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Openness and innovation in the US: Collaboration form, idea generation and implementation

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ABSTRACT

Much current work in management of innovation argues that it is becoming increasingly necessary for inventors and their firms to exploit information and capabilities outside the firm in order to combine one's own resources with resources from the external environment. Building on this prior work, we examine the relationship between collaboration and innovation. Using detailed information on a sample of triadic patents, with over 1900 responses in the US, we report on the rates of collaboration of various forms, and test the effects of collaboration. Our results suggest that just over 10% of inventions involve an external co-inventor and about 23% involve external (non-co-inventor) collaborators (with 27% involving any external collaborators). We find evidence that heterogeneous collaboration and university-industry collaboration in inventing drive higher invention quality. However, vertical collaboration at the inventing stage is relatively more critical to commercialization at the implementation stage than is university-industry collaboration. These results suggest that the impact of different forms of collaborative innovation may vary depending on the stage of the innovation process.

1. Introduction

While individual inventors are key to technological progress, it is becoming increasingly necessary for inventors and their firms to exploit information and opportunities outside the firm in order to combine one's own capabilities and resources with those from the external environment (Dahlander and Gann, 2010). Open innovation allows firms to better exploit information and the complementary capabilities of external organizations (Chesbrough, 2003; Hayashi, 2003; Motohashi, 2005; Powell et al., 1996).

Building on the literature on innovation collaboration, this study examines rates of collaborative inventing in the US and the effects of research collaboration on innovative performance. Dahlander and Gann (2010) note that open innovation includes different forms of openness: openness in the inputs (for example, through in-licensing or collaborative R&D) and openness in the exploitation of the invention (for example, through out-licensing). In this paper, we are concentrating on openness in the inputs, especially, research collaboration, and test its effects on two different stages: idea generation (i.e., invention) and idea implementation (i.e., commercialization), following the Schumpeterian notion of innovation as a two-step process. In other words, we examine how openness in the inputs (i.e., information gained at the idea generation stage) not only affects the quality of the invention as a result of idea generation, but also has an impact on exploitation of the invention at the idea implementation stage.

The first stage, invention, involves the creation of a new, potentially useful technology. Therefore, invention is likely to benefit from broad information access. Moreover, firms' collaborations with universities will be important to obtain radical or novel knowledge and create high-value inventions. The second stage is commercialization, translating that invention into practice (i.e., innovation). Here, information obtained through firms' collaboration with suppliers or customers in the inventing stage may be more beneficial in commercializing the invention even after the collaboration is over (March, 1991).

In this paper, we contribute to developing a theory of the differential impact of collaboration across the two stages of the innovation process, examining collaboration patterns in the US. First, using original survey data providing project-level information on a large sample of inventions in the US, we describe openness in the inventing process. We then examine the effects of research collaboration, considering the heterogeneity of collaboration and different types of partnerships in the inventing stage, on invention quality (invention) and commercialization (innovation). By heterogeneity, we mean the span of information space covered by the

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collaboration, or, put differently, the distance in the information set of partners from that of the focal inventor's firm. The results show that heterogeneous collaborations, including university-industry (U-I) collaborations, are associated with higher quality inventions. Furthermore, we find that, net of quality, vertical collaborations (i.e., collaboration with suppliers or customers) in the inventing stage lead to greater likelihood of commercialization at the implementation stage. This shows the relative importance of different types of partnerships in inventing to the different stages of innovation. We finish with a discussion of the theoretical, policy and methodological implications of our findings.

2. Literature review and theory development on collaboration and innovation

Arguments about the potential benefits of collaborative innovation are grounded in the more fundamental literatures on evolutionary economics, cognitive psychology and network theories of innovation. Evolutionary economists argue that bounded, local search limits the ability of a firm to fully exploit potentially valuable information (Cohen and Levinthal, 1990; Nelson and Winter, 1982; Nooteboom, 2008). Evolutionary economics also contends that broadening the search can improve innovation performance (Nelson and Winter, 1982). Cognitive psychology and computer science models of problem solvers show that functional diversity in the problem solving team should increase team performance by allowing broader search (Ancona and Caldwell, 1992; Hong and Page, 2004; Pieterse et al., 2013). Similarly, network ties, such as R&D collaborations and alliances, can facilitate information flows and encourage innovation (Owen-Smith and Powell, 2004). Moreover, the literatures on transaction costs, strategic management and industrial organization have seen research partnership as an alternative, intermediate form falling between the market and the firm and as a means of increasing efficiency and synergy, accessing complementary assets and internalizing knowledge spillovers (Bougrain and Haudeville, 2002; Hagedoorn et al., 2000; Nooteboom, 2008; Powell, 1990). Even though collaboration studies are grounded in diverse theoretical literatures, they all agree on the importance of research collaboration for knowledge-seeking and knowledge-creation (Powell, 1998). The locus of innovation is not limited to individual firms, but found in networks of learning, which encourages specialization and cross-fertilization across participants and helps learning and transfer of tacit knowledge (Bougrain and Haudeville, 2002; Katz and Martin, 1997; Powell, 1998).

Although much of the theory on knowledge source diversity and inter-organizational collaboration is focused on how collaboration contributes to generating novel combination, seen as a precursor to valuable innovation, many collaboration studies use novelty of innovation (e.g. radical or incremental), impact (e.g. patent citations), or commercial value (e.g. sales from the innovation) as an outcome, collapsing the innovation process into its outcome to test the effects of collaboration (e.g., Bougrain and Haudeville, 2002; Hottenrott and Lopes-Bento, 2015; Katila and Ahuja, 2002; Laursen and Salter, 2006; Leiponen and Helfat, 2010). However, research collaboration or partnerships may have different effects on the different stages of the innovation process. For example, building on the Schumpeterian two-stage process and March's (1991) distinction between exploration and exploitation, Rothaermel and Deeds (2004) find that exploration alliances are associated with more invention, while exploitation alliances are associated with more innovation. Likewise, building on but extending these prior studies, in this section, we develop a testable theory of the relative effectiveness of collaboration in inventing on the different stages of the innovation process: idea generation (i.e. invention) and idea implementation (i.e. commercialization).

2.1. Effects of knowledge heterogeneity on invention quality and commercialization

There is substantial prior work discussing the advantages of collaboration for innovation (Chesbrough, 2003; Laursen and Salter, 2006; Owen-Smith and Powell, 2004). Laursen and Salter (2006) find that firms that draw from a broader range of information sources, and those that draw more deeply from those sources, are more innovative. Leiponen and Helfat (2010) and Love et al. (2013) argue that more linkages to external knowledge sources or a broader span of knowledge sources increase the probability of gaining useful knowledge leading to a more valuable innovation outcome, and knowledge obtained from different types of linkages increases the complementarity between external knowledge and internal capability. Prior work from the information processing perspective also suggests that task-related dimension of diversity (including different knowledge backgrounds) should increase the task-related information and perspectives available to the group and hence innovative performance (Hulsheger et al., 2009; Stewart, 2006; Van Knippenberg et al., 2004; Williams and O'Reilly, 1998). Thus, knowledge transfer among different knowledge sources generates new combination of knowledge through integration of disparate knowledge elements broadly drawn from different organizations (Lee and Walsh, 2011; Miller et al., 2007).

