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Does combining different types of collaboration always benefit firms? Collaboration, complementarity and product innovation in Norway

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ABSTRACT

Product innovation is widely thought to benefit from collaboration with both scientific and supply-chain partners. The combination of exploration and exploitation capacity, and of scientific and experience-based knowledge, are expected to yield multiplicative effects. However, the assumption that scientific and supply-chain collaboration are complementary and reinforce firm-level innovation has not been examined empirically. This paper tests this assumption on an unbalanced panel sample of 8337 firm observations in Norway, covering the period 2006–2010. The results of the econometric analysis go against the orthodoxy. They show that Norwegian firms do not benefit from doing "more of all" on their road to innovation. While individually both scientific and supply-chain collaboration improve the chances of firm-level innovation, there is a significant negative interaction between them. This implies that scientific and supply-chain collaboration, in contrast to what has been often highlighted, are substitutes rather than complements. The results are robust to the introduction of different controls and hold for all tested innovation outcomes: product innovation, new-to-market product innovation, and share of turnover from new products.

1. Introduction

Networking and collaborating with external agents are widely seen as essential factors for innovation (e.g. Powell et al., 1996; Chesbrough, 2003). Knowledge and information are distributed across a wide range of different actors in the economy and new knowledge is constantly being generated. Firms thus cannot only rely on in-house knowledge and internal processes to develop innovation. Collaboration with various types of partners is a crucial path to new innovation. Different types of collaboration – with suppliers (e.g. Liker et al., 1996; Bidault et al., 1998), customers or users (e.g. von Hippel, 1986; Bogers et al., 2010), competitors (e.g. Hamel, 1991; Gnyawali and Park, 2011), universities (e.g. Perkmann and Walsh, 2007; Ponds et al., 2010), consultants and other research organisations (e.g. Tether and Tajar, 2008) – facilitate access to new knowledge and accelerate the propensity to innovate. But diverse types of collaboration play different roles in a firm's knowledge network, as each type of partner has its own perspective and access to different sources of knowledge and information. Using a variety of different partners is therefore considered desirable, as it provides a variety of knowledge that contributes to enhancing a firm's innovation potential (Faems et al., 2005; Laursen and Salter, 2006).

Innovation research focusing on collaboration has frequently argued for combining interactions and collaborations with suppliers and customers, on the one hand, and with universities and other research organisations, on the other, as the right mix to foster firm-level innovation. Supply-chain and scientific partners are considered to bring different types of knowledge to the firm. These different knowledge strands are mostly regarded as complementary (e.g. Tether, 2002; Faems et al., 2005). However, most studies examine the two types of collaboration separately and can only uncover whether there is an additive effect of collaboration (e.g. Faems et al., 2005; Fitjar and Rodríguez-Pose, 2013). Whether scientific and supply-chain collaboration are actually complementary – in the sense that using both types of partners simultaneously has a multiplicative effect on firm-level innovation – has seldom been tested.

The idea of complementarity of collaboration types brings the literature on collaboration scope into contact with that on innovation modes. Jensen et al. (2007:680), for example, refer to a "tension between two ideal type modes of learning and innovation". These are a) the Science, Technology and Innovation (STI) mode and b) the Doing, Using and Interacting (DUI) mode. A key insight in their work is that the combination of both modes yields the best results for innovation. Firms that manage to pursue innovation based on science and

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complement such efforts with learning by doing and interacting with other economic actors innovate more. Other studies of innovation modes report similar results (Chen et al., 2011; Aslesen et al., 2012; Parrilli and Heras, 2016). Jensen et al. (2007) address the complementarity between modes of innovation by dividing firms into four mutually exclusive clusters. They find coefficient estimates for the DUI/STI cluster which are roughly similar to the sum of the coefficients for the DUI and STI clusters. Parrilli and Heras (2016) use a comparable approach, focusing on collaboration partners, and reach the same results. These approaches, while pushing the boundaries of our knowledge, also focus on the additive rather than the potential multiplicative effects of scientific and industrial collaboration (see e.g. Laursen and Foss, 2003; Love et al., 2014). If the two are complementary, we should expect their product to be greater than the sum of its parts.

In this paper, we move the debate forward by formally testing for complementarities between the two types of collaboration. In line with previous literature on innovation modes (e.g. Fitjar and Rodríguez-Pose, 2013; Parrilli and Heras, 2016) and on collaboration scope (e.g. Faems et al., 2005; Vega-Jurado et al., 2009), we focus on collaboration with scientific and supply-chain partners. The analysis is conducted on an unbalanced panel sample of 8337 firm observations in Norway, covering the period 2006–2010. The panel is constructed using data from three waves of the Community Innovation Survey, supplemented with linked employer-employee data on the composition of each firm's workforce. On this dataset, we first examine the effects of collaborating with scientific and supply-chain partners on the likelihood of firms introducing product innovations and their share of turnover from these innovations. Second, we test whether scientific and supply-chain collaboration are complementary. We specifically assess whether a firm's likelihood of introducing innovations increases to a greater extent from collaborating with scientific partners when they also collaborate with supply-chain partners, and vice versa.

This paper contributes to the literature in several ways. First, by formally examining complementarities between scientific and supply-chain collaboration with the inclusion of an interaction term, it tests a core proposition in the literature stressing that combining different types of collaboration is beneficial to innovation. Second, no previous research on innovation modes has used comparable fine-grained panel data to analyse the effects of scientific and supply-chain collaboration on innovation performance. Third, the use of reliable data from the Norwegian part of the Community Innovation Survey (CIS) – where participation is mandatory – practically eliminates the risk of non-response bias and provides data on the full population of larger firms. The Norwegian CIS furthermore allows for a meaningful examination of the effects of collaboration on innovation, as all firms (not just innovative ones) are (since 2006) required to report collaboration.

The paper is organized into four sections. In the next section, we discuss theory and earlier research on the role of different sources of knowledge and their complementarity for firm innovation. We present the case and describe the data in section 3, while section 4 presents the results from the empirical analysis of the relationship between collaboration and innovation outcomes. Conclusions and suggestions for future research are presented in the final section.

2. The role of different types of collaboration partners for innovation

2.1. Collaboration with scientific and supply-chain partners

The knowledge, skills and resources necessary for innovation are widely distributed, and the ability of firms to identify, access, absorb and use these is crucial for innovation (Cohen and Levinthal, 1990). Innovation depends critically on how firms absorb external knowledge and combine it with their own internal knowledge to develop new market offerings (Chesbrough, 2003). Firms can use various channels to access external knowledge. These include recruitment, acquisition, and formal as well as informal exchanges with other actors. They can also source knowledge from individuals (e.g. crowdsourcing) as well as from organizations. However, collaboration with other organizations is considered to be one of the most important mechanisms for innovation, as it allows for mutually beneficial exchanges in which both sides make long-term investments (Hagedoorn, 2002; Nooteboom, 2004). We define collaboration as active participation by both partners in a joint R&D or innovation project (Cassiman and Veugelers, 2002).

