Open innovation deficiency: evidence on project abandonment and delay

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Abstract

The concept of Open Innovation (OI) has breathed new life into both empirical research and industry practice concerned with distributed and collaborative modes of innovating. Certainly, the volume of OI research and its impact on practice has been remarkable. However, equally remarkable is the lack of balance. With few exceptions, the stories of OI are positive stories. An unbalanced focus on successes leads to open innovation imperatives and the conclusion that, for most firms, openness is good, and more openness is better. In this paper, we nuance this perception by empirically investigating the relationships between innovation openness and its effects on project abandonment and delays. Using survey data from Belgium, we find that open innovation associates with an increased risk of both project abandonment and project delays. We also find that project abandonment is related negatively to the growth of value-added.

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1 Introduction

This paper investigates the effects of Open Innovation (OI) strategies on firms' innovation project portfolios by studying project abandonment as well as project completion rates. According to Chesbrough (2003), OI offers a range of significant benefits for organizations by leveraging both internal and external sources of ideas, knowledge, and resources. OI may enhance creativity and idea generation by fostering diverse perspectives and expertise, which increases the likelihood of breakthrough innovations. OI may also accelerate time to market by enabling organizations to quickly access external knowledge and technology, thereby streamlining research and development processes and expediting commercialization. Cost efficiency could be another advantage, as organizations can share the costs and risks associated with innovation, attract external funding, and make innovation initiatives more sustainable. Furthermore, OI may help mitigating risks by facilitating collaborative problem-solving and tapping into the collective intelligence of external partners. It may also expands market opportunities by allowing firms to sense and respond to a broader range of technological and market developments, thus enhancing competitiveness and adaptability in dynamic business environments.

We, however, argue theoretically that OI practices may also entail larger costs due to coordination and additional risks when compared to other innovation practices, and that negative attributes may outweigh the benefits of pooling resources and competences, on average. Our empirical study focuses on project portfolio effects of OI strategies. We show that OI practices are associated with higher rates of project failure and lower rates of project completion. We also study future firm performance and find that higher rates of project abandonment are associated with lower performance in terms of value added. It can therefore be concluded that the "lost opportunities" of project abandonment are outweighing the positive effect of resource savings, on average.

1.1 Literature on the concept of open innovation

The conviction that "…interactive learning and collective entrepreneurship are fundamental to the process of innovation" (Lundvall, 1992, p. 9) is longstanding. Yet, there can be little doubt that the concept of Open Innovation (OI) (Chesbrough, 2003) has breathed new life into both empirical research and industry practice concerned with distributed and collaborative modes of innovating. The frequency of journal special issues (e.g. Gassmann, 2006; Enkel et al., 2009; Carlsson and Corvello, 2011; West et al., 2014; Tucci et al., 2016), review articles (e.g. Dahlander and Gann, 2010; Lichtenthaler, 2011; West and Bogers, 2014; Randhawa et al., 2016), and recently 'The Oxford Handbook of Open Innovation' (Chesbrough et al., 2024) is testament to the former. For the latter, informed commentary suggests that "…academic scholarship has been more than matched by the response of industry to the ideas of open innovation" (Tucci et al., 2016, p. 283; Du et al., 2014), manifest, for instance, in more attention to connections with external actors, the development of specialist departments and employees, and the evolution of specialised consulting services.

Certainly, the volume of OI research and its impact on practice has been remarkable (Lopes and de Carvalho, 2018); but, equally, it has often been uncritical (Salge et al., 2013). Consistent with OI's establishment "as a new *imperative* for organizing innovation" (Bogers et al., 2019, p. 77, emphasis added), much of the empirical literature has emphasised the innovation enhancing benefits of boundary-spanning knowledge and information search activities (West et al., 2014). In this view, innovating is concerned with searching for new combinations (Ehls et al., 2020), and an open innovation strategy is fundamentally a search strategy (e.g. Lopez-Vega et al., 2016). Here, the common conclusion is that firms drawing more broadly from diverse sources of knowledge and ideas are likely to be more successful innovators (Faems et al., 2005).

1.2 Limited critical evidence on Open Innovation

Following Laursen and Salter's (2006, p. 135) observation that "some firms have a tendency to 'over-search'", a growing body of work has explored the potential for diminishing returns to openness (e.g. Leiponen and Helfat, 2010; Love et al., 2014); nuancing discussions by exploring, among other factors, the influence of strength of partner relationships (D'Ambrosio et al., 2017), partner combinations (Criscuolo et al., 2018) and the varying role of science-based and supply chain collaborations (Haus-Reve et al., 2019). While these studies highlight important contingencies and contribute to an awareness of the identification, assimilation and utilization costs associated with increasing openness (Salge et al., 2013), the focus is invariably on the likelihood of successfully innovating.

In practical terms, this is manifest in the use of new product and process introductions or new product sales as dependent variables. While welcome, this presents only a partial view of the potential limits to open search. Measures that capture new product introductions, for instance, fail to capture the essentially project and portfolio nature of new product development (NPD) activities in most firms (Cooper, 1979;, 2021). Simply put, larger networks may allow firms to pursue more innovation projects, increasing the likelihood of at least one success and overstating the innovation benefits of openness. Here, we argue that a focus on the portfolio of a firm's innovation projects will provide additional insight. In particular, the extent to which firms' open search activities associate with variable rates of project abandonment and completion may be revealing.

1.3 Abandonment of innovation projects

It is particularly surprising that there have been so few studies on the relationship between openness and innovation abandonment in light of persistent evidence on the high rates of failure in innovation projects generally (e.g. Link and Wright, 2015). To the extent that innovation activity is inherently uncertain (Leoncini, 2016; García-Quevedo et al., 2018), both scholars and practitioners seem to recognise that innovation projects, and especially projects concerned with the development of more novel innovations, will fail "at an alarming rate" (D'Este et al., 2016, p. 280).

Moreover, a parallel stream of literature has reflected upon the "dismal failure record" of strategic alliances (Gomes et al., 2016, p. 15). High coordination and monitoring costs, knowledge disclosure, and the risk of partner opportunism are typical in collaborative innovation (Hottenrott and Lopes-Bento, 2016). Coupled with asymmetries in expectations and commitment, and the difficulty in tightly specifying outputs in innovation contracts (Felin and Zenger, 2014), the rate at which research partnerships lead to 'failed' outcomes is likely to be particularly high (Hagedoorn et al., 2000).

Of course, the abandonment of an innovation project need not constitute a failure. Indeed, recent work has positioned project abandonment as signalling selectivity and, in this sense, as a positive outcome of effective innovation portfolio management (Klingebiel and Rammer, 2014; 2021). Even where it does signal failure, it need not be wholly negative. Failure and learning are tightly linked in innovation processes, given the role of trial-and-error discovery (Chesbrough, 2010; Leoncini, 2016). Nonetheless, many of the resources committed to a specific innovation project are likely to be sunk and imperfectly transferable. Where there are additional search, negotiation, coordination and monitoring costs, the resources bound to an innovation project may be particularly high in the case of collaborative innovation (Vivona et al., 2023). When abandonments constitute a larger component of innovation projects, the negative impact on firm performance may outweigh any positive learning effects. Indeed, it is common in the NPD literature to distinguish abandoned from delayed projects, characterising the former as "project failures" and recording the negative impacts on stakeholder perceptions and firm performance (e.g. Hu et al., 2017).

1.4 Innovation openness and failure

Regardless, the tension between failure as a learning opportunity and failure as a cost is apparent in the few studies that look at the relationship between openness and failure (Lhuillery and Pfister, 2009; Hyll and Pippel, 2016; Leoncini, 2016; D'Este et al., 2016; Guzzini and Iacobucci, 2017; García-Quevedo et al., 2018). However, these studies are invariably limited by a binary measure of failure. Indeed, while their explicit concern is with innovation failure, as in the current study they observe project abandonment. Specifically, they observe firms either recording abandoning at least one innovation project or not. However, if openness enables firms to pursue a greater number of projects by allowing them to better spread costs and risks (Du et al., 2014), a greater likelihood of project abandonment may simply reflect selectivity in larger portfolios (Klingebiel and Rammer, 2021). In the current study, we are able to exploit unique data from the Flemish Innovation Survey that records the number of abandoned projects, and to scale these relative to the total number of innovation projects that firms engage in. In most firms, innovation is undertaken in a multi-project environment (Radas and Bozic, 2012). An inability to account for project numbers (abandoned, successful and ongoing) is a significant constraint on our understanding of the limits to open search strategies. A better understanding of the relative incidence of abandonment is likely to be critical to identifying the limits to external search breadth and depth (Laursen and Salter, 2006) and to understanding why many firms eschew collaboration and innovate independently (Drechsler and Natter, 2012; Criscuolo et al., 2018). The current work makes a contribution to this better understanding.

1.5 The contribution of this study

This study contributes to the limited evidence on failures of open innovation. Chesbrough (2024) states that the "[…] study of Open Innovation arguably suffers from too little attention being paid to situations where Open Innovation fails [...]" (Chesbrough, 2024: 885), and he presents three case studies of OI failures. Existing quantitative studies are limited to binary indicators of failure. We instead focus on portfolio effects by employing continuous variables of project abandonment rates and completion rates. The studies using a binary variable for project abandonment (Lhuillery and Pfister, 2009; Hyll and Pippel, 2016; Leoncini, 2016; D'Este et al., 2016; Guzzini and Iacobucci, 2017; García-Quevedo et al., 2018) can in our opinion not comprehensively address the portfolio effects that open innovation strategies might trigger. Typically, firms that engage in collaboration have more projects than firms that do not collaborate, and then it can be expected that at least one project fails. We show in our empirical study that collaborating firms have on average more than twice as many projects than non collaborating firms. We also show descriptively and within our multiple regression analysis that the collaboration intensity coincides with larger shares of abandoned and lower shares of completed projects. This is a much more detailed picture than what can be obtained with binary variables. While the existing studies exclusively focus on abandonment we also show the detrimental effects of open innovation practices for project completion rates which accounts also for delayed projects that are not (yet) abandoned.

Furthermore, we are also the first to address endogeneity concerns in the stream of literature on OI and innovation project management by implementing an instrumental variable approach.

