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Collaboration scope and product innovation in B2B Markets: Are there too many cooks or is it the customer who spoils the broth?

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Abstract:

Purpose

Product innovations are often the result of combinations of internal and external knowledge. A significant amount of open innovation literature has argued that working with external partners can be beneficial, in particular, when this is complemented by internal R&D, yet a wholesale shift to open innovation has not occurred. The purpose of this study is to demonstrate two new limits of openness, grounded in attention-based theory, that help explain why such a shift has not occurred. This study argues that specific combinations of identities a firm collaborates with, that is, whether a partner is classified as a customer, supplier, competitor or university and/or technological center, predictably increase and decrease product innovation.

Design/methodology/approach

This study demonstrates these findings using econometric techniques on a large-scale panel data set, comprising 14,682 observations.

Findings

The authors observe positive effects of customer collaboration, partner scope (collaboration with other outside identities) and internal R&D when considered separately. Critically, they observe two important situations where these positive effects are reduced. First, they argue and observe that when customers are added to the mix of identities, diminished returns on product innovation result. Second, they argue and observe that technological customer collaboration reduces the benefits from an internal R&D department (more than collaboration with other identities). The findings of this study are robust in that singling out another partner identity does not reveal such patterns.

Research limitations/implications

The findings stress the importance of considering the identity of collaborating parties in studying the impact of openness on innovation success. This study conceptually and empirically rejects the – implicitly held – assumption in the literature that different partners provide similar benefits and are interchangeable.

Practical implications

This study proposes new limits to the “open innovation” literature. As identities are easy to observe by managers and are shown to impact product innovation, this study argues they are highly relevant to managerial decision-making. This study also observes, through counterfactual analysis, that attention limits are critical, as a theoretical setting of no attention limits would significantly lift product innovations.

Originality/value

This study shows important limitations to the open innovation literature by showing that customer collaboration leads to declining rates of product innovation when combined with greater collaboration scope or the internal R&D department. This study adds the novel insight that customer collaboration weakens the positive effect of collaboration scope and internal R&D on product innovations.

Keywords R&D, Product innovation, Customer collaboration, Collaboration diversity

Paper type Research paper

Introduction

To create product innovations, products significantly different from those produced earlier, firms in business-to-business (B2B) contexts often collaborate technologically with outside partners. Past research, typically under the aegis of the "Open Innovation" paradigm, has suggested that these outside partners usefully contribute to product innovation, whether these are customers (Noordhoff *et al.*, 2011), suppliers (Raassens *et al.*, 2012) or other partners (Cui and O'Connor, 2012). Furthermore, Cassiman and Veugelers (2006) showed that these outside partners can also effectively leverage collaborations with internal R&D.

However, not all these "open innovation" strategies appear equally successful, something that might underpin the observation of Love *et al.* (2014) that there is little evidence of a broad shift toward the joint use of internal and external knowledge in innovation. Past work has documented some challenges in collaboration strategies. For example, "macro"-focused work argued that too much diversity or scope can be detrimental to innovation (Laursen and Salter, 2006; Mooi *et al.*, 2016), but such work does not specifically focus on customers, while more "micro"-focused work, such as by Noordhoff *et al.* (2011), shows that collaborations between different partner identities such as customers and suppliers can be problematic because of misaligned incentives or opportunism. This line of work does not account for R&D or other collaborations. Yet, in "open innovation" strategies, the internal R&D department may not "mix" well with collaboration with customers or other identities.

In this paper, we argue that difficulties to create product innovations arise because of critical variation in the identities of the external partners a firm draws on and the challenges that this generates in terms of focusing time and effort by the focal organization as reflected in the number of product innovations. We measure innovation as the number of product innovations a firm produces [1] and focus on technological collaborations with external partners in a B2B context [2], one of the key research priorities in B2B as identified by the Institute for the Study of Business Markets (ISBM, 2021). We distinguish four possible identities of external partners: customer, supplier, competitor and university and/or technological center. Thus, if a firm collaborates with a supplier and a university, then the firm collaborates with two external identities. We ascribe a particular role to *customer collaboration*, that is, technological collaboration with customers, and we refer to the number of other identities a firm technologically collaborates with as *collaboration scope*. The central problem that we study is whether the number of product innovations predictably correlates with combinations of customer collaboration, collaborations with other external partner identities and the internal R&D department.

We draw on the attention-based theory (Ocasio, 1997, p. 189), which defines attention as the noticing, encoding, interpreting and focusing of time and effort by organizational decision-makers on issues and answers to hypothesize that customer collaboration:

- reduces the positive effect of collaboration scope on the number of product innovations;
- reduces the positive effect of the internal R&D department on the number of product innovations; and
- weakens the positive effect of the internal R&D department on the number of product innovations more than collaboration scope.

We test our hypotheses on a large-scale panel data set, comprising 2,994 firms for the period of 1998–2006 and covering the entire Spanish manufacturing industry. Because the traditional "conditional negative binomial model for panel data, [. . .] is not a true fixed-effects method" (Allison, 2009), we adopt the econometric procedure introduced by Blundell *et al.* (1999) to control for unobserved heterogeneity and resulting endogeneity. In doing so, this study is among the first to provide large-scale and robust empirical evidence on the innovation effects of collaborations with external partners while controlling for unobserved heterogeneity.

Our empirical results support our hypothesizing. Customer collaboration is associated with a strong increase in the number of product innovations; however, it also reduces the benefits of collaboration scope. We not only show a positive effect of having an internal R&D department on the number of product innovations but also find that the internal R&D department has a reduced effect on product innovations when combined with customer collaboration. Yet no such effect can be discerned for other identities. These findings provide key insights into the limits of the open innovation paradigm. Overall, the three critical elements of the open innovation paradigm, customer collaboration, partner scope and internal R&D, are individually beneficial to the number of product innovations, but combined reliance can significantly reduce their marginal benefits.

Our theory and findings provide several key contributions. Academics have produced considerable evidence establishing the reasons for collaboration (Noordhoff *et al.*, 2011) but have spent far less effort theorizing and collecting evidence on the limits of openness. We develop middle range theory and show that an important reason is to be found in the identity of the partners. We demonstrate that the identities of the collaboration partners are critical. Specifically, by counting the number of involved identities, as previous papers have done (Laursen and Salter, 2006; Mooi *et al.*, 2016), one assumes that these identities can be exchanged. This assumption can be problematic because, as we show, some combinations of identities promote product innovation, whereas other combinations reduce the respective benefits these identities provide. In Table 1, we document how the current paper advances our understanding beyond these, and other, key papers. As we document, our key insights are based on:

- differential effects of partner identities;
- our focus on customer effects on innovation;
- our empirical evidence; and
- our ability to account for unobserved heterogeneity.

Next, we rely on the attention-based theory (Ocasio, 1997) to develop a theoretical grounding for our hypotheses. We then introduce our data and methodology. We end with a discussion of our findings and implications for scholars and practitioners.