Given the importance of broad information access, we expect that, due to bounded rationality, projects that draw from a broader team of researchers (representing different fields, institutions and sectors) are likely to produce more technologically significant inventions (Page, 2007; Taylor and Greve, 2006; Van Knippenberg et al., 2004; Williams and O'Reilly, 1998). Hong and Page (2004) use the concept of functional diversity of the problem solving team, which includes both diversity in perspectives and diversity in heuristics. They show (through simulation and mathematical proof) that even a randomly selected set of agents can outperform a set of high ability agents, because the random sample is likely to have higher functional diversity. They argue that the value of an additional agent may depend more on the functional distinctiveness of the additional agent than on the ability of that agent (Hong and Page, 2004). In the case of industrial projects for invention, this suggests that projects that span organizations, and especially types of organizations (heterogeneous projects), are likely to produce higher quality inventions, and that this effect is due to greater breadth of information access (Nooteboom, 2008; Taylor and Greve, 2006). Therefore, more heterogeneous collaboration (i.e., higher diversity in the types of collaborators) will generate more technically novel or significant inventions.

Hypothesis 1. Higher heterogeneity of knowledge sources (at the idea generation stage) will increase invention quality.

This relationship should hold even net of the number of inventors (Hong and Page, 2004).

2.2. Collaboration partners and invention quality

We can think of heterogeneity not only in terms of the number of types of organizations (suppliers, customers, rivals, universities, government labs, etc.), but also in terms of whether it involves cross-sector (university-industry collaboration) or vertical linkages (collaboration with suppliers and customers), which are related to different kinds of knowledge.

To generate invention, firms need to attract those who can provide cutting-edge scientific knowledge (Gittelman and Kogut, 2003). Since universities are particularly broad repositories of

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generic knowledge that has a wide range of applications and radical knowledge which potentially can produce dramatically better technology, firms' interacting with universities, through formal activities such as collaborative or contract research and consulting or informal activities such as ad hoc advice and networking, will advance their scientific understanding and more likely generate radical invention (Goto, 2000; Maine and Garnsey, 2006; Perkmann et al., 2013). Baba et al. (2009) show that interactions between firms and universities through "Pasteur scientists" who are involved in many patent applications as well as high-quality scientific papers facilitate knowledge recombination and tacit knowledge flows. Fleming and Sorenson (2004) argue that science can provide likely fruitful paths of research, identifying useless directions and avoiding wasted effort, and motivate pursuing novel and untried experiments (see also Nelson, 1959). This implies that firms' collaborations with universities are an important tool to generate technically advanced or significant inventions. Thus, we have the following:

Hypothesis 2. University-industry (U-I) collaborations should generate relatively higher quality inventions (technical significance) than do collaborations with suppliers and/or customers.

2.3. Collaboration partners and commercialization

While diversity of knowledge may contribute to generating novel ideas, integration is important for identifying, evaluating and selecting the best novel ideas (Harvey and Kou, 2013; Singh and Fleming, 2010; Skilton and Dooley, 2010). Therefore, increasing heterogeneity of knowledge sources may not add more value to generating novel outcomes, but rather make integration more difficult after a certain point (Lee et al., 2015). For example, Laursen and Salter (2006) and Nooteboom (2008) show a curvilinear (inverted-U) effect of broad information. Extending these prior studies, our focus is not limited to the relationship between collaboration heterogeneity and novel combinations of knowledge (i.e. invention), but extends to the relationship between collaboration heterogeneity and commercialization of the novel outcomes (i.e. innovation), exploring the relative importance of collaboration heterogeneity between invention and commercialization.

Contrary to inventing, the transition from invention to innovation (i.e. commercialization) raises additional problems. Commercialization is a follow-on activity from inventing and requires replicating laboratory attributes in real, viable production processes (Maine and Garnsey, 2006). Novel technology will be embedded with high technological uncertainty and may require investment in prototype development and pilot plant development for specific market applications (Maine and Garnsey, 2006). In particular, implementing an invention into an interdependent system of production requires matching the invention to existing routines, capabilities and equipment, as well as modifying existing processes to accommodate the invention. This process is fraught with difficulties, and we suspect that inventions that more closely target the existing routines or readily acquired complementary capabilities are more likely to be commercialized (Nelson and Winter, 1982).

While invention is likely to benefit greatly from broad access to information sources or from upstream, radical or generic knowledge from U-I collaboration, commercializing an invention may depend more on detailed understanding of the routines of potential customers or suppliers (Freeman and Soete, 1997; Teece, 1992). To the extent that information is linked to the specific activities of the firm or its partners, such as, for example, the particular equipment used and its requirements in terms of raw materials or other details of the product and process, it should increase the potential for commercialization. Therefore, collaboration with customers or suppliers conducted in the inventing stage should provide fine-grained information transfer (and joint problem solving) at the early stage that allows choosing the implementation of a technical idea that best matches with the complementary capabilities and routines of the commercializing organization(s) at the time of commercialization (Uzzi, 1996).

Kubota et al. (2011) give the example of developing next generation ArF resist materials for semiconductor manufacturing, where Fujitsu's success in developing the innovation was strongly related to its ability to incorporate the requirements and capabilities of customers and other suppliers into the R&D search process (i.e., idea generation stage). In other words, tight links between the research division and the operations units helped ensure that the choice set of potential solutions was matched to the detailed requirements of the production system of customers and suppliers that would use such innovations. In contrast, IBM, where R&D was less linked with production, and therefore customers and suppliers, came up with solutions that were technically superior (and patented), but difficult to implement (as they would require major reorganizations of the routines and capabilities of suppliers and customers). Moreover, links with customers or suppliers may provide important insights into potential market opportunities for the technology in advance. Thus, for commercialization, fine-grained information flows from specific partnerships in the invention stage may become more beneficial than breadth of information (net of invention quality). Thus, vertical collaboration may be especially useful, because of information similarity and asset complementarity.

Therefore, access to information from other firms such as customers and supplies at the early, inventing stage should be most critical for predicting commercialization rates, net of invention quality. In other words, for commercialization, the effect of vertical collaborations (at the idea generation), which should provide knowledge sharing more closely specified to the ongoing routines of the users of the technology, should be stronger than the effect of U-I collaborations (at the idea generation), which likely represent more diffused, general knowledge (Arora and Gambardella, 1994). We will empirically examine the relative effectiveness of different collaboration partners (universities versus customers/suppliers) on the different innovation stages.

Hypothesis 3. Vertical collaborations (at the idea generation stage) should have a greater impact on commercialization rates than do university-industry collaborations, net of invention quality.

At the same time, multiparty collaboration creates significant barriers to success, including higher coordination costs, communication barriers (distance and cultural barriers, lack of shared understanding), and disagreements over invention and innovation strategy (Cummings and Kiesler, 2007; Walsh and Maloney, 2007). While such coordination costs may interfere with both the invention stage and the innovation stage, these issues may be especially salient during the commercialization stage, because it is at this point in the innovation process that the firms involved have to make bets on which of several alternatives to make (often significant) investments in. Thus, the coordination costs and difficulties of matching the invention with the capabilities of the implementing firm in heterogeneous collaborations may result in heterogeneous collaborations, or U-I collaborations, at the invention stage being relatively less beneficial for commercialization, controlling for invention quality (Lhuillery and Pfister, 2009).

Hypothesis 4. The effect of knowledge heterogeneity (at the idea generation stage) should be less beneficial (null or negative) on the commercialization of the invention (at the idea implementation stage) than that on creation of high-quality invention.