Firms have the option of using various types of organizations as partners in such collaboration. These partners may serve different functions. Tether (2002) distinguishes between collaborations within and beyond the supply-chain. The benefits from each form of collaboration differs. Collaboration with suppliers and customers allows firms to extend pure market transactions into long-term strategic relationships characterized by mutual trust. This gives them more information about customers' needs as well as access to new and potentially tailor-made solutions from suppliers. Collaborations beyond the supply-chain include interactions with competitors and with universities and other research or knowledge-broking organizations. These do not emerge from a market relationship, but are set up separately for a variety of reasons.

Collaborations with universities and research organizations are typically more explorative, aiming at the creation of new knowledge, with sometimes uncertain commercial applications. Collaboration with suppliers and customers tend, by contrast, to optimize core competencies, helping firms to exploit technological and market opportunities (Faems et al., 2005). Knowledge from research organizations is also less targeted to firms' needs and places higher demands on their absorptive capacity (Vega-Jurado et al., 2009). Turning to scientific and supply-chain partners in innovation collaboration can also be linked to the broader literature on modes of innovation (Fitjar and Rodríguez-Pose, 2013; Parrilli and Heras, 2016).

This literature emerged from Jensen et al.'s (2007) distinction between two ideal types of firm learning mechanisms: 'Science, Technology and Innovation' (STI) and 'Doing, Using and Interacting' (DUI). STI refers to innovation "based on the production and use of codified scientific and technical knowledge" (Jensen et al., 2007:680). The DUI mode refers to innovation based on learning from experience in making or using products, or from interacting with those who do (Jensen et al., 2007). STI and DUI innovation modes encompass both internal activities as well as external knowledge sourcing. In the latter dimension, they relate to different types of collaboration partners.[1] While universities and research organizations are important in the STI mode, the DUI mode relies more on collaboration with suppliers and customers. On this basis, these two types of collaboration have sometimes been used as proxies for innovation modes (e.g. Fitjar and Rodríguez-Pose, 2013; Parrilli and Heras, 2016).

The literature highlighting the importance of different modes of collaboration leads us to the formulation of our first two hypotheses:

H1. Firms that collaborate with scientific partners are more likely to innovate than firms that do not collaborate with scientific partners.

H2. Firms that collaborate with supply-chain partners are more likely to innovate than firms that do not collaborate with supply-chain partners.

[1] While Jensen et al.'s (2007) definition of STI and DUI includes both internal and external activities related to each dimension, the internal and external dimensions are not necessarily aligned. Firms may instead focus on working with external collaboration partners that complement their internal strengths. For instance, firms with established internal DUI processes may collaborate with scientific partners to source in new types of knowledge (see e.g. Hoang and Rothaermel, 2010 for a related argument). Conversely, external collaboration can depend on internal absorptive capacity in the same innovation mode. For instance, the returns to scientific collaboration may depend on internal R&D activities (Cohen and Levinthal, 1990). We leave these discussions for future research.

These hypotheses are not new and have been tested in previous literature (e.g. Faems et al., 2005; Vega-Jurado et al., 2009; Fitjar and Rodríguez-Pose, 2013; Parrilli and Heras, 2016). Most studies tend to confirm both hypotheses. However, supply-chain partners are often found to be more important for incremental product innovation, while scientific partners drive more radical and new-to-market product innovation (Faems et al., 2005; Parrilli and Heras, 2016). There are also differences across sectors in the importance of each type of collaboration (Vega-Jurado et al., 2009; Fitjar and Rodríguez-Pose, 2015).

2.2. Complementarity of collaboration types

How firms best organize their use of different sources of knowledge is a strategic challenge. Major theoretical approaches provide conflicting guidance on this issue. Transaction cost theory has often been used to inform this discussion (e.g. Veugelers and Cassiman, 1999; Love et al., 2014). In terms of the choice between external sourcing and internal knowledge, transaction cost theory considers them substitutes: a 'make or buy' decision (Coase, 1937; Arrow, 1962; Veugelers and Cassiman, 1999). However, other theories stress the complementarity between them, as firms need internal capabilities to 'absorb' external knowledge (Cohen and Levinthal, 1990). A similar approach can be used to develop theories about interactions between the use of scientific and supply-chain partners. Different types of partners may be substitutes, allowing firms to switch between them. However, they may also be complements, as scientific and industrial partners provide access to different types of knowledge. In this latter case, collaborating with both types of partners simultaneously becomes crucially important for innovation. Theory, however, does not necessarily offer unambiguous hypotheses, providing a clear role for empirical research.

Different types of collaboration can have additive effects. Firms with larger search scope and search depth are more likely to innovate, as they can draw on a wider range of ideas (Laursen and Salter, 2006). However, the literature on innovation modes goes beyond this to claim that STI and DUI are also complementary, i.e. that there are multiplicative effects of using both modes. Jensen et al. (2007: 690) argue that "what really improves innovation performance is using mixed strategies that combine strong versions of the two modes". Similarly, literature in organizational learning sees exploration and exploitation as complementary processes (Tushman and O'Reilly, 1996; Hoang and Rothaermel, 2010). In order to benefit fully from their exploration activities, firms also need exploitation capacity. Conversely, exploitation cannot survive long without exploration to generate new ideas.

Equally, scientific collaboration can give access to potentially valuable new knowledge from research. However, firms may not be able to exploit this knowledge without working closely with suppliers in developing the production process, or with customers to identify how they would use new technology. On the flipside, customers or suppliers may come up with new ideas that can only be developed in collaboration with research communities. Such complementarities can manifest themselves in different ways. First, they may increase the likelihood of introducing new products by enabling new combinations of different types of knowledge. Second, they can enhance the market success of new products, by improving the exploitation of new ideas generated from exploration. They could also improve the quality or complexity of new products, or allow firms to introduce a larger variety of innovations.