Theoretical framework

Product innovation and attention

Prior literature has ascribed significant benefit to collaborating with external partners, whether these are customers (Noordhoff *et al.*, 2011), suppliers (Raassens *et al.*, 2012) or any other type of partner (Cui and O'Connor, 2012). However, key work has also alluded to important limitations. For example, Laursen and Salter (2006) suggest that the marginal returns to working with outside parties increase when moving from low to medium levels of partner scope but diminish or even decrease when partner scope increases further. Limitations have also been observed for the combination of collaborations with external

Table 1.
Contributions

Paper	Partner identities considered	Theory used	Dependent variable	Partner identity effects considered separately	Customer effects observed	Empirical	Accounts for unobserved heterogeneity
Kim, Kim, and Foss (2016)	• No explicit partner identities considered	The attention-based view	A cyclic interplay between absorptive capacity and inbound innovation	N	–	N	–
Laursen and Salter (2006)	• Suppliers • Clients or customers • Competitors • Consultants • Commercial • Laboratories/R&D enterprises • Universities or • Other higher education institutes • Government • Research organizations private research • Institutes	The open innovation paradigm	Innovative performance across three dimensions	N	N	Y	N
Mooi, Wathne and Kayande (2016)	• Joint research and development • Joint buying • Integrated supply chain • Joint marketing or distribution • Other cooperative arrangements	The open innovation paradigm	Product and service innovation, process innovation and marketing innovation	N	N	Y	Tested for
Cui and Wu (2016)	• Customers	Knowledge-based view	New product performance	N	Y	Y	N
Noordhoff	• Suppliers • Customers	Tie-strength literature	Supplier innovation, strategic advantage and financial performance	N	N	Y	N
This paper	• Supplier • University/Technological center • Competitor • Customer	The attention-based view	The number of product innovations	Y	Y	Y	Y

partners and internal R&D: key works such as Laursen and Salter (2006) and Audretsch *et al.* (1996) observed a negative interaction between internal R&D and collaboration on innovation.

We approach the potential limitations of technological collaborations with external partners in a B2B context through the lens of attention-based theory, which focuses on the noticing, encoding, interpreting and focusing of time and effort by organizational decision-makers on "issues" and "answers" (Ocasio, 1997, p. 189). The cornerstone of Ocasio's theory is that attention is a scarce resource and that competing demands put significant strain on this resource, whose pressure managers aim to relieve through selective deployment of attention to "issues" and "answers" (March, 1991; Ocasio, 1997). In our setting, managers attend to the "issue" of innovation and receive "answers" from interactions with external parties, such as customers, suppliers, competitors and universities, and from the internal R&D department. When it becomes too demanding for managers to give attention to all issues and potential answers, they will prioritize certain issues and answers and allocate attention to the most important one(s).

We build on this theoretical grounding introduced by Ocasio (1997) to argue that some configurations of customer collaboration, collaboration scope and the internal R&D department are better, and some worse, at producing product innovations because of their differential drawing on managerial attention (which underlies resource allocation) because of difficulties in noticing, encoding, interpreting and focusing of time and effort from different sources. We argue that such difficulties particularly apply when complementing technological customer collaboration with technological collaboration with other identities, such as universities or technological centers. Moreover, we argue that technological customer collaboration can create difficulties when complemented with an internal R&D department. In the hypothesis development, we provide details on how these difficulties predictably correlate with product innovation. In doing so, we shed important light on prior findings (Laursen and Salter, 2006) that there may be "too few" or "too many" identities. Critically, previous work implicitly assumes – by counting the number of identities – that the identity of the partners is effectively exchangeable (with the notable exception of Kang and Kang, 2010). A central thesis of our paper is that heterogeneity exists across partner identities with important consequences for managerial attention and innovation outcomes.

Customer collaboration and collaboration scope

The first hypothesis concerns the scenario when customer collaboration and collaboration scope interact and their predictable effect on the number of product innovations. Firms collaborate with external identities to obtain "answers" to product innovation questions. A long line of literature has demonstrated that collaboration with customers confers benefits, such as an ability to better understand customers (di Fiori and Vetter, 2016) and ultimately increased innovation (Noordhoff *et al.*, 2011). Similarly, collaborations with other identities confer significant benefits too. For example, Murtha *et al.* (2001) document how suppliers may share operations, technologies, equipment and design to increase innovation. Un and Asakawa (2015) argue that collaboration with a university enables firms to question how processes are undertaken and to reanalyze the whole process to improve product quality.

However, these collaborations with external identities need to be monitored and coordinated, the interpretation of which requires managerial attention. While collaboration with any partner identity would raise monitoring and coordination costs (Hottenrott and Lopes–Bento, 2016), we argue that the significantly different situation of customer collaboration amplifies these costs compared to other identities. A nascent body of work (Homburg *et al.*, 2011) suggests that customer interactions require significant managerial attention in the form of 1) need and problem identification and the encoding this requires, 2) presentation and demonstration of customer solutions and the interpretation this involves and 3) dealing with objections and negotiation. Past work has also documented how customer relationships require specific investments and may also require significant formalization of the relationship (Noordhoff *et al.*, 2011) and implies that schemas need to be used by decision-makers that require managerial attention. Moreover, Narver *et al.* (2004) argue that customers have specific use needs that customers find often difficult to express (Blocker *et al.*, 2011) which generates noticing and encoding difficulties. Additionally, customers' focus on *needs and use* makes such collaborations more application-oriented (Knudsen, 2007) and, thus, stand out from collaborations with other identities, again requiring more significant managerial attention to be encoded and interpreted.

As the focal firm starts to work with customers, in addition to several other partner identities, the unique information from customers' needs, that are typically imperfectly expressed, need to be combined with inputs from others, which requires additional noticing, encoding and interpreting and, thus, significant attention from managers. When the demand for managerial attention increases, managers must selectively focus their attention to the most important issues and provide answer(s) (Ocasio, 1997). Such a selective focus makes that some answers will just not be developed, thus resulting in a diminished number of product innovations. Formally:

H1. Customer collaboration reduces the positive effect of collaboration scope on the number of product innovations.

Customer collaboration, collaboration scope and the internal R&D department

The second hypothesis concerns the scenario of when an internal R&D department is combined with technological customer collaboration and its expected effect on the number of product innovations. A R&D department benefits innovation through input, knowledge and answers [3]. West *et al.* (2014) articulate how R&D has "two faces" where, on the one hand, internal R&D generates new knowledge but, on the other hand, also generates the absorptive capacity to effectively scan, screen and absorb external know-how (Cohen and Levinthal, 1989). We predict that the presence of an internal R&D department, when combined with technological customer collaboration, requires greater managerial attention.