This effect is expected because reduction to practice (i.e. commercialization) of invention requires relatively higher integration

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of knowledge with existing practice or selective knowledge closely related to downstream implementation.

Similarly, U-I collaboration (which are also high on heterogeneity) are likely to be less effective for successfully commercializing the invention. U-I collaborations are drawing on a broader knowledge base and such inventions are likely to be removed from tight linkages with a firm's routines, capabilities and market opportunities.

Hypothesis 5. The effect of U-I collaboration (at the idea generation stage) should be less beneficial (null or negative) on the commercialization of the invention (at the idea implementation stage) than that on creation of high-quality invention.

In other words, we are predicting that the impact of heterogeneous collaborations in inventing (variety of partners, university-industry collaborations) will have differential impacts on the invention stage and on the commercialization stage.

3. Data

For the empirical analyses, we make use of a survey of inventors in the US. These survey data allow us to collect information on research collaborations of different types and the outcomes of the invention (including the technical significance of the invention and whether it was commercialized). The data come from a survey of inventors on triadic patents (patents filed in Japan and the EPO and granted by the USPTO), with 2000–2003 priority years. We sampled 9060 patents with US-addressed inventors, stratified by NBER technology class (Hall et al., 2001). Taking the first available US inventor as a representative inventor of each patent, we have 7933 unique inventors. To increase response rate and reduce respondent burden, we surveyed one (randomly chosen) patent from each inventor. The final mail out sample was, thus, a set of 7933 unique U.S. patents/inventors. We received responses from 1919 US inventors (24% response rate, 32% adjusted).[1] We asked respondents to tell us about a specific patented invention (named on the cover of the survey). This grounds the survey in a particular invention and the specific project that generated it, which should increase the reliability of our measures. Furthermore, by asking the inventor, we collect information on the project from someone who was actively involved, and who is likely to be well informed about collaboration during the project.

These survey data have an important advantage in terms of collecting information on research collaboration that does not depend on the existence of a publicly accessible formal agreement or codified information. Much of the prior work on inter-organizational cooperation, especially on the invention process, uses patent document data such as co-inventorship, co-assignee, or citations, as measures of cooperation and uses of outside information (Hagedoorn, 2003; Hicks and Narin, 2001; Jaffe et al., 1993; Narin et al., 1997). Another stream of research uses licensing data, joint ventures or formal R&D collaborations or consortia as measures of cooperative innovation, generally collecting data from government documents, press releases and similar archival sources (Aldrich and Sasaki, 1995; Branstetter and Sakakibara, 1998; Rothaermel and Deeds, 2004; Sakakibara, 2002).

[1] Comparing respondents and non-respondents based on bibliometric indicators revealed few differences on measures related to collaboration or patent quality that were either statistically or substantively significant. In particular, measures of collaboration (solo inventions: 27% for respondents, 26% for non-respondents; average number of inventors: 2.71 for respondents, 2.80 for non-respondents), links to universities (citations to non-patent literature: 2.4 for respondents v. 2.7 for non-respondents) and measures of patent value (forward citations: 2.2 for respondents and 2.4 for non-respondents) are all similar (none are significantly different, $\alpha = 0.05$, $N = 7933$).

Table 1
Basic profile of inventors for US triadic patents.

	Sample size	1739
Academic Background	University graduate (%)	94.1
	Doctorate (%)	44.8
Demographics	Female (%)	4.4
	Mean age (std. dev.)	46.8 (9.7)
Organizational Affiliation	Large firm (>500 employees) (%)	81.4
	SME (≤500) (%)	18.6

While this prior work has provided important insights into the relations between collaboration and innovation, these data depend on a formalized codification of the cooperation, ignoring informal collaboration. Firms may generate codified information that only weakly reflects the underlying activities. For example, inventions that involve inventors from multiple organizations might be assigned to a single organization in order to simplify the property rights (Fontana and Geuna, 2009; Hagedoorn, 2003). Therefore, not just formal collaboration, but also informal collaboration may be an important component of cooperative inventing and of uses of outside information (Sattler et al., 2003). Our data provide this advantage.

For this paper, we will limit the sample to firm respondents, in order to reduce the variance caused by comparing across different institutional settings. Table 1 gives a basic profile for our sample. We see that 81% of the inventors are employed in large firms (over 500 employees), while 19% are from SMEs. We also find that about 94% of the inventors have at least a college degree, with 45% having a doctorate. The average age of inventors is 47 years old. Four percent of the sample is female.

4. Description of co-invention, co-assignee and collaboration in the US

This section describes the general phenomenon of invention collaboration in the US based on our data. Cooperative inventive activity can take many forms, including co-inventing (which has a legal meaning and can affect the validity of a patent), co-assignment (which involves sharing the property right in the invention) (Fontana and Geuna, 2009) and informal or formal collaboration (excluding co-invention and co-assignment). Bibliometric measures of co-assignment capture only one of these forms (Hagedoorn, 2003; Hicks and Narin, 2001). To complement results from bibliometric measures, we use our inventor survey data to estimate the relative incidence of different types of cooperative inventing.

First, we examine the size of the research teams, using bibliometric data (inventor lists) from the patent documents. We find that the average American triadic patent has 2.7 inventors. However, when we examine the patent documents, we find that less than 2% of US triadic patents have co-assignees (consistent with prior work on US patents by Hagedoorn (2003) and Hicks and Narin (2001), and on European patents by Giuri et al. (2007)). Moreover, we find that co-assignment is higher (in the range of 5–6% of patents) in drugs, biotech and semiconductors, which is consistent with Hicks and Narin (2001). However, Fig. 1 shows the percent external co-inventions (that is, co-invention with an inventor affiliated with an external organization), broken out by the organizational type of the co-inventors. In contrast to co-assignment, we see that 11% of triadic patents have an external co-inventor. Fig. 1 also shows that vertical links (to suppliers and customers) are the most common types of co-inventors. This finding is consistent with findings from Arora et al. (2016) that customers and suppliers are the most common sources for firms' commercialized innovations. If we add the co-inventions either with suppliers or with users, they amount to about 9% of triadic patents. These verti-

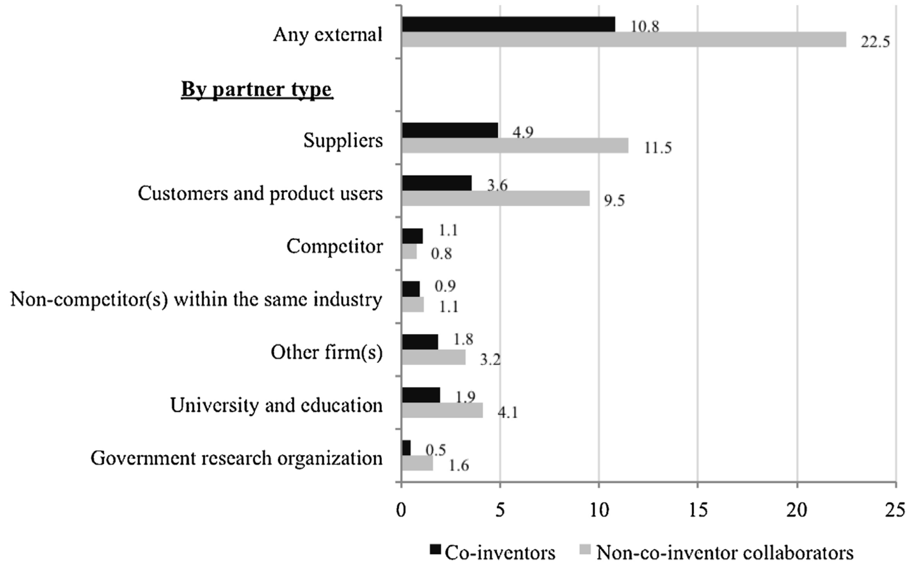

Fig. 1. Percent external co-inventors and external non-co-inventor collaborators by partner type (N = 1611).

cal links (with both customers and suppliers) are most common in materials handling and measuring/testing patents. Materials processing patents also tend to have above average rates of collaboration with competitors, non-competitors in the same industry, and with universities, suggesting that this industry, in particular, is actively involved in open innovation. Industry co-inventions with university inventors represent about 2% of the triadic patents. Co-invention with competitors or non-competitors in the same industry is rare.

