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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. A 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 strongly associates with an increased risk of both project abandonment and project delays.

Keywords:Open innovation, collaboration, project abandonmentJEL Classification:O31

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1 Introduction

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) (Chesborough 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) and review articles (e.g. Dahlander and Gann 2010; Lichtenthaler 2011; West and Bogers 2014; Randhawa et al. 2016) is testament to the former. For the latter, recent 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). However, equally remarkable is the lack of balance. With few exceptions (e.g. Lhuillery and Pfister 2009; Hyll and Pippel 2015), our stories of OI are positive stories. The focus on successes leads to open innovation imperatives and the conclusion that, where 'openness' falls below some optimum, as is frequently the case, there is 'market failure'¹ (Hewitt-Dundas and Roper 2017). Despite suggestions of eventual diminishing returns (Laursen and Salter 2006; Hottenrott and Lopes-Bento 2016), the

¹ Hewitt-Dundas and Roper (2017) "identify and examine three market failures which may help to explain this result [that engagement in OI falls below some optimum level]. These relate to a lack of understanding of the potential benefits of OI by firms, a lack of information about the capabilities of potential partners and a lack of information about the trustworthiness of potential partners".

inference we are asked to draw is that, for most firms, openness is good and more openness is better.

That there are so few studies of the relationship between openness and innovation failure is particularly surprising 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., 2015, 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, innovation failure, generally, and the failures resulting from collaborative innovation, in particular, need not be negative. Indeed, failure and learning are tightly linked in innovation processes, given the role of trial-and-error discovery (Chesbrough 2010; Leoncini 2016). However, 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. When failures constitute a larger component of innovation projects, the negative impact on firm performance may outweigh any positive learning effects.

This 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 2015; Leoncini 2016; D'Este et al. 2015; Guzzini and lacobucci 2017; García-Quevedo et al. 2018). However, these studies are invariably limited by a binary measure of failure: firms either fail or not. Or, more precisely, firms either record abandoning at least one innovation project or not. Consistent with evidence that the most innovative active firms are those that perceive the greatest barriers to innovation (e.g. D'Este et al. 2012), it also seems likely that collaborative innovators will be more likely to report an abandonment simply as a result of being more innovation active. In the current study, we are able to exploit 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 (failed, successful and ongoing) is a significant limitation in understanding the link between openness and failure. It remains that we know relatively little about the failure of open innovation (West and Bogers 2014). Yet, a better understanding of the incidence of failure is likely to be critical to identifying the limitations of collaborative innovation and to understanding why collaboration is rarely observed to be the modal form of innovating (Drechsler and Natter 2012). The current work makes a contribution to this better understanding.

The rest of the paper is structured as follows: Section 2 outlines the conceptual background of our study and concludes with our hypotheses to be tested. Section 3 presents the data sources, variables and descriptive statistics, and section 4 discusses the econometric study and its results. Section 5 concludes.

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. However, a third mode, encompassing varying degrees of both outbound and inbound flows of knowledge and resources in reciprocal relationships between focal firms and other organisations, is perhaps most prominent in the empirical literature (West and Bogers 2017). This is Enkel and colleagues' "coupled" open innovation (Enkel et al. 2009) and is closely aligned with the larger, prior body of work concerned with innovation collaboration and networking (e.g. DeBresson and Amesse 1991).

In this, 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).

Notwithstanding a disproportionate focus on the benefits of collaboration, there is sufficient work outlining the challenges associated with collaborating to make sense of this empirical regularity without recourse to 'market failure' arguments. Moreover, many of the reasons why firms may choose not to collaborate are also likely to be useful in explaining the instability of collaborations. In the simplest terms, for instance, the failure of collaboration may result from resource limitations (Guzzini et al., 2018). Collaboration entails costs associated with searching for suitable partners, and with coordination and monitoring (Hottenrott and Lopes-Bento 2016). Smaller firms, in particular, may encounter resource constraints as a barrier to effective collaboration (Van De Vrande et al. 2009; Vahter et al. 2015).