Other related studies focusing on staged financing and internal resource allocation (Andries and Hünermund, 2020, Klingebiel and Rammer, 2014, 2021) do not consider open innovation when examining project abandonment. We investigate whether the benefits of improved resource allocation by possible staged-financing approaches (that are unobserved by us) are outweighed by the effects of lost opportunities due to abandonment. We therefore specify a dynamic firm performance model on value added and find that higher project abandonment rates are associated with lower future performance. Our empirical study shows that a 10% higher project abandonment rate in year t, coincides with a loss of 4.5% of the firm's expected value added in year t+3.

2 Conceptual background

2.1 Coupled-open innovation and abandonment

Chesbrough's (2003) initial work identified two OI processes that entailed, separately, the leveraging of external expertise for the development and commercialisation of innovations internally, and the external commercialisation of internally developed innovations. Respectively, these are inbound and outbound modes of open innovation. Studies of the former have dominated the empirical OI literature (Randhawa et al., 2016), with openness frequently characterised as a searching or sourcing (Laursen and Salter, 2006; Dahlander and Gann, 2010). However, while notions of 'searching' or 'sourcing' suggest unidirectional flows of ideas and information, studies of inbound open innovation frequently also include measures of collaborative innovation (for a recent example see Ebersberger et al., 2021). Yet, collaboration entails varying degrees of both outbound and inbound flows of knowledge and resources in reciprocal relationships between focal firms and other organisations. This is Enkel and colleagues' "coupled" open innovation (Enkel et al., 2009) and is closely aligned with the more venerable body of work concerned with innovation collaboration and networking (e.g. DeBresson and Amesse, 1991).

Here, the potential benefits of collaborating for innovation are well established (Powell et al., 1996; Van Beers and Zand, 2014). Partnering allows firms to pool resources and competences; it enables cost and risk sharing; it increases creativity and accelerates innovation; and broadens search spaces and facilitates learning (Pittaway et al., 2004). Certainly, the recent empirical literature is broadly consistent in demonstrating a link between 'coupled' open innovation (i.e. collaboration) and innovation outputs, variously measured (e.g. Leiponen and Helfat, 2010; Love et al., 2014; Fitjar and Rodríguez-Pose, 2013; Bjerke and Johansson, 2015).

Yet, despite the apparent manifold benefits of collaborating, and the enduring belief that "the locus of innovation will be found in networks, not individual firms" (Powell et al., 1996, p. 116), empirical evidence frequently records collaborative innovation as a minority activity (Drechsler and Natter, 2012; Hewitt-Dundas and Roper, 2017). Simply put, coupled 'openness' does not appear to be the modal form of innovating (Walsh et al., 2016)[1].

Understanding why this might be the case is helped by an understanding of why firms abandon individual innovation projects in the context of their overall innovation endeavours. At the project level, the NPD literature has outlined how the complexity of the product development process requires firms to develop "temporal coordination mechanisms" that "enable management to make "go/kill/hold/recycle" decisions on the project" (Hu et al., 2017, p. 38). A prominent exemplar is the stage-gate model developed by Cooper (1990) and common in most innovation management textbooks. The goal of this approach is to facilitate the (re)allocation of resources to projects that are assessed as having good investment potential, on some predetermined screening criteria, from projects that do not. At the level of the firm, then, the concern is with resources and risks; with how to prioritise the allocation of finite innovation resources and mitigate innovation risks. In this vein, firm-level research on innovation abandonment has often employed a resource-based lens (Radas and Bozic, 2012). Drawing on the literature concerned with innovation constraints (e.g. Canepa and Stoneman, 2007; D'Este et al., 2012; Coad et al., 2016), this work positions innovation abandonment as rooted in resource deficiencies and the intrinsic uncertainty involved in innovating (Greco et al., 2020). For example, using data from the third Dutch innovation survey Mohnen et al. (2008) note that economic and market uncertainties and high innovation costs were the most common "hampering factors" identified by firms that had abandoned an innovation.

Given this focus on resources and risks, it is not surprising that some work has positioned collaboration as a means to reduce the risk of abandonment (e.g. Greco et al., 2020). As noted, above, cost and risk sharing have long been positioned as the primary benefits to

[1] Even in softer forms of inbound openness, indicated using "sources of knowledge for the firm's innovative activities" recent work suggests a large minority are not open. For instance, using data from the 4th UK Innovation Survey, Criscuolo et al. (2018) record 29% of firms using no sources of knowledge and a further 2.5% only using internal sources. Indeed, using no sources is "the most popular strategy" (p. 128).

collaborative innovation (Bayona et al., 2001). However, consistent with more general evidence on the positive association between collaboration and at least once instance of project abandonment (Lhuillery and Pfister, 2009; Hyll and Pippel, 2016; Leoncini, 2016; D'Este et al., 2016; Guzzini and Iacobucci, 2017; García-Quevedo et al., 2018), we take our point of departure from evidence on the cost-increasing effects of collaboration (Faems et al., 2010; Vivona et al., 2023) and the additional risks associated with partner opportunism (Lokshin et al., 2011). In this way, unsuccessful collaborations may compound the common challenges of innovating, rather than alleviate them.

In terms of resources, collaboration entails more complex management due to additional coordinating and monitoring requirements (Guzzini and Iacobucci, 2017; Vivona et al., 2023). Moreover, collaborative projects incur assimilation and utilization costs resulting from, for instance, the requirement to integrate external knowledge and manage appropriability (Salge et al., 2013). In a multi-project environment, this implies competition for resources; and greater collaborative breadth is likely to associate with increased competition for innovation resources (Klingebiel and Rammer, 2014). Greater resource competition is, in turn, likely to associate with greater abandonment. Either the collaborative project may be abandoned as increasing resource requirements alter NPV calculations, or other project may be abandoned to allow the necessary reallocation of resources. As Hagedoorn et al. (2018) note, the costs associated with collaborating limit the resources that a firm could otherwise allocate to direct innovation activities.

Beyond resources, and to the extent that knowledge disclosure is intrinsic to innovation collaboration, firms may identify legitimate concerns over partner opportunism (Bogers, 2011), the loss of intellectual property (Laursen and Salter, 2014) and, more generally, unintended knowledge spillovers (Arora et al., 2016). These concerns are likely to be exacerbated by challenges associated with what Kogut (1989, p. 184) called "a fundamental instability in governance". The hold-up problem associated with contracting for uncertain outcomes (i.e. innovation), and the related challenges of assessing qualities of solutions, is likely to lead to contracting on the basis of effort and resources rather than outputs. As Felin and Zenger (2014) note, contracts of this nature are characterised by lower-powered incentives and may lead to disagreements over the distribution of returns relative to value created. In this case, collaborative "instability" may result in the frequent abandonment of collaborative innovation projects. Moreover, if increasing partner diversity associates with greater challenges in managing goal alignment, it seems likely to associate with a greater incidence of abandonment.

The expectation that the challenges of collaborative innovation will increase with the number and diversity of partners is consistent with the idea 'over-searching' (Laursen and Salter, 2006). The inverted U-shaped relationship frequently observed between open innovation and innovation performance is thought to point to some optimal level of openness after which the returns to openness diminish. While the reported optimum number of sources of information or partner types is typically high in the empirical literature[2] - and beyond the level practiced by 'average' firms – there are clear implications concerning the managerial and cognitive limits to effective searching and collaboration. In simple terms, collaborating with multiple partners increases coordination and communication costs and reduces the likelihood that goals and expectations will be well aligned (Walsh et al., 2016; Vivona et al., 2023). In addition, while diversity provides the spark for creative abrasion, increasing heterogeneity may retard integration, making it difficult to evaluate, select and advance 'good' projects (Lee et al., 2015). Salge et al. (2013, p. 663) characterise this as a "trade-off between exposure to and manageability of variety". In summary, collaborative innovation is costly and risky, with costs and risks increasing with the number and variety of partners. These greater costs and risks, in turn, increase the likelihood of project abandonment; not only of the focal project but of other projects in the firm's portfolio that must compete for resources or balance risks.
This leads us to hypothesise that:

H1A: The proportion of abandoned projects is positively associated with collaboration and increases with the number of partner types.

[2] For instance, in their study of UK manufacturers, Laursen and Salter (2006) suggest an optimum of 11 external knowledge sources (with a maximum of 16 and a mean of 7.22). Hewitt-Dundas and Roper (2018), in their study of Northern Irish micro-businesses, report an optimum of around 5.2 partner types (with a maximum number of 7 and an observed mean of 0.594). In a study on lead-time advantage in Belgian firms Van Criekingen (2020), finds an optimum of 5 'important' knowledge sources (with a maximum of 11 and a mean of 2.07).

In addition to project abandonment, we add a supplemental hypothesis on project completion. In this, our concern is with project stoppages and delays that fall short of abandonment. There is some evidence that delayed projects may have a greater negative impact on firm performance than abandoned projects (Radas and Bozic, 2012). Delays induced by technical difficulties, changing firm priorities, or changing market circumstances are likely to draw managerial attention and resources from other projects (Mikkola, 2001). Unplanned delays are likely to increase project costs and reduce projected profitability (Guzzini and Iacobucci, 2017). Temporary project interruptions or delays in project completion may represent a weaker form of project abandonment. To the extent that the arguments leading to hypothesis 1A above may all, in weaker form, also lead to project interruptions and delays, we also investigate successful project completion. Specifically, we anticipate that challenges in coordinating the goals and activities of multiple partners (Lokshin et al., 2011) increase the likelihood of project delays. The resources required to overcome these delays will either alter the attractiveness of the project, leading to abandonment, or draw resources from other projects in the firm's portfolio, necessitating delays or abandonments elsewhere. Unfortunately, we cannot observe project delays. Rather, we infer delays from completions. Of course, a low rate of completions may simply indicate engagement in larger or more exploratory projects that are not anticipated to be completed in the timescale captured by the survey. However, conditional on average project size and firms' innovation ambitions, a lower rate of project completion, in a given time period, also accounting for ongoing projects, may signal interruptions and delays in addition to abandonments.

Accordingly, we hypothesise that:

H1B: The proportion of successfully completed projects is negatively associated with collaboration and decreases with the number of partner types.