The research that has questioned the complementarity of innovation modes is, in contrast, much more limited (e.g. González-Pernía et al., 2012; Parrilli and Elola, 2012; Malaver Rodríguez and Vargas Pérez, 2013). Yet, there may also be tensions between different types of collaboration. Laursen and Salter (2006) raise the notion that firms may 'over-search' for knowledge, as excessive search scope may produce too many ideas for a firm to absorb and devote proper attention. This can apply in particular to knowledge derived from scientific and supply-chain collaboration, as these types of knowledge are, by nature, very different and hence more demanding to process. Experience-based knowledge from suppliers or customers is often more tacit, and core aspects of the idea may be lost in the translation to a more research-based innovation process. Meanwhile, suppliers and customers often lack the absorptive capacity to understand and fully exploit new ideas emerging from scientific collaboration. Furthermore, sectors differ in their reliance on scientific and experience-based inputs (Pavitt, 1984; Asheim and Gertler, 2005), suggesting that scientific knowledge may be less important in sectors where experience-based learning is at the heart of innovation, and vice versa.

The question of complementarities has been important in the broader innovation literature (e.g. Young, 1993; Golovko and Valentini, 2011; Ballot et al., 2015) and in relation to innovation collaboration specifically. As mentioned above, there has, in particular, been considerable debate over whether the use of external collaboration complements or substitutes internal R&D (Veugelers and Cassiman, 1999; Cassiman and Veugelers, 2006; Schmiedeberg, 2008; Hagedoorn and Wang, 2012; Love et al., 2014). However, this literature has so far not focused on potential complementarities between collaboration with different types of partners. In this paper, we delve into this gap in the literature by analysing to what extent collaboration with scientific and supply-chain partners is associated with higher probabilities of innovation and if so, whether the two types of collaboration are complementary. On the basis of the above discussion, the literature on innovation modes generally expects scientific and supply-chain collaboration to be complementary, but arguments of over-searching and sector specificity suggest they may also be substitutes.

This leads to our third, two-pronged, hypothesis:

H3a. The effect of collaborating with scientific partners on the likelihood of innovation is larger for firms that also collaborate with supply-chain partners, and vice versa.

H3b. The effect of collaborating with scientific partners on the likelihood of innovation is smaller for firms that also collaborate with supply-chain partners, and vice versa.

These two variants of our third hypothesis have not been tested by previous literature. As a footnote in Jensen et al. (2007:690) acknowledges, their findings are not sufficient to prove complementarities between the innovation modes. Nonetheless, many have followed up on the notion that the STI and DUI modes are complementary (e.g. Chen and Guo, 2010; Chen et al., 2011; Aslesen et al., 2012; Isaksen and Karlsen, 2012; Isaksen and Nilsson, 2013; Nunes and Lopes, 2015; Apanasovich et al., 2016). This includes research focusing specifically on collaboration with scientific and supply-chain partners (Parrilli and Heras, 2016). Despite the richness of this literature, no previous studies have taken up the baton of trying to demonstrate that scientific and supply-chain collaboration (or STI and DUI more broadly) are actually complementary, in the sense that their effects are multiplicative. Previous literature has mostly followed Jensen et al.'s (2007) original approach in examining the combination of the two as a separate category and comparing it with firms which exclusively rely on scientific or on supply-chain collaboration. They subsequently compare the effect of the combined mode with the effects of the two individual modes, finding a higher likelihood of innovation in the combined mode. This approach has, however, the drawback that it is not able to identify whether these outcomes are simply the result of independent additive effects of scientific and supply-chain collaboration, or whether there is an interaction between them – and if so, whether they are complements or substitutes. As there is no prior test of such an interaction, we cannot say a priori whether the effects of scientific and supply-chain collaboration are additive or multiplicative.

3. Methods

3.1. Sample and data

We test the hypotheses presented above using data from the Norwegian part of the Community Innovation Survey (CIS). Three consecutive waves[2] of the CIS are used – covering the period 2006–2010 – in order to create an unbalanced panel of firms. This approach has been used in previous analyses of CIS data for Norway (e.g. Castellacci, 2011; Clausen and Pohjola, 2013; Srholec, 2014) and other countries (e.g. Frenz and Ietto-Gillies, 2009; Parrilli and Heras, 2016; Criscuolo et al., 2017; Crescenzi and Gagliardi, 2018; Gagliardi and Iammarino, 2018).

The CIS data provides information on the innovation activities of firms and comprises firm-level surveys conducted every two years in the survey period. Over this period, the Norwegian CIS has used similar survey questionnaires, including consistent indicators for product innovation and for types of collaboration partners in innovation processes. The same indicators for firm's innovation collaboration and innovation output are therefore available throughout the survey period. The Norwegian CIS differs from the harmonized survey in that – from 2006 onwards – all respondents report innovation collaboration activities independent of their innovation status. This unique feature of the Norwegian data makes it possible to analyse the relationship between collaboration and actual innovation outcomes. We furthermore merge the CIS data with linked employer-employee data (LEED) from Statistics Norway to add more information on each firm.

Participation in the CIS is mandatory for sampled firms in Norway and non-respondents are fined. This results in a response rate ranging from 94 percent of sampled firms in 2006 to 97 percent in 2008 and 2010, almost ruling out the risk of non-response bias. The sample includes the full population of Norwegian firms with 50 or more employees, as well as all firms with 10–49 employees that have reported significant R&D activities in the previous waves of the survey. Other firms with 5–49 employees are sampled through a procedure which stratifies firms by size and industry, with higher likelihood of inclusion for larger firms. Overall, the sample comprises 6412 firm observations from the 2006 survey, 5980 from 2008, and 6532 from 2010. We combine these into an unbalanced panel with 18,924 observations in total. The sample is equivalent to a third of firms and two thirds of employees in the sampling population of Norwegian firms with more than five employees. All the empirical models are run with lagged dependent variables in order to control for unobserved heterogeneity. This restricts the sample to firms that participate in two consecutive surveys. Hence, the final sample consists of 8337 observations. There are slight variations in the sampling procedure from year to year, due to both entry and exit of firms and varying survey samples (see Wilhelmsen and Foyn, 2012 and earlier editions for details). This implies that sample averages and other descriptive statistics cannot be compared directly across years.

3.2. Dependent variables

We use three measures of innovation from the CIS as dependent variables: product innovation, new-to-market product innovation, and share of turnover from new products. This allows us to test for complementarities in the likelihood of introducing new products, in the novelty of these products, and in their market success. A product innovation is registered if the firm has introduced new or significantly improved goods or services to the market in the preceding three years. On average, 24 percent of all firms, and 32 percent of those present in two consecutive periods, report product innovation. New-to-market product innovation only includes product innovations that were new to the firm's market, excluding innovations that were new to the firm but already existed in the market. An average of 15 percent of firms observed in any given survey, and 20 percent of those present in two consecutive periods, report this type of innovation. New-to-firm and new-to-market product innovation are generally associated with similar procedures. However, new-to-market innovation is more explorative and therefore expected to be more closely associated with scientific collaboration than new-to-firm innovation (Parrilli and Heras, 2016). These measures are similar to those used in previous studies (Jensen et al., 2007; Parrilli and Heras, 2016).