The increased need for managerial attention is because of several reasons. First, the focus of customer collaboration (similar to *H1*) is most likely on *use* situations, generating a need to coordinate with the internal R&D department. Such coordination needs will be considerable, for example, because external information from the customer is often localized and hard to transfer, creating what Von Hippel (1994) calls "sticky" information that is harder to encode. The result is a transfer from one knowledge domain to another, and this boundary spanning creates, as Kim *et al.* (2016) describe, difficulties. When greater requests for attention are made, managers will selectively allocate their attention to the most important issues and answer(s) where importance is determined by legitimacy, value and relevance to the organization (Ocasio, 1997). Answers from customers likely score high on all three criteria. Customers have an incentive to provide answers that lead to the development of products that are valued in the market, as they themselves would benefit and they are typically considered the most important stakeholder (Jaworski and Kohli, 1993). The greater attention for answers from customers reduces (perceived) autonomy or decision-making freedom of the internal R&D department, and greater reactance is likely to occur (Brehm and Brehm, 2013). Such resistance will manifest in reduced absorptive capacity and a not-invented-here syndrome (Laursen and Salter, 2006) and, thus, reduced product innovation (Noble and Mokwa, 1999). Hence, we hypothesize:

> *H2*. Customer collaboration reduces the positive effect of the internal R&D department on the number of product innovations.

The third, and final, hypothesis concerns the scenario of when an internal R&D department is complemented by customer collaboration and collaboration(s) with other parties. Specifically, our hypothesis compares the relative effects on product innovation of complementing the internal R&D department with:

- customer collaboration; and
- collaboration scope.

Our key arguments draw on the relative managerial ease or difficulty of complementing the internal R&D department with collaborations with different external identities. Firms can more easily assimilate information and knowledge sufficiently like their own (Sampson, 2007). Technological customer collaboration differs from collaboration with other identities in that answers from customers are more application-oriented (Knudsen, 2007). Hence, while the internal schemas of noticing, encoding and interpreting are unlikely identical to those that apply to outside knowledge (Ocasio, 1997), assimilation of customer knowledge will require managerial attention because of the unique "use" aspects. Collaboration scope requires less encoding and interpretation than customer collaboration, therefore freeing up important managerial attention (and subsequent resource allocation) for innovation. Moreover, Chan *et al.* (2010) document that customer participation creates loss of power and control in the organization, increases input uncertainty and often generates incompatible role expectations, ones that often go beyond technical aspects, as customers also have use requirements, which creates higher role stress (Singh, 1998). These elements all draw on scarce managerial attention. As a result, we expect that customer collaboration weakens the benefits of the internal R&D department more than collaborations with other external identities. In addition, it is more likely that the not-invented-here syndrome (Laursen and Salter, 2006) surfaces when dealing with customers, in part because their significant legitimacy is harder to brush off. Accordingly, we hypothesize:

> *H3*. The positive effect of the internal R&D department on the number of product innovations weakens more by customer collaboration than by collaboration scope.

Methodology

Data

The data used to test our hypotheses originate from the ESEE survey (*Encuesta sobre Estrategias Empresariales*) collected by the Spanish Science, Culture and Sports Ministry since 1990 to produce annual reports and statistics for the government. The ESEE surveys firms which have ten or more employees and whose principal economic activity is listed in one of the two-digit manufacturing industries (as classified per NACE-Rev.1; Huergo, 2006). Firms with between 10 and 200 employees are sampled, while a census is performed on firms with more than 200 employees. As reported in Table 2, the sample covers the whole manufacturing sector. While product innovation and technological collaborations are reported across all sectors, we also see that some sectors, such as chemicals, office machinery and computers, motor vehicles and other transportation equipment, report higher levels of product innovation and technological collaboration. The survey includes a

		% of cases belonging to each industry	Average no. of product innovations per firm	Average customer collaboration per firm	Average collaboration scope per firm
1	Production, procession meat	2.7	0.17	0.04	0.31
2	Food products and tobacco	9.2	0.23	0.07	0.40
3	Beverages	1.8	0.26	0.07	0.49
4	Textiles and wearing apparel	9.0	0.23	0.11	0.27
5	Leather and leather products	2.8	0.18	0.10	0.25
6	Wood and wood products	3.3	0.09	0.05	0.20
7	Pulp, paper and paper products	3.2	0.19	0.21	0.47
8	Publishing and printing	5.4	0.09	0.04	0.13
9	Chemicals and chemical products	6.5	0.37	0.40	0.92
10	Rubber and plastic products	5.6	0.27	0.22	0.40
11	Non-metallic mineral products	7.1	0.14	0.10	0.44
12	Basic metals	3.6	0.21	0.35	0.76
13	Fabricated metal products	11.2	0.14	0.15	0.30
14	Machinery and equipment	7.3	0.31	0.29	0.63
15	Office machinery, computers	1.4	0.43	0.40	0.88
16	Electrical machinery and apparatus	6.0	0.34	0.33	0.69
17	Motor vehicles, trailers	5.1	0.28	0.36	0.85
18	Other transport equipment	2.0	0.32	0.28	0.85
19	Furniture	5.0	0.24	0.07	0.21
20	Other manufacturing	2.0	0.19	0.04	0.17

Table 2.
Data description

set of items on innovation, R&D, customer and suppliers, employment and accounting data and has been used extensively in academic research. For example, Cassiman and Martinez-Ros (2007) consider the link between innovation and exports, while Doraszelski and Jaumandreu (2013) estimate production functions with endogenous innovation. Earlier work has adopted the ESEE to explore how R&D spending is driven by subsidies (González *et al.*, 2005).

We have access to ESEE data for the period of 1998–2006 inclusive and report on an unbalanced sample of 2,994 firms for a total of 14,682 firm-year observations [4]. On average, we observe 1,631 firms yearly, and each firm reports for about five years. The ESEE has attempted to avoid attrition in the data set by bringing back firms that failed to respond but continue to exist. The rigor applied to the sampling approach, and the legal requirement of compliance, supports claims of representativeness of the Spanish manufacturing sector [we refer to Cassiman and Martinez-Ros (2007) for an overview]. This representativeness is exceedingly hard to achieve by academics yet greatly strengthens valid inference.

We also note that as we have panel data (data for multiple firms across multiple time periods), we can focus our analysis on temporal variation in the data. In doing so, we can alleviate endogeneity concerns and make stronger claims of association, representing an additional strength of this study. Endogeneity can be a serious concern for cross-sectional studies in marketing (Rossi, 2014). The reason is that the opportunities that make firms innovate may be the same reasons that make firms collaborate. Examples of such variables include corporate culture, collaboration characteristics, customer attributes or a firm's baseline propensity to innovate. The omission of such variables, which may come in many different forms and guises and can be hard to measure, may positively or negatively bias estimates. Provided that these unobserved variables vary between firms (cross-sectional variation) but are relatively stable over time, fixed effects estimation allows us to focus on temporal within-firm variation and estimate the parameters while avoiding an endogeneity bias because of time-invariant unobserved heterogeneity.