2.2 Partner type and innovation abandonment

Beyond size and variety in collaborative networks, we anticipate that collaborations with different partner types will variously associate with innovation abandonment (Hyll and Pippel, 2016). This is consistent with extensive prior work that points to the different roles played by different partners in producing different innovation outcomes (Faems, et al., 2005; Du et al., 2014; Fitjar and Rodríguez-Pose, 2013; Belderbos et al., 2014). For instance, customers and suppliers are typically shown to be the most common innovation partners (Arora et al., 2016; Walsh et al., 2016) and to associate with higher incidences of product and process innovation, respectively (Belderbos et al., 2006; Freel and Harrison, 2006). Cooperative projects involving Public Research Organisations (PROs, including universities) and the private knowledge infrastructure are less frequent, but may support the development of more novel innovations (Tether and Tajar, 2008; Robin and Schubert, 2013); while cooperation activities involving competitors, perhaps unsurprisingly, display more mixed results (Wu, 2014). Different collaborative research interactions may also require different absorptive capacities (Corral de Zubielqui et al., 2019), to the extent that the knowledge content of different types of partnership differs (Schmidt, 2010). For instance, collaboration with supply chain partners may require less internal technical expertise than connections to universities or external laboratories (Tomlinson and Fai, 2013), with important implications for the identification, assimilation and utilization costs identified by Salge et al. (2013).

How this bears on abandonment, is likely to rest in larger part on increasing costs of coordination and goal alignment as partners become increasingly organisationally distant from the focal firm. Torre and Rallet (2005) define organizationally proximate actors as those whose interactions are facilitated by (explicit or implicit) rules and routines of behaviour and that share the same system of representations or beliefs. Organizational proximity facilitates shared understanding and increases the ease with which tacit knowledge or other intangible resources will be effectively transferred (Knoben and Oerlemans, 2006). Of course, this shares much in common with Nooteboom's (2000) conception of cognitive distance between organizations as reflected in organizational 'focus' and "established by means of shared fundamental categories of perception, interpretation and evaluation inculcated by organizational culture" (Nooteboom et al., 2007, p. 1017). The likely outcome of greater proximity is fewer innovation "bumps in the road" (Lokshin et al., 2011) for partnerships involving customers and suppliers relative to those involving competitors and research organisations.

In some ways, this may also reflect the balance of exploitation and exploration in market and non-market collaborations (Weber and Heidenreich, 2018). Vertical collaborations, for instance, will frequently be concerned with exploitation (Faems et al., 2005) and may be particularly suited to transmitting information that is specific to the routines of the customer or supplier and that is critical to integration (Walsh et al., 2016). Accordingly, vertical collaboration is particularly likely to result in successful commercialisation. While there is some evidence that firms that intensively draw on external information within the value chain are more likely to report both innovating and abandoning innovation (D'Este et al., 2016), collaborating with suppliers, in particular, has been shown to associate with a reduced risk of 'cooperation failure' (Lhuillery and Pfister, 2009). Suppliers and customers are likely to hold complementary, non-redundant knowledge, which provides the basis for a "good and open relationship" (Bogers, 2011, p. 105) and reduces the relative costs and risks of collaboration.

With respect to collaborations involving non-market partners (e.g. universities and public research organisations), these are typically more exploratory, often with uncertain commercial applications (Haus-Reve et al., 2019). In this way, higher rates of abandonments and delays may simply reflect the more speculative nature of the innovation project. However, anecdotes surrounding the additional challenges of, particularly, university cooperation are pervasive. Often these begin with observations on divergent goals. For instance, Lhuillery and Pfister (2009, p. 47) note that "managers often complain that universities operate on extended time lines and have little regard to the urgent deadline of business"[3]. Similarly, Du et al. (2014, 831) suggest that "researchers at universities follow an institutionalized way of doing (scientific) research and they have their own academic (slow) clock-speed which is hard to be influenced from the outside". These observations speak to organisational or cognitive distance between firms and universities/PROs. And the result is likely to be increasing costs, independent of technology or market risks, and a higher likelihood of abandoning focal projects or, in the face of resource competition, abandonment of other projects in the innovation portfolio.

Any cost concerns are likely to be exacerbated by revealed challenges to profiting from the innovation project. It is often suggested, for instance, that universities' commitment to

[3] They are reporting on an observation made by Pavitt (2003), rather than one they make directly.

‘open science’ results in weaker appropriation opportunities for partnering firms (Perkmann and Walsh, 2007). Research activities undertaken by PROs (including universities) operate under a different incentive system; one that rewards disclosure rather than the exploitation of knowledge (D’Este and Patel, 2007). Universities have not traditionally focused on the needs of firms, resulting in a ‘ridge’ between the basic and applied research foci of PROs and private firms (Drejer and Jørgensen, 2005). And, regardless of the complementarity of research interests, divergent incentives are likely to challenge effective collaboration (Freel et al., 2019). In short, given the increased cost implications attendant upon relatively greater organizational and cognitive distance, we would anticipate that firms collaborating with universities will report higher rates of innovation abandonment. This would be consistent with Lhuillery and Pfister's (2009) observation that, after competitors, PROs had the highest risk of “cooperation failure”.

On the other hand, competitors are likely to be organizationally and cognitive proximate, in the sense of common routines or shared understanding. However, overlapping knowledge bases and competing organisational goals create strong incentives for opportunism (Hyll and Pippel, 2016). Since competitors remain market rivals, they are likely to be reluctant knowledge sharers and to seek to appropriate a greater share of the value created (Ritala and Hurmelinna-Laukkanen, 2013). As a result, cooperative innovation with competitors is more likely to break down or to incur costly delays (Lokshin et al., 2011). Indeed, Lhuillery and Pfister (2009, p. 51) observe that “firms collaborating with competitors are *most* likely to encounter cooperation failures” (emphasis added).

In the case of partners drawn from the private knowledge infrastructure (in the survey this is restricted to “consultants”), the evidence from which to hypothesise is limited. However, here again, issues of relative organizational or cognitive proximity may bear on the challenges firms face in successfully innovating (de Faria et al., 2010). As before, distance is likely to implicate higher identification, assimilation and utilization costs, even when the collaborative innovation is successful. Indeed, given the difficulties of ‘good’ partner selection in busy markets characterised by extensive information asymmetries (Tether and Tajar, 2008), identification costs are likely to be particularly high. However, monitoring costs are also likely to be high to ensure that "the consultant is sufficiently interested to commit to the task” (Tether and Tajar, 2008, p. 1082). As before, we anticipate that the incidence of abandonment is likely to be greater when resource competition across projects is highest. In common with university cooperation, cooperation with consultants is relatively costly when things are going well, with costs likely to increase as projects encounter problems.

Taken together, the foregoing leads us to hypothesise that:

H2A: Innovation collaborations with competitors (horizontal collaboration), consultants and PROs are likely to associate with a higher rate of abandonment than Innovation collaborations with customers and suppliers (vertical collaboration).

As with hypothesis 1, we also set-up supplemental hypotheses that account for delays and project interruptions by analysing the proportion of successfully completed projects. Again, the logic underpinning these is that delays are likely to result from the increasing costs associated with collaborating with organisationally and cognitively distant partners or with partners with a strong incentive to engage in opportunistic behaviour. That is, the issue is one of relative costs and risks such that:

H2B: Innovation collaborations with competitors (horizontal collaboration), consultants and PROs are likely to associate with a lower rate of successful project completion than collaborations with customers and suppliers (vertical collaboration).

3 Data and descriptive statistics

The data used to conduct the analysis originates from the Flemish component of the Community Innovation Survey (CIS), which is an inquiry into innovative activity in the Belgian economy. The CIS is harmonized across European Member States with regards to core question. However, each country-specific edition (partly) has unique questions that are not available at the European scale. The data at hand consists of two cross-sections from 2015 and 2013, i.e. the data collected in the survey refer to the time periods 2010-2012 and 2012-2014. These two cross-sections included specific questions on the management of firms' innovation projects that can be used for investigating our research questions. We also merge some information on firms' annual accounts from the Orbis database to the sample; specifically, firms' debt ratios and working capital. These variables will be used as further controls in the regression analyses.

The survey sample is a stratified, random sample of the Flemish economy (the northern part of Belgium). As firms are asked in great detail about their innovation activity, we can differentiate between firms that innovated, or at least attempted to innovate, and those that did not engage in any innovation projects. The latter are set aside in the present analyses, since we are interested in comparing firms that implement an open innovation strategy with other innovators. After deleting observations with missing values of interest, our final sample amounts to 999 observations on firms that at least attempted to innovate, i.e. they could have successfully brought at least one new product to the market, implemented a new production process, or have ongoing innovation activity or have at least had one project that has been abandoned before completion.

Unfortunately, we will not be able to use the data as a panel in econometric terms, i.e. we cannot control for firm-specific effects. The sample consists of 999 observations which are based on 879 different firms. We only observe 60 firms in both years. Accordingly, we are constrained to use the data as pooled cross-sections and cannot apply panel econometric techniques.

3.1 Dependent variable: shares of abandonment and completion

The surveyed companies were requested to report the number of innovation projects that were (i) finished, (ii) abandoned or (iii) ongoing during the reference periods of the survey. One slight drawback of this variable is that the survey instrument does not unambiguously specify how the term "project" is defined or how it should be interpreted. This results in a somewhat fuzzy measurement. The median number of projects is 10 and the average is about 23. The first quartile of firms reports that they have up to four projects, whereas the number of projects in the fourth quartile is 25 and above; reaching up to almost 200 projects. Moreover, when looking at the number of projects per R&D employee it becomes clear that firms have (not surprisingly) no common, comparable definition of projects in mind when responding to the survey. For instance, in the first quartile of firms the number of projects per R&D employee is at maximum 1. This suggests that multiple persons work jointly on a long-term project. However, in the fourth quartile of the distribution this number is between 9 and more than 30 projects per person, which suggests that one person works on many projects during the survey reference period. This makes clear that one should not use the number of projects as nominal value without some normalization of reference point.

Given this fuzziness of the "project" definition, we construct two relative outcome variables. The first is the share of projects that were abandoned during the reference period of the survey. We believe that this scaling of the dependent variable makes the numbers comparable across firms, as it is compelling that the survey respondent has answered the three questions on project numbers with the same project definition in mind. On average among all firms, the share of abandoned projects amounts to 0.11.

In the subsequent econometric exercise, we also consider the share of completed projects in order to compare these numbers to abandonment. As the third type of projects are ongoing ones, it is not trivial that the rate of abandonment is simply the opposite of completion. Openness could lead to both accelerated or delayed completion. The average share of completed projects equals 0.55 in the sample.

