. This suggests that they are keen to recover not only the costs involved in formulating a competitive project proposal but also the search costs involved in finding appropriate partners, negotiating and consolidating a working relationship with them. In addition, re-applying with the same partner, following a rejection, provides opportunities for mutual learning and an improvement of strategic decision-making processes (Rhaiem and Amara 2021). Prior research suggests that organisational partners' social proximity favours effective capitalisation on the lessons learned from failure (Carmeli 2007).

Second, it seems that the experience of forming a partnership, even in the case of an unsuccessful project application, can increase the social proximity between partners. While extant literature has illustrated the organisational propensity to reinstate ties with former collaboration partners, our study suggests that this type of retention mechanism might be at play even when the two entities have had only unsuccessful applications. The organisations in our sample seemed to be more inclined to partner with firms with which they had enjoyed *some form* of shared experience – successful or not – as opposed to partnering with an organisation, with which they had no level of social proximity, at least, not in the case of the three competitive programmes analysed. Therefore, our study disputes assumptions about the types of prior interaction necessary to trigger further engagement and demonstrates empirically that the social proximity accumulated during a failed project application is a sufficient condition for renewed partnership.

Third, the strong influence of prior partnership in unsuccessful project applications signals that studies relying exclusively on financed R&D projects may be overlooking an important antecedent of tie formation in their analyses of interorganisational networks. We did not expect the well-documented effect of past collaborative experience to be outweighed by the effect of joint experience of a rejected application. We considered the possibility that re-application following a rejection may occur faster, since implementation of an R&D project is likely to take a few years. However, in our sample, average project duration was only two years and neither of the policy programmes examined explicitly prohibited funded actors from reapplying in the following year. We also conducted a robustness test, by applying a two-year time lag; this confirmed the strength of the coefficient of past failed applications. Hence, our results suggest that research on R&D network dynamics may be systematically underrating partnerships with unsuccessful project applications as a fundamental antecedent of tie formation.

Next, we move to the results of the second model, where we tested the moderating effect of cognitive proximity on the relationship between past failure and tie formation using a subsample of firm-firm dyads. For comparison, we estimated the interaction effect for partnerships with successful experience as well. Table 5 presents a summary of the results; Appendix Table A1 presents the correlations between the relevant variables.

In Model 2.0, once again *FailedExp* is associated positively with tie formation and the effect is greater than the effect for *SuccessExp* (based on a Wald test, p value = 9.11e-4). In all three models, the cognitive distance between firms is associated negatively to tie formation. Exponentiating the coefficient for *CogDist,* in Model 2.0 we find that the presence in the dyad of two cognitively distant firms decreases the odds of their

Table 5. Firth's bias reduction logit regression results for assessing the probability of R&D alliance formation in a subsample of firm-firm dyads.

	Dependent variable: *Partner*		
	(Model 2.0)	(Model 2.1)	(Model 2.2)
FailedExp	4.068***	1.946	4.059***
	(0.281)	(0.859)	(0.282)
CogDist	−1.260***	−1.431***	−1.299***
	(0.164)	(0.162)	(0.164)
(FailedExp) (CogDist)		2.730***	
		(0.904)	
(SuccessExp) (CogDist)			1.827
			(1.522)
SuccessExp	2.225***	2.187***	0.874***
	(0.490)	(0.492)	(1.442)
MixedExp	3.130	3.156	3.137
	(1.471)	(1.471)	(1.471)
GeoDist	−0.010***	−0.010***	−0.010***
	(0.001)	(0.001)	(0.001)
ExpDiff	0.001	−0.003	−0.001
	(0.050)	(0.050)	(0.050)
TC	−0.266	−0.280	−0.269
	(0.537)	(0.537)	(0.537)
LargeFirm	0.701***	0.706***	0.698***
	(0.124)	(0.124)	(0.124)
AgeDiff	0.005	0.005	0.005
	(0.003)	(0.003)	(0.003)
Constant	−4.760***	−4.615***	−4.722***
	(0.173)	(0.169)	(0.173)
Observations	123,753	123,753	123,753
Log likelihood	−1893.594	−1885.784	−1892.539
Pseudo R^2	0.076	0.080	0.076