Measures

Dependent variable

We analyze the number of product innovations introduced by firm i in year t (PI_{it}) and define product innovations as "completely new products, or with such modifications that they are different from those produced earlier." We find that the average firm produces 1.6 product innovations per year with 77% of the firm-year observations equal to zero product innovations per year. Conditional on observing a non-zero number of product innovations, we observe an average of 7.3 and a median of 3 product innovations. As this is a count variable, outliers are likely. To limit their influence, we use a standard approach to deal with outliers (Ruppert, 2006) and winsorize our dependent variable at the 99th percentile, that is, we set all values larger than the 99th percentile (50 product innovations) to the 99th percentile. This affects about 150 firm-year observations with more than 50 product innovations.

Independent variables

For each firm i in year t, we observe whether it collaborates technologically with external identities. Specifically, we observe whether firms engage in technological collaboration with 1) customers, 2) suppliers, 3) competitors and 4) universities and/or technological centers [5]. We use this information to create our independent variables. First, we specify $CustColl_{it}$ as a binary variable that takes the value of 1 if firm i collaborates technologically with customers in year t and 0 otherwise. In nearly 20% of all observations, a firm collaborates technologically with a customer, suggesting that technological collaboration with the customer is common but not ubiquitous. We use the information on collaboration with other external identities to define collaboration scope ($CollScope_{it}$) as a count of whether a firm collaborated technologically with suppliers, competitors or with universities and/or technological centers. Thus, $CollScope_{it}$ ranges from 0 to 3. We observe that the average firm engages in technological collaboration with 0.5 identities, other than the customer.

We include $R\&D_{it}$ and define this variable as the existence of an internal R&D department in a focal firm. The variable is measured using a dummy variable taking the value 1 (0) when the focal firm has (does not have) its own internal R&D department. In our sample, about 22% of companies report having an internal R&D department.

Control variables

We include several control variables. First, we control for internal R&D ($IntR\&D_{it}$) and external R&D ($ExtR\&D_{it}$) intensity. We operationalize these intensity variables as the expenditures on internal and external R&D relative to sales. Greater R&D intensity increases the likelihood of engaging in innovation activities in general (Cassiman and Veugelers, 2006) and is, thus, likely reflected in the number of product innovations, which we control for. We winsorize both R&D intensity variables at the top 1% because of outliers. Second, we account for a firm's leverage ($Leverage_{it}$), defined as the ratio of total long- and short-term debt to total long- and short-term debt plus equity. More highly leveraged firms must service relatively more debt, reducing slack resources, thereby potentially compromising their ability to innovate (O'Brien, 2003). Third, we account for a firm's size, which is typically associated with more innovations (Santos, 2017), by including the natural logarithm of the number of employees ($Size_{it}$). Fourth, we include a dummy variable that indicates whether a firm exports its goods ($Export_{it}$; 1 = yes, 0 = no), as there is evidence that firms operating in international markets develop more innovations (Berchicci, 2013). Finally, we control for possible heterogeneity over time by including year fixed effects (γ_t).

Descriptive statistics

We present correlations and descriptive statistics in Table 3, including the mean, standard deviation, and the minimum and maximum. As expected, based on the prior literature, customer collaboration, collaboration scope and the internal R&D department all are positively correlated with the number of product innovations. Just like Laursen and Salter (2006), we observe a strong correlation between $CollScope_{it}$ and $CustColl_{it}$ (0.656), indicating that firms that engage in customer collaboration typically, but not necessarily, also engage in collaboration with other identities.

Model specification

General specification. The number of product innovations is a count variable, and therefore, we specify a negative binomial model. The standard negative binomial model is characterized by:

$$E(y_{it}) = \mu_{it}, \tag{1}$$

$$Var(y_{it}) = \mu_{it}(1 + \mu_{it}/\lambda), \tag{2}$$

where:

$$\ln(\mu_{it}) = \alpha + X_{it}\beta. \tag{3}$$

The negative binomial model extends the Poisson model by allowing for overdispersion in the dependent variable through λ [6]. In our application of the negative binomial model, the dependent variable, y_{it}, is the number of product innovations, and the independent and control variables are included in the vector X_{it}. As unobserved heterogeneity is one of the

Table 3. Bivariate correlations and summary statistics

	1.	2.	3.	4.	5.	6.	7.	8.	9.
1. Product innovation (PI_{it})	1.000								
2. Customer collaboration ($CustColl_{it}$)	0.169	1.000							
3. Collaboration scope ($CollScope_{it}$)	0.164	0.656	1.000						
4. R&D (RD_{it})	0.181	0.525	0.642	1.000					
5. Internal R&D to sales ($intRD_{it}$)	0.148	0.359	0.417	0.434	1.000				
6. External R&D to sales ($extRD_{it}$)	0.069	0.274	0.351	0.291	0.416	1.000			
7. Leverage ($Leverage_{it}$)	0.005	−0.082	−0.095	−0.093	−0.041	−0.072	1.000		
8. Size ($Size_{it}$)	0.135	0.365	0.521	0.465	0.197	0.215	−0.135	1.000	
9. Export dummy ($Export_{it}$)	0.141	0.259	0.330	0.308	0.174	0.141	−0.052	0.503	1.000
Mean	1.611	0.181	0.461	0.221	0.005	0.002	0.284	4.257	0.635
SD	6.235	0.385	0.769	0.415	0.012	0.006	0.276	1.497	0.481
Minimum	0	0	0	0	0	0	0	0	0
Maximum	50	1	3	1	0.080	0.040	1.000	9.616	1

Note: Correlations based on 14,682 observations for 2,994 firms main reasons why cross-sectional studies may present biased results (through omitted variable bias), we specify a firm-specific intercept [7]. The possibility to control for firm-specific heterogeneity is a substantial advantage afforded by panel data. For example, if firms with a strong innovation culture (a variable not observed by us researchers) engage in technological collaboration with customers and introduce many new product innovations, then a cross-sectional study would reveal strong association between customer collaboration and the number of product innovations. However, using firm fixed effects to control for unobserved variables such as innovation culture, this association may weaken, disappear or even reverse.

It is well known that "the conditional negative binomial model for panel data, [. . .] is not a true fixed–effects method" (Allison, 2009). Including fixed effects is, thus, not trivial in a negative binomial model (Guimarães, 2008), and we, therefore, rely on the approach proposed by Blundell *et al.* (1999) for the specification of fixed effects to control for firms' propensity to innovate because of firm culture, their line of business or other time-invariant causes. This approach requires pre-sample information, that is, years 1990–1997, to construct a measure of the sum of the number of product innovations introduced by firms in those earlier years. Note that for these years, item missingness precludes us from using these data as part of the main sample. We then use the (log-transformed) sum of the number of product innovations drawn from the pre-sample information to estimate firm fixed effects. We expect that firms that were previously more innovative remain more innovative and, therefore, expect a positive coefficient of Blundell *et al.*'s (1999) fixed effect. We let firm-specific heterogeneity affect the mean (α_i) as well as the variance (overdispersion parameter λ_i, which is clustered at the firm level to account for heteroskedasticity) by using the traditional conditional negative binomial model for panel data. Finally, we control for year-specific effects through year dummies (γ_i).