If we expand our definition of cooperative inventive activity to include formal or informal collaborations other than co-invention, we find even more cross-organizational cooperation. As the non-co-inventor collaborator statistics show in Fig. 1, overall, about 23% of US patents involved non-co-invention collaboration with members of outside organizations. Again, most of these formal or informal collaborations are with customers (10%) and suppliers (12%). Universities are involved in about 4% of inventions. And, again, firms report very little horizontal cooperation with competitors or non-competitors in the same industry. For example, even if we add co-inventions and formal or informal collaborations with competitors, the sum adds up only to 2% of the inventions, which is a very small share. Difficulty of managing research collaboration among competitors may account for the very low incidence of horizontal collaboration. It is also possible that concerns about anti-trust regulations may have dampened either the activity, or the reporting of the activity, or both.

We also split the statistics of any external collaboration (co-inventor, formal or informal non-co-inventor) with suppliers, customers and universities, by firm size (Fig. 2). SMEs (compared to large firms) show higher rates of any collaboration with customers and universities ($p < 0.10$) while the difference for any collaboration with suppliers was not statistically significant. Moreover, the percent co-invention out of any type of collaboration with suppliers and customers is also higher for SMEs than large firms, although these differences are not statistically significant ($\alpha = 0.10$). The percentage co-invention out of any collaboration with universities is very similar for both large firms and SMEs (40% vs. 38%). This shows that the governance forms of collaboration with universities are very similar for both large firms and SMEs, with about 40% co-invention and 60% non-co-invention collaboration. In other words, Fig. 2 shows that a) large firms have less open innovation, on a per invention basis, but b) if they engage in open innovation, the governance forms of collaborations may not be significantly different between large firms and SMEs (cf. Fontana and Geuna, 2007).

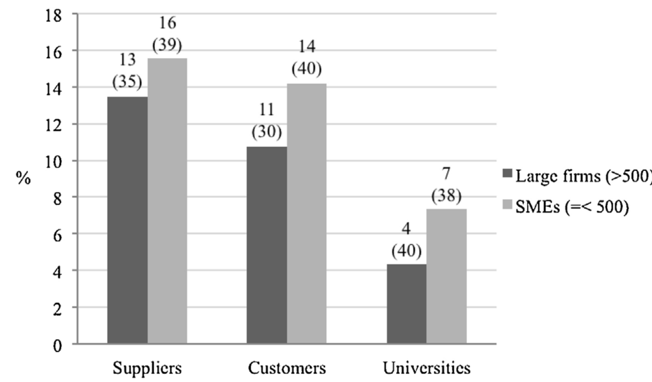

Fig. 2. Any external collaboration with suppliers, customers and universities, by firm size (N = 1638).
Note: Numbers in parentheses shows the percent co-invention out of any collaboration. For example, for large firms, 13% have any collaboration (co-invention, formal or informal non-co-inventor collaboration) with suppliers, and 35% of those have suppliers as a co-inventor (i.e. 5% of all large firms).

Table 2
Co-application, co-invention, and collaboration for US triadic patents compared to Japan and EU triadic patents.

	US	Japan	EU
Co-application, based on patent documents	1.8%	10.3%	6.1%
External co-invention	12.4%	13.2%	15%
Research collaborations not including co-invention	22.7%	28.5%	20.5%

Notes: Means are unweighted.
This comparison is across all organization types (not limiting to firms).
Japanese data from authors' Inventor Survey for Japanese triadic patents.
EU data provided by Dietmar Harhoff from PATVAL-EU survey.

Table 2 summarizes the different measures of collaboration, and also compares US triadic patents to Japanese and European triadic patents to measure how open the US is relative to other countries. We see that bibliometric indicators of co-application (i.e. co-assignment) show much less open innovation in the US than in Japan or Europe. In the US, a co-assignee can freely license his right to use the invention to a third party, while in Japan a co-assigned patent can be licensed only if all co-assignees agree (with some

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countries in Europe such as France falling in between, allowing unilateral licensing, but sometimes requiring compensation to a co-assignee). This gives Japanese co-assignees greater rights to exclude rivals than American co-assignees, which may account for the low rate of co-assignment in the US (because co-assignment involves giving up greater control in the US than in Japan). The European statistics of co-application are bounded between the US and Japan. On the other hand, the overall rates of external co-invention are similar in the three regions, as are the rates of non-co-invention collaboration (with Japan somewhat higher than the US and especially Europe).

Thus, these indicators suggest that invention is much more open than bibliometric indicators would suggest, and that cross-region variation is less than bibliometric indicators have shown. Using co-assignment would miss 85% of US external co-invention and over 90% of non-co-invention collaboration. Even for Japan, co-assignment would miss over 20% of the external co-invention and almost two-thirds of the non-co-invention collaboration. For Europe, co-assignment would miss 60% of the external co-invention and 70% of non-co-invention collaboration.

On the other hand, it should be noted that, despite the importance of open innovation, it is still the case that the vast majority of triadic patent inventions are internally generated, relying neither on external co-inventors nor on external non-co-inventor collaborators. In fact, almost 90% of these inventions have no external co-inventors. Of course, these inventions may make significant use of external information sources (see Frenz and Ietto-Gillies, 2009; Laursen and Salter, 2006; Walsh and Nagaoka, 2009). And, these firms may make use of external partners when developing the invention into a commercial product. But, in the invention process, autarkic invention is common in all three regions (cf. Kneller, 2003). Thus, while open innovation is more common than generally observed based on bibliometric or archival data, it is not the modal form of invention.

5. Measures: technical significance, commercialization, and collaboration

In this section, we describe the variables used to test our theoretical arguments of the effect of knowledge heterogeneity and the relative benefits of different types of partnerships in collaboration on invention quality and commercialization.

5.1. Dependent variables

5.1.1. Technical significance as invention quality

Our first arguments concern the effects of collaboration form on invention quality. We measured invention quality using a self-reported measure asking the inventor how he rated the *technical significance* of the invention, compared to other technical developments in his field in the US in that year. We asked the inventor to rank his invention as being either in the top 10%, top 25% but not top 10%, top half but not top 25%, or bottom half, compared to others in the field at the same time (see Appendix A for question wording).

While self-evaluated measures may suffer from potential reporting biases, they also represent an expert assessment of relative value. In addition, such measures are not confounded with the various drivers of patent citations that may be unrelated to value (Alcacer et al., 2009; Hegde and Sampat, 2009). In our sample, 15% of the inventors rated their patents in the top 10% in technical significance. We also find that 34% reported being in the bottom 50% on technical significance. Since we would expect some oversampling of high-value patents in a sample of triadic patents, these figures suggest that our inventors were reasonably accurate in their assessments of the relative value of their patents.