Additionally, we go beyond these binary measures and also examine the share of turnover from new products as a dependent variable.[3] This allows for more variance across observed firms and enables us to distinguish between innovative firms with a higher and lower share of innovative products in their portfolio. This measure has been utilised by other studies using CIS data (e.g. Cassiman and Veugelers, 2006; Laursen and Salter, 2006).

3.3. Independent variables

Following previous research (e.g. Faems et al., 2005; Vega-Jurado et al., 2009; Fitjar and Rodríguez-Pose, 2013; Parrilli and Heras, 2016), we distinguish between collaboration with scientific and supply-chain partners. Scientific collaboration (STI) includes collaboration with universities, research institutes and consultancy firms. Supply-chain collaboration (DUI) encompasses linkages with suppliers and customers. The responses to the question about firms' collaboration partners are binary: 1 if the partner is used and 0 if not. Unfortunately, the data do not include information on the intensity of collaboration, or on the number of different partners of each type.

Throughout the period, supply-chain collaboration is used by 12.5 percent of firms, while scientific collaboration is used by 12.0 percent. Among firms present in two consecutive surveys, over 18 percent of firms report both types of collaboration. The correlation matrix (Appendix Table A.1) shows that there is a significant positive correlation between the two types of collaboration ($R = 0.70$).

Positive correlations between the activities, here innovation collaboration, is neither necessary nor sufficient for determining complementarity between them (Arora, 1996). However, pairwise correlations indicate that firms that engage in one type of collaboration are more likely also to engage in the other type of collaboration. The other correlation estimates tend to be low, suggesting that severe multicollinearity is not a problem.

3.4. Control variables

We control for several characteristics that could influence collaboration as well as innovation performance: *Collaboration with competitors, Firm size, Firm age, Export focus, R&D expenditure* and *Share of educated employees.*[4]

Collaboration with competitors is a dummy variable taking the value 1 if the firm collaborated with any of its competitors during the preceding

[2] We examine innovation outcomes and collaboration using CIS2006 (covering the 2004-2006 period), CIS2008 (covering the 2006-2008 period), and CIS2010 (covering the 2008-2010 period). In addition, we use lagged dependent variables that also include data from CIS2004 (covering the 2004-2006 period).

[3] The CIS asks firms to distribute their turnover in the survey year over new or significantly improved products introduced in the preceding three years, and unchanged or not significantly improved products. These add to 100 percent. The 2010 survey also distinguishes between turnover from new-to-firm and new-to-market products, which we add to obtain an equivalent measure to the 2004, 2006 and 2008 surveys of the share of turnover from all new products.

[4] The variables *Firm size*, *Firm age*, *R&D expenditure* and *Share of educated employees* are all log-transformed because of skewness in the distributions.

three years. This is drawn from the questionnaire item on collaboration partners used above. Collaboration with competitors has been treated separately by previous literature and has been found to have a negative effect on innovation (Fitjar and Rodríguez-Pose, 2013).

Firm size is the number of full-time employees in the firm. This variable is based on linked employer-employee data from tax registers, from which we count the number of people listed as employed in the firm in the year of the survey. Larger firms have the resources to cope with the risks associated with innovation processes and are more likely to engage in innovation activities (Schumpeter, 1939). However, smaller firms benefit from less rigidity in their innovation process (Cohen, 1995).

Firm age is proxied by the number of years for which we observe the firm in the register data between 2000 and the year of the survey. It is thus censored at 6, 8 and 10 years for the 2006, 2008 and 2010 survey, respectively. However, it is used to distinguish young firms from more established ones. Older firms may benefit from building on previous routines and capabilities (Levitt and March, 1988), but may also have drawbacks in the form of a rigid organizational structure (Coad et al., 2016).

Export focus is a dummy variable taking value 1 if the firm has the European or international arena as its main market of reference (using local and national market as the baseline). This variable is based on a question in the CIS data asking firms to indicate which of four markets they perceive to be the most important for their products. Firms operating in the international market tend to be more innovative (Salomon and Jin, 2008).

R&D expenditure is the total amount of internal expenditure on research and development by the firm in the year preceding the survey. Expenditure on internal R&D is assumed to increase internal knowledge and the ability to utilize this knowledge (Cohen and Levinthal, 1990). We also control for the *share of educated employees* in the year the CIS survey was conducted. This is defined as the percentage of the firm's workers who have completed a higher education degree. This variable is drawn from linked employer-employee data, using the Norwegian education database for details on each employee's educational background.

Industry is also controlled for by means of a set of dummy variables for the two-digit NACE industry of the firm. In total 58 different two-digit industries are present in the data. We also include dummies for each *year* of observation to account for any time trends. Finally, dummy variables for economic *regions* are used in the analysis.[5]

We also include lagged dependent variables to control for consistent innovation activities and absorb some of the bias related to heterogeneity among firms. In order to keep as many observations as possible, we also use data from CIS2004 to construct this variable.[6] Due to the inclusion of lagged dependent variable, the analysis focuses on firms that participate in at least two consecutive waves of the survey (e.g. CIS2006 and CIS2008).

Table 1 shows descriptive statistics for the variables included in the analysis. For comparison, the first column shows the mean values for the full sample, while the second column shows the mean values for the firms participating in two consecutive periods (which are included in the empirical analyses). Overall, firms participating in two consecutive periods have higher rates of innovation and collaboration, making this a more relevant sample for investigating whether different collaboration types have complementary or substitutive effects on innovation. They are also larger, and spend more on R&D. This is expected, as the CIS includes the full population of larger and more R&D intensive firms, and only a sample of smaller and less R&D intensive ones (see Section 3.1).