We, thus, obtain:

$$E(PI_{it}) = \mu_{it,} \tag{4}$$

$$\mathrm{Var}(PI_{it}) = \mu_{it}\left(1 + \mu_{it}/\lambda_i\right), \tag{5}$$

where:

$$\ln(\mu_{it}) = \alpha_i + X_{it}\beta + \gamma_t. \tag{6}$$

Detailed specifications. We specify two alternative models by varying the specification of $X_{it}\beta$ as shown in equation (6). First, we specify our focal model that allows us to test our hypotheses. We specify a linear and quadratic effect for $CollScope_{it}$, given by β_1 and β_2, respectively, and include the main effect of $CustColl_{it}$ (β_4) [8]. Moreover, we include the interaction between $CollScope_{it}$ and $CustColl_{it}$ (β_3). This interaction term is a direct test of *H1* which predicts a negative interaction term coefficient (β_3), such that collaboration with identities other than the customer becomes less rewarding when collaborating with customers. *H2* posits that customer collaboration weakens the positive effect of the internal R&D department on the number of product innovations. Including an interaction between $R\&D_{it}$ and $CustColl_{it}$ allows us to directly test *H2* (β_7). To test whether the positive effect of the internal R&D department on the number of product innovations weakens more by customer collaboration than by collaboration scope, we compare β_6 and β_7, that is, the interactions between the internal R&D department and collaboration scope and customer collaboration, respectively. As per standard practice, we include the main effect of $R\&D_{it}$ (β_5) to rule out that the interaction effects simply pick up a main effect. Finally, we include all the aforementioned control variables. We, thus, obtain:

$$
\begin{aligned}
X_{it}\beta = {} & (\beta_1 + \beta_2 CollScope_{it} + \beta_3 CustColl_{it})CollScope_{it} + \beta_4 CustColl_{it} \\
& + (\beta_5 + \beta_6 CollScope_{it} + \beta_7 CustColl_{it})R\&D_{it} + \beta_8 IntR\&D_{it} + \beta_9 ExtR\&D_{it} \\
& + \beta_{10} Leverage_{it} + \beta_{11} Size_{it} + \beta_{12} Export_{it}
\end{aligned} \tag{7}
$$

Next, in equation (8), we specify a benchmark model that does not differentiate between collaborations with customers and collaborations with other identities (collaboration scope). This benchmark specification allows us to judge the value of distinguishing between collaborations with customers and collaborations with other identities as shown in equation (7). Moreover, this benchmark specification allows some comparison of our results with Laursen and Salter (2006) and Mooi *et al.* (2016), who establish an inverted U-shaped relationship between collaboration scope, including customer collaboration, and innovation. Our benchmark model specification includes a linear [β_1 in equation (8)] and quadratic effect [β_2 in equation (8)] of the total number of collaboration identities ($CollScope_{it}$ + $CustColl_{it}$), that is, a variable that counts the number of identities the focal firm collaborates with while treating all identities equal. Moreover, we include the main effect of an internal R&D department [$R\&D_{it}$; effect given by β_3 in equation (8)] and the interaction between the internal R&D department and the total number of collaborations [effect given by β_4 in equation (8)]. We again include all control variables to obtain:

$$
\begin{aligned}
X_{it}\beta = {} & \beta_1(CollScope_{it} + CustColl_{it}) + \beta_2(CollScope_{it} + CustColl_{it})^2 \\
& + \big(\beta_3 + \beta_4(CollScope_{it} + CustColl_{it})\big)R\&D_{it} + \beta_5 IntR\&D_{it} + \beta_6 ExtR\&D_{it} \\
& + \beta_7 Leverage_{it} + \beta_8 Size_{it} + \beta_9 Export_{it}
\end{aligned} \tag{8}
$$

Results

We estimate the two models specified above and present our estimation results in Table 4. Columns I and II display the results for the models shown in equations (7) and (8), respectively.

We first focus on our focal model (Column I) and observe that the linear effect of collaboration scope is positive and significant (β = 0.370, $p < 0.001$), while the quadratic term of collaboration scope is not significant (β = −0.014, p = 0.680), that is, in our focal model, we find no evidence for an inverse U-shaped curve for collaboration scope. The main effect of customer collaboration is positive and significant (β = 0.793, $p < 0.001$), while the interaction effect between customer collaboration and collaboration scope is significant and negative (β = −0.250, $p < 0.001$). The negative interaction effect provides direct evidence in support of *H1*, that is, we find evidence that customer collaboration reduces the positive effect of collaboration scope (of other outside identities) on the number of product innovations.

We illustrate these findings in Figure 1 where we plot the expected number of production innovations for different levels of collaboration scope for companies with and without customer collaboration. In line with *H1*, the expected number of product innovations keeps increasing with collaboration scope for firms without customer collaboration, while they are statistically flat (i.e. insignificant) for companies with customer collaboration. Hence, we find that the more identities other than the customer the firm collaborates with, the higher the

Variable	Parameter estimate, (SE) and p-value I	II
Collaboration scope	0.370***	
	(0.083)	
	0.000	
Collaboration scope squared	−0.014	
	(0.033)	
	0.680	
(Collaboration scope + Customer collaboration)		0.533***
		(0.061)
		0.000
(Collaboration scope + Customer collaboration) squared		−0.067***
		(0.018)
		0.000
Customer collaboration	0.793***	
	(0.117)	
	0.000	
Collaboration scope × customer collaboration	−0.250***	
	(0.067)	
	0.000	
Internal R&D department	0.727***	0.745***
	(0.090)	(0.090)
	0.000	0.000
Collaboration scope × Internal R&D department	−0.010	
	(0.066)	
	0.879	
Customer collaboration × Internal R&D department	−0.397***	
	(0.109)	
	0.000	
(Collaboration scope + Customer collaboration) × internal R&D department		−0.137***
		(0.045)
		0.002
Internal R&D intensity	9.515***	9.596***
	(1.543)	(1.542)
	0.000	0.000
External R&D intensity	9.969***	10.188***
	(2.634)	(2.635)
	0.000	0.000
Leverage	0.087	0.095
	(0.102)	(0.102)
	0.393	0.350
Size	−0.028	−0.028
	(0.026)	(0.026)
	0.287	0.278
Export	0.319***	0.320***
	(0.086)	(0.086)
	0.000	0.000
Year fixed effects	Included	Included
Number of observations	6,867	6,867
Number of firms	1,069	1,069
Log likelihood	−7,953	−7,960
Chi-squared	823***	805***

Notes: Dependent variable is the number of product innovations. Columns I and II pertain to the model specification assuming equations (7) and (8), respectively. ***indicates $p < 0.01$. All standard errors are cluster robust, using the firm as clustering variable. Year fixed effects and firm fixed effects correction not shown to conserve space