Using the European inventor survey data, Gambardella et al. (2008) find a very high correlation between inventor assessments and manager assessments of patent value among French inventions, also suggesting that inventors may be reasonably accurate at ranking the relative value of their patents. Furthermore, our self-reported measures are correlated with the size of the project, whether the patent was commercialized, and number of IPC classes. Forward citations are also correlated with these value indicators, but the associations are not as strong, suggesting that there may be substantial noise in forward citations (see No and Walsh, 2010). Gambardella et al. (2008) also show that inventor-based measures of value are strongly correlated with other measures of value: such as number of countries the patent is filed in (family size), opposition hearings, and number of claims, although the correlation with the noisier forward citation measure tends to be weaker. Similarly, as in our case, Harhoff et al. (1999) find that patent owners' self-assessed value of the patent is correlated with number of forward citations, but also note that the relation is quite noisy, with an R-squared of about 0.06 for the US data and 0.01 for the German data. Thus, we have some confidence that our self-reported measure of value is a valid measure, complementing the limitation of measures of forward citations. This may be especially true for triadic patents, which exclude many of the low-value, low-citation inventions, and hence would attenuate the correlation between citations and value in our sample (No and Walsh, 2010). We will use this ordinal measure (ranging from 1 = "bottom half" to 4 = "top 10%") as our measure of invention quality.

5.1.2. Commercialization

For our second outcome variable, commercialized innovation, we asked whether the invention is commercialized either through internal use, license or startups. We measure *commercialization* as 1 if the patent was used for any of these commercial uses, and 0 otherwise. We also use a narrower definition of commercialization, *in-house* commercialization, that is 1 if the invention was commercialized by the respondent's firm (to exclude cases where the only commercialization was a license that was part of the initial collaboration agreement).

5.2. Independent variables

For the focal invention, we asked the surveyed inventor how many inventors are on the patent, and which types of organizations the co-inventors worked for (own firm, supplier, customer, university, etc.) (see Appendix A). These were recoded as a set of dummy variables with a value of 1 if there was an external co-inventor from that type of organization, and 0 otherwise. We also asked if, in addition to co-inventors, there were any formal or informal collaborations and what types of organizations these collaborators represented. Again, these were coded as a set of dummy variables representing types of external collaborators.

5.2.1. Collaboration heterogeneity

We measure the *heterogeneity* of the collaboration by using our measure of the number of different kinds of partners (e.g., universities, suppliers, customers, competitors, etc.) that were either co-inventors or with whom there was a formal or informal collaboration (i.e., the union of the two types of collaboration). This measure reflects the constrained search (bounded rationality) model of information access (Cohen and Levinthal, 1990; Nelson and Winter, 1982; Simon, 1947), where, in this case, the search space is structured by the position of an organization in an organizational field (DiMaggio and Powell, 1983). Each type of organization (focal firm, suppliers, customers, universities, etc.) has better access to certain types of information and more difficulty getting unmediated access to other types of information (due to its localization, its

Table 3
Distribution of the heterogeneity of the cooperating organizations.

Number of different partners for any external collaboration	%
0	73.3
1	17.0
2	6.8
3	2.0
4+	1.0
Total (N)	100 (1638)

tacit nature, or the limited absorptive capacity of the focal firm for that type of information). Therefore, collaboration with other kinds of organizations for research can increase the richness of the search space, and therefore the probability of a high-value discovery (Nelson and Winter, 1982). Based on the measure of heterogeneous collaborations, 27% involve some collaboration, with 37% of those involving multiple external partners (see Table 3).

5.2.2. Specific types of partnerships

We also distinguish two kinds of collaboration partners: *U-I collaboration* and *vertical collaboration* with either suppliers, customers or both. These two measures allow us to distinguish our arguments about the relative importance of distant information (breadth of search) versus specified information (fine-grained information transfer) for the two stages of the innovation process (invention versus commercialization). We argue that U-I collaborations are broader, because they cross sectors and because universities are repositories for a wide range of information, including recently created information, and hence should be relatively more important for generating inventions of higher quality (technical significance), compared to vertical collaborations with suppliers and/or customers. In contrast, vertical collaborations may be better at transmitting fine-grained information specified to the particulars of the routines of suppliers and customers that are critical for integrating the invention into the on-going activities of the firm and its partners. Therefore, having vertical collaborations early on at the inventing stage helps reflect that information even when conceptualizing new ideas, and should be more effective at generating commercializable inventions later, compared to university-industry collaborations (net of technical significance).

5.3. Control variables

In addition to these measures of our dependent and independent variables, we also control for some variables likely related to invention quality and/or commercialization. We created and controlled for a dummy variable for having a PhD or not based on the question asking highest degree of the responding inventor, as inventor's education level may affect invention outcomes. We also control for the number of researcher-months used by the project, since bigger projects may have higher technical significance and perhaps higher likelihoods of commercialization. We control for size of the respondent's firm: large (over 500 employees), and SMEs ($\leq$500 employees), as large firms are more likely to patent for reasons other than commercialization, so called strategic patenting (Blind et al., 2006; Cohen et al., 2002; Walsh et al., 2016). From the patent publication, we collected data on the number of inventors to see the effect of collaboration net of group size. We also collected the primary technology class of the invention to control for technology environment. In the regressions, we use five one-digit NBER class dummy variables to control for technology class, based on the primary technology class of the invention (with "Other" as the excluded category) (Hall et al., 2001). We also control for the extent to which the primary inventor was engaged in upstream (basic and applied) research, likely driving radical invention and also affecting difficulty of immediate implementation of the invention. We control for the filed year for the patent to control for a cohort effect.

5.4. Descriptive statistics

Table 4 displays descriptive statistics for the variables.[2] We see that 54% of patents were commercialized in some form. The table also shows that 20% involve vertical collaborations and 5% involve university-industry collaborations (where collaboration includes co-invention and other formal or informal collaboration). The average patent has 2.7 inventors and requires 19 researcher-months.

6. Empirical findings: relationships among collaboration, invention quality and commercialization

6.1. Hypothesis tests

Based on the discussion in Section 2 above, here, we empirically examine the relationships between collaboration and innovation. First, we begin with models predicting the quality of the invention: technical significance. Based on the theories described above, we expect more heterogeneous project teams should be associated with higher invention quality, and U-I collaboration should be relatively more effective on invention quality than is vertical collaboration.