Robust standard errors are in brackets. **p* < 0.05; ***p* < 0.01; ****p* <0.001.

re-engaging by roughly three times. However, the interaction term between prior experience in failed project applications and cognitive distance has a positive and significant coefficient. Prior successful experiences (*SuccessExp*) remain associated positively with the probability of further engagement. In the subsample of firm-firm pairs, the variable *MixedExp* is no longer a significant predictor of tie formation, and the observed standard errors are quite large, most likely because mixed experience is rare in our subsample. It should be noted, also, that two of the control variables (*ExpDiff* and *TC*) included in the previous models (1.0–1.3) seem to lose their significance in this set-up, while the control variable *AgeDiff* has little effect on the probability of tie formation.

The negative coefficient of *CogDist* is in line with the theory on transaction cost economics. Cognitive distance increases the cost of establishing an R&D partnership, since organisations have to overcome significant barriers to understanding and interpreting the knowledge, routines and practices of potential partners. As expected, organisations are generally unwilling to embark on partnerships that entail high cognitive distance. However, the positive coefficient of the interaction term in model 2.1 supports H2. Since interpretation of interaction effects is difficult in nonlinear models, including logistic regression (Hoetker 2007; Murphy and Aguinis 2022), we examine the effect graphically. Figure 2 displays the interaction at 90% confidence intervals. It appears that once two cognitively distant firms have invested in establishing a partnership, they are more likely than cognitively proximate firms, to try to benefit from their initial investment when faced with a rejected project proposal. The relationship, once established, proves to be particularly 'sticky'. Yet, this moderating effect of cognitive distance does not hold for prior successful experiences. In Model 2.2. the interaction coefficient is smaller and not statistically significant, suggesting that partnerships with successful applications between cognitively distant partners do not exhibit the same level of persistence as partnerships with unsuccessful applications. This might be because when funded partnerships between cognitively distant partners involve mutual learning or knowledge sharing, the cognitive distance between the respective partners gradually decreases. This depletes the potential for novelty and reduces the incentives to continue collaborating (Wuyts et al. 2005). In contrast, failed applications leave the potential for knowledge exchange unrealised. Having already incurred the costs,

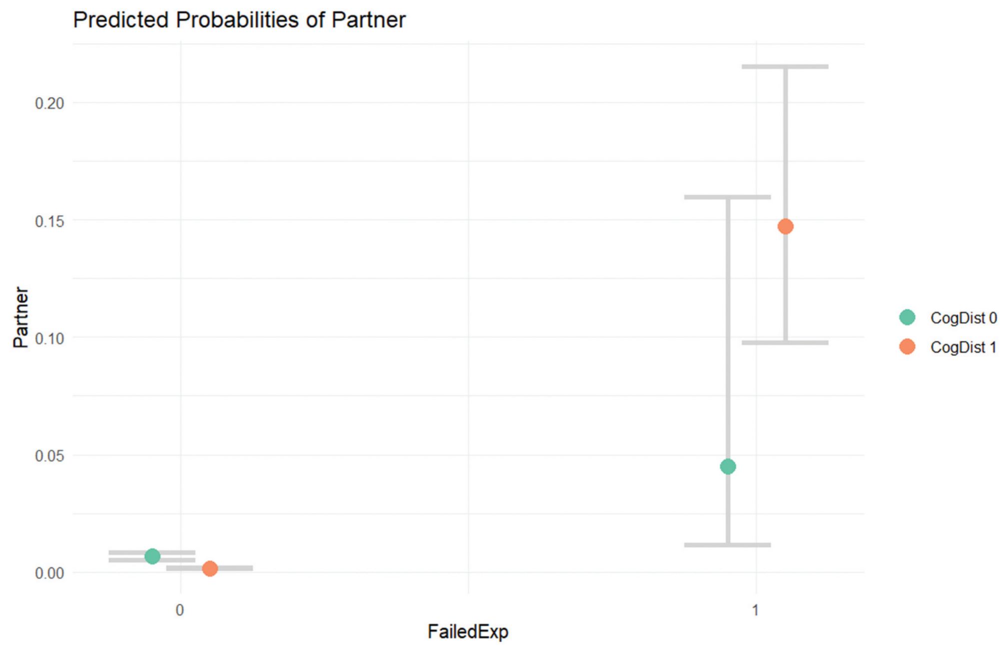

Figure 2. Moderation effect of cognitive distance on the relationship between joint experience in failed project applications and predicted tie formation (Partner) at 90% confidence interval.