Table 4.
Estimation results

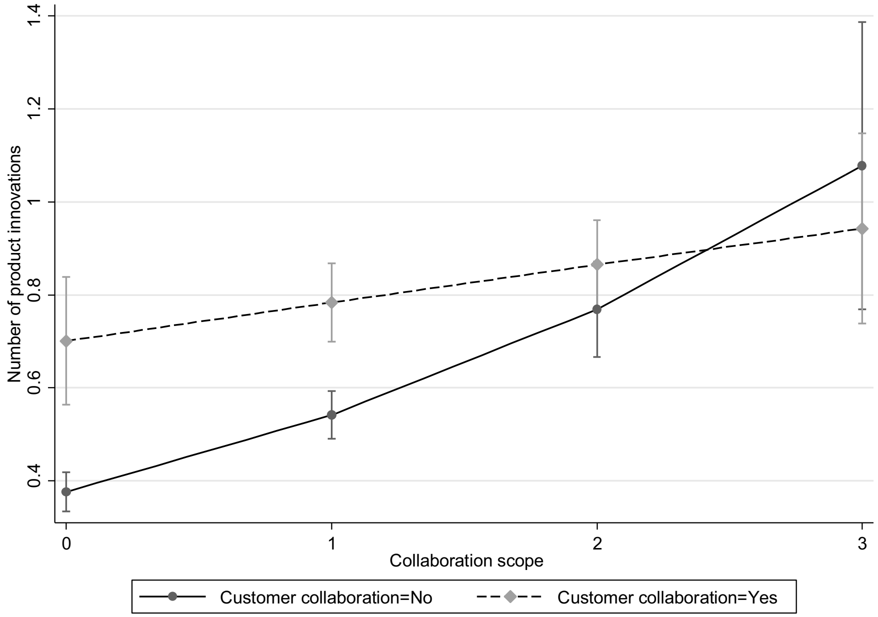


Figure 1.
Expected number of product innovations from customer collaboration and collaboration scope on product innovations

Note: Average estimated number of product innovations. Evaluated at the means of the remaining covariates

number of product innovations, particularly when *not* collaborating with customers. Figure 1 illustrates that customer collaboration reduces a) the steepness of the slope and, thus, the marginal benefit and b) that at the highest level of collaboration scope, customer collaboration reduces the expected number of product innovations from about 1.1 to 0.9.

We now turn our attention to *H2* which posits that the positive effect of the internal R&D department on the number of product innovations is weakened by customer collaboration. We first establish that the internal R&D department has a positive and significant main effect on product innovation ($\beta = 0.727$, $p < 0.001$). The interaction between customer collaboration and the internal R&D department is negative and highly significant ($\beta = -0.397, p < 0.001$), thus providing support for *H2*.

Next, *H3* states that the positive effect of the internal R&D department on the number of product innovations weakens more by customer collaboration than by collaboration scope. A direct test of *H3* involves comparing the coefficients for the two interactions with the internal R&D department using a z-test, while considering the covariance between the two coefficients. The interaction between collaboration scope and the internal R&D department is close to zero and not significant ($\beta = -0.010$, $p = 0.879$). A formal z-test demonstrates that the coefficient for the interaction between customer collaboration and the internal R&D department is significantly larger in absolute sense (i.e. more negative) than the coefficient for the interaction between collaboration scope and the internal R&D department ($z = 6.58$, $p = 0.010$). We, thus, obtain strong support for *H3*: the positive effect of the internal R&D department is weakened significantly more by customer collaboration than by collaborations with other identities. We finally find that internal R&D intensity and export have a significant and positive effect on innovation ($\beta = 9.515, p < 0.001$ and $\beta = 0.319, p < 0.001$).

The results in Column II for our benchmark specification [equation (8)] are somewhat similar to those of Laursen and Salter (2006) and Mooi, Wathne and Kayande (2016) in that the results show that collaboration scope, including customer collaboration, has a positive and significant linear effect on product innovations ($\beta = 0.533$, $p < 0.001$), while the quadratic effect is negative and significant ($\beta = -0.067$, $p < 0.001$). Hence, when we *do not separate the identities* of customers and other collaboration partners, we are able to obtain similar effects as reported by these two prior studies, thereby showing a good degree of construct validity. The main effect of the internal R&D department is positive and significant ($\beta = 0.745$, $p < 0.001$), while the interaction with collaboration scope, including collaborations with customers, is negative and significant ($\beta = -0.137$, $p = 0.002$). Internal R&D intensity and export have the expected positive effect on innovation ($\beta = 9.596$, $p < 0.001$ and $\beta = 0.320$, $p < 0.001$).

Importantly, we can use this benchmark model to demonstrate that model fit increases when allowing for differential effects of collaborations with customers and with other identities. A comparison of the models based on equations 7 and 8 (Columns I and II, respectively) shows that the improvement in log-likelihood is significant (χ^2 (three degrees of freedom) = 18, $p < 0.001$). Our focal model [equation (7)], where we specify differential effects of collaborations with customers and with other identities, thus better fits the data than the benchmark model [equation (8)], where we assume identical effects for collaborations with different identities.

Robustness checks

We perform additional analyses to show robustness of our findings to alternative expectations. The critical argument we forward is that collaborations with customers are different from collaborations with other identities. However, it is possible to argue that other types of identities are *also* qualitatively different in terms of how these combine to produce product innovations. To test this alternative view, we verify whether our results hold when including each of the collaboration partners separately in our empirical model, that is, instead of using our collaboration scope variable to capture the effects of all other identities, we include a separate dummy variable indicating each identity. Moreover, we allow for full factorial interaction effects between each set of identities, for example, customer and supplier, supplier and competitor, etc., as well as between the internal R&D department and each identity. We, thus, obtain:

$$\begin{aligned} X_{it}\beta = {} & (\beta_1 + \beta_2 SupplColl_{it} + \beta_3 CompColl_{it} + \beta_4 UniColl_{it}) CustColl_{it} \\ & + (\beta_5 + \beta_6 CompColl_{it} + \beta_7 UniColl_{it}) SupplColl_{it} + (\beta_8 + \beta_9 UniColl_{it}) CompColl_{it} \\ & + \beta_{10} UniColl_{it} + (\beta_{11} + \beta_{12} CustColl_{it} + \beta_{13} \mathrm{SupplColl}_{it} + \beta_{14} \mathrm{CompColl}_{it} \\ & + \beta_{15} \mathrm{UniColl}_{it}) R\&D_{it} + \beta_{16} \mathrm{IntR\&}D_{it} + \beta_{17} \mathrm{ExtR\&}D_{it} + \beta_{18} \mathrm{Leverage}_{it} \\ & + \beta_{19} \mathrm{Size}_{it} + \beta_{20} \mathrm{Export}_{it}. \end{aligned} \tag{9}$$

We present the estimation results for equation (9) in Table 5. These results support a unique role of customer collaboration that is different from collaborations with other identities. Table 5 shows that only the interaction of the customer with either suppliers or the internal R&D department is associated with a reduction in the number of product innovations. We do not find any evidence that the interactions of the other partners among themselves or