Models 1–5 in Table 5 show the results of ordered logit regressions predicting the technical significance of the patent. We first find in Model 1 that inventions that were based on a more heterogeneous collaboration (more kinds of organizations represented) are of significantly higher technical significance (controlling for technology class, firm size, inventor human capital, and project size and type). To see if closeness of the collaboration (form of governance) differentially affects this relation, we further decompose collaboration heterogeneity into co-invention collaboration heterogeneity and non-co-invention heterogeneity in Models 2–4 and find this result is robust across heterogeneity measures with different governance forms. Thus, we find strong support for our first hypothesis. Next, Model 5 in Table 5 shows the effects of U-I collaboration and vertical collaboration. Both U-I collaboration and vertical collaboration increase technology significance. We further test the equality of the effects of U-I and vertical collaborations and do not find significant difference ($\alpha = 0.10$). Therefore, we cannot conclude that university-industry collaboration is significantly more effective for increasing technical significance than is vertical collaboration (Hypothesis 2 is not supported).[3]

Our second argument is that heterogeneity of collaboration and specific types of partnerships in the collaboration can have different influences on the commercialization stage. The difficulty of coordination, which is more necessary for commercial use of the invention, may cancel out the positive information benefits of mul-

[2] This survey used a stratified sample with equal probability, except for multi-invention inventors. The number of patents belonging to each unique inventor was recorded to use as a weight to check the effect of the weight. For descriptive statistics and graphs in this paper, we applied weights. Regression analyses do not incorporate the sampling weights. However, comparing statistics with weights and without weights, we found that the weights have minimal effect on the estimates.

[3] For the main ordered logit models, i.e., Models 1 and 5, we test if the parallel lines assumption is violated. Based on an approximate LR test, the parallel regression assumption cannot be rejected ($p = 0.13$ for Model 1 and $p = 0.15$ for Model 2). Based on the Brant test, the omnibus test rejects the hypothesis of parallel regressions for Model 1 at 0.10 level ($p = 0.08$). However, the tests for individual coefficients show that the assumption is not violated for the collaboration heterogeneity variable ($p = 0.47$). For Model 5, the Brant test shows that in the omnibus test, the hypothesis of parallel regressions cannot be rejected ($\alpha = 0.10$), and also in the tests for individual coefficients, the assumption is not violated for both U-I collaboration ($p = 0.21$) and vertical collaboration ($p = 0.93$).

Table 4
Descriptive statistics and correlation matrix.

	Variable	N	Mean	S.D.	Correlation 1	2	3	4	5	6	7	8	9	10
1	Technical significance (1–4)	1420	2.19	1.07	1.00									
2	Any commercialization	1618	0.54	0.50	**0.22**	1.00								
3	Collaboration heterogeneity	1638	0.41	0.82	**0.12**	**0.12**	1.00							
4	Vertical collaboration	1638	0.20	0.40	**0.06**	**0.14**	**0.73**	1.00						
5	U-I collaboration	1638	0.05	0.22	**0.09**	−0.02	**0.48**	**0.09**	1.00					
6	PhD degree	1737	0.45	0.50	**0.07**	**−0.13**	**−0.06**	**−0.10**	**0.05**	1.00				
7	Researcher-months	1647	19.00	23.43	**0.18**	−0.01	**0.14**	**0.08**	**0.09**	**0.13**	1.00			
8	Number of inventors	1739	2.70	1.81	**0.07**	0.01	0.02	0.01	0.02	**0.09**	**0.25**	1.00		
9	Large firm	1739	0.81	0.39	**−0.13**	**−0.13**	**−0.07**	−0.03	**−0.05**	0.02	−0.03	0.04	1.00	
10	Upstream research	1669	0.19	0.39	0.04	**−0.18**	−0.03	**−0.08**	**0.07**	**0.26**	**0.12**	**0.05**	0.05	1.00
11	Filed year	1739	2001	0.99	**0.07**	−0.03	0.00	−0.02	0.01	0.02	0.02	0.02	−0.03	0.02

Bold: p < 0.05.

Table 5
Regressions of invention quality and commercialization on research collaboration.

	Ordered logit Technical significance					Logit Any commercialization						In-house use
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Technical significance						0.420***	0.445***	0.412***	0.425***	0.426***	0.404***	0.419***
						(0.062)	(0.063)	(0.064)	(0.065)	(0.063)	(0.124)	(0.063)
Collab. heterogeneity	0.238***					0.167**						
	(0.062)					(0.078)						
Co-inventor hetero.		0.259***		0.222**			−0.072		−0.142			
		(0.096)		(0.098)			(0.113)		(0.118)			
Non-co-inv hetero.			0.214***	0.185**				0.275***	0.315***			
			(0.071)	(0.073)				(0.094)	(0.099)			
U-I collaboration					0.527**					−0.145	−0.026	−0.447
					(0.230)					(0.284)	(0.673)	(0.287)
Vertical collaboration					0.258**					0.529***	0.953***	0.590***
					(0.127)					(0.157)	(0.350)	(0.155)
PhD degree	0.458***	0.450***	0.431***	0.458***	0.437***	−0.404***	−0.466***	−0.460***	−0.502***	−0.381***	−0.604**	−0.415***
	(0.109)	(0.109)	(0.110)	(0.111)	(0.109)	(0.131)	(0.132)	(0.133)	(0.135)	(0.132)	(0.264)	(0.132)
No. of inventors	0.035	0.022	0.040	0.032	0.034	0.038	0.048	0.047	0.062*	0.038	−0.051	0.067**
	(0.028)	(0.029)	(0.029)	(0.029)	(0.028)	(0.034)	(0.035)	(0.035)	(0.036)	(0.034)	(0.078)	(0.034)
Researcher-months	0.016***	0.017***	0.016***	0.016***	0.016***	−0.001	0.000	−0.001	−0.001	−0.001	−0.002	−0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.003)
Large firm	−0.592***	−0.612***	−0.624***	−0.635***	−0.586***	−0.642***	−0.686***	−0.592***	−0.627***	−0.655***	−0.508	−0.434***
	(0.134)	(0.135)	(0.138)	(0.139)	(0.134)	(0.166)	(0.167)	(0.170)	(0.172)	(0.166)	(0.332)	(0.162)
Upstream research	0.116	0.066	0.132	0.113	0.099	−0.795***	−0.843***	−0.754***	−0.766***	−0.767***	−0.574	−1.026***
	(0.142)	(0.144)	(0.147)	(0.149)	(0.142)	(0.174)	(0.177)	(0.179)	(0.183)	(0.174)	(0.367)	(0.185)
Filed year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NBER classes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1284	1263	1246	1225	1284	1214	1194	1177	1157	1214	307	1196
LR Chi2	125.9***	118.2***	121.5***	126.1***	121.7***	132.4***	131.4***	134.0***	139.7***	139.3***	42.7***	153.9***

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

tiparty collaborations at the inventing stage. This will make the effect of heterogeneous collaboration weaker on commercialization, net of invention quality, which already reflects the benefits of heterogeneous collaborations and U-I collaboration spanning institutional spheres at the invention stage. However, collaboratively generated inventions may benefit from more customization of the invention to improve the match between technological opportunities and the user's needs (Kubota et al., 2011), and fine-grained information transfer that can facilitate commercialization (Uzzi, 1996). This should be especially true for the case of vertical collaborations, which should become more beneficial at the stage of commercialization.