3.2 Covariates of main interest: number and type of collaborations for innovation projects

The openness of the firms' innovation strategy is measured through collaboration patterns in this study. A first indicator of openness could simply be a dummy variable indicating whether firms collaborate within the innovation projects. In the subsequent econometric study, however, we quantity the degree of openness to a greater extent. Following prior work (e.g. Laursen and Salter, 2006; Leiponen and Helfat, 2010; Love et al., 2014), we create a variable *OPEN* which is a 'collaboration count' describing the number of different partner types a company had in its collaborations. The survey inquired about seven potential types: suppliers, private clients, government clients, competitors, consultants, universities and other research organisations. And, therefore, the variable *OPEN* ranges from 0 to 7. The innovators in our sample had on average 2.1 types of collaboration partners. This number increases to about 3.2 when we condition on openness, i.e. for the subsample with D(*OPEN*>0) = 1.

In the second step of the analysis, we group the collaboration types into meaningful subgroups in order to investigate the heterogeneous effects on project success of varying open innovation strategies and to test our hypotheses. These groups reflect common distinctions in the literature between horizontal and vertical collaboration (Tomlinson, 2010) and between market and non-market collaboration (Tether and Tajar, 2008; Bruneel et al., 2010). Accordingly, we construct four dummy variables for collaborations with respectively:

i. clients and suppliers (*VERTICAL*):
as outlined in the second section of the paper these collaborations are the typically the most common ones and this also holds in our data. 59% of firms report such collaborations within their innovation projects. These projects are most likely among the routine innovation tasks and we do not expect them to fail often or be significantly delayed, as they focus on exploitation rather than exploration capabilities.

ii. competitors (*HORIZONTAL*):
also as outlined above, openness towards firms in the same industry might be more delicate. While potentially highly useful and not subject to antitrust according to the European block exemption for R&D and innovation as pre-competitive activities, they might touch upon sensitive tacit knowledge and projects may therefore be disrupted. These collaborations are also least frequent at about 16%.

iii. consultants (*CONSULT*):
in line with the literature, we expect high degrees of information asymmetries in collaborations with partners from the private knowledge infrastructure and also manifold selection problems in partner choice. However, roughly every third firm in the sample engages in such collaborations.

iv. university and other public research organisations (*SCIENCE*):
last but not least, we expect that collaborations with public science organizations are subject to the highest asymmetries in incentives and at the same time entail the largest promise on future breakthrough innovations and market novelties which typically coincide with a high level of technological (and market) uncertainties. We thus expect that such collaborations are associated with higher project abandonment and delays,

i.e. lower shares of project completions. Given the prospect of high returns (but with high variance), such collaborations are not uncommon. Almost 42% of the (innovation active) firms in the sample report such collaborations.

3.3 Descriptive analysis of project abandonment, completion and openness

In this subsection, we briefly report descriptive results on our hypotheses. We anticipated that the more open a firm implements its innovation strategy, the more are the projects prone to abandonment or delays. We show this by correlating the share of abandoned projects with collaboration counts. In order to get an idea about delays, we use the share of completed projects in the survey period and expect a negative relationship between openness and completion.

The collaboration count as a measure for openness of the innovation process is distributed as follows (see Table 1). About a third of all firms follow a closed innovation regime, i.e. they do not collaborate at all within their projects. Another quarter of innovators had either one or two collaboration partner types, and the remaining 40% of firms have three or more collaboration partner types.

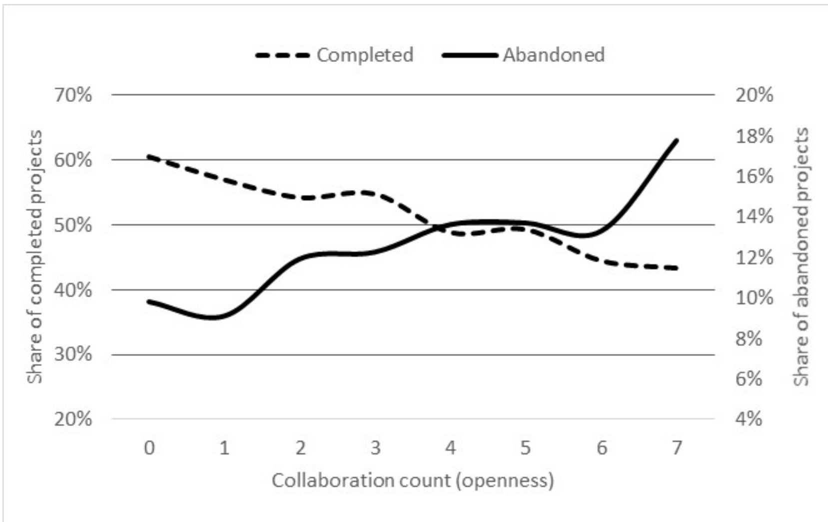
Table 1: Distribution of collaboration partner types

OPEN	#obs	Rel. Freq.	Cum freq.
0	341	34.13	34.13
1	134	13.41	47.55
2	137	13.71	61.26
3	112	11.21	72.47
4	111	11.11	83.58
5	79	7.91	91.49
6	57	5.71	97.20
7	28	2.80	100.00

Figure 1 shows the relationship between the openness of the innovation strategy, as measured by the collaboration count, and the shares of completed and abandoned projects. As hypothesized the rate of project abandonment increases with the degree of openness. Firms reporting to have zero or one collaboration partner show a rate of project abandonment below

10%. As the collaboration variable increases, however, this share goes up to about 14% for higher levels of collaboration (4 to 6 partners). Note that this is a sizable marginal effect of a 40%-increase (4 percentage points) with more intense collaboration. The rate of abandonment reaches its maximum of about 18% for those companies with the most open innovation regime (all 7 partner types).

Figure 1: Shares of abandoned and completed projects by level of openness



As hypothesized, we find a negative relationship between the successfully completed projects and the openness of the innovation strategy. Firms with a closed innovation regime (collaboration count equals zero) complete about 60% of their projects in the survey period. As openness increases, however, this share reduces to around 50% when four or five collaborator types are involved and lowers further to about 44% with six or more partners. Note that this is, again, a sizable marginal change of roughly a 27%-decrease (16 percentage points) in successful project completion over the range of openness.

3.4 Control variables

In the subsequent econometric study, we control for a number of other covariates that might affect project abandonment and successful completion independent of the openness of the innovation strategy.

The first set of controls is related to the innovation projects themselves. As firms with more projects might be more likely to abandon some than firms with only a few projects, we account for the total number of projects (*TOTALPROJ*). We can derive a measure of average project size by dividing total innovation expenditure at the firm level by the number of innovation projects the firm conducts. The variable *AVG PROJ SIZE* might affect the likelihood to abandon projects and to complete them. A firm with relatively small projects might naturally have a higher flow than a firm with relatively large projects. We also include the squared value of *AVG PROJ SIZE* in order to allow for non-linearity. In addition, we attempt to control for the 'ambition' of the innovation projects. Here, we use the sales of products new to the firms' market which stem from their recent innovation projects. Czarnitzki and Hottenrott (2011) argued that firms scoring high on such a variable are performing more cutting-edge research rather than routine tasks, which in turn may of course also coincide with the chance of higher project abandonment rates and less successful project completion. We use this variable scaled by total sales in order avoid collinearity with firm size (*NOVELTY*).

A prominent topic in the innovation literature is the debate about financial constraints resulting from asymmetric information between borrowers and lenders (see e.g. Hall and Lerner, 2010, for a survey). Both internal and external access to capital might directly affect project management (see Andries and Hünermund, 2020), and thus abandonment and completion. We have therefore collected the companies' debt ratio and working capital. *DEBT* is measured as debt divided by total capital and *WCAP* is measured as working capital per employee. It is a-priori ambiguous what sign one should expect for their estimated coefficients. One the one hand, a high debt ratio might lead to project abandonment as the firm cannot borrow more money. On the other, a high debt ratio might simply indicate good access to capital. A low working capital per employee could lead to more project abandonment due to cash flow restrictions. These could, however, be compensated by external capital. Given the literature, it is certainly desirable to control for the firms' financial situation. However, we do not have clear priors on the expected signs of the coefficients in our specific context.

Related to the financial situation, according to the balance sheet, is whether the firms have received public subsidies for R&D projects (see Zúñiga-Vicente et al., 2014, for a survey on R&D subsidies; and Hünermund and Czarnitzki, 2019, for a recent contribution). We include a dummy variable, *SUBSIDY*, in the regression indicating whether the firm has at least one subsidized project in the survey reference periods. Receiving a subsidy implies that the firms do not only use their private financial resources for the project but that a non-negligible share of the cost is publicly financed. Accordingly, we anticipate that firms that are subsidy-backed are less likely to abandon a project in a certain time period. The effect on project completion is expected to be negative, as subsidized projects might be the more challenging ones in the portfolio. Projects clearly below any technological frontier might never be awarded subsidies in the first place.

Aghion et al. (2002) and Farè (2022), for example, have argued that competition may have a significant effect on innovation, in particular that the relationship might be in the form of an inverse U-shape. We have therefore added a variable that accounts for competition in our regression model. Farè had survey data on the degree of perceived competition. As we do not have such data, we followed related literature that suggested that the price-cost-margin or related measures of profitability are reasonable approximations of competition. It can be expected that in perfect competition no larger positive margins can be realized, and in quasi-monopolistic situations the margins are high. We have therefore opted to include the firms' profits before taxes relative to firm size (we divide by number of employees) as measure that could approximate competition (see Boone, 2008, who discusses the use of profit-based measures to model competition). In addition to the linear term, we also include the square of profits in the regression.

We also include a patent dummy variable that indicates whether the firm has applied for at least one patent in the past. We collected this information from the PATSTAT database for each firm. Active use of intellectual property rights may avoid IP disputes during the project implementation and may therefore lead to less abandonment or delays.

Finally, we include common firm level controls that might affect project management. We use firm size measured as employment. Because of the skewness of employment, we use log(*EMP*) in the regressions. Similarly, firm age might affect innovation project management (see e.g. García-Quevedo, et al., 2014; Coad et al., 2016). The age also enters the regression in logarithmic form, log(AGE). We also include a dummy variable indicating whether a firm is a member of a firm consortium, *GROUP*, which might also affect the management of innovation projects.

Finally, we control for unobserved sectoral differences by including a set of nine industry dummies (see Table 8 in the appendix) and a time dummy for 2015, which controls for other non-observed macro-economic changes that might have affected project management relative to the 2013 survey.