3.5. Estimation strategy and identification approach

In order to test H1-H3, we first fit our basic regression model, which takes the following form:

$$logit\ (P(Innovation_{i,t})) = \beta_0 + \beta_1 \boldsymbol{C}_{i,\,t} + \beta_2 \boldsymbol{Z}_{i,t} + \beta_3 Innovation_{i,\,t-1} + \varepsilon_{i,t} + \alpha_i \quad (1)$$

$P(Innovation_{i,t})$ is the probability of product innovation or new-to-market product innovation for firm i at time t. Firms' collaboration is captured by the vector $\boldsymbol{C}_{i.\,t} = (STI_{i.\,t},\ DUI_{i.\,t})$. STI refers to scientific collaboration, while DUI refers to supply-chain collaboration, both included as dummies that take the value 1 if firm i is using one of the collaboration types at time t and 0 otherwise. $\boldsymbol{Z}_{i.t}$ are the controls. The specification also controls for sectoral, time and regional fixed effects. $Innovation_{i,\,t-1}$ is included to control for previous innovation by the firm, which can capture some unobserved heterogeneity in firms' ability to innovate.

For the models using share of turnover from new products as the dependent variable, $Innovation^{*}_{i,t}$, we fit an equivalent Tobit model:

$$Innovation^{*}_{i,t} = \beta_0 + \beta_1 \boldsymbol{C}_{i,\,t} + \beta_2 \boldsymbol{Z}_{i,t} + \beta_3 Innovation^{*}_{i,t-1} + \varepsilon_{it} + \alpha_i \quad (2)$$

The use of a logit model (as in model 1) is consistent with previous studies of innovation modes (Jensen et al., 2007; Fitjar and Rodríguez-Pose, 2013; Apanasovich et al., 2016; Parrilli and Heras, 2016), while the Tobit model has featured in e.g. Faems et al. (2005) and Laursen and Salter (2006).

Due to unobservable time-invariant influences at e.g. firm, sectoral or regional level, endogeneity remains a concern in this type of analysis. Ideally, a panel model could account for this, and as a robustness check of our models, we also estimate Eq. (1) using a panel fixed-effects model (see Table 6). This approach allows us to control for firm-level heterogeneity which could cause bias. However, the lack of variation in core variables, such as innovation outcome and collaboration, imply that these analyses are on a significantly smaller sample of firms. While the use of panel data mitigates to some extent the issue of firm heterogeneity, the issue of endogeneity and therefore reverse causality may still occur. Another approach would be to use instrumental variable regression, but these have generally proved unsuccessful in research using CIS data (Mohnen and Röller, 2005; Cassiman and Veugelers, 2006), due to the lack of strong exogenous instruments.

Instead, in all our basic models, we control for time-invariant characteristics by including a lagged dependent variable in the analysis. This will capture some of the heterogeneity across firms by controlling for whether or not the firm innovated in the preceding period.[7] In addition, a large battery of control variables are considered in the model, comprising sectoral and regional fixed effects, as well as firm-level control variables. We nevertheless acknowledge the potential for endogeneity, even with the robustness checks done, and recognize that our results must be interpreted in this light.

[5] These are defined at the level of economic regions according to Statistics Norway, corresponding to local administrative units at level 2 (LAU 2). Regions that are functionally integrated into the same labour market are merged following Gundersen and Juvkam (2013). This leaves a total of 78 different economic regions which are roughly equivalent to labour market regions. These economic regions have been commonly used in previous studies on the impact of location on firm innovation in Norway (e.g. Herstad and Ebersberger, 2015; Aarstad et al., 2016; Fitjar and Timmermans, 2017).

[6] Questions pertaining to collaboration were only asked to all firms from CIS2006 onwards. In CIS2004, only innovators or firms with ongoing or abandoned innovation activities were asked these questions – as is still the case in most other countries. Hence, we consider collaboration measures only from 2006 onwards. However, as information on innovation outcomes for all firms from CIS2004 is available, this information is included in the empirical analysis.

[7] Indeed, the variation in e.g. product innovation is higher between firms (0.31) than across time (0.24), suggesting that innovation outcomes are relatively consistent across time.

Table 1
Descriptive statistics.

Variables	Description	Total		Two consecutive periods	
		Obs.	Mean (Sd.)	Obs.	Mean (Sd.)
Product innovation	Dummy variable taking the value 1 if the firm introduced any new or significantly improved products in the preceding three years.	18,924	0.240 (0.427)	8,337	0.318 (0.461)
New-to-market product innovation	Dummy variable taking the value 1 if the firm developed any product innovations that were new to the firm's market.	18,924	0.150 (0.357)	8,337	0.208 (0.401)
Product innovation t_1	Dummy variable taking the value 1 if the firm introduced any new or significantly improved products in the preceding three years. Lagged one survey period.	8,337	0.349 (0.476)	8,337	0.349 (0.469)
New-to-market product innov. t_1	Dummy variable taking the value 1 if the firm developed any product innovations that were new to the firm's market. Lagged one survey period.	8,337	0.198 (0.398)	8,337	0.198 (0.398)
Scientific collaboration, STI	Dummy variable taking the value 1 if the firm collaborated with universities, research institutes or consultancy firms in the preceding three years.	18,924	0.120 (0.324)	8,337	0.187 (0.390)
Supply-chain collaboration, DUI	Dummy variables taking the value 1 if the firm collaborated with suppliers or customers in the preceding three years.	18,924	0.125 (0.330)	8,337	0.188 (0.391)
Collaboration with competitors	Dummy variables taking the value 1 if the firm collaborated with competitors in the preceding three years.	18,924	0.038 (0.192)	8,337	0.051 (0.231)
R&D expenditure (log)	Total amount of internal expenditure on research and development by the firm.	18,924	1.885 (3.448)	8,337	3.001 (4.032)
Firm size (log)	Number of full-time employees in the firm in the year of the survey.	18,924	3.377 (1.273)	8,337	4.120 (1.261)
Firm age (log)	Number of years the firm is present in register data since 2000.	18,924	0.210 (0.982)	8,337	0.493 (0.780)
Share of educated employees (log)	Share of the firm's workers who have completed a higher education (university) degree.	18,924	0.211 (0.196)	8,337	0.220 (0.181)
Innovation active	Dummy variable taking the value 1 if the firm reported positive innovation expenditure, collaboration in innovation processes, or any kind of innovation outcome.	18,924	0.481 (0.500)	8,337	0.600 (0.481)
Export focus	Dummy variable taking the value 1 if the firm's most important market is non-domestic.	18,924	0.140 (0.347)	8,337	0.198 (0.398)
Innoshare (log)	Share of turnover in the survey year from new or significantly improved products developed in the preceding three years.	18,679	0.694 (1.363)	8,337	0.902 (1.471)
Innoshare(log) t_1	Share of turnover in the survey year from new or significantly improved products developed in the preceding three years. Lagged one survey period	8,337	0.961 (1.491)	8,337	0.961 (1.481)

4. Empirical results

Table 2 presents the results of the estimation of Eq. (1). Columns (1) and (2) show the estimates for product innovation, and (3) and (4) show the estimates for new-to-market product innovation.