Beyond this, 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 2013) 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.

Crucially, the challenges of collaborative innovation are likely to increase with the number and diversity of partners. The U-shaped relationship frequently observed between open innovation and innovation performance (e.g. Laursen and Salter 2006; Leiponen and Helfat 2010; Vahter et al. 2015; Van Criekingen 2020) 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 literature² - 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, Lee, and Nagaoka 2016). 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). In short, large, complex collaborative arrangements are likely to associate with higher rates of innovation abandonment.

The foregoing leads us to hypothesise that:

H1A: The proportion of abandoned projects is positively associated with collaboration and

increases with the number of partner types.

In addition to project abandonment, we add a supplemental hypothesis on project completion. Temporary project interruptions or delays in project completion may represent

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).

a weaker form of project abandonment. To the extent that the arguments leading to hypothesis 1 above may all, in weaker form, also lead to project interruptions and delays, we also investigate successful project completion. 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 2015). 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) 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, 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).

This is consistent with the common distinction drawn in the empirical literature between market and non-market collaborative partners (Weber and Heidenreich 2018). The former are likely to be sources of key technologies or market insights. Vertical collaborations, for instance, will frequently be concerned with exploitation (Faems et al. 2005) and may be particularly suited for transmitting information that is specific to the routines of the customer or supplier and that it 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. 2015), 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).

In contrast, although cooperation with competitors provides the opportunity to share costs and risks, overlapping knowledge bases and competing organisational goals create strong incentives for opportunism (Hyll and Pippel 2015). 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. Indeed, Lhuillery and Pfister (2009, p. 51) observe that "firms collaborating with competitors are most likely to encounter cooperation failures".

With respect to collaborations involving non-market partners (i.e. universities and public research organisations, or consultants, designers or private R&D laboratories), anecdotes surrounding cooperation challenges 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. More generally, it is suggested that universities' commitment to 'open science' will result in weaker appropriation opportunities for partnering firms (Perkmann and Walsh 2007). Research activities undertaken by PROs (including 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, 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".

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, the challenges are likely to flow from partner selection in busy markets characterised by extensive information asymmetries (Tether and Tajar 2008). Beyond this, the challenges in contracting for innovation outcomes, discussed earlier (Felin and Zenger 2014), are also likely to loom large.

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

It is tempting to cast our expectations on the varying rates of abandonment by partner type in terms of relative cognitive proximity. As Nooteboom (1999, p. 795) argues, to innovate a firm "needs complementary, outside sources of cognition: cognition by others which is relevant but also different". A cognition that is too proximate leads to redundancies and limited novelty. A cognition that is too distant retards shared understanding. However, while issues of shared cognition illuminate the scope for learning from collaboration, they say little about governance. Our intuition is that abandonment and delays in collaboration are likely to reflect both issues of complementary competence and adequate governance.

To that end, our expectations on the varying failure rates of cooperative innovations by partner type may be better framed in terms of the varying role of trust in collaborative relationships. Successful delegation (or, in the current case, collaboration) "...requires trust in a dual sense: the other party (to whom judgement is delegated) has no interest in giving wrong advice (disinterestedness), and is capable of giving good advice (competence)" (Nooteboom 1994, p. 342). Universities are likely to be highly disinterested, but have variable competence (where competence extends, for instance, to assessments on speed and application); competitors are likely to be highly competent, but rank very low on disinterestedness; while, supply chain partners are likely to exhibit both high competence and high disinterestedness, at least to the extent that goals are well aligned. Again, with respect to consultants, our intuition is that the greatest challenge will be in the a priori assessment of competence and disinterestedness.

Taken together, the foregoing leads us to hypothesise that:

H2a: Innovation collaborations with customers and suppliers (vertical collaboration) are likely to associate with a lower rate of abandonment.

H2b: Innovation collaborations with competitors (horizontal collaboration), consultants and

PROs are likely to associate with a higher rate of abandonment.