A pairwise correlation table is included in appendix (table 9).

Table 2: Descriptive statistics

		All innovators N=999				Non cooperating innovators N = 341			Cooperation active innovators N = 658		
Variable	Unit	Mean	Std. Dev.	Min	Max	Mean	Min	Max	Mean	Min	Max
Dependent variables											
Abandoned projects	share	0.11	0.16	0	1	0.10	0	1	0.12	0	1
Finished projects	share	0.55	0.28	0	1	0.61	0	1	0.52	0	1
Openness variables											
OPEN (Collaboration count)	count	2.12	2.09	0	7	0	0	0	3.22	1	7
VERTICAL	dummy	0.59	0.49	0	1	0	0	0	0.90	0	1
HORIZONTAL	dummy	0.16	0.36	0	1	0	0	0	0.24	0	1
CONSULT	dummy	0.32	0.47	0	1	0	0	0	0.49	0	1
SCIENCE	dummy	0.42	0.49	0	1	0	0	0	0.63	0	1
Controls variables											
TOTALPROJ (Total number of projects)	count	21.39	38.26	1	332	11.68	1	303	26.41	1	332
AVG PROJ SIZE (R&D expenses/projects)	Mill. €	0.09	0.15	0	0.90	0.06	0	0.90	0.11	0	0.83
NOVELTY (share of new products in total sales)	share	0.07	0.16	0	1	0.07	0	1	0.08	0	1
PATENT	dummy	0.27	0.44	0	1	0.17	0	1	0.32	0	1
DEBT (debt / total assets)	share	0.60	0.19	0.04	1	0.61	0.04	1	0.59	0.05	1
WCAP/EMP (= Working Capital per employee)	Mill. €	0.07	0.13	-0.07	1.82	0.06	-0.06	0.9	0.08	-0.07	1.82
SUBSIDY	dummy	0.48	0.50	0	1	0.28	0	1	0.58	0	1
COMPETITION (Profits/*EMP*)	Mill. €	0.016	0.045	-0.12	0.29	0.011	-0.12	0.29	0.018	-0.12	0.29
EMP (Employment)	count	119	217	1	2718	79	1	1055	139	1	2718
AGE	count	28	18	1	143	27	2	143	29	1	127
GROUP (membership dummy)	dummy	0.64	0.48	0	1	0.55	0	1	0.69	0	1
Year 2015 dummy	dummy	0.55	0.50	0	1	0.52	0	1	0.56	0	1

Note: 9 industry dummies not presented.

4 Econometric study

In the subsequent econometric study, we estimate fractional response models (cf. Papke and Wooldridge, 1996) as our dependent variables are fractions ranging between 0 and 1. It is often seen as more compelling to fit fractional response models that account for the boundedness of the dependent variable than simply using linear regressions. In our case, we use the probit link function to account for the bounds at 0 and 1. We thus specify

$$E(y_{it}|x_{it}) = \Phi\left(\frac{x_{it}'\beta}{\sigma_{it}}\right),$$

where y is our dependent variable, x is the vector of covariates, and Φ denotes the standard normal CDF, β are the slope coefficients and σ the standard error to be estimated. In order to interpret the economic magnitude, the marginal effects for some continuous x_k are calculated accordingly as

$$\frac{\partial E(y_{it}|x_{it})}{\partial x_k} = \emptyset\left(\frac{x_{it}'\beta}{\sigma_{it}}\right)\frac{\beta_k}{\sigma_{it}}.$$

In case of dummy variables, we calculate the marginal effects as difference in expected values for a discrete change from 0 to 1. As the marginal effects will vary among the observations i, we will show the average marginal effects in the result section. In all estimated models, we employ clustered standard errors at the firm level. It is noteworthy that all results reported below also hold when linear OLS regressions are employed.

4.1 Abandonment, delays, and openness

In Table 3, we show the average marginal effects for a unit change in x. Initially we only include the collaboration count as measure for openness and controls for the sector and the survey year. Next, we add the full set of firm level controls into the specification. Regarding project abandonment, we find in line with our hypothesis H1A that the collaboration count is associated with higher abandonment rates. Each extension of the openness by one collaboration channel increases the share of abandoned projects by 0.6%-points. As the mean of firms that do not follow an open innovation strategy is about 10%, it is quite a sizable impact: 6% per collaboration count, on average.

Interestingly, most covariates have no systematic relationship with abandonment. The only variables that show a statistically significant effect are the subsidy dummy and firm size.

The subsidy dummy has a large negative effect, i.e. firms that receive public funds for their innovation projects are less likely to abandon projects. This is consistent with financial management implications (cf. Andries and Hünermund, 2020); the more restrictive project funds are, the more careful firms manage their project portfolio. The financial argument seems to outweigh the hypothesis that publicly financed projects are more challenging and would therefore be more often abandoned. Of course, it may also signal a selection effect, with 'better' firms receiving funds for 'better' projects. Eventually, larger firms also tend to have a higher abandonment rate (though only weakly statistically significant at 10%). This may indicate the availability of more and more specialised resources to support, for instance, more professional (financial) project management.

In the regressions on project completion, which indicate project delays or interruptions in addition to abandonment, we also find a statistically significant and economically sizeable effect of openness, in line with hypothesis H1B. Here the marginal effect amounts to 2.2%-points for each expansion of the openness regime. As the average completion rate is about 59%, firms face a 3% lower completion rate for each extra collaboration channel.

Except the R&D project size, none of the other controls is statistically significant in the regression. The marginal effect of the average project size is -0.38 for a unit change. However, a unit change is not a meaningful number in this case. The median project size is 0.06, i.e. € 60,000 per project. If the project size would double to € 120,000, the implied change in completion rate would amount to - 2.3%. This average negative effect suggests that the larger projects are more ambitious and are therefore more often delayed or interrupted than smaller ones.

Table 3: Marginal effects in fractional response models on project abandonment and completion[4]

	Project abandonment		Project completion	
	Marg. Eff. (Std. err.)	Marg. Eff. (Std. err.)	Marg. Eff. (Std. err.)	Marg. Eff. (Std. err.)
OPEN	0.006***	0.006***	-0.023***	-0.022***
	(0.002)	(0.002)	(0.004)	(0.004)
AVG PROJ SIZE		0.034		-0.383***
		(0.080)		(0.123)
NOVELTY		0.015		0.032
		(0.030)		(0.053)
PATENT		0.011		-0.035*
		(0.012)		(0.020)
WCAP/EMP		-0.074		0.079
		(0.045)		(0.072)
DEBT		0.016		-0.021
		(0.024)		(0.050)
SUBSIDY		-0.032***		-0.005
		(0.012)		(0.021)
COMPETITION		-0.058		0.351
		(0.152)		(0.299)
TOTALPROJ		0.491**		1.079**
		(0.201)		(0.430)
log(*EMP*)		0.007		-0.021**
		(0.005)		(0.009)
log(*AGE)*		-0.006		-0.010
		(0.008)		(0.013)
GROUP		-0.009		-0.009
		(0.012)		(0.021)
Y2015	-0.011	-0.010	0.004	0.011
	(0.010)	(0.010)	(0.017)	(0.017)
Sector dummies $\chi^2(8)$	33.95	24.93	10.40	14.13
Prob > χ^2	0.0000	0.0016	0.2381	0.0784
Log Pseudo-likelihood	-349.76	-346.87	-680.42	-673.50

Notes: N= 999; Significance levels: *** 1% or less; ** less than 5% , * less than 10%;
All regressions include a constant term. Standard errors clustered at the firm level.

In order to present the marginal effects in the corresponding way to the unconditional descriptive statistics, we calculated the expected project abandonment and completion rates at the different levels of openness in Table 4. In a closed innovation regime, the average firm would abandon about 10% (10.1%) of its projects and complete about 59% (59.6%) of them.

[4] The regression includes *AVG PROJ SIZE* and also (*AVG PROJ SIZE*)^2. When calculating average marginal effects, we of course get only one effect from the two estimated coefficients that describe a non-linear curve. It turns out that the estimated effect is not inverse U-shaped or U-shaped. Instead, in the data range it is just a non-linear, downward sloping curve in the regression on project completion. There are no statistically significant results in the regression on abandonment. The regression also includes a squared term of our *COMPETITION* variable. We show all coefficients estimated in the appendix table 10.

Table 4: Conditional means of abandonment and completion as function of openness

MEs	**Project abandonment**	**Project completion**
at OPEN = 0	0.101***	0.596***
	(0.007)	(0.013)
at OPEN = 1	0.107***	0.575***
	(0.006)	(0.010)
at OPEN = 2	0.113***	0.553***
	(0.005)	(0.009)
at OPEN = 3	0.119***	0.531***
	(0.005)	(0.010)
at OPEN = 4	0.126***	0.509***
	(0.006)	(0.012)
at OPEN = 5	0.133***	0.487***
	(0.008)	(0.015)
at OPEN = 6	0.140***	0.465***
	(0.011)	(0.019)
at OPEN = 7	0.147***	0.443***
	(0.014)	(0.023)

Notes: N= 999; Significance levels: *** 1% or less; ** less than 5% , * less than 10%.
The numbers are derived from the regressions including the full set of covariates as shown in Table 3.

An increasing level of openness is associated with higher rates of abandonment and lower rates of completion. These rates would change to 14.7% and 44.3% at the maximum level of openness, i.e. abandonment rises by about 45% and completion falls by 28%. This shows that open innovation regimes may entail substantial costs for the firm. As most of innovation expenses are R&D cost for personnel, these cost are also immediately sunk and no corresponding value of these expenses remains in the balance sheet.

4.2 Abandonment, delays and type of collaboration

In table 5, we show the results of fractional response models on project abandonment and completion where we split the collaboration variable into four dummies which differentiate the openness by type of collaboration. We find that collaborations with consultants and with science are associated with project abandonment and delays.