Variable	Parameter estimate, (SE) and p-value
Customer collaboration	0.825*** (0.124) 0.000
Supplier collaboration	0.506*** (0.109) 0.000
University/TC collaboration	0.394*** (0.093) 0.000
Competitor collaboration	−0.532* (0.321) 0.098
Customer collaboration × Supplier collaboration	−0.429*** (0.109) 0.000
Customer collaboration × University/TC collaboration	−0.088 (0.103) 0.397
Customer collaboration × Competitor collaboration	−0.173 (0.208) 0.406
Supplier collaboration × University/TC collaboration	−0.133 (0.103) 0.195
Supplier collaboration × Competitor collaboration	0.007 (0.239) 0.976
University/TC collaboration × Competitor collaboration	0.505** (0.229) 0.027
Internal R&D department	−0.406*** (0.114) 0.000
Customer collaboration × Internal R&D department	−0.042 (0.112) 0.711
Supplier collaboration × Internal R&D department	0.368 (0.233) 0.115
Competitor collaboration × Internal R&D department	−0.066 (0.102) 0.521
University/TC collaboration × Internal R&D department	0.825*** (0.124) 0.000
Year fixed effects	Included
Number of observations	6,867
Number of firms	1,069
Log likelihood	−7,944
Chi-squared	841***

Notes: Dependent variable is the number of product innovations. Results pertain to the model specification assuming equation (9). ***indicates $p < 0.01$, **indicates $p < 0.05$ and *indicates $p < 0.1$. All standard errors are cluster robust, using the firm as clustering variable. Covariates (internal and external R&D intensity, leverage, size and export), year fixed effects and firm fixed effects correction not shown to conserve space

Table 5.
Estimation results – robustness check

with the internal R&D department are associated with such a reduction in the number of product innovations.

Finally, we estimate the effect of product innovations on sales. We also account for potential moderating effects of customer collaboration and collaboration scope. In doing so, we are able to:

- assess whether there are further benefits from product innovation; and
- address possible influences of collaborations on the sales success of innovations.

We follow the literature (Castellacci and Natera, 2013) and assume that it takes some time for sales to result from innovation and collaboration. Specifically, we estimate the following regression specification:

$$\begin{aligned}\ln\left(\text{Sales}_{i,t+1}\right) = \beta_1 + (\beta_2 + \beta_3\text{CollScope}_{it} + \beta_4 \mathit{CustColl}_{it}) \\ \ln(PI_{it}) + \beta_5 \mathit{CustColl}_{it} + \beta_6\text{CollScope}_{it} + \varepsilon_{i,t+1}.\end{aligned} \tag{10}$$

We present the estimation results for equation (10) in Table 6. Critically, we find that the number of product innovations is positively associated with sales ($\beta_2 = 0.019$, $p = 0.026$). Our results suggest that this main effect is not significantly stronger or weaker when these innovations are developed together with customers ($\beta_4 = 0.002$, $p = 0.907$) or other external identities ($\beta_3 = -0.009$, $p = 0.166$). Taking the results of equations (7) and (10) together, we conclude that collaborations with external identities explain the number of product innovations, but we find no evidence that these collaborations affect the sales success of innovations.

Discussion

For a long time, scholars have noted the importance of open innovation (Chesbrough, 2003) and of collaborating with external partners. Based on the articulated benefits, including more innovations, one would expect a wholesale shift toward open innovation. Such a shift has, however, not materialized as Love *et al.* (2014) argue. Likely, there are, hitherto undocumented, drawbacks of open innovation. We add to the small body of work that has documented such drawbacks (Laursen and Salter, 2006 and Mooi *et al.*, 2016) and we hypothesize, and empirically demonstrate, two new key limitations to openness that, together, might help explain why a wholesale shift to open innovation has not occurred.

	Dependent variable: Sales (logarithm) Parameter estimate	SE	p-value
Number of product innovations	0.019	0.009	0.026
Customer collaboration	0.040	0.023	0.076
Collaboration scope	0.018	0.012	0.141
Number of product innovations ×			
Customer collaboration	0.002	0.013	0.907
Collaboration scope	−0.009	0.007	0.166
Year fixed effects		Yes	
Firm fixed effects		Yes	
Number of observations		12,054	
Number of firms		2,487	

Table 6. Estimation results – sales

First, customer collaboration reduces the positive effect of collaboration scope on the number of product innovations. While prior research explains the limitations of openness using the *number* of parties a firm collaborates with, our focus on the *identity* of these parties allows us to unravel an important limitation in that firms that technologically collaborate with customers have lower returns from technological collaboration with identities other than the customer. This limitation is significant in that, unlike any other partner type, every firm has customers. When B2B firms move from *having* customers to *collaborating* technologically with them – something which applies to 20% of the firms we observe – the benefits that collaborations with other identities bring are significantly reduced. We emphasize that this result is independent from all other characteristics of the firm, as our results include firm-specific ("fixed") effects and key control variables. We also advance the literature by showing an effect of technological collaboration, which is distinct from a party being an information source only, as most past work has considered (Laursen and Salter, 2006). Technological collaboration stands out, as it implies a greater degree of cooperation than serving as an information source, which could not require any two-way interaction.

Second, we find that the positive effect of the internal R&D department on the number of product innovations weakens more by customer collaboration than by collaboration scope. This finding is based on the observation of a negative and significant interaction between customer collaboration and the internal R&D department (as captured by *H2*) and a comparison of this effect to collaboration with other identities (as captured by *H3*). These results are *only* obtained when we separate out the customer. Counting the number of identities the firm collaborates with would result in a drastically different conclusion that the returns to the internal R&D department decline with external collaborations. However, our decomposition of collaboration into customer and other collaboration reveals that this effect is because of collaboration with customers only and not because of collaboration with other identities. This suggests a certain incompatibility of customer collaboration. A small body of work (Chan *et al.*, 2010; Noordhoff *et al.*, 2011) notes certain difficulties of collaborating with customers to which we add that customers, when combined with internal R&D, are more likely to draw on the attention of management, resulting in a somewhat reduced number of product innovations, on average. Thus, to scholars, our findings stress the importance of considering the identity of collaborating parties in studying the impact of openness on innovation success. We, thus, conceptually and empirically reject the implicitly held assumption in the literature that different partners provide similar benefits and are effectively interchangeable. For example, Cassiman and Veugelers (2006) find complementarities between internal R&D and external knowledge acquisition but remain agnostic about the identity of the partners that provide external knowledge. We draw on the attention-based theory (Ocasio, 1997) to hypothesize that particularly customer collaborations adversely impact the returns to collaboration scope and the internal R&D department. Our results provide strong support for our hypotheses. We also note that supplementary analyses show that product innovations lift sales but that external collaboration does not strengthen (nor weaken) this linkage.