but none of the benefits related to overcoming cognitive barriers, unsuccessful firms may be more inclined to persist in hopes of leveraging their initial investment.

The coefficients of *ExpDiff* and *TC* are not entirely surprising, given that the difference in collaborative experience is more relevant if the sample includes a wider variety of institutional partners (as corroborated by the correlation coefficient between *PRO* and *ExpDiff*, see Table 3). PROs, by virtue of their mission, human and technical resources, can afford to engage in multiple alliances at a time, as opposed to private companies which generally find it difficult to accrue such levels of collaborative experience. As for *AgeDiff*, we note that despite our initial expectations that startups and mature companies might gravitate towards each other in search of complementary assets, we find little evidence of disassortative behaviour among the firms in our subsample.

We conducted a range of sensitivity analyses and robustness checks to ensure the validity of our results. First, we ran Model 1 on a sample that excluded large firms and PROs, which occupy central positions in R&D networks and might disproportionately influence the results. As shown in Appendix Tables B1 and B2, results are mostly in line with those presented in Table 4, with the exception of the coefficient of *TC* which is no longer significant. This is likely because excluding the most central network actors eliminates many of the triads in the network. We then repeated the analysis by transforming the main explanatory variables (*FailedExp* and *SuccessExp*) from binary to count variables (*FailedCount* and *SuccessCount*). These count variables reflect the cumulative number of failed (non-funded) or successful (funded) project applications attributable to a pair of organisations in period t. We applied the transformation to Model 1 (the full sample) and Model 2 (the firm-firm subsample). The results in Appendix Table B3 remain consistent with our expectations. As a robustness check, we re-estimated Model 1 using standard logistic regression with clustered standard errors at the ego level (Appendix Table B4); the results are similar to those reported in Table 4. We also introduced a time lag to account for the possibility of a longer time before re-applications for funded compared to non-funded partnerships. Specifically, we split the data to leave a two-year gap between periods 1 and 2, to align with the average project duration in our sample. Appendix Table B5 shows that the influence of prior rejection on re-application remains positive and significant after a two-year-lag and the coefficient for prior success, though positive, is significant only at the 10% level. This suggests that the effect of failed applications is robust to a time-lag and does not 'fade out' when compared to successful applications. Nevertheless, timing does seem to influence the effect of prior success on future re-engagement.

5. Conclusion

This study aimed to investigate empirically how prior joint participation in an unsuccessful project application influences tie formation in the context of policy-supported R&D networks and how this effect varies for partners with different levels of cognitive proximity. We used a unique dataset that included both approved and rejected collaborative project applications, in the Spanish region of Valencia, in 2016–2022. Considering the prevalence of rejection in competitive R&D schemes, more work is needed to assess the impact of rejection on organisations' collaborative behaviour.