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 represent a weaker form of abandonment and are driven by the same factors.

H2c: Innovation collaborations with customers and suppliers (vertical collaboration) are likely to associate with a higher rate of successful project completion.

H2d: Innovation collaborations with competitors (horizontal collaboration), consultants and PROs are likely to associate with a lower rate of successful project completion.

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. 2013), 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).

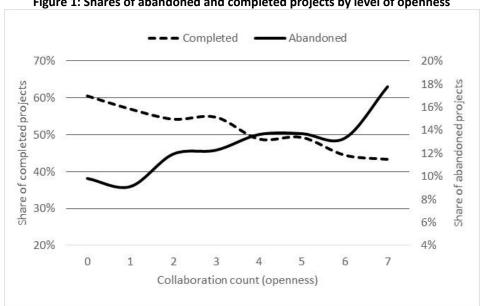


Figure 1: Shares of abandoned and completed projects by level of openness

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.

Control variables 3.4

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. 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 Zunica 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.

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.

All innovators N=999			Non cooperating innovators N = 341			Cooperation active innovators N = 658				
Unit	Mean	Std. Dev.	Min	Max	Mean	Min	Max	Mean	Min	Max
		Depender	nt variables							
share	0.11	0.16	0	1	0.10	0	1	0.12	0	1
share	0.55	0.28	0	1	0.61	0	1	0.52	0	1
		Opennes	s variables							
count	2.12	2.09	0	7	0	0	0	3.22	1	7
dummy	0.59	0.49	0	1	0	0	0	0.90	0	1
dummy	0.16	0.36	0	1	0	0	0	0.24	0	1
dummy	0.32	0.47	0	1	0	0	0	0.49	0	1
dummy	0.42	0.49	0	1	0	0	0	0.63	0	1
		Controls	variables							
Mill.€	0.09	0.15	0	0.90	0.06	0	0.90	0.11	0	0.83
share	0.07	0.16	0	1	0.07	0	1	0.08	0	1
dummy	0.27	0.44	0	1	0.17	0	1	0.32	0	1
share	0.60	0.19	0.04	1	0.61	0.04	1	0.59	0.05	1
Mill.€	0.07	0.13	-0.07	1.82	0.06	-0.06	0.9	0.08	-0.07	1.82
dummy	0.48	0.50	0	1	0.28	0	1	0.58	0	1
count	119	217	1	2718	79	1	1055	139	1	2718
count	28	18	1	143	27	2	143	29	1	127
dummy	0.64	0.48	0	1	0.55	0	1	0.69	0	1
dummy	0.55	0.50	0	1	0.52	0	1	0.56	0	1
	share share count dummy dummy dummy dummy dummy dummy share Mill. € dummy count count count	share 0.11 share 0.55 count 2.12 dummy 0.59 dummy 0.16 dummy 0.32 dummy 0.42 Mill. € 0.09 share 0.07 dummy 0.27 share 0.60 Mill. € 0.07 dummy 0.48 count 119 count 28 dummy 0.64	Unit Mean Std. Dev. Share 0.11 0.16 share 0.55 0.28 Share 0.55 0.28 Count 2.12 2.09 dummy 0.59 0.49 dummy 0.16 0.36 dummy 0.42 0.49 dummy 0.42 0.49 dummy 0.42 0.49 Mill. € 0.09 0.15 Share 0.07 0.16 dummy 0.27 0.44 share 0.60 0.19 Mill. € 0.07 0.13 dummy 0.48 0.50 count 119 217 count 28 18 dummy 0.64 0.48	Unit Mean Std. Dev. Min Share 0.11 0.16 0 share 0.55 0.28 0 Share 0.55 0.28 0 count 2.12 2.09 0 dummy 0.59 0.49 0 dummy 0.59 0.49 0 dummy 0.16 0.36 0 dummy 0.42 0.47 0 dummy 0.42 0.49 0 share 0.07 0.16 0 share 0.07 0.16 0 share 0.60 0.19 0.04 Mill. € 0.07 0.13 -0.07 dummy 0.48 0.50 0 count	UnitMeanStd. Dev.MinMax $Dependent variablesDependent variables1share0.110.1601share0.550.2801Count2.122.0907dummy0.590.4901dummy0.160.3601dummy0.420.4701dummy0.420.4901dummy0.420.4901dummy0.420.4901dummy0.420.4901fill.