In the basic models, (1) and (3), firm innovation is a function of innovation in the previous period and innovation collaboration. Firms that reported innovation in the preceding period are significantly more likely to innovate also in the following period. Furthermore, the estimates confirm that firms collaborating with scientific as well as supply-

Table 2
Estimated result. Reported coefficient from the binary logit model, product and new-to-market product innovation (1) – (4).

	(1) Product innovation	(2) Product innovation	(3) New-to-market prod. innov.	(4) New-to-market prod. innov.
Product innovation t_1	1.747*** (0.067)	1.281*** (0.072)		
New-to-market prod. innov. t_1			1.536*** (0.076)	1.066*** (0.081)
Scientific collaborations, STI	0.973*** (0.108)	0.384*** (0.122)	0.908*** (0.113)	0.358*** (0.118)
Supply-chain collaboration, DUI	1.141*** (0.105)	0.891*** (0.120)	0.973*** (0.110)	0.672*** (0.120)
Collaboration with competitors		−0.054 (0.158)		−0.043 (0.138)
R&D expenditure (log)		0.232*** (0.010)		0.240*** (0.012)
Firm size (log)		−0.088*** (0.030)		−0.101*** (0.031)
Share of educated employees (log)		−0.074 (0.294)		−0.015 (0.326)
Export focus		0.034 (0.090)		−0.052 (0.089)
Firm age (log)		0.013 (0.052)		0.075 (0.057)
Constant	−2.740*** (0.532)	−3.172*** (0.567)	−2.895*** (0.561)	−3.380*** (0.607)
Observations	8,198	8,195	8,095	8,092
Log Likelihood	−3529.6	−3209.9	−3096.3	−2816.5
Firms	4,612	4,612	4,534	4,534
Pseudo R^2	0.315	0.377	0.263	0.329

Note: Robust standard errors clustered over firms in parentheses. All models includes year, industry and regional fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3
Reported estimated coefficient. Tobit model. Dependent variables: Share of turnover in the survey year from new or significantly improved products developed in the preceding three years.

	(1)	(2)
Share of turnover t_1	0.826***	0.532***
	(0.026)	(0.027)
Scientific collaboration, STI	1.180***	0.351***
	(0.127)	(0.124)
Supply-chain collaboration, DUI	1.383***	0.870***
	(0.124)	(0.123)
Collaboration with competitors		0.055
		(0.141)
R&D expenditure (log)		0.339***
		(0.013)
Firm size (log)		−0.181***
		(0.034)
Share of educated employees (log)		−0.095
		(0.342)
Export focus		0.017
		(0.099)
Firm age (log)		0.006
		(0.007)
Sigma	2.760***	0.305***
	(0.038)	(0.010)
Constant	−3.454***	−1.201***
	(0.625)	(0.169)
Observations	8,262	8,259
Log Likelihood	−8324.4	−7920.1
Pseudo R^2	0.167	0.207

Note: Robust standard errors clustered over firms in parentheses. Both models includes year, industry and regional fixed effects. Share of turnover related to product and new-to-market product innovation. 5720 observations are left-censored. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

chain partners are also more likely to innovate. In column (2) and (4), we include additional firm-level control variables. The patterns remain the same. Hence, we find support for H1 and H2 for all innovation outcomes.

The results for the controls are in line with expectations. R&D expenditure has a significant effect on innovation, as does firm size. However, education, firm age and export focus are not significantly correlated with any of the innovation outcomes.

Table 3 shows the results from Eq. (2), where the dependent variable is the share of turnover from new or significantly improved products in the preceding three years. The overall results are similar to those in the logit regression. Scientific and supply-chain collaboration both have a significant and positive effect on innovation. These results hold when all the controls and the lagged dependent variable are included. Overall, the analysis confirms the results from the logit regression also for a more fine-grained measure of innovation.

4.1. Measuring and estimating complementarities

Next, we turn to our main contribution and examine the relationship of interest for H3, i.e. whether scientific and supply-chain collaboration are complementary or substitutes. The concept of complementarity implies that the implementation of one activity pays off more if the complementary activity is present too. In a standard framework, complementarity between a set of variables means that the marginal returns to one variable increases with the level of another variable. For instance, if scientific and supply-chain collaboration are complementary, the marginal effect of scientific collaboration on innovation is higher when the firm also conducts supply-chain collaboration and vice versa. The study of complementarities between activities can be traced back to the theory of supermodularity (e.g. Milgrom and Roberts, 1990, 1995; Topkis, 1998).

To analyse complementarities, we first estimate the function given by an expanded version of Eq. (1). While Eq. (1) included two separate variables for innovation collaboration, we expand it to also take into consideration the interaction terms between the innovation collaboration types to observe in greater detail how firm-level innovation is affected when firms practice both types of interactions.

By expanding Eq. (1), we get:

$$logit(P(Innovation_{i,t})) = \beta_0 + \beta_1 Innovation_{i,t-1} + \beta_2 STI_{i,t} + \beta_3 DUI_{i,t} + \beta_4 STI_{i,t} \times DUI_{i,t} + \beta_5 \boldsymbol{Z}_{i,t} + \varepsilon_{i,t} + \alpha_i \quad (3)$$

The independent variables in Eq. (3) are as in Eq. (1). We add an interaction term between the two different collaboration types in firm i at time t. Table 4 presents the results of running a logit model on Eq. (3) and the equivalent Tobit model.

For comparison, Table 4 first shows the basic model for all dependent variables without any interaction terms, as in Tables 2 and 3, while the next column includes the interaction term between the innovation

Table 4
Estimated results. Product innovation, New-to-market product innovation and Share of turnover.