Table 5: Marginal effects in fractional response models by type of collaboration

Variables	Project abandonment		Project completion	
	Marg. Eff. (Std. err.)	Marg. Eff. (Std. err.)	Marg. Eff. (Std. err.)	Marg. Eff. (Std. err.)
VERTICAL	-0.012	-0.015	0.009	0.007
	(0.014)	(0.014)	(0.024)	(0.023)
HORIZONTAL	-0.012	-0.011	0.008	0.004
	(0.012)	(0.013)	(0.024)	(0.023)
CONSULT	0.033***	0.034***	-0.042**	-0.035*
	(0.012)	(0.012)	(0.021)	(0.021)
SCIENCE	0.018	0.022	-0.091***	-0.091***
	(0.013)	(0.014)	(0.022)	(0.022)
AVG PROJ SIZE		0.018		-0.361***
		(0.081)		(0.124)
NOVELTY		0.016		0.031
		(0.030)		(0.052)
PATENT		0.013		-0.037*
		(0.012)		(0.020)
WCAP/EMP		-0.076*		0.078
		(0.045)		(0.070)
DEBT		0.009		-0.013
		(0.024)		(0.050)
SUBSIDY		-0.034***		0.006
		(0.012)		(0.021)
COMPETITION		-0.078		0.360
		(0.151)		(0.298)
TOTALPROJ		0.493**		1.120***
		(0.203)		(0.420)
log(EMP)		0.007		-0.022**
		(0.005)		(0.009)
log(AGE)		-0.007		-0.009
		(0.008)		(0.013)
GROUP		-0.009		-0.010
		(0.012)		(0.021)
Y2015	-0.013	-0.011	0.007	0.013
	(0.010)	(0.010)	(0.017)	(0.017)
Sector dummies $\chi^2(8)$	31.32	22.24	9.03	13.31
Prob > χ^2	0.0001	0.0045	0.3395	0.1015
Log Pseudo-likelihood	-348.99	-345.89	-679.23	-672.56

Notes: N= 999; Significance levels: *** 1% or less; ** less than 5% , * less than 10%;
All regressions include a constant term. Standard errors clustered at the firm level. For all coefficients estimated, see appendix table 11

In the regressions on project abandonment (hypothesis H2A), consultants are associated with higher failure rates. The marginal effects amount to 3.4%-points. In the regression on project completion (hypothesis H2B), we only find a statistically significant negative effect for *SCIENCE*, i.e. partners from the public research sector. These findings are in line with the notion that divergent incentives of scientists in firms and public research institutions challenge effective collaboration (Freel et al., 2019). The complaints of managers that universities operate on extended timelines and have little regard to the urgent deadline of business, as mentioned by Lhuillery and Pfister (2009), also seem to apply to our sample. We find, not only that projects are more likely to be abandoned, but also that the rate of completion is lower. This can be interpreted as more frequent disruptions and delays in university collaborations. Of course, it may also simply reflect the longer average duration of research joint ventures involving public science. Caloghirou et al. (2001), for instance, note that the "average duration of an RJV with a university is 34 months, whereas RJVs without a university last on average 3 months less"[5]. However, to the extent that we control for a variety of factors that may be thought to lead to longer projects, we are comfortable with our interpretation.

With respect to the involvement of consultants in the innovation process, we interpret our finding as evidence for challenges in partner selection due to information asymmetries (Tether and Tajar, 2008).

4.3 Robustness test I: Seemingly Unrelated least squares Regressions (SUR)

In addition to fractional response models that account for the fact that the dependent variables are bounded between 0 and 1, we have also estimated linear regressions. As we have two equations, abandonment and completion, we estimated the equations jointly by employing a seemingly unrelated regressions (SUR) approach. This method utilizes possible correlations among the error terms of the equations and is thus an efficient estimator. In addition, one can test cross-equation restrictions. This is interesting because of the following reason: if it is true that in addition to abandonment, openness leads to significant interruptions and delays, the coefficient of openness in the regression on completion should be, in terms of its absolute magnitude, larger than the coefficient in the abandonment equation.

The regression results are displayed in Table 6. The results are remarkably similar to those of the fractional response models and therefore we refrain from discussing them in detail.

[5] The reported median figures were 36 and 31 months, respectively.

When testing whether the absolute magnitude of the coefficient of *OPEN* is larger in the completion regression (coef. = -0.022) than in the abandonment regression (coef. = 0.006), we set up the hypothesis

H0: 0.006 = abs(-0.022).

The test rejects the Null with $\chi^2(1)$ =10.56, Prob > χ^2=0.0012. This reaffirms our logic that testing project completion in addition to abandonment carries extra information, as one could formulate this as:

"abandonment = Total projects - completion - interruption - delay".

Project abandonment is therefore just the most extreme form of 'failure', but the innovation process might also the impeded significantly by weaker forms of 'failure', such as delays.

Table 6: SUR on abandonment and completion

	Abandonment	Completion
	Coeff. (Std. err.)	Coeff. (Std. err.)
OPEN	0.006**	-0.022***
	(0.003)	(0.005)
AVG PROJ SIZE	0.064	-0.557***
	(0.094)	(0.169)
AVG PROJ SIZE^2	-0.146	0.951***
	(0.142)	(0.256)
NOVELTY	0.015	0.031
	(0.033)	(0.059)
PATENT	0.010	-0.035
	(0.012)	(0.022)
WCAP/EMP	-0.071*	0.077
	(0.040)	(0.073)
DEBT	0.015	-0.021
	(0.025)	(0.046)
SUBSIDY	-0.033***	-0.005
	(0.011)	(0.020)
COMPETITION	-0.106	0.432
	(0.179)	(0.322)
COMPETITION^2	1.371*	-2.564*
	(0.804)	(1.451)
TOTALPROJ	0.646**	1.181**
	(0.305)	(0.550)
TOTALPROJ^2	-1.557	-2.173
	(1.327)	(2.393)
log(*EMP*)	0.007	-0.021**
	(0.005)	(0.009)
log*(AGE)*	-0.007	-0.010
	(0.008)	(0.014)
GROUP	-0.008	-0.009
	(0.011)	(0.020)
Y2015	-0.010	0.011
	(0.010)	(0.018)
Sector dummies $\chi^2(8)$	26.83	13.28
Prob > χ^2	0.0008	0.1027

Notes: N= 999; Significance levels: *** 1% or less; ** less than 5% , * less than 10%;
All regressions include a constant term.

4.4 Robustness test II: accounting for endogeneity of openness

Some readers might be concerned that our findings are partly driven by a simultaneous equation bias, e.g. both the project outcomes and openness are determined by some unobserved variables. In that case a classic endogeneity problem would occur. The unobserved variable would be correlated with openness but is hidden in the error term of our econometric model. This would result in the covariance between openness, i.e. a violation of a fundamental assumption of the aforementioned regression models. In order to conduct a robustness test, we run instrumental variable (IV) regressions that account for such endogeneity. The challenge is to find relevant and exogeneous instrumental variables.

The IVs have to be correlated with openness, but must be exogenous to our regression model; or in other words they must not depend on a firm's project outcomes. We have experimented with a number of instruments at the firm-level, the industry level and regional level. The instruments at the firm-level such as hampering factor for innovation projects turned out to be not exogenous (in Sargan tests). The instruments such as number of firms in a region or number of innovating firms in a region turned out not to be relevant, i.e. they were insignificant in the first stage of an IV regression.

Two variables at the sector level were found to be relevant and exogenous IVs, though. First we use the share of innovating companies at the two-digit NACE sector level. This variable may constitute options for collaboration for each firm, at least at the national level. We find that it is positively correlated with openness. Furthermore, it cannot be determined by the decision-making of an individual firm, and is therefore exogenous to the original regression model. In addition, we created an index variable that measures to what degree firms in an industry rely on external knowledge sources. In the first year of the survey data that we are using, firms were asked whether they use certain channels for seeking information for their innovation projects and how important these are (this is different from formal collaboration). Firms are asked how important are (i) market sources (suppliers, customers, firms in the same industry and consultants), (ii) universities and other institutions of higher education, and (iii) conferences, fairs, exhibitions, journals and patents as well as sector associations. Drawing from Laursen and Salter's (2006) conceptualization of breadth and depth of search strategies, we combine these variables to a single index measuring knowledge spillovers, however (see Czarnitzki and Kraft, 2012, and Cappelli et al., 2014, for similar approaches). The companies could indicate the importance of each channel from 0 to 3. We sum up all scores and average them at the 3-digit industry level to obtain a measure on how much the industry generally relies on externally available knowledge, or the level of knowledge spillovers in the industry. The level of spillovers could be both positively or negatively related to the search for collaboration partners. If knowledge is circulating intensely in an industry, it could imply that firms are also heavily engaging in collaboration as external knowledge is essential for innovation. If knowledge is freely available, however, it might also lead to a lower necessity of formal collaborations in such industries. In the regression, we find that the industry level of knowledge spillovers is positively related to our openness variable. It turns out that the average spillover level is relevant, i.e. highly correlated with our collaboration count variable, and it should also be exogenous as a single firm will not determine the industry level of knowledge spillovers (this is also confirmed by Sargan tests).

Our regression results are presented in Table 7. We find that both IVs are positive and significant in the first stage of the 2SLS regressions. Furthermore, the F-statistic of the IVs in the first stage is higher than 10, i.e. we do not face a weak instrument problem according to Stock and Yogo (2005). The Hansen J statistic does not reject the validity of our instrumental variables. In the regression on project completion, the coefficient of openness is negative, - 0.088, and statistically significant at the 5% level. The previous results thus hold. In the abandonment regression, the coefficient amounts to 0.019, but is just significant at the 5% level. In order to gain efficiency, we therefore also applied the Lewbel (2012) IV estimation technique where one generates additional instrumental variables by exploiting heteroscedasticity in the first stage of the regression. The error term is multiplied with the centered regressors of the first stage, and these terms can be used as instruments in the 2nd stage. All regular IV regression diagnostics on relevance and exogeneity can be applied. It turned out that we three additional instruments are relevant: the cross-terms of the residuals with the variables *SUBSIDY*, log(*EMP*) and *NOVELTY*. Consequently we re-run the IV regressions for the abandonment equation as explained before with these three additional instruments. The results are shown in the right panel of the table. The magnitude of the *OPEN* coefficient remains 0.019 and is significant at the 5% level. Therefore all previously reported results also hold when accounting for possible endogeneity of openness in the regression models.