€0.090.1500.90share0.070.1601dummy0.270.4401share0.600.190.041Mill.€0.070.13-0.071.82dummy0.480.5001count11921712718dummy0.640.4801$	N=999UnitMeanStd. Dev.MinMaxMeanDependent variablesNamMaxMeanshare0.110.16010.10share0.550.28010.61Openness variablesCount2.122.09070dummy0.590.49010dummy0.590.49010dummy0.320.47010dummy0.420.49010dummy0.420.49010dummy0.420.49010.07dummy0.420.49010.07dummy0.420.49010.07fill.€0.070.1500.900.06share0.070.16010.17share0.600.190.0410.61Mill.€0.070.13-0.071.820.06dummy0.480.50010.28count1818114327dummy0.640.48010.55	N=999N = 341UnitMean $\frac{Std.}{Dev.}$ MinMaxMeanMinDependent variablesshare0.110.16010.100share0.550.28010.610share0.550.28010.610count2.122.090700dummy0.590.490100dummy0.160.360100dummy0.420.470100dummy0.420.490100dummy0.420.49010.00dummy0.420.49010.00dummy0.420.49010.00dummy0.420.49010.00share0.070.16010.070share0.070.16010.170share0.600.190.0410.610.04Mill.€0.070.13-0.071.820.06-0.06dummy0.480.50010.280count11921712718791count28181143272dummy0.640.48010.550 <td>N=999N = 341UnitMean$\frac{Std.}{Dev.}$MinMaxMeanMinMaxDependent variablesshare0.110.16010.1001share0.550.28010.6101Openness variablescount2.122.0907000dummy0.590.4901000dummy0.160.3601000dummy0.420.4901000dummy0.420.49010.0000dummy0.420.49010.0701fill.€0.090.1500.900.0609share0.070.16010.0701fill.€0.070.13-0.071.820.06-0.060.9fill.€0.070.13-0.071.820.06-0.060.9dummy0.480.50010.28011055count18143272143143272143</td> <td>N=999N = 341UnitMeanStd. Dev.MinMaxMeanMinMaxMeanShare0.110.16010.10010.12share0.550.28010.61010.12Share0.110.16010.61010.12Count2.122.09070003.22dummy0.590.49010000.90dummy0.160.36010000.24dummy0.320.47010000.49dummy0.420.49010.07010.08Mill €0.090.1500.900.060010.32Share0.070.16010.07010.32share0.070.13-0.071.820.06-0.060.90.08dummy0.480.50010.28010.551139count119217127187911055139count2818114327214329dummy0.640.48010.55010.69</td> <td>N=999 N = 341 Innovator N = 658 Unit Mean Mean Min Max Mun Mun Mun Mun <th< td=""></th<></td>	N=999N = 341UnitMean $\frac{Std.}{Dev.}$ MinMaxMeanMinMaxDependent variablesshare0.110.16010.1001share0.550.28010.6101Openness variablescount2.122.0907000dummy0.590.4901000dummy0.160.3601000dummy0.420.4901000dummy0.420.49010.0000dummy0.420.49010.0701fill.€0.090.1500.900.0609share0.070.16010.0701fill.€0.070.13-0.071.820.06-0.060.9fill.€0.070.13-0.071.820.06-0.060.9dummy0.480.50010.28011055count18143272143143272143	N=999N = 341UnitMeanStd. Dev.MinMaxMeanMinMaxMeanShare0.110.16010.10010.12share0.550.28010.61010.12Share0.110.16010.61010.12Count2.122.09070003.22dummy0.590.49010000.90dummy0.160.36010000.24dummy0.320.47010000.49dummy0.420.49010.07010.08Mill €0.090.1500.900.060010.32Share0.070.16010.07010.32share0.070.13-0.071.820.06-0.060.90.08dummy0.480.50010.28010.551139count119217127187911055139count2818114327214329dummy0.640.48010.55010.69	N=999 N = 341 Innovator N = 658 Unit Mean Mean Min Max Mun Mun Mun Mun <th< td=""></th<>