Our study has several implications for managers. First, managers need to carefully select which external identities to involve in innovation. If we use equation (7) to calculate the expected number of product innovations for all possible combinations of customer collaboration, collaboration scope and the internal R&D department, then a clear pattern results as shown in Table 7. Firms without an internal R&D department and with no existing collaborations with external partners benefit the most from customer collaboration. However, for firms at the *highest* level of collaboration scope, there is a marked *reduction* in the expected number of product innovations when collaborating with customers. Moreover, this reduction is particularly strong for firms with an internal R&D department.

Second, we attribute the negative interactions between customer collaboration and collaboration scope and the internal R&D department to managers' attention limits. What would happen if firms would allow managers to dedicate more or even unlimited attention to the management of the different identities involved in innovation? To answer this question, we perform a counterfactual analysis where we compare the estimated number of product innovations implied by our estimated model with a counterfactual case where firms would be able to suppress the negative interactions between customer collaboration and collaboration scope and the internal R&D department, that is, conforming to a scenario where managers face trivial or no attention limits. We present the results from this counterfactual analysis in Figure 2. In the absence of negative interactions, our counterfactual shows that the number of product innovations increases more strongly with collaboration scope. This effect is of considerable magnitude. For example, in the absence of negative interactions, we estimate more than three product innovations when collaboration with all partner identities (the customer, the internal R&D department and three for collaboration scope) occurs, while this number falls to one product innovation when we do allow for negative interactions. That is, if we could address the attention limits to joint collaboration with customers, then we could triple the number of product innovations in the most complex scenario where all partners are involved in the collaboration.

Limitations and future research

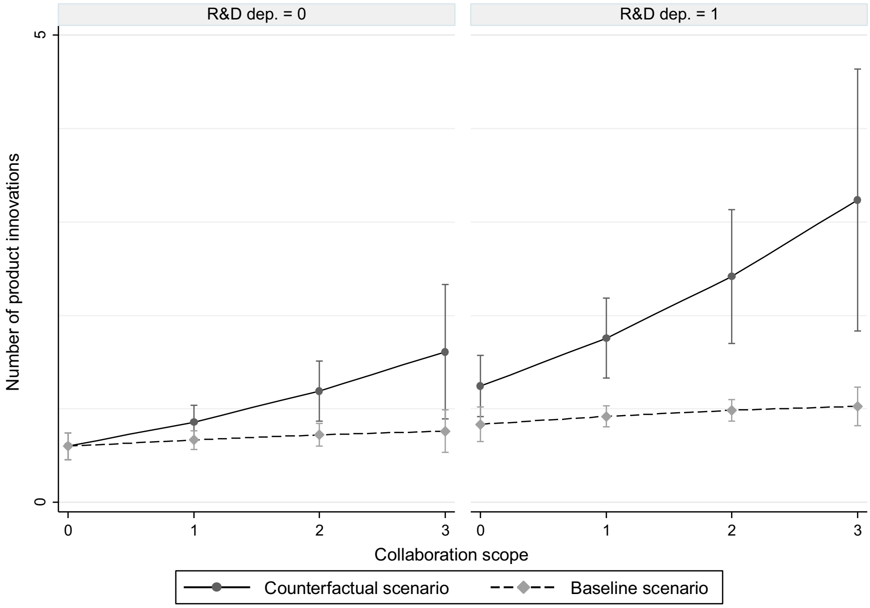
We make an important contribution to the literature on openness and product innovation but acknowledge that our study, as any, has its limitations. First, we rely on a binary measure for customer collaboration and count the number of other identities a firm collaborates with. We are unable to account for the number of customers (or number of suppliers, competitors, or universities or technological centers) a firm collaborates with or the depth or intensity of each individual relationship, as the longitudinal ESEE data does not report on these [9]. Although technological collaboration, which we study, is suggestive of repeated exchange and quite well-developed relationships with a limited number of partners, future research could focus on potential attention-related problems *within* collaboration identities, for example, problems resulting from working with multiple customers, and attention problems related to the depth of the relationship.

Second, we use the number of product innovations as our key dependent variable and have explored the potential impact of collaborations with external identities on the commercial success of product innovations. Future research could be usefully directed

	Internal R&D department	No		Yes	
	Customer collaboration	No	Yes	No	Yes
Collaboration scope	None	0.27	0.60	0.56	0.84
	1	0.39	0.67	0.80	0.92
	2	0.54	0.72	1.09	0.99
	3	0.73	0.76	1.46	1.03

Notes: Predicted number of innovations with varying levels of customer collaboration, collaboration scope and internal R&D department. Fixed effects set to 0 and all remaining covariates evaluated as observed

Table 7. Number of innovations with varying levels of customer collaboration, collaboration scope and internal R&D department



Note: Average estimated number of product innovations. Evaluated when customer collaboration = yes and at the means of the remaining covariates. The "baseline scenario" corresponds to the estimates from the model reported in Table 4 (Column I), while the "counterfactual scenario" corresponds to the case where the negative interactions with collaboration scope and the R&D department are both set to zero

Figure 2.
Counterfactual expected number of product innovations

toward studying other innovation metrics, such as the novelty of the innovation, the source of the innovation (e.g. new design or new materials) and how long they survive in the market.

Finally, our metrics are all at the firm level, which does not allow us to consider how customer collaboration, collaboration scope and the internal R&D department work at the individual or project level (Kobarg *et al.*, 2019). Future research could analyze individual innovation projects, specifically focusing on how managers allocate their attention to inputs from external parties and the internal R&D department.

Notes

1. We note that whereas several previous studies have focused on the (financial) success of product innovations, the number of product innovations is a particularly useful metric, as it is the direct result of a firm's actions and does not confound the introduction of a new product and its success, which is influenced by many factors and may only be observed after many years. As such, product innovation is a more proximal indicator of the processes we argue for.
2. Co-creation is one of the potential forms of the observed technological collaborations with external partners. We note that given our focus on technological collaboration, we purposely restrict the focus to B2B, as consumers are highly unlikely to be partners to organizations when it comes to addressing or solving technological aspects.

3. Note that our focus is on the internal *R&D department*, as our arguments are about human attention and interaction. In our empirical model, we control for internal and external R&D intensity.

4. When specifying firm fixed effects, our sample size is reduced from 2,994 firms and 14,682 observations to 1,069 firms and 6,868 observations because of lack of variation in the dependent variable for certain companies, for example, companies that always report zero for product innovation.

5. Note that this measure captures the top three market knowledge sources and the top source of institutional knowledge as reported by Laursen and Salter (2006). Moreover, these sources have been quite constant as Urban and Von Hippel (1988) identified the four most useful sources of external knowledge 1) suppliers and customers; 2) university, government and private laboratories; 3) competitors; and 4) other nations (which does not apply to our study).

6. The Poisson model is a special case of the negative binomial model when $\lambda \to \infty$.

7. These firm fixed effects encompass industry fixed effects, which thus cannot be estimated separately.

8. Since $CustColl_{it}$ is a dummy variable, we cannot include a quadratic effect of this variable.

9. We note that our fixed effects control for all unobservable and time invariant characteristics, such as the degree to which a relationship remains "deep".

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