	(1) Product innovation	(2) Product innovation	(3) New-to-market prod.innov	(4) New-to-market prod.innov	(5) Share of turnover	(6) Share of turnover
Product innovation t_1	1.281***	1.276***				
	(0.072)	(0.072)				
New-to-market prod.innov t_1			1.066***	1.066***		
			(0.081)	(0.081)		
Share of turnover t_1					0.532***	0.530***
					(0.027)	(0.027)
Scientific collaboration, STI	0.384***	0.715***	0.358***	0.789***	0.351***	0.809***
	(0.122)	(0.162)	(0.118)	(0.156)	(0.124)	(0.174)
Supply-chain collaboration, DUI	0.891***	1.221***	0.672***	1.072***	0.870***	1.259***
	(0.120)	(0.164)	(0.120)	(0.154)	(0.123)	(0.152)
STI*DUI		−0.744***		−0.887***		−0.910***
		(0.235)		(0.215)		(0.228)
Constant	−3.172***	−3.181***	−3.380***	−3.401***	−3.602***	−3.603***
	(0.567)	(0.568)	(0.607)	(0.606)	(0.578)	(0.581)
Observations	8,195	8,195	8,092	8,092	8,259	8,259
Sigma					2.528***	2.527***
					(0.037)	(0.037)
Log Likelihood	−3209.9	−3203.6	−2816.5	−2806.8	−8324.4	−7920.1
Firms	4,612	4,612	4,534	4,534	2,539	2,539
Pseudo R^2	0.377	0.378	0.329	0.332	0.167	0.207

Note: Robust standard errors clustered over firms in parentheses. All models includes all controls, year, industry and regional fixed effects. Share of turnover related to product and new-to-market product innovation. 5720 observations are left-censored in model (5) and (6). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5
Average marginal effects of innovation collaboration at mean values of all other variables.

	New-to-market prod. innovation		Product innovation	
	Supply-chain collaboration		Supply-chain collaboration	
Scientific collaboration	0	1	0	1
0	0.17 (0.01)	0.30 (0.02)	0.28 (0.05)	0.45 (0.02)
1	0.26 (0.01)	0.29 (0.02)	0.37 (0.02)	0.45 (0.02)

Note: Robust standard errors in parentheses. All coefficients are significant at 1 percent level.

collaboration types, STI*DUI. This allows us to examine how the likelihood of product innovation changes when firms collaborate with both scientific and supply-chain partners. The coefficients show a negative and significant interaction between the two for all three innovation outcomes. Separately, scientific and supply-chain collaboration both increase the likelihood of product innovation, new-to-market innovation and share of turnover from product innovation. However, the interaction term indicates that they are substitutes, meaning that there are declining returns to collaborating with both types of partners.

As the estimation model in models 2 and 4 is a nonlinear (logit) model with an interaction term, the marginal effects of collaborating with different types of partners on the probability of innovation are given by the cross-partial derivation of the interaction term. Table 5 presents the marginal effects of the different types of collaboration at the average levels of the control variables in the model[8] for product innovation and new-to-market innovation.

Scientific and supply-chain collaboration appear to be substitutes rather than complements. We can illustrate this more clearly by examining the estimated marginal effect for STI and DUI in greater detail. The marginal effects of scientific collaboration on the probability of firm innovation conditional on supply-chain collaboration are shown in Fig. 1.

Fig. 1 shows that collaboration with scientific partners increases the probability of innovation substantially for firms that do not collaborate with supply-chain partners (blue solid line, DUI = 0). The probability of product innovation is 28 percent for firms that do not collaborate with any partners, compared to 37 percent for firms that collaborate with scientific partners only. However, there is no effect of reaching out to scientific partners for firms that already engage in supply-chain collaboration (red line, DUI = 1). The slope of the line has a slightly negative trajectory, although the difference is marginal. For practical purposes, the probability of innovation remains the same if firms collaborate only with supply-chain partners, or if they collaborate with both scientific and supply-chain partners. On the flipside, the probability of innovation is much higher for firms collaborating with supply-chain partners than for firms not participating in any partnerships.

Fig. 2 shows the effects on new-to-market product innovation. Collaboration with scientific partners increases the probability of innovation substantially for firms that do not collaborate with supply-chain partners (blue solid line, DUI = 0). The probability of new-to-market product innovation is just below 17 percent for firms that do not

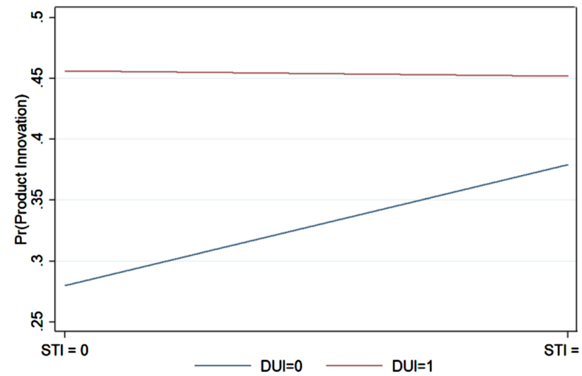

Fig. 1. Combining scientific and supply-chain collaboration and the probability of product innovation.

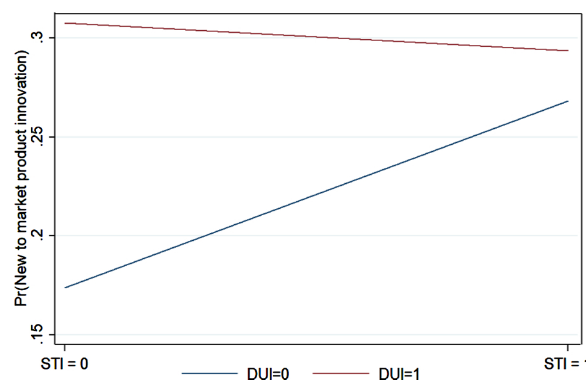

Fig. 2. Combining scientific and supply-chain collaboration and the probability of new-to-market product innovation.

collaborate with any partners, compared to 26 percent for firms that collaborate with scientific partners only. However, if firms already collaborate with scientific partners, supply-chain collaboration does not increase the probability of innovation.

4.2. Robustness checks

We perform two checks on the robustness of our main findings. In particular, we run a panel fixed-effect model on our data. This approach allows us to control for firm-level heterogeneity which could cause bias. However, given the structure of the data and the lack of variation in the main dependent variables, the sample size decreases substantially. Table 6 shows the estimated results for the fixed-effect model for a balanced panel data set. Overall, the effects of both scientific and supply-chain collaboration are positive and significant also in this model. The interaction term is negative, but not statistically significant. The direction of the coefficient is consistent with the results of the previous analyses. Overall, this indicates that H1 and H2 are supported, while there is no evidence to substantiate H3a with the panel model. The negative sign of the interaction term shows a story consistent with the previous analysis.

As a further robustness check, we also run our models restricting the analysis to innovation-active[9] firms (Table 7). The results are very similar to those of the full sample. The effects of scientific and supply-chain collaboration are both positive and significant, but the interaction between them is negative. The interaction term is significant only for

[8] In nonlinear models, such as a logit model, one needs to be careful when assessing the marginal effect of interactions in isolation. The risk in the interpretation is derived from a potential skewness in the tail of the logit distribution. The marginal effect is dependent on the values of other variables in the model, which may also affect the significance level for the marginal effect within the variance of other variables. There are several ways of dealing with this potential problem. One would involve examining changes in the odds ratio (e.g. Buis, 2010). The alternative we follow involves analysing the marginal effect at the average level of all variables (e.g. Cameron and Trivedi, 2005).