Our study contributes several insights. First, it adds to the existing literature on R&D network evolution by showing that failed experiences can be a source of social proximity between organisations. While former studies flagged the organisational propensity to repeat ties with prior collaborators from awarded projects, our paper demonstrates that this retention mechanism is triggered also by rejected grant applications. Thus, our work responds to calls for a more comprehensive portfolio view of interorganisational networking (Balland, Boschma, and Frenken 2022), by considering the full blend of possible interactions – successful, unsuccessful and mixed. It suggests that, generally, organisations are reluctant to abandon established research relationships that required significant search costs, even if funding was not granted for the execution of a joint project. Second, we show that the stickiness of this relationship between partners who experienced rejection is stronger when they are cognitively distant. Thus, we provide evidence of a dynamic and asymmetric relationship between cognitive and social proximity and show that social proximity can 'compensate' for cognitive distance if the proximity is based on prior joint experience of failure and the partners perceive untapped potential from persisting. When partners have already collaborated, the interplay between cognitive and social proximity becomes less predictable. This aligns with the work of Broekel and Bednarz (2018), who found that while cognitive proximity is a strong predictor of collaboration, its role in tie persistence is inconclusive. Our findings shed some light on this ambiguity by suggesting that the impact of cognitive distance on persistence may be conditional on the nature of the prior experience. Third, we found that, in the absence of information on failed project applications, researchers may struggle to disentangle the influence of prior collaboration, since some of the observed effect may be boosted by the presence of unobserved failures accompanying the successes. More research is needed to determine whether this holds true for different types of publicly funded R&D networks.

Finally, our findings should be useful for policymakers, as the introduction of competitive R&D schemes to stimulate collaboration between heterogeneous actors has become a key go-to instrument for many regional and national government (Nauwelaers et al., 2014). Our analysis of three regional programmes highlights the important role these tools play in generating a 'hidden' network of partners, whose experience of preparing a joint application, even if rejected, is strong motivation for further re-engagement. The observed propensity for cost optimisation implies that local actors will pursue alternative ways to finance their projects, either by re-applying to the same programme, seeking support from a different national or international R&D scheme or proceeding privately without external funding. In that sense, the social proximity generated by government-run programmes is hardly an 'expendable' asset that we can expect to disappear after a project application has been rejected. Rather, it persists as an unobserved factor driving the evolution of interorganisational relations over time. For government funding agencies, this means that the impact of their investments extends beyond the immediate and measurable outputs suggested by traditional policy assessment exercises. Moreover, when collaborative programmes are designed to steer innovation activities in a specific direction – such as, addressing societal challenges or advancing key technologies – the stickiness of partnerships with previously rejected project applications may amplify the desired outcomes by generating additional interactions aligned with policy goals. At the same time, our findings suggest that policymakers should exercise some caution when designing collaborative R&D programmes and take account of the documented strength of social proximity even in the cases of rejected applications. To avoid potential lock-in effects and ensure participation of new actors, funding agencies could adjust evaluation criteria to reward diversity and inclusivity, especially in repeat collaborations.

Our study has some limitations. First, it is focused on a single region, which may not fully capture the diversity of the R&D practices in other settings. Second, in modelling future tie formation, we rely exclusively on formal R&D project applications, even though in practice local actors may have experience with each other through other funding schemes. Third, we rely on open calls from two independent institutions, which have unique requirements that might influence the organisational composition of the respective projects. Although we have made every effort to control for these differences in the empirical model, they should be borne in mind when interpreting the results.

Future research could address these shortcomings by incorporating primary data into the analysis. This would involve supplementing the observed collaborative behaviour of regional actors with self-reported motivations for selecting one partner over another. In turn, this would require a survey or interviews with a sample of the regional actors and could provide valuable insights that would allow policymakers to better predict and manage the evolution of the regional knowledge network. Future research could also try to disentangle the reasons for application rejection and examine their individual moderating effects on the likelihood of future reengagement. Although we currently lack sufficient data to undertake this analysis, we believe that exploring these dynamics could provide a better understanding of organisational behaviour in the context of regional and national R&D networks.

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Data availability statement

The data that support the findings of this study are available from the corresponding author, DY, upon reasonable request.

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Appendix

Appendix A. Correlation matrix of variables

Table A1. Variables correlation matrix (firm-firm subsample).