Table 7: IV (2SLS) regressions and Lewbel-IV regression

	IV regression (First stage is identical for both 2nd stages)			IV regression with supplemental Lewbel IVs	
	First stage *OPEN*	Second stage Abandonment	Second stage Completion	First stage *OPEN*	Second stage Abandonment
OPEN		0.019**	-0.088**		0.019**
		(0.009)	(0.038)		(0.009)
AVG PROJ SIZE	1.252	0.054	-0.421**	1.048	0.054
	(1.149)	(0.103)	(0.191)	(1.017)	(0.103)
AVG PROJ SIZE^2	-0.286	-0.135	0.841***	-0.225	-0.135
	(1.832)	(0.142)	(0.265)	(1.500)	(0.142)
NOVELTY	0.530	0.008	0.075	0.693*	0.008
	(0.431)	(0.030)	(0.062)	(0.357)	(0.030)
PATENT	0.313**	0.008	-0.007	0.216	0.008
	(0.155)	(0.012)	(0.026)	(0.138)	(0.012)
WCAP/EMP	0.596*	-0.070*	0.128	0.593*	-0.070*
	(0.350)	(0.038)	(0.080)	(0.359)	(0.038)
DEBT	-0.242	0.023	-0.041	-0.141	0.023
	(0.309)	(0.025)	(0.058)	(0.300)	(0.025)
SUBSIDY	1.173***	-0.048***	0.073	1.191***	-0.048***
	(0.136)	(0.016)	(0.052)	(0.134)	(0.016)
COMPETITION	-1.111	0.024	0.404	-1.587	0.024
	(2.116)	(0.153)	(0.408)	(1.936)	(0.153)
COMPETITION^2	-4.489	0.684	-3.139*	-2.379	0.684
	(8.990)	(0.859)	(1.681)	(8.138)	(0.859)
TOTALPROJ	22.063***	0.420	2.848***	22.737***	0.420
	(4.264)	(0.335)	(1.052)	(3.721)	(0.335)
TOTALPROJ^2	-55.250**	-0.939	-6.499*	-59.498***	-0.939
	(22.031)	(1.142)	(3.634)	(17.291)	(1.142)
log(*EMP*)	0.083	0.002	-0.016	0.095	0.002
	(0.066)	(0.005)	(0.011)	(0.060)	(0.005)
log*(AGE)*	-0.108	-0.007	-0.014	-0.110	-0.007
	(0.094)	(0.008)	(0.015)	(0.094)	(0.008)
GROUP	0.103	-0.006	-0.009	0.127	-0.006
	(0.139)	(0.012)	(0.024)	(0.136)	(0.012)
Y2015	-0.211*	-0.010	-0.005	-0.213*	-0.010
	(0.120)	(0.010)	(0.022)	(0.116)	(0.010)
PCT. OF INNOVATION ACTIVE FIRMS PER NACE	0.870			0.843	

	(0.569)			(0.529)	
INDUSTRY AVG. RELIANCE ON EXTERNAL KNOWLEDGE	0.069***			0.067***	
	(0.020)			(0.018)	
LEWBEL INSTUMENTS (joint F-statistic)				F(3,929) = 8.35***	
Sector dummies	F(8,932)=2.35**	$\chi^2(8)$=18.97**	$\chi^2(8)$ =7.72	F(8,929)=2.74***	$\chi^2(8)$=23.97***
Hansen J statistic		$\chi^2(1)$= 0.366	$\chi^2(1)$= 0.287		$\chi^2(4)$=1.1
Test of excluded instruments	F(2,932)= 7.67***			F(5,929)=9.42***	

Notes: N= 958; Significance levels: *** 1% or less; ** less than 5% , * less than 10%; all regressions include an intercept; standard errors are robust.
The Lewbel (2012) IV regression has three extra instruments that are based on heteroscedasticity in the first stage. The variables used to construct the instruments are *SUBSIDY*, log(*EMP*) and *NOVELTY.*

4.5 Robustness test III: Heckman selection models

As a final robustness test, we have also accounted for non-innovators in the sample and investigate whether we find evidence for firms' self-selection into innovation and how it might affect our results. We adapted the approach of Signori and Vismara (2018) to our setting and re-run our regression models as Heckman selection models. Our sample then increases from the 999 observations on innovators in the regression models discussed above by 318 non-innovators. The sample thus contains 1,317 observations in total.

We tested several versions of different selection model specifications. In econometric theory, the selection equation may contain the same variables as the outcome equation (Heckman, 1979). In empirical practice, however, it turns out that the commonly used two-step estimator may be subject to identification problems as the inverse mills ratio is a quasi-linear term over a large range of its distribution. This has been documented by Puhani (2000). It is therefore desirable to work with an exclusion restriction, i.e. a variable that appears in the selection equation but not in the outcome equation. As it is difficult to think (and collect) variables that could influence the selection into innovation but not project abandonment or completion, we opted for a pragmatic solution. We first used all variables that we can observe also for non-innovators from our list of covariates in the selection equation. In order to obtain one or more exclusion restriction, we omitted those variables from the outcome equation that were statistically insignificant and tested whether the fit of the model remains similar (the latter avoids erroneously omitting variables that may not have been individually significant but jointly).

In the selection equation, firm size (ln*EMP*), the dummy whether firms patented in the past, and the working capital per employee are positively and statistically associated with a selection into innovation. In none of our estimations, however, the selection into innovation turned out to the relevant. The selection term, i.e. the inverse mills ratio, was always insignificant, and none of our results on openness was altered. We therefore refrain from a detailed presentation of these regression models to save space.

5 Discussion and supplementary analysis of firm performance

Our results show that the proportion of abandoned projects is positively associated with the openness of firms' innovation strategies, where openness is measured by innovation-related cooperation. The rate of project completion, which in addition to abandonment also accounts for project interruptions and delays, shows a negative relationship with openness.

Furthermore, openness towards non-market partners such as public research institutions and consultants seems to be most challenging in terms of successful project management. While both public science and consultants may have unique resources that a firm could not access in a closed innovation regime, at large scale these collaborations are associated with lower success rates. Importantly, our data do not allow us to say that collaborations involving specific partner types are more likely to be subject to abandonment or delay. Rather, we are able to observe only that collaborating with specific partner types associates with a greater incidence of abandonment and delay in a firm's *portfolio* of innovation projects. Determining whether it is projects involving cognitively distant partners that, themselves, are more frequently abandoned or delayed requires more fine-grained information on individual projects than is available in our survey data. Given our arguments on increasing cost and resource competition across projects, it seems plausible that, for instance, collaborative projects involving universities would be more likely to be abandoned or delayed *and* would lead to abandonments and delays in other projects. But the extent of either of these effects is an open empirical question.

Notwithstanding issues of partner type, we interpret our general findings as indicating limitations to open search beyond prior observations concerning diminishing returns on innovativeness (Laursen and Salter, 2006; Leiponen and Helfat, 2010; Love et al., 2013). This negative interpretation rests on the arguing that, in a multi-project environment, a higher proportion of abandoned projects, controlling for average project size and ambition, represents lost opportunities. Engaging in more costly collaborative innovation increases resource competition across projects and limits the resources that can be applied directly to innovating (Hagedoorn et al., 2018). Recognising that many of the resources committed to innovation projects are sunk or imperfectly transferable (Cohen, 2010), delays and abandonments will further limit the resources available to 'good' innovation projects (Radas and Bozic, 2012). In short, to the extent that increased collaboration leads to increased abandonment, which in our data occurs when firms engage with more than one partner type (recall Figure 1), it is likely to have a negative effect on firm performance.

However, as we indicate in the introduction, recent work has positioned innovation abandonment as selectivity and selectivity as a positive component of effective portfolio management (Klingebiel and Rammer, 2014; 2021). Here, the argument is that since "some projects inevitably turn out to be unsuccessful, firms have an interest in prioritizing the allocation of scarce development resources on the most promising projects" (Klingebiel and Rammer, 2021, p. 329). Selection is, of course, a fundamental characteristic of portfolio management (Adams et al., 2006) and (de)selection processes inevitably entail abandonment. However, our concern was not with a binary distinction between selectors and non-selectors, but with the extent of selection or abandonment. While some selection (or abandonment) may indicate effective portfolio management, too much selection (or abandonment), where it is driven by increasing costs and resource competition, may represent resource losses and lost opportunities that, in turn, compromise firm performance.

At the heart of these competing arguments is an empirical question: how does abandonment affect firm performance? While answering this question comprehensively is beyond the scope of the current paper (and is not attempted by Klingebiel and Rammer, 2021), we are able to offer a 'glimpse'.

We estimate supplemental regressions on firm performance in the form of dynamic OLS regressions. In particular, we specify

$$lnVA_{i,t+1} = \beta_0 + \beta_1 lnVA_{i,t} + \beta_2 PA_{i,t} + \beta_3 X_{i,t} + e_{it}$$

where ln*VA* denotes the logarithm of value-added and *PA* refers to the percentage of abandoned projects. X represents a vector of control variables as described in the regression results' table below. β are the coefficients to be estimated and *e* is the statistical error term. We also estimate a version of the model where we use the log of value added in *t*+3 as dependent variable in order to explore effects at the medium term.

Table 8 reports the results of this supplementary analysis. In simple terms, the results suggest that higher rates of abandonment associate with poorer value-added performance in t+1 (columns 1 and 3) and that this effect increases over the medium term (columns 2 and 4). In other words, (too much) abandonment seems to be a bad thing. Of course, while this supplemental analysis aids in the interpretation of our main findings, much remains to be done to establish the relationship between increasing rates of abandonment and the various dimensions of firm performance.