[9] Innovation-active firms are defined as those reporting positive innovation expenditure, collaboration in innovation processes, or any kind of innovation outcome (Herstad et al., 2014). In total, 8,337 firms of the original 18,924 firms are innovation-active.

Table 6
Fixed effect model, Product innovation and New-to-market innovation. Unbalanced panel, time-period 2006–2010.

	(1)	(2)	(3)	(4)
	Product innovation	Product innovation	New-to-market prod.innov.	New-to-market prod.innov.
Scientific collaboration, STI	0.640***	0.812***	0.517***	0.736***
	(0.161)	(0.233)	(0.168)	(0.239)
Supply-chain collaboration, DUI	0.830***	0.985***	0.570***	0.757***
	(0.141)	(0.212)	(0.145)	(0.201)
STI*DUI		−0.406		−0.448
		(0.300)		(0.305)
Collaboration with competitors	−0.038	−0.002	0.038	0.068
	(0.204)	(0.225)	(0.188)	(0.215)
R&D expenditure (log)	0.193***	0.193***	0.152***	0.151***
	(0.024)	(0.022)	(0.020)	(0.020)
Firm size (log)	0.217	0.213	0.329**	0.328*
	(0.183)	(0.141)	(0.168)	(0.173)
Share of educated employees (log)	1.156	1.107	−0.726	−0.720
	(1.302)	(1.361)	(1.093)	(1.035)
Export focus	0.260	0.266	0.345*	0.354*
	(0.206)	(0.176)	(0.190)	(0.187)
Observations	3,081	3,081	2,714	2,714
Numbers of firms	1,196	1,196	1,042	1,042
Log Likelihood	−925.16	−924.2	−838.5	−837.0

Note: Balanced data set. Bootstrapped standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7
Only innovation-active firms. Product innovation and New-to-market innovation.

	(1)	(2)	(3)	(4)
	Product innovation	Product innovation	New-to-market prod. innov.	New-to-market prod. innov.
Product innovation t_1	1.107***	1.106***		
	(0.077)	(0.077)		
New-to-market prod. innov t_1			0.963***	0.964***
			(0.078)	(0.078)
Scientific collaboration, STI	0.290***	0.337**	0.309***	0.533***
	(0.111)	(0.146)	(0.107)	(0.143)
Supply-chain collaboration, DUI	0.648***	0.695***	0.525***	0.729***
	(0.107)	(0.144)	(0.106)	(0.137)
STI*DUI		−0.105		−0.457**
		(0.209)		(0.196)
Constant	−1.648***	−1.652***	−2.263***	−2.285***
	(0.595)	(0.596)	(0.618)	(0.619)
Observations	4,948	4,948	4,916	4,916
Firms	2,892	2,892	2863	2863
Pseudo R^2	0.228	0.228	0.205	0.206
Log Likelihood	−2637.8	−2637.7	−2531.1	−2529.3

Note: Robust standard errors clustered over firms in parentheses. All models includes all controls, year, industry and regional fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

new-to-market innovation. Once again, the hypothesis of complementarity between the innovation modes cannot be supported.

5. Conclusion

Prior literature has argued that firms combining science-based and experience-based knowledge in innovation processes are more likely to innovate as a consequence of the complementarities between the two types of knowledge. This is a core tenet of the literature on innovation modes since the publication of Jensen et al.'s (2007) seminal article. They suggested that a combination of STI and DUI resulted in higher levels of innovation. Literature on innovation collaboration has also suggested that different types of partners provide access to different knowledge and a wider scope of new ideas. Scientific partners give access to knowledge from a different realm than do suppliers and customers, and combining both scientific and supply-chain collaboration is therefore ideal for innovation (Faems et al., 2005). However, some have cautioned against the risk of 'over-searching' and questioned whether most firms have the capacity to manage radically different types of knowledge inputs (Laursen and Salter, 2006).

Testing of whether this complementarity really exists and benefits innovation has, however, never taken place. In this paper, we have conducted such an analysis by evaluating the interaction between collaboration with scientific and supply-chain partners in Norway. The results show that there is a need to rethink the assumption that the two types of collaboration are complementary. Engaging in more supply-chain collaboration for firms already conducting scientific collaboration – and vice versa – is unlikely to unleash complementarities that lead to radically higher levels of innovation. The results demonstrate that, at least in the case of Norway, scientific and supply-chain collaboration rather than being complementary, appear to be substitutes or – at best – that they only have additive effects on innovation. The analysis finds a negative interaction effect between scientific and supply-chain collaboration for innovation. Firms benefit strongly from collaborating with scientific or supply-chain partners, but collaborating with both types of partners simultaneously does not yield multiplicative benefits. On the contrary, the effect of collaborating with scientific partners is more limited for firms that also collaborate with supply-chain partners.

These findings challenge the dominating views about the benefits of different types of collaboration and their complementarity. However, they should be considered with some caution, given, first, that the analysis focuses exclusively on product innovation. Furthermore, the binary structure of the dependent variables places some limitations on our understanding of the scope of the innovation. While to a considerable extent the share of sales from new products takes this to account and leads to the same conclusion, we do not know how many new products were introduced by each firm and have no information on the quality or complexity of these products. Therefore, complementarities in these dimensions cannot be ruled out. Certainly, more complex and advanced innovations may, to a greater extent, require different types of inputs. We also do not have information on the intensity or the number of partners of each type and can therefore only examine effects of whether or not different types of partners were used. Finally, we have not been able to explore how firms integrate the knowledge from scientific and supply-chain collaboration into internal innovation practices.

Taking these caveats into account, the results, nevertheless, provide considerable food for thought about the scope of collaboration that is needed for firms to innovate. More research covering other areas of the world will be needed in order to corroborate or challenge these results. Overall, the results supply new ideas about how to collaborate and what types of collaboration are needed to increase innovation at the level of the firm. Collaboration is clearly an important factor for innovation. Firms engaging in scientific or supply-chain partnerships independently from one another innovate more. However, our results raise questions about the prevailing wisdom about how much collaboration is needed in order to maximise innovation outputs and about whether firms need to consider more of different types of collaborations. They also represent a challenge for officials and decision-makers in their quest to design policies that would create more adequate conditions and environments for firms to innovate, as promoting more and more complex types of collaboration for innovation does not always help firms to become more innovative and competitive.

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