Based on these arguments, we test the effects of collaboration forms on commercialization using a logistic regression (Models 6–10 in Table 5) where the outcome variable is the commercialization of the invention (either in-house, licensing or through a startup, see Appendix A), controlling for invention quality and for inventor, project and firm characteristics. Across Models 6–10 in Table 5, first, invention quality has a significantly positive effect on the probability of commercialization (which helps validate our measure of technical significance). Next, Model 6 shows that heterogeneity still has a strong positive effect on commercialization (net of invention quality). However, when decomposing this composite measure of heterogeneity into co-invention collaboration heterogeneity and non-co-invention collaboration heterogeneity in Models 7–9, we can see that only non-co-invention collaboration heterogeneity has a positive significant effect whereas co-invention collaboration heterogeneity has a negative direction, losing significance. This distinct effect between co-invention collaboration heterogeneity and non-co-invention collaboration heterogeneity partially supports our theory of a null or negative effect of heterogeneity, net of invention quality (Hypothesis 4), due to the difficulty of integration. Co-invention collaboration is more formalized collaboration, specifying the objectives of the collaboration and the contributions of all participants from different organizations, while non-co-invention collaboration is more loosely defined and relatively more dependent on informal interaction (Janowicz-Panjaitan and Noorderhaven, 2008; Van Aken and Weggeman, 2000). Therefore, in heterogeneous co-invention collaboration, participants from different organizations may need to reach an agreement on the direction for developing the invention, making the focal firm less able to incorporate their own production knowledge into the invention and thereby making it harder to reduce the invention to practice for commercialization. Moreover, licensing the technology to another party is also very limited in such collaborations because all assignees must agree. This causes a null or even negative effect on commercialization. However, in heterogeneous non-co-invention collaboration, the inventor in the focal firm can acquire external knowledge but also reflect their production capabilities in the invention in advance, free from pressure for reaching a formalized agreement. Hence, we can still observe a significant positive effect for heterogeneous non-co-invention collaboration on commercialization, net of invention quality. Hence, we have partial support for Hypothesis 4.

As noted above, this heterogeneity variable also contains distinct forms of collaboration, including U-I collaborations and vertical collaborations with suppliers/customers, which we expect to have distinct effects on commercialization. In Model 10, we see that vertical collaboration has a large positive effect. On the other hand, a link with universities has a negative, but not significant, effect on commercialization, net of invention quality.[4] Thus, we find Hypothesis 3 is supported. Furthermore, we find that, while U-I industry collaborations have a significant positive association with invention quality (technical significance), the relation with commercialization is non-significant (and even negative), supporting Hypothesis 5. These results are consistent with the argument that vertical collaboration provides targeted information flows at the inventing stage that increase the likelihood of turning an invention into an innovation and hence will have a greater effect on commercialization than do U-I linkages, which are likely to provide less specified information. This may be due to the links with, for example, customers and suppliers allowing a ready market for the technology, and to the technology being developed with those markets (and their detailed needs) clearly in mind (cf. Kubota et al., 2011).

We can also see that the control variables give the expected results. Having a PhD is associated with an invention with higher technical significance. On the other hand, a PhD inventor and the degree to which this invention is based on upstream research are negatively related to commercialization, net of technical significance. Also, the average invention for large firms is of lower technical significance and has a lower commercialization rate, most likely because large firms engage in more preemptive patenting (Cohen et al., 2002; Walsh et al., 2016).

In summary, first, the empirical results show that heterogeneity (or breadth of knowledge) generally has a positive impact on both invention quality and commercialization. However, when we decompose collaboration heterogeneity into co-invention collaboration heterogeneity and non-co-invention collaboration heterogeneity, we can see distinct effects of heterogeneity on invention quality and commercialization, consistent with our theory of integration difficulty generating commercialization difficulty. Moreover, the effects of specific partnerships show different strengths on the different stages of innovation. Both types of partnerships are important for generating high quality inventions. However, when the invention goes to the commercialization stage, information collected from vertical collaboration at the inventing stage becomes much more beneficial for commercialization than information collected at the inventing stage from U-I collaboration.

6.2. Robustness checks

We have some concerns that our results might be affected by confounds in our measures. We ran several robustness checks to see how sensitive these results are to different specifications.

There may be some concerns that the effect of vertical collaboration on commercialization is biased due to endogeneity of vertical collaboration. We would like to reemphasize several points here in terms of this concern. What we analyze is the effect of collaboration at the inventing stage (with universities or suppliers/customers) on commercialization, regardless of the existence of collaboration to practice the invention at the commercialization stage. There is an order of behaviors and a time gap between collaboration during inventing and commercialization of the invention, mitigating against endogeneity. Furthermore, to see if there were different *a priori* expectations for commercialization between U-I collaboration and vertical collaboration, we test the difference in commercial motive between these two groups of patents. For conducting the *t*-test for group differences, we first create exclusive categories of U-I collaboration and vertical collaboration, excluding cases having both. We also measured the commercial motive associated with each patent. For motive to patent, the survey asked "how important were the following reasons for patenting this invention at the time of the invention? (1 = not important to 5 = very important)." Out of the available items, we define items, "Commercial exploitation (to obtain exclusive rights to exploit the invention economically)" and "Licensing (to obtain exclusive rights to license the invention in order to generate licensing revenues)", as commercial motives. Other items present strategic reasons for patenting or reasons for patenting to increase the firm's reputation and hence are excluded. If the union of the two items for commercial motive has the maximum value, 5 (=very important), commercial motive is coded as high and if it has lower values (1–4), commercial motive is coded as low. Using these two variables (U-I vs. vertical, high vs. low commercial motive), we do a *t*-test and find there is no significant difference in the rates of high commercial motive between patents from exclusively U-I collaboration and those from exclusively vertical collaboration (68.9% v 69.4%, $p = 0.94$). Therefore, we do not find evidence that patents from vertical collaborations are more commercially motivated than are inventions from U-I collaborations, suggesting that differential expectations of commercialization are not driving the differences in the impacts of collaboration structure of commercialization.

As additional checks against the results being due to endogeneity of the collaboration structure (being the result of the commercialization), we did two other robustness checks. First, to reduce the possible impact of *a priori* expectations, we limit the cases in our analysis to those where the invention was either an unexpected byproduct of the R&D project or was the result of pure inspiration/creativity (based on a question in the survey asking about the creative process that led to the invention). Model 11 in Table 5 shows the results. We find that the impact of vertical collaboration on commercialization is still positive (with the coefficient at least as large as before), and statistically significant (even with the greatly reduced sample size).[5]

A related concern is that the effect of commercialization is driven by collaboration partners agreeing *a priori* to assign the patent to one partner and license it to the other, so that collab-

[4] Further, we test the equality of these two effects of U-I and vertical collaborations and find a significant difference ($p < 0.05$).

[5] If we limit the sample to only "unexpected byproduct of an R&D project" the N goes down further, but the coefficient is still positive (and at least as large as before) and significant ($p < 0.10$).

oration is endogenous to commercialization. To check that this licensing effect is not driving the results, we reran the regression using in-house commercialization (using the invention in the firm's own products or processes) as the measure of commercialization, since this variable is not related to *a priori* out-licensing agreements by the focal firm. In Model 12 of Table 5, we replicate model 10, but with in-house use as the dependent variable. As we see in Model 12, even limiting to in-house use, the results are consistent. In particular, vertical collaboration during the invention stage still has a significant positive effect on commercialization, even if we focus on in-house commercialization.

There may also be concern that collaboration is endogenous to the value of the project, perhaps because when firms are faced with potentially high-value projects, they are more likely to take on partners (or, perhaps, partners are more willing to take on collaboration if it seems that the project will be high value). Therefore, we estimated an instrumental variable (IV) probit model for the first model from Table 5, using a binary variable of being in the top 10% or not on technical significance as the outcome variable and using a regional-level variable of patents per capita in the respondent's SMSA as the instrument. We argue that patents per capita will represent the degree of information spillovers in a region, and hence reduce the need for collaboration (Jaffe et al., 1993; Owen-Smith and Powell, 2004; Partha and David, 1994). Thus, patents per capita in the region should directly affect collaboration heterogeneity, but not be correlated with variation in the quality of the particular invention (net of other exogenous variables) because generating an invention of observed quality occurs after creative use of technology or industry-related knowledge, not from having large information spillovers.