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 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 0.8%-points. As the mean of firms that do not follow an open innovation strategy is about 10%, it is quite a sizable impact: 8% 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. Here the marginal effect amounts to 1.8%-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.

Table 3: Marginal effects in fractional response models on project abandonment and completion								
	Project aba	andonment	Project co	ompletion				
	Marg. Eff.	Marg. Eff.	Marg. Eff.	Marg. Eff.				
	(Std. err.)	(Std. err.)	(Std. err.)	(Std. err.)				
OPEN	0.006***	0.008***	-0.023***	-0.018***				
	(0.002)	(0.002)	(0.004)	(0.004)				
AVG PROJ SIZE ⁴		0.017		-0.443***				
		(0.077)		(0.120)				
NOVELTY		0.026		0.045				
		(0.029)		(0.055)				
PATENT		0.015		-0.031				
		(0.012)		(0.020)				
WCAP/EMP		-0.045		0.067				
		(0.040)		(0.068)				
DEBT		0.017		-0.028				
		(0.024)		(0.049)				
SUBSIDY		-0.029**		-0.002				
		(0.012)		(0.021)				
log(EMP)		0.009*		-0.014				
		(0.005)		(0.009)				
log(AGE)		-0.007		-0.012				
		(0.008)		(0.013)				
GROUP		-0.006		-0.008				
		(0.012)		(0.021)				
Y2015	-0.011	-0.009	0.004	0.012				
	(0.010)	(0.010)	(0.017)	(0.017)				
Sector dummies $\chi^2(8)$	33.95***	26.96***	10.40	10.43				
$Prob > \chi^2$	0.000	0.001	0.238	0.236				
Log Pseudo-likelihood	-349.76	-348.09	-680.42	-675.37				

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

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.

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 -0.44 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. \in 60,000 per project. If the project size would double to \in 120,000, the implied change in completion rate would amount to - 2.7%. This average negative effect suggests that the larger projects are more ambitious and are therefore more often delayed or interrupted than smaller ones.

⁴ The regression includes AVG PROJ SIZE and also (AVG PROJ SIZE)². When calculating 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.

In order to present the marginal effects in the corresponding way to the unconditional descriptive statistics as shown in Figure 1, 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% (9.8%) of its projects and complete about 59% (58.9%) of them.

MEs	Project abandonment	Project completion
at OPEN = 0	0.098***	0.589***
	(0.007)	(0.014)
at OPEN = 1	0.105***	0.571***
	(0.006)	(0.011)
at OPEN = 2	0.113***	0.553***
	(0.005)	(0.009)
at OPEN = 3	0.120***	0.534***
	(0.005)	(0.009)
at OPEN = 4	0.129***	0.516***
	(0.006)	(0.011)
at OPEN = 5	0.137***	0.498***
	(0.008)	(0.015)
at OPEN = 6	0.146***	0.480***
	(0.011)	(0.018)
at OPEN = 7	0.156***	0.461***
	(0.014)	(0.022)

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 15.6% and 46.1% at the maximum level of openness, i.e. abandonment rises by about 59% and completion falls by 22%. 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.

In the regressions on project abandonment, both consultants and science are associated with higher failure rates. The marginal effects amount 3.4%-points and 2.8%points, respectively. In the regression on project completion, we only find a statistically significant negative effect for 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, Persaud, and Chamberlin 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.

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).