Parameter	SuccessExp	FailedExp	MixedExp	CogDist	GeoDist	ExpDiff	TC	LargeFirm	AgeDiff
Partner	**0.019**	**0.093**	0.000	**−0.027**	**−0.023**	0.003	−0.001	**0.016**	0.006
SuccessExp		−0.001	0.000	**−0.015**	**−0.016**	**0.013**	−0.004	**0.012**	0.004
FailedExp			0.000	**−0.021**	**−0.018**	−0.001	−0.003	−0.008	−0.005
MixedExp				0.002	−0.003	0.007	−0.001	0.005	0.000
CogDist					**0.046**	0.002	**−0.016**	**0.040**	**0.056**
GeoDist						**−0.059**	**−0.050**	**−0.017**	**0.026**
ExpDiff							**0.033**	**0.103**	**0.051**
TC								**0.015**	**0.014**
LargeFirm									**0.204**

Note: Values in bold are statistically significant ($p < 0.01$).

Appendix B. Sensitivity analyses and robustness checks

Table B1. Firth's bias reduction logit regression results for assessing the probability of R&D alliance formation (subsample excluding large firms).

	Dependent variable: *Partner*			
	(Model 1.0)	(Model 1.1)	(Model 1.2)	(Model 1.3)
CollabExp		1.405***		
		(0.323)		
FailedExp			3.449***	3.477***
			(0.167)	(0.167)
SuccessExp				1.094*
				(0.392)
MixedExp				3.653***
				(0.641)
GeoDist	−0.008***	−0.008***	−0.007***	−0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
ExpDiff	0.123***	0.122***	0.119***	0.117***
	(0.005)	(0.005)	(0.005)	(0.005)
TC	0.179	0.209	0.395*	0.434**
	(0.150)	(0.150)	(0.151)	(0.151)
PRO	1.543***	1.537***	1.443***	1.424***
	(0.093)	(0.093)	(0.095)	(0.095)
Constant	−5.496***	−5.502***	−5.604***	−5.615***
	(0.070)	(0.070)	(0.072)	(0.072)
Observations	116,403	116,403	116,403	116,403
Log likelihood	−3527.159	−3518.502	−3366.749	−3349.749
Pseudo R^2	0.191	0.193	0.228	0.232

Robust standard errors are in brackets. *p <0.05; **p <0.01; ***p <0.001.

Table B2. Firth's bias reduction logit regression results for assessing the probability of R&D alliance formation (subsample excluding PROs).

	Dependent variable: *Partner*			
	(Model 1.0)	(Model 1.1)	(Model 1.2)	(Model 1.3)
CollabExp		1.845***		
		(0.372)		
FailedExp			3.882***	3.900***
			(0.220)	(0.219)
SuccessExp				1.870***
				(0.387)
MixedExp				3.882**
				(0.901)
GeoDist	−0.009***	−0.009***	−0.008***	−0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
ExpDiff	0.171***	0.168***	0.163***	0.159***
	(0.007)	(0.007)	(0.008)	(0.008)
TC	0.190	0.228	0.342	0.382
	(0.239)	(0.239)	(0.239)	(0.238)
LargeFirm	0.402***	0.388***	0.450***	0.436***
	(0.096)	(0.096)	(0.097)	(0.097)
Constant	−5.591***	−5.591***	−5.684***	−5.687***
	(0.078)	(0.078)	(0.080)	(0.080)
Observations	141,778	141,778	141,778	141,778
Log likelihood	−3114.675	−3105.980	−3025.933	−3015.426
Pseudo R^2	0.071	0.074	0.098	0.101

*Robust standard errors are in brackets. *p <0.05; **p <0.01; ***p <0.001.*

Table B3. Firth's bias reduction logit regression results for assessing the probability of R&D alliance formation: full sample & firm-firm subsample (using count-based explanatory variables instead of binary ones).