Table 6 shows the results of a probit model in Model 1, using a binary variable of being in the top 10% or not on technical significance as the outcome variable, and an IV probit model in Models 2 and 3, using a regional-level variable of patents per capita in the respondent's SMSA as an instrument. The results of the first stage (Model 3) shows that patents per capital has a negative significant effect on collaboration heterogeneity, as described above. Then, in the results of the second stage, instrumenting for collaboration heterogeneity still shows a positive significant effect on invention quality, consistent with the probit model in Model 1, although the coefficient is adjusted. Therefore, possible endogeneity in our measure of collaboration heterogeneity does not nullify our results.

As an alternative instrument, we followed Hottenrott and Lopes-Bento (2015) and used the percent of collaborating firms in the respondent's technology class as an instrument. Hottenrott and Lopes-Bento (2015) argue that this should increase the pool of potential collaborators, but also should be unrelated to the technical significance of a particular invention. Models 5 and 6 in Table 6 show the results. In the first stage (Model 6) we see a significant positive effect of the instrument on collaboration heterogeneity. In the second stage, we still see a significant positive effect of heterogeneity on technical significance. Thus, using two different instruments (with distinct effects in the first stage regressions), we find our main result robust to possible endogeneity.

In summary, we have some evidence that collaboratively produced inventions are more likely to be of greater technical significance. Vertical collaboration tends to increase both the technical significance and the probability of commercialization while collaboration with a university tends to enhance only the technical significance of the invention, but does not increase commercialization net of its impact on technical significance. These results show the benefits from open innovation (Chesbrough, 2003). However, the details of the relationships also are consistent with predictions from the evolutionary perspective, with its emphasis on bounded rationality, local search, the lumpiness of information space and the importance of existing routines as a constraint on the paths of innovation (Nelson and Winter, 1982).

7. Conclusions

Adding to the debate on open innovation, our results suggest several important findings from decomposing the innovation processes into inventing and commercializing. First, we find that, in the US, just over 10% of triadic patents have external co-inventors. These results suggest that co-assignee data are not a good predictor of cooperative inventive activity and understate the rates of open innovation. The results also show that most co-invention is with vertically related firms (suppliers or customers/users), and co-invention with competitors is very rare. We also find that about 23% of triadic patent inventions involve external (non-co-inventor) collaborators (with 27% involving any external collaborators, spanning co-inventors and non-co-inventors).

Open innovation through collaborations is associated with enhanced quality and commercialization rates of the invention. To be specific, heterogeneous collaboration and collaboration with a university are associated with higher invention quality, as is vertical collaboration. Vertical collaboration in inventing is especially likely to result in commercialized inventions (compared to collaborations with universities). For example, vertical collaboration may provide information that is useful for guiding the development of the invention into a commercial product (so that it better matches the needs of customers or the capabilities of suppliers). In addition, heterogeneity of non-co-inventor collaborators increases commercialization, but heterogeneity of co-inventors does not (suggesting that coordination costs may make commercialization difficult). While vertical collaboration increases both invention quality and commercialization, collaboration with universities primarily increases invention quality, but not commercialization (net of quality).

Interestingly, despite calls for more open innovation, and the value of research collaboration, we find that the vast majority of inventions did not involve any outside partner. This suggests that there may be opportunities for improving innovative performance by partnering with external sources. However, at the same time, although openness in inventing may be beneficial to invention quality and its commercialization, that is not the dominant norm in industry, with internally generated inventions still being the majority. Thus, while open innovation is in vogue, innovation researchers may be missing opportunities to explore the strengths of internally generated innovations and why firms choose to innovate internally even when open innovation generates inventions of higher technical significance or commercializability. Our statistics suggest that we need a more nuanced approach to this question of the conditions under which open innovation versus internally developed innovation may be more beneficial.

We also find that the ideal partner may vary by the goals of the research. The technical significance of the invention is influenced by the breadth of information access, with heterogeneous partnerships being the most effective. In contrast, the commercialization rate is most heavily influenced by more specific partnering with those in the vertical supply chain (customers or suppliers) in inventing. This suggests that the types of information that benefit invention and innovation may be distinct, and that managers in research and development and policy-makers need to balance an interest in promoting broad information access with a need to match information searching to the needs and capabilities of the innovating firm.

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Table 6
Instrumental variable (IV) probit regressions of top 10% of technical significance on collaboration heterogeneity.

	Probit	IV Probit		IV Probit	
		Second stage	First stage	Second stage	First stage
	(1)	(2)	(3)	(4)	(5)
Collab. hetero.	0.100**	1.038***		0.879***	
	(0.049)	(0.241)		(0.259)	
PhD degree	0.110	0.228***	−0.161***	0.215**	−0.150***
	(0.095)	(0.079)	(0.051)	(0.084)	(0.049)
No. of inventors	0.031	0.032	−0.006	0.032	−0.009
	(0.023)	(0.022)	(0.013)	(0.020)	(0.013)
Researcher-months	0.008***	0.000	0.005***	0.002	0.005***
	(0.002)	(0.004)	(0.001)	(0.003)	(0.001)
Large firm	−0.450***	−0.184	−0.091	−0.252*	−0.101*
	(0.105)	(0.188)	(0.063)	(0.151)	(0.059)
Upstream research	0.090	0.143	−0.083	0.158	−0.099
	(0.121)	(0.100)	(0.066)	(0.106)	(0.064)
Filed year	Yes	Yes	Yes	Yes	Yes
NBER class	Yes	Yes	Yes	Yes	Yes
Patents per Capita			−0.491**		
			(0.204)		
Collaboration pool					1.434***
					(0.438)
N	1284		1145		1284
Wald Chi2	59.3***		233.4***		147.03***

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Appendix A. Questions for main variables

The measures of collaboration structure are built from the following questions:

"The following questions ask about the collaboration that created this invention. First, please indicate the number of inventors on the focal patent (including yourself), listed by the organizations to which they belonged. [Answer categories: your firm; suppliers for parts, materials, equipment, software, etc. (including contract manufacturers); customers and product users; competitors; non-competitors in the same industry; other firms; universities; government research organizations; hospitals (including university hospitals), foundations, or private research organizations; other]. Second, for the research leading to this patent was there any (formal or informal) collaboration between your employer/organization and other partners (excluding co-inventors to the focal patent)? Please check all that apply. [Same answer categories.]"

The measure of invention quality (technical significance) is built from the following questions:

"Compared to other technical developments in your field during the year the focal patent was applied for, how would you rate the technical significance of your invention, in the US?". [Answer categories: Top 10%; Top 25% but not top 10%; Top half, but not top 25%; bottom half; Don't know.]"

The measures of invention commercialization (overall and in-house) are built from the following questions:

[in-house use] "Has the applicant/owner ever used the patented invention in a product/process/service that has been commercialized? [Yes; No; Not yet, but still investigating the possibilities; Don't know.]"

[license] "Has the focal patent been licensed by (one of) the patent-holder(s) to an independent party? [Yes; No; No, but willing to license; Don't know.]"

[start-up] "Has this patent been exploited by yourself or any of your co-inventors for starting a new company? [Yes; No; Don't know.]"

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