Variables	Project aba	andonment	Project co	Project completion		
	Marg. Eff.	Marg. Eff.	Marg. Eff.	Marg. Eff.		
	(Std. err.)	(Std. err.)	(Std. err.)	(Std. err.)		
VERTICAL	-0.012	-0.013	0.009	0.01		
	(0.014)	(0.014)	(0.024)	(0.023)		
HORIZONTAL	-0.012	-0.011	0.008	0.007		
	(0.012)	(0.012)	(0.024)	(0.023)		
CONSULT	0.033***	0.034***	-0.042**	-0.031		
	(0.012)	(0.012)	(0.021)	(0.021)		
SCIENCE	0.018	0.028**	-0.091***	-0.082***		
	(0.013)	(0.014)	(0.022)	(0.022)		
AVG PROJ SIZE		-0.001		-0.421***		
		(0.078)		(0.120)		
NOVELTY		0.027		0.045		
		(0.029)		(0.054)		
PATENT		0.017		-0.033		
		(0.012)		(0.020)		
WCAP/EMP		-0.05		0.068		
		(0.040)		(0.066)		
DEBT		0.011		-0.021		
		(0.024)		(0.049)		
SUBSIDY		-0.032***		0.009		
		(0.012)		(0.021)		
log(EMP)		0.009*		-0.015*		
		(0.005)		(0.009)		
log(AGE)		-0.008		-0.011		
		(0.008)		(0.013)		
GROUP		-0.005		-0.009		
		(0.012)		(0.021)		
Y2015	-0.013	-0.011	0.007	0.014		
	(0.010)	(0.010)	(0.017)	(0.017)		
Sector dummies $\chi^2(8)$	31.23	24.06	9.03	9.80		
Prob > χ^2	0.000	0.002	0.339	0.279		
Log Pseudo-likelihood	-348.99	-347.12	-679.23	-674.42		

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

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.

4.3 Robustness test: Seemingly unrelated least squares regressions

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 easily 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.

Table 6: SOK on abandonment and completion						
	Abandonment	Completion				
	Coeff.	Coeff.				
	(Std. err.)	(Std. err.)				
OPEN	0.008***	-0.018***				
	(0.003)	(0.005)				
AVG PROJ SIZE	0.041	-0.633***				
	(0.094)	(0.169)				
AVG PROJ SIZE^2	-0.130	1.031***				
	(0.142)	(0.257)				
NOVELTY	0.025	0.045				
	(0.033)	(0.059)				
PATENT	0.015	-0.031				
	(0.012)	(0.022)				
WCAP/EMP	-0.042	0.065				
	(0.038)	(0.068)				
DEBT	0.017	-0.028				
	(0.025)	(0.046)				
SUBSIDY	-0.029***	-0.002				
	(0.011)	(0.020)				
log(EMP)	0.009*	-0.014				
	(0.005)	(0.009)				
log(AGE)	-0.008	-0.012				
	(0.008)	(0.014)				
GROUP	-0.004	-0.008				
	(0.011)	(0.020)				
Y2015	-0.010	0.012				
	(0.010)	(0.018)				
Sector dummies $\chi^2(8)$	29.52***	9.83				
Prob > χ^2	(0.000)	(0.278)				

Table 6: SUR on abandonment and completion

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

When testing whether the absolute magnitude of the coefficient of OPEN is larger in

the completion regression (coef. = -0.018) than in the abandonment regression (coef. =

0.008), we set up the hypothesis

H0: 0.008 = abs(-0.018).

The test rejects the Null with $\chi^2(1) = 5.04$, Prob > $\chi^2 = 0.025$. 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.

4.4 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, - 0.07, and statistically significant at the 5% level. The previous results thus hold. IN the abandonment regression, the coefficient amount to 0.027, but is only weakly significant at the 10% level. In order to gain some 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 drops slightly to 0.17 but is now significant at the 5% level. Therefore all previously reported results also hold when accounting for possible endogeneity of openness in the regression models.