Table 8: Dynamic OLS regressions of value-added on project abandonment

	Value-added t+1 (1)	Value-added t+3 (2)	Value-added t+1 (3)	Value-added t+3 (4)
Value-added at t	0.922 (0.016)***	0.936 (0.019)***	0.905 (0.019)***	0.907 (0.022)***
abandoned projects (in %)	-0.189 (0.098)*	-0.394 (0.150)***	-0.257 (0.104)**	-0.447 (0.154)***
OPEN			0.010 (0.010)	-0.005 (0.012)
Total # projects			0.002 (0.001)**	0.001 (0.001)*
AVG PROJ SIZE			0.806 (0.323)**	1.110 (0.436)**
$(\text{AVG PROJ SIZE})^2$			-0.967 (0.571)*	-1.098 (0.733)
NOVELTY			-0.058 (0.162)	-0.063 (0.173)
PATENT			0.066 (0.042)	0.170 (0.050)
Ln(AGE)			-0.123 (0.031)***	-0.115 (0.052)**
Sector dummies	F(8, 941) = 1.79*	F(8, 905) = 2.00**	F(8, 934) = 2.00**	F(8, 898) = 1.97**
N	953	917	953	917
R-squared	0.86	0.78	0.87	0.79

Notes: All regressions include an intercept. Robust std. errors in parentheses.
Significance levels: *** 1% or less; ** less than 5% , * less than 10%;

6 Conclusion

In conclusion, our study extends existing work that has recorded the limits to open innovation. While much of this work has been concerned with the relationship between openness and innovativeness (following Laursen and Salter, 2006), and positions open innovation as a contingent process (Salge, 2013), our concern was with the extent to which collaborative innovation leads to higher rates of innovation project abandonment. While innovation activity is surely characterized by high uncertainty, and collaborations may help to bundle competences and share risks, the results of this study also highlight the downside of openness as measured by collaboration. As Vivona et al. (2023, p. 874) note, "…collaboration for the sake of collaborating may be highly detrimental for organizations: collaboration is costly, as it requires greater use of resources of money, time, and effort. In short, openness entails increasing costs (Salge et al., 2013). These costs include increased negotiation, coordination and monitoring cost, compounded by problems of imperfect and asymmetric information. Increasing costs entail resource competition across projects and drive higher rates of abandonment. Given the negative results we observe on project success, our study complements the literature highlighting failures in strategic alliances (Hagedoorn et al., 2000; Lokshin et al., 2011).

Of course, as the literature notes (Chesbrough, 2010; Leoncini, 2016) innovation failure, including failures resulting from collaborative innovation, need not be negative. Failure and learning are linked in innovation processes, given the role of trial-and-error discovery. However, when failures, interruptions and delays constitute a larger component of innovation projects, the negative impact on firm performance may outweigh any positive learning effects.

Both managers and policy makers may find these results useful. First, managers may want to pay more attention to collaborative projects and install rigorous project management, monitoring and evaluation because of the possible negative effects of openness. In short, firms must be cautious collaborators; assessing benefits and costs and selecting partners with care, and ensuring adequate resources are set aside for project management. Policy makers may want to critically review their subsidy schemes for R&D and innovation. In most industrialized countries, pre-competitive collaboration is welcomed for the reason of bundling competences; in particular, collaboration with public science has become a desired pattern in subsidy schemes, since technology transfer activities from public science to industry have been subject of numerous policy initiatives. Given the higher rate of failure and lower rates of project completion, policy makers may want to re-think the requirement of openness in subsidy schemes.

While our study utilizes quite unique data on innovation project management, the study is, of course, not without limitations. Our data is rich on quantitative information on project outcomes. However, we lack detailed information on the importance of any given project for the firm. If only peripheral projects fail or are delayed, it may not threaten the long-run competitiveness of the focal firm. It would thus be desirable to be able to weight the projects with respect to their importance to the firms' core business. In addition, there might be further detrimental effects of openness that are beyond the scope of project abandonment, interruptions and delays. Openness in the innovation process may lead to involuntary knowledge leakage that may harm the current competitive position due to imitation, and also to unintended staff mobility that may threaten the firm's knowledge base embedded in its human capital.

Furthermore, it would be desirable to conduct a similar study with a larger and longer panel of firms in order to account for unobserved heterogeneity. While we have a rich set of covariates, it may still be the case that some remaining time-constant heterogeneity across firms exists.

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Appendix

Table 8: Industry composition of the sample

Industry	Freq.	Rel. Freq.	Means OPEN	Share of abandoned projects	share of completed projects
Food, beverage, tobacco	129	12.91	2.22	0.14	0.57
Textile, clothing and leather industry	46	4.6	2.60	0.17	0.51
Manufacture of cokes, chemicals, pharmaceuticals, rubber and plastic	141	14.11	2.91	0.16	0.48
Manufacture of non-ferro minerals, metals and metal products (no machinery and equipment)	90	9.01	2.04	0.13	0.59
Manufacture of electrical equipment, IT-products, electronic and optical products	62	6.21	2.18	0.10	0.57
Manufacture of machinery, equipment, tools and transport	84	8.41	1.95	0.09	0.58
Wholesale	103	10.31	1.63	0.10	0.60
Telecommunication, software design and programming, computer-consultancy, information services, architects and engineering, R&D	185	18.52	1.85	0.09	0.54
Remaining sectors not classified above	159	15.92	1.94	0.08	0.57
Total	999	100.00			

Table 9: Correlation table

	Abandoned	Finished	*TOTALPROJ*	*OPEN*	Collaboration dummy	*AVG PROJ SIZE*	*NOVELTY*	*PATENT*	*WCP/EMP*	*DEBT*	*SUBSIDY*	*COMPETITION*	*Ln(EMP)*	*Ln(AGE)*	*GROUP*
Abandoned	1.000														
Finished	-0.389	1.000													
TOTALPROJ s	0.137	-0.003	1.000												
OPEN	0.119	-0.183	0.327	1.000											
Collaboration dummy	0.075	-0.142	0.183	0.732	1.000										
AVG PROJ SIZE	-0.022	-0.070	0.024	0.204	0.135	1.000									
NOVELTY	-0.005	0.017	0.057	0.097	0.008	0.227	1.000								
PATENT	0.069	-0.119	0.170	0.251	0.163	0.222	0.101	1.000							
WCP/EMP	-0.027	0.015	0.020	0.054	0.066	0.041	-0.020	0.027	1.000						
DEBT	-0.003	0.021	-0.032	-0.067	-0.050	-0.079	-0.045	-0.106	0.006	1.000					
SUBSIDY	-0.032	-0.108	0.189	0.392	0.284	0.311	0.150	0.287	0.036	-0.066	1.000				
COMPETITION	0.037	-0.005	0.104	0.067	0.067	0.013	0.020	0.093	0.349	-0.097	0.101	1.000			
Ln(EMP)	0.084	-0.132	0.256	0.215	0.142	0.227	-0.185	0.198	-0.045	-0.107	0.166	0.025	1.000		
Ln(AGE)	0.011	-0.056	0.055	0.033	0.024	0.009	-0.141	0.100	0.039	-0.101	0.050	0.052	0.378	1.000	
GROUP	0.024	-0.073	0.145	0.125	0.138	0.169	-0.049	0.135	0.061	-0.018	0.072	0.097	0.447	0.108	1.000

Table 10: Coefficient estimates of fractional response models on project abandonment and completion

	Project abandonment		Project completion	
	Coeff. (Std. err.)	Coeff. (Std. err.)	Coeff. (Std. err.)	Coeff . (Std. err.)
OPEN	0.033***	0.033***	-0.058***	-0.056***
	(0.011)	(0.012)	(0.010)	(0.011)
AVG PROJ SIZE		0.318		-1.448***
		(0.561)		(0.420)
AVG PROJ SIZE ^{2}		-0.772		2.483***
		(0.792)		(0.591)
NOVELTY		0.082		0.082
		(0.159)		(0.136)
PATENT		0.059		-0.090*
		(0.064)		(0.051)
WCAP/EMP		-0.390		0.205
		(0.240)		(0.186)
DEBT		0.082		-0.054
		(0.126)		(0.129)
SUBSIDY		-0.170***		-0.012
		(0.065)		(0.053)
COMPETITION		-0.551		1.111
		(0.896)		(0.853)
COMPETITION^2		7.093*		-6.575*
		(4.175)		(3.447)
TOTALPROJ		2.994**		3.027**
		(1.316)		(1.326)
TOTALPROJ^2		-7.612		-5.607
		(4.743)		(5.624)
log(*EMP*)		0.035		-0.055**
		(0.027)		(0.024)
log*(AGE)*		-0.033		-0.026
		(0.040)		(0.035)
GROUP		-0.047		-0.022
		(0.063)		(0.054)
Y2015	-0.058	-0.050	0.011	0.030
	(0.051)	(0.052)	(0.044)	(0.045)
Sector dummies $\chi^2(8)$	33.95	24.93	10.40	14.13
Prob > χ^2	0.0000	0.0016	0.2381	0.0784
Log Pseudo-likelihood	-349.76	-346.87	-680.42	-673.50

Notes: All regressions include an intercept. Robust std. errors in parentheses.
Significance levels: *** 1% or less; ** less than 5% , * less than 10%;

Table 11: Coefficient estimates of fractional response models by type of collaboration

Variables	Project abandonment		Project completion	
	Coeff. (Std. err.)	Coeff. (Std. err.)	Coeff. (Std. err.)	Coeff. (Std. err.)
VERTICAL	-0.061	-0.079	0.023	0.017
	(0.074)	(0.075)	(0.061)	(0.060)
HORIZONTAL	-0.061	-0.060	0.019	0.012
	(0.064)	(0.067)	(0.061)	(0.060)
CONSULT	0.173***	0.180***	-0.108**	-0.090*
	(0.062)	(0.064)	(0.054)	(0.055)
SCIENCE	0.095	0.119	-0.233***	-0.236***
	(0.071)	(0.075)	(0.057)	(0.058)
AVG PROJ SIZE		0.214		-1.375***
		(0.564)		(0.423)
AVG PROJ SIZE ^{2}		-0.650		2.390***
		(0.794)		(0.593)
NOVELTY		0.085		0.080
		(0.158)		(0.135)
PATENT		0.070		-0.097*
		(0.064)		(0.051)
WCAP/EMP		-0.405*		0.203
		(0.239)		(0.180)
DEBT		0.050		-0.032
		(0.127)		(0.129)
SUBSIDY		-0.183***		0.016
		(0.065)		(0.054)
COMPETITION		-0.668		1.132
		(0.894)		(0.852)
COMPETITION ^{2}		7.414*		-6.470*
		(4.121)		(3.439)
TOTALPROJ		3.004**		3.180**
		(1.342)		(1.290)
TOTALPROJ		-7.394		-6.608
		(4.920)		(5.349)
log(EMP)		0.035		-0.057**
		(0.027)		(0.024)
log(AGE)		-0.039		-0.024
		(0.040)		(0.035)
GROUP		-0.047		-0.026
		(0.062)		(0.054)
Y2015	-0.067	-0.058	0.017	0.033
	(0.051)	(0.052)	(0.045)	(0.045)
Sector dummies $\chi^2(8)$	31.32	22.24	9.03	13.31
Prob > χ^2	0.0001	0.0045	0.3395	0.1015
Log Pseudo-likelihood	-348.99	-345.89	-679.23	-672.56

Notes: All regressions include an intercept. Robust std. errors in parentheses.
Significance levels: *** 1% or less; ** less than 5% , * less than 10%;