	Dependent variable: *Partner*						
	(Model 1.0)	(Model 1.1)	(Model 1.2)	(Model 1.3)	(Model 2.0)	(Model 2.1)	(Model 2.2)
FailedCount			2.492***	2.436***	3.564***	1.879***	3.544***
			(0.137)	(0.139)	(0.294)	(0.557)	(0.295)
SuccessCount		1.575***		1.235***	1.470***	1.369***	0.936
		(0.195)		(0.211)	(0.289)	(0.278)	(1.140)
CogDist					−1.288***	−1.431***	−1.309***
					(0.164)	(0.162)	(0.164)
(FailedExp)(CogDist)						2.388***	
						(0.631)	
(SuccessExp)(CogDist)							0.654***
							(1.181)
GeoDist	−0.008***	−0.008***	−0.008***	−0.007***	−0.010***	−0.010***	−0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ExpDiff	0.127***	0.125***	0.123***	0.121***	−0.006	−0.012	−0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.051)	(0.051)	(0.051)
TC	0.244	0.289*	0.418**	0.444**	−0.273	−0.282	−0.277
	(0.131)	(0.131)	(0.131)	(0.131)	(0.537)	(0.537)	(0.537)
LargeFirm	0.342***	0.324***	0.415***	0.398***	0.679***	0.681***	0.676***
	(0.079)	(0.079)	(0.080)	(0.080)	(0.125)	(0.125)	(0.125)
Constant	−5.472***	−5.484***	−5.570***	−5.575***	−4.718***	−4.598***	−4.696***
	(0.064)	(0.064)	(0.066)	(0.066)	(0.172)	(0.169)	(0.173)
Observations	153,181	153,181	153,181	153,181	123,753	123,753	123,753
Log likelihood	−4747.2	−4717.2	−4570.6	−4555.7	−1891.5	−1883.3	−1891.1
Pseudo R^2	0.180	0.186	0.211	0.214	0.077	0.081	0.078

Robust standard errors are in brackets. *p <0.05; **p <0.01; ***p <0.001.

Table B4. Standard logistic regression analysis of R&D alliance formation probability with ego-level clustered standard errors (full sample estimation).

	Dependent variable: *Partner*			
	(Model 1.0)	(Model 1.1)	(Model 1.2)	(Model 1.3)
CollabExp		1.677***		
		(0.325)		
FailedExp			3.410***	3.444***
			(0.283)	(0.279)
SuccessExp				1.601***
				(0.369)
MixedExp				3.019***
				(0.788)
GeoDist	−0.008***	−0.008***	−0.008***	−0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
ExpDiff	0.127***	0.125***	0.123***	0.121***
	(0.005)	(0.005)	(0.005)	(0.005)
TC	0.239	0.280*	0.417***	0.468***
	(0.154)	(0.158)	(0.159)	(0.163)
PRO	1.475***	1.468***	1.398***	1.381***
	(0.098)	(0.098)	(0.095)	(0.097)
LargeFirm	0.342***	0.330***	0.414***	0.401***
	(0.079)	(0.079)	(0.080)	(0.080)
Constant	−5.472***	−5.480***	−5.579***	−5.590***
	(0.064)	(0.064)	(0.066)	(0.066)
Observations	153,181	153,181	153,181	153,181
Log likelihood	−4770.546	−4753–483	−4603.504	−4580.465
Pseudo R^2	0.177	0.180	0.206	0.210

Robust standard errors are in brackets *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table B5. Firth's bias reduction logit regression results for assessing the probability of R&D alliance formation (applying a 2-year lag).

	Dependent variable: *Partner*			
	(Model 1.0)	(Model 1.1)	(Model 1.2)	(Model 1.3)
CollabExp		1.262***		
		(0.382)		
FailedExp			1.188***	1.211***
			(0.292)	(0.292)
SuccessExp				0.914+
				(0.479)
MixedExp				2.466**
				(0.681)
GeoDist	−0.007***	−0.007***	−0.007***	−0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
ExpDiff	0.304***	0.302***	0.301***	0.299***
	(0.013)	(0.013)	(0.013)	(0.014)
TC	−0.289	−0.269	−0.252	−0.230
	(0.238)	(0.238)	(0.238)	(0.238)
PRO	1.665***	1.661***	1.655***	1.644***
	(0.099)	(0.099)	(0.099)	(0.099)
Constant	−5.693***	−5.701***	−5.708***	−5.715***
	(0.094)	(0.094)	(0.094)	(0.094)
Observations	75,078	75,078	75,078	75,078
Log likelihood	−2568.925	−2564.093	−2561.407	−2554.667
Pseudo R^2	0.180	0.182	0.183	0.185

Robust standard errors are in brackets. +$p < 0.1$, *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.