	(First stage i	IV regression (First stage is identical for both 2 nd stages)			IV regression with supplemental Lewbel IVs		
	First stage	Second stage	Second stage	First stage	Second stage		
	OPEN	Abandonment	Completion	OPEN	Abandonment		
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.		
	(Std. err.)	(Std. err.)	(Std. err.)	(Std. err.)	(Std. err.)		
OPEN	(300.011)	0.027*	-0.070**	(300.011)	0.017**		
		(0.016)	(0.031)		(0.008)		
AVG PROJ SIZE	0.288	0.03	-0.571***	0.171	0.037		
	(1.164)	(0.102)	(0.174)	(1.036)	(0.100)		
AVG PROJ SIZE^2	0.796	-0.12	0.987***	0.808	-0.119		
AVO FROJ SIZE Z	(1.836)	(0.145)	(0.248)	(1.512)	(0.140)		
NOVELTY	0.803*	0.009	0.098	0.966***	0.019		
NOVELIT	(0.45)	(0.033)	(0.065)	(0.363)	(0.030)		
PATENT	0.407**	0.008	-0.003	0.320**	0.013		
FAILM	(0.159)	(0.014)	(0.025)	(0.144)	(0.012)		
WCAP/EMP	0.456	-0.051	0.096	0.463	-0.046		
WCAF/LWF	(0.356)	(0.033)	(0.070)	(0.35)	(0.031)		
DEBT	-0.201	0.025	-0.043	-0.084	0.021		
DEDI	(0.315)	(0.025)	(0.054)	(0.302)	(0.025)		
SUBSIDY	1.290***	-0.055**	0.066	1.298***	-0.041**		
SUBSIDY							
	(0.138) 0.199***	(0.025) 0.002	(0.048) -0.003	(0.135) 0.201***	(0.016) 0.005		
log(EMP)							
	(0.065)	(0.006)	(0.011)	(0.058)	(0.005)		
log(AGE)	-0.157	-0.007	-0.017	-0.167*	-0.009		
C2.0.1/2	(0.097)	(0.008)	(0.014)	(0.097)	(0.008)		
GROUP	0.142	-0.005	-0.007	0.165	-0.004		
N2045	(0.141)	(0.012)	(0.023)	(0.138)	(0.011)		
Y2015	-0.196	-0.009	0.000	-0.203*	-0.011		
	(0.122)	(0.011)	(0.020)	(0.119)	(0.010)		
PCT. OF INNOVATION ACTIVE FIRMS PER NACE	1.222**			1.243**			
	(0.591)			(0.542)			
INDUSTRY AVG. RELIANCE ON EXTERNAL KNOWLEDGE	0.079***			0.078***			
	(0.021)			(0.019)			
LEWBEL INSTUMENTS (joint F-statistic)			24-1	9.12***	2 /-1		
Sector dummies	F(8,936)=3.03***	$\chi^2(8) = 17.45^{***}$	$\chi^2(8) = 5.48$	F(8,933)=3.66***	$\chi^2(8) = 25.61^{***}$		
Hansen J statistic		$\chi^2(1) = 0.265$	$\chi^2(1)=0.152$		$\chi^2(4)$ = 1.17		
Test of excluded instruments	F(2,936)=			F(5,933)=			
	10.29***			11.59***			

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

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.

5 Discussion and conclusion

Our results show that the proportion of abandoned projects is positively associated with the openness of firms' innovation strategy; 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 problematic 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.

Our study thus adds to the scarce literature on failures in innovation projects, especially in the context of open innovation (cf. Link and Wright 2015). 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. Openness entails transaction cost, including coordination and monitoring cost, and is associated with problems of asymmetric information. Given the negative results on project success, our study is thus in line with the literature highlighting failures in strategic alliances (Hagedoorn et al. 2000; D'Este et al. 2015).

As the literature points out (Chesbrough 2010; Leoncini 2016) that 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 project 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

E

			Means		
Industry	Freq.	Rel. Freq.	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	185	18.52	1.85	0.09	0.54
services, architects and engineering, R&D					
Remaining sectors not classified above	159	15.92	1.94	0.08	0.57
Total	999	